Personal Loan Acceptance

Notebook File - Loan_Acceptance.ipynb

Github Repo - Bank Loan Acceptance

Dataset Repo - Universal bank data for classification

Context:

This case is about a bank (Universal bank) which has a growing customer base. Majority of these customers are liability customers (depositors) with varying size 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 to better target marketing to increase the success ratio with a minimal budget.

The department wants 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.

Problem Statement:

The classification goal is to predict the likelihood of a liability customer buying personal loans.

Attribute Information

The file UniversalBank.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.

Input variables:

1) **ID** (Customer ID)

2) **Age:** Customer's age in completed years

3) **Experience:** years of professional experience

4) **Income:** Annual income of the customer ($000)

5) **ZIP Code:** Home Address ZIP code.

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

7) **Education:** Education Level

- 1 - Undergrad
- 2 - Graduate
- 3 - Advanced/Professional

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

9) **Family:** Family size of the customer

10) **Securities Account:** Does the customer have a securities account with the bank?

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

12) **Online:** Does the customer use internet banking facilities?

13) **Credit card:** Does the customer use a credit card issued by

Output variable (desired target):

14) **Personal Loan:** Did this customer accept the personal loan offered in the last campaign?

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1. Environment Setup

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1.1. Install Packages

Install required packages

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In [1]:

```
# Install pandas
! pip install pandas

# Install matplotlib
! pip install matplotlib

# Install seaborn
! pip install seaborn

# Install sklearn
! pip install sklearn

# Install tqdm to visualize iterations
! pip install tqdm
```

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\site-packages (4.59.0)
```

1.2. Load Dependencies

Import required packages

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In [2]:

```python
# Import libraries necessary for this project
import numpy as np
import pandas as pd
import scipy.stats as stats
import math
from tqdm import tqdm
import matplotlib.pyplot as plt

# Pretty display for notebooks
%matplotlib inline

import seaborn as sns

# Set default setting of seaborn
sns.set()
```

In [3]:

```python
# Import label encoder
from sklearn.preprocessing import LabelEncoder

# Import the required function for normalization
from sklearn.preprocessing import StandardScaler

# Import train and test split function
from sklearn.model_selection import train_test_split
```

In [4]:

```python
# Import Classifiers to be used

# Import Logistic regressor
```

```
from sklearn.linear_model import LogisticRegression

# Import Naive bayes classifier
from sklearn.naive_bayes import GaussianNB

# Import Support Vector Machine
from sklearn.svm import SVC

# Import Grid Search Cross Validation for tunning
from sklearn.model_selection import GridSearchCV

# Import Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
```

In [5]:

```
# Import packages to calculate performance of the models
from sklearn import metrics

# Function to compute confusion metric
from sklearn.metrics import confusion_matrix

# Function to generate classification report
from sklearn.metrics import classification_report

# Function to calculate PR AUC Score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import auc
from sklearn.metrics import f1_score
```

In [6]:

```
# To save the model
import joblib
```

In [7]:

```
# Create output folder to save model and plots
import os

# Get current working directory
current_dir = os.getcwd()

# Folder to save model
model_dir = current_dir + "/model"
os.makedirs(model_dir, exist_ok=True)

# Folder to save plots
plots_dir = current_dir + "/plots"
os.makedirs(plots_dir, exist_ok=True)
```

2. Load dataset

Read data from personal_loan.csv file using pandas method read_csv().

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In [8]:

```
# read the data
raw_data = pd.read_csv(current_dir + '/data/UniversalBank.csv')

# print the first five rows of the data
raw_data.head()
```

Out[8]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account
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

3. Data Types and Dimensions

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In [9]:

```
print("Universal Bank Data Set has \033[4m\033[1m{}\033[0m\033[0m data points with \
```

```
Universal Bank Data Set has 5000 data points with 14 variables each.
```

In [10]:

```
# check the data types of the features
raw_data.info()
```

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

Note:

Features like **Family**, **Education**, **Personal Loan**, **Securities Account**, **CD Account**, **Online** and **CreditCard** are actually categorical in nature but are represemted as numeric so we need to convert them for better analysis.

4. Data Preprocessing

Data preprocessing is a data mining technique which is used to transform the raw data in a useful and efficient format.

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4.1. Data Cleaning

Data cleaning refers to preparing data for analysis by removing or modifying data that is incomplete, irrelevant, duplicated, or improperly formatted.

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In [11]:
```
# Rename features
raw_data.columns = ["ID", "Age", "Experience", "Income", "ZIPCode", "Family", "CCAvg
                    "Mortgage", "PersonalLoan", "SecuritiesAccount", "CDAccount", "O
```

4.1.1. Remove irrelevant features

The first and foremost thing you should do is remove useless pieces of data from your system. Any useless or irrelevant data is the one you don't need. It might not fit the context of your issue.

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In [12]:
```
# Create copy of the dataframe
data_1 = raw_data.copy(deep = True)
```

In [13]:
```
# Dropping Unneccesary columns
data_1.drop(["ID","ZIPCode"], axis=1, inplace=True)

# print first five rows
data_1.head()
```

Out[13]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	PersonalLoan	SecuritiesAccount
0	25	1	49	4	1.6	1	0	0	1
1	45	19	34	3	1.5	1	0	0	1
2	39	15	11	1	1.0	1	0	0	0
3	35	9	100	1	2.7	2	0	0	0
4	35	8	45	4	1.0	2	0	0	0

4.1.2. Convert Data Types

Data types should be uniform across your dataset. A string can't be numeric nor can a numeric be a boolean.

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In [14]:
```
# Create copy of the dataframe
```

```
data_2 = data_1.copy(deep = True)
```

In [15]:

```
# Create list of features to be converted into category
cat_cols = ["Family","Education","PersonalLoan","SecuritiesAccount","CDAccount","Onl
```

In [16]:

```
# Convert numeric to categorical
for feature in cat_cols:
    data_2[feature] = pd.Categorical(data_2[feature])
```

In [17]:

```
# Check for datatypes
data_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Age                5000 non-null   int64
 1   Experience         5000 non-null   int64
 2   Income             5000 non-null   int64
 3   Family             5000 non-null   category
 4   CCAvg              5000 non-null   float64
 5   Education          5000 non-null   category
 6   Mortgage           5000 non-null   int64
 7   PersonalLoan       5000 non-null   category
 8   SecuritiesAccount  5000 non-null   category
 9   CDAccount          5000 non-null   category
 10  Online             5000 non-null   category
 11  CreditCard         5000 non-null   category
dtypes: category(7), float64(1), int64(4)
memory usage: 230.6 KB
```

4.1.3. Missing Data Treatment

If the missing values are not handled properly we may end up drawing an inaccurate inference about the data. Due to improper handling, the result obtained will differ from the ones where the missing values are present.

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In [18]:

```
# get the count of missing values
missing_values = data_2.isnull().sum()

# print the count of missing values
print(missing_values)
```

```
Age                  0
Experience           0
Income               0
Family               0
CCAvg                0
Education            0
Mortgage             0
PersonalLoan         0
SecuritiesAccount    0
CDAccount            0
Online               0
CreditCard           0
dtype: int64
```

Note: There are no missing values in the dataset so we can proceed further

In [19]:
```
# Get categorical features
categorical_features = data_2.select_dtypes('category').columns.values.tolist()

# Get nuemric features
numerical_features = [col for col in data_2.columns.values if col not in categorical
```

In [20]:
```
print("Universal Bank Data Set has \033[4m\033[1m{}\033[0m\033[0m data points with \
print(f"Numeric features: \033[4m\033[1m{len(numerical_features)}\033[0m\033[0m \nCa
```

```
Universal Bank Data Set has 5000 data points with 12 variables each.
Numeric features: 5
Categorical features: 7
```

Summary

Number of Instances	Number of Attributes	Numeric Features	Categorical Features	Missing Values
5000	12	5	7	Null

4.2. Exploratory Analysis

The preliminary analysis of data to discover relationships between measures in the data and to gain an insight on the trends, patterns, and relationships among various entities present in the data set with the help of statistics and visualization tools is called Exploratory Data Analysis (EDA).

Exploratory data analysis is cross-classified in two different ways where each method is either graphical or non-graphical. And then, each method is either univariate, bivariate or multivariate.

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In [21]:
```
# Create copy of the dataframe
data = data_2.copy()
```

4.2.1. Numerical Features

Analysis of only numeric features

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In [22]:
```
# Get only numeric features for analysis
numeric_data = data[numerical_features]
numeric_data.head()
```

Out[22]:

	Age	Experience	Income	CCAvg	Mortgage
0	25	1	49	1.6	0

	Age	Experience	Income	CCAvg	Mortgage
1	45	19	34	1.5	0
2	39	15	11	1.0	0
3	35	9	100	2.7	0
4	35	8	45	1.0	0

In [23]:

```
# Summary of the data
numeric_data.describe()
```

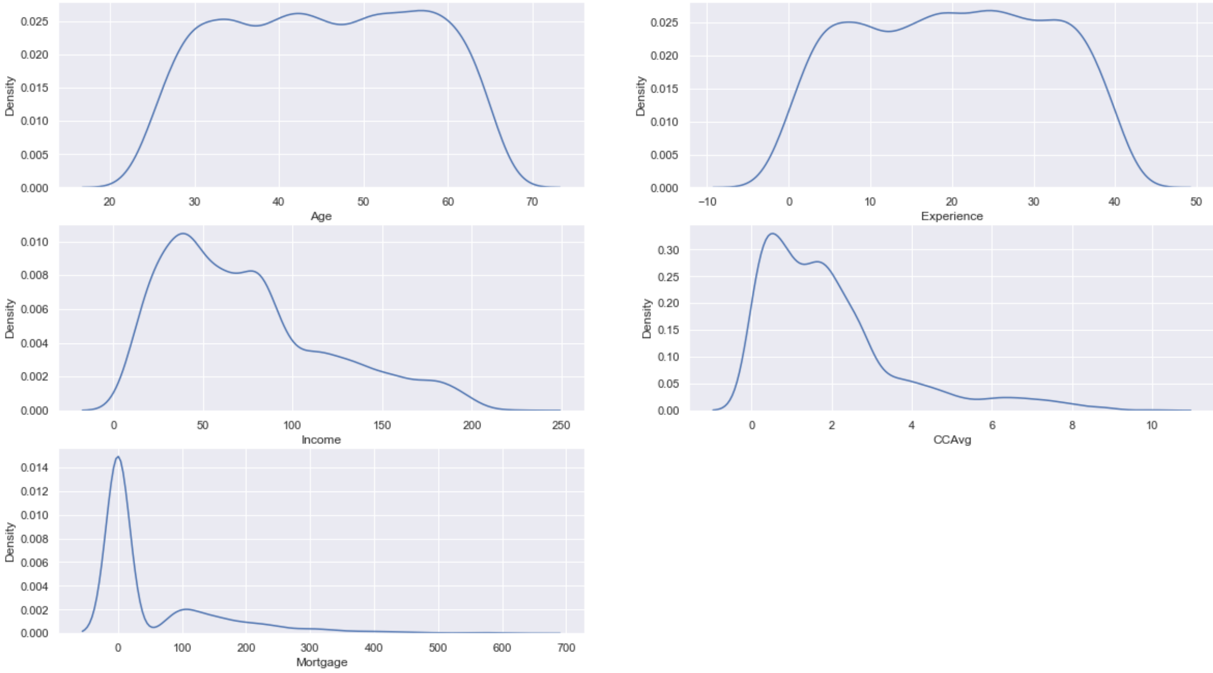
Out[23]:

	Age	Experience	Income	CCAvg	Mortgage
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	45.338400	20.104600	73.774200	1.937938	56.498800
std	11.463166	11.467954	46.033729	1.747659	101.713802
min	23.000000	-3.000000	8.000000	0.000000	0.000000
25%	35.000000	10.000000	39.000000	0.700000	0.000000
50%	45.000000	20.000000	64.000000	1.500000	0.000000
75%	55.000000	30.000000	98.000000	2.500000	101.000000
max	67.000000	43.000000	224.000000	10.000000	635.000000

Note: Experience is negeative for some entries which is invalid and cannot be accepted.

In [24]:

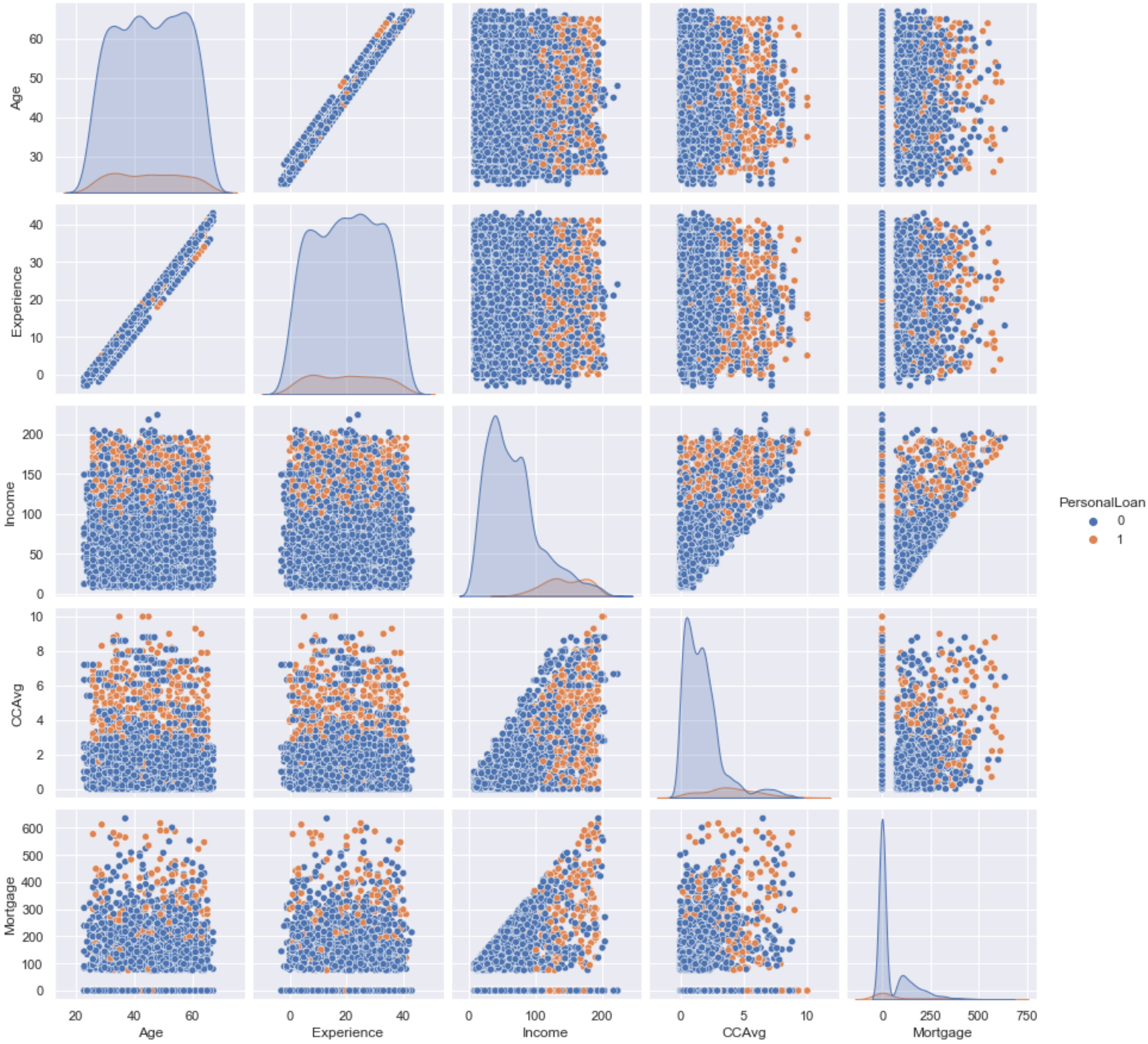
```
# PLot KDE for all features

# Set size of the figure
plt.figure(figsize=(20,35))

# Iterate on list of features
for i, col in enumerate(numerical_features):
    if numeric_data[col].dtype != 'object':
        ax = plt.subplot(9, 2, i+1)
        kde = sns.kdeplot(numeric_data[col], ax=ax)
        plt.xlabel(col)

# Save the plot
plt.savefig("plots/Numeric_Features_1.png")

# Show plot
plt.show()
```



In [25]:

```
# Create a temp dataframe
temp = data[numerical_features]

# Add target feature
temp.insert(len(numerical_features), "PersonalLoan", data['PersonalLoan'].values.tol

# Visualizing numerical variables
plt.figure(figsize = (18, 9))
sns.pairplot(data = temp, hue='PersonalLoan')

# Save the plot
plt.savefig("plots/Numeric_Features_2.png")

# Show plot
plt.show()
```

```
<Figure size 1296x648 with 0 Axes>
```



Important Inferences:

- **Age** feature is normally distributed with majority of customers falling between **30 years and 60 years** of age. We can confirm this by looking at the describe statement above, which shows mean is almost equal to median

- **Experience** is normally distributed with more customer having experience starting from **8 years**. Here the mean is equal to median. There are negative values in the Experience.

  - This could be a data input error as in general it is not possible to measure negative years of experience. We will replace with the negeative records with median of entries having save age as age and experience are related to each other.
- Additionally, scatter plot of **Age** and **experience** indicated that they are positively correlated. As experience increase age also increases.

- **Income** is positively skewed. Majority of the customers have income between **45K** and **55K**. We can confirm this by saying the mean is greater than the median

- **CCAvg** is also a positively skewed variable and average spending is between **0K to 10K** and majority spends less than **2.5K**

- Customers having a personal loan have a higher credit card average. Average credit card spending with a median of **3800** dollar indicates a **higher probability** of personal loan. Lower credit card spending with a median of **1400** dollars is less likely to take a loan.

- **70%** of the individuals have a **mortgage** of less than **40K**. However the max value is **635K**.

In [26]:

```
# Get count records having negeative experience
print(f"Total number of negeative records for Experience feature are \033[4m\033[1m{
```

Total number of negeative records for Experience feature are <u>**52**</u>

In [27]:

```
# Handling negeative entries of experience

# Get all entries with positive experience
temp_exp = data.loc[data['Experience'] > 0]

# Get all entries with negeative experience
temp_neg_exp = data.Experience < 0

# Get the customer's ID having negeative experience
id_neg_list = raw_data.loc[temp_neg_exp]['ID'].tolist()
```

Steps to handle negeative experience

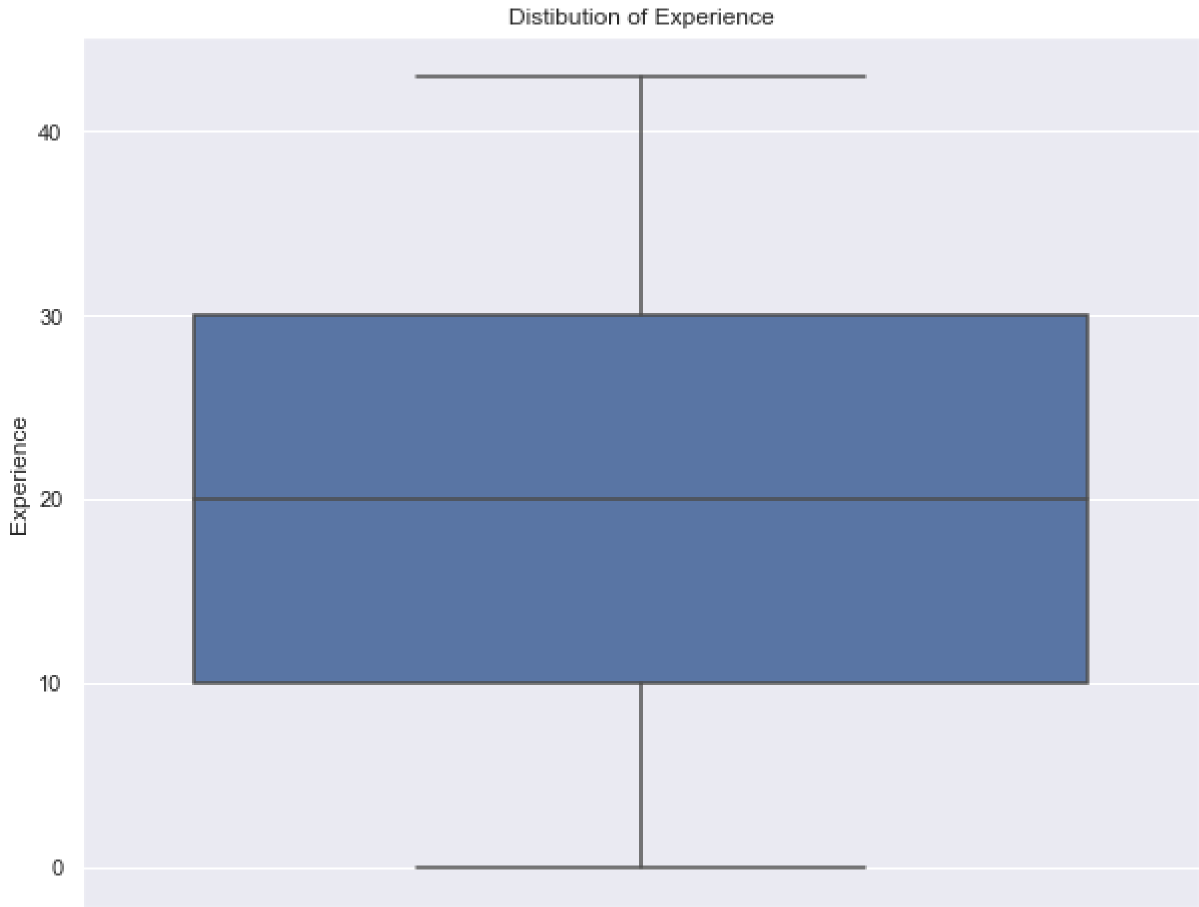
- For all the record with the ID in id_neg_list, get the value of Age and Education
- Filter the records matching the above criteria from the data frame which has records with positive experience, then calculate the median of the matched records
- Apply the median back to the location which had negative experience

In [28]:

```
# Handle negeative experience
for cust_id in id_neg_list:

    # Records with the ID in id_neg_list, get the value of Age
    age = data.loc[np.where(raw_data['ID'] == cust_id)]["Age"].tolist()[0]

    # Record with the ID in id_neg_list, get the value of Education
    education = data.loc[np.where(raw_data['ID'] == cust_id)]["Education"].tolist()[

    # Dataframe to store matched records
    temp_filtered = temp_exp[(temp_exp.Age == age) & (temp_exp.Education == educatio

    # Calculate median of experience feature
    median_exp = temp_filtered['Experience'].median()

    # Apply the median back to the location which had negative experience
    data.loc[data.loc[np.where(raw_data['ID'] == cust_id)].index, 'Experience'] = me
```

In [29]:

```
# Check the distribution of experience

# Set size of figure
plt.figure(figsize = (10,8))

# Plot boxplot of experience
sns.boxplot(data = data, y = "Experience")

# Add title to the plot
plt.title("Distibution of Experience")

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



Correlation

In [30]:

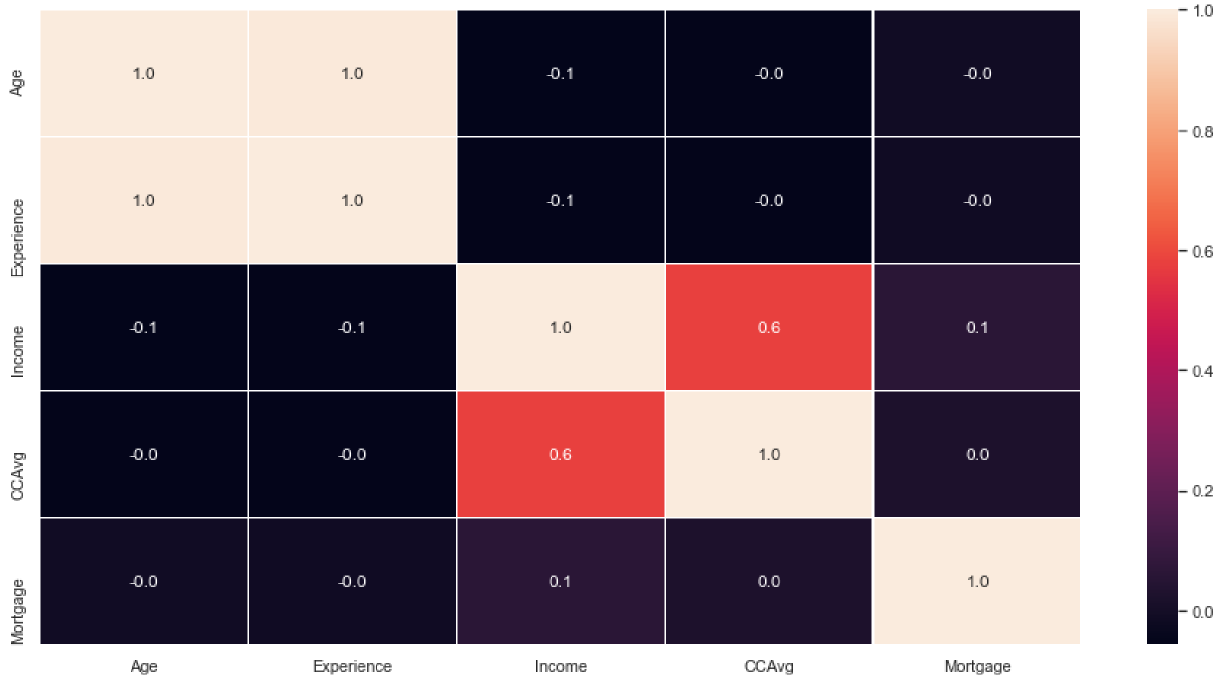
```
# check correlation
corr = data.corr(method = 'spearman')
corr
```

Out[30]:

	Age	Experience	Income	CCAvg	Mortgage
Age	1.000000	0.994341	-0.056772	-0.049617	-0.010655
Experience	0.994341	1.000000	-0.050887	-0.049518	-0.011637
Income	-0.056772	-0.050887	1.000000	0.580210	0.061087
CCAvg	-0.049617	-0.049518	0.580210	1.000000	0.023807
Mortgage	-0.010655	-0.011637	0.061087	0.023807	1.000000

In [31]:

```
# correlation map
f,ax = plt.subplots(figsize=(16, 8))
sns_plot = sns.heatmap(corr, annot=True, linewidths=.5, fmt= '.1f', ax=ax)

# Save the plot
f.savefig("plots/correlation.png")

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



Important Inferences:

- Income and CCAvg are moderately correlated.
- Age and Experience are highly correlated

In [32]:
```
# We will drop 'Experience' feature
numeric_data = numeric_data.drop('Experience', axis = 1)
```

In [33]:
```
numeric_data.shape
```

Out[33]: (5000, 4)

4.4.2. Categorical Features

In Analysis of categorical features we will explore them using some visualizations. Additionally, we will be performing **Chi-Squared Test** to identify relationship of a categorical feature with other features.

...goto toc

In [34]:
```
# Get only categorical features for analysis
categorical_data = data[categorical_features]
categorical_data.head()
```

Out[34]:

	Family	Education	PersonalLoan	SecuritiesAccount	CDAccount	Online	CreditCard
0	4	1	0	1	0	0	0
1	3	1	0	1	0	0	0
2	1	1	0	0	0	0	0
3	1	2	0	0	0	0	0
4	4	2	0	0	0	0	1

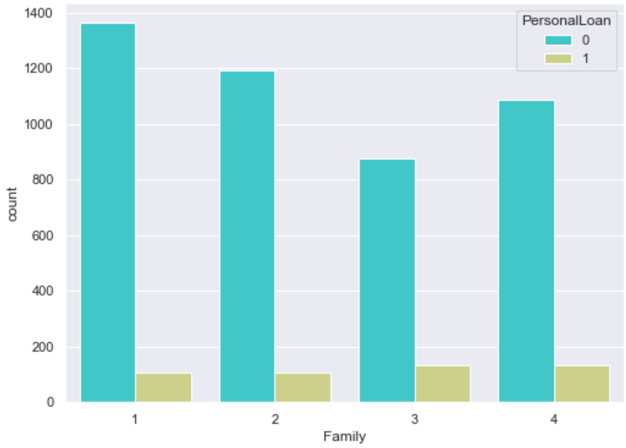
In [35]:

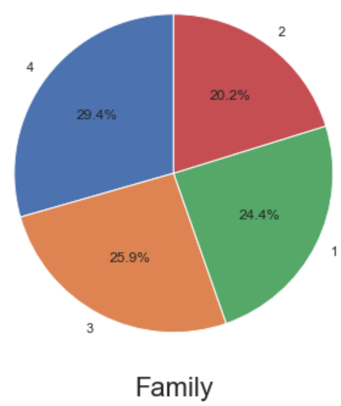
```
def plot_categorical_features(data, categorical_features, target):
    count = 0
    for feature in categorical_features:

        if feature == target:
            continue

        print("-"*150)
        print(f"Feature : \033[4m\033[1m{feature}\033[0m\033[0m")
        print("-"*150)

        labels = data[feature].unique().tolist()

        # Create subplots figure
        fig, axes = plt.subplots(1, 2, figsize=(18, 6))

        if count % 2 == 0:
            # Plot countplot of feature with respect to target
            sns.countplot(x = feature, data = data, hue = target, ax = axes[0], pale

            # Plot pie chart to show distribution of feature
            axes[1].pie(data[feature].value_counts().values, labels = labels, autopc
            axes[1].set_xlabel(feature, size=22)

        else:
            # Plot pie chart to show distribution of feature
            axes[0].pie(data[feature].value_counts().values, labels = labels, autopc
            axes[0].set_xlabel(feature, size=22)

            # Plot countplot of feature with respect to target
            sns.countplot(x = feature, data = data, hue = target, ax = axes[1], pale

        # Increase the counter
        count += 1

        # Save features
        fig.savefig(f"plots/{feature}_feature.png")

        # Show all plots
        plt.show()
```

In [36]:

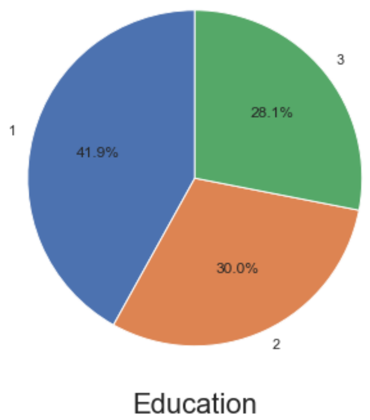
```
plot_categorical_features(categorical_data, categorical_features, target = "Personal
```

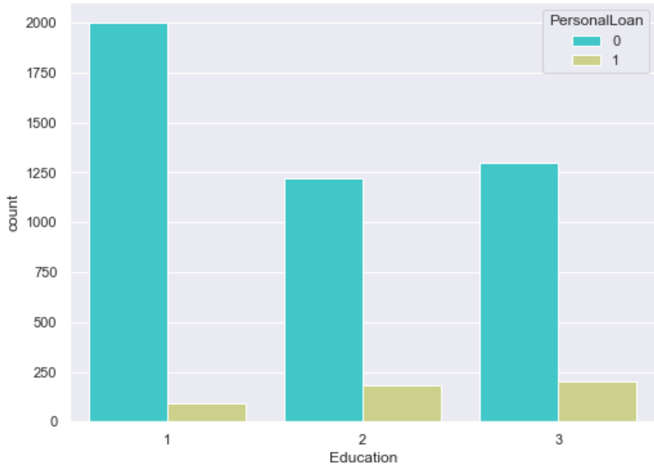
```
------------------------------------------------------------------------------------------------------------------------------------------------------
Feature : Family
------------------------------------------------------------------------------------------------------------------------------------------------------
```



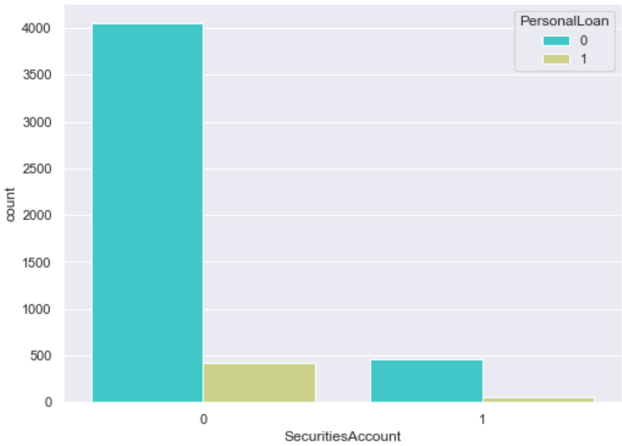


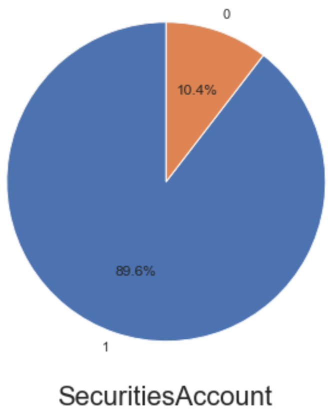
Feature : **Education**



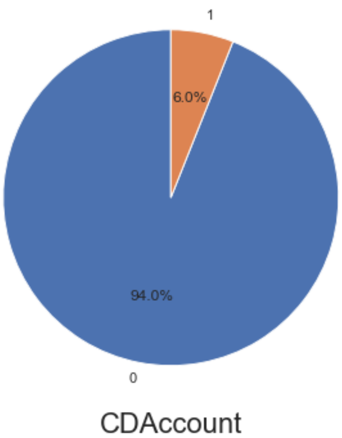


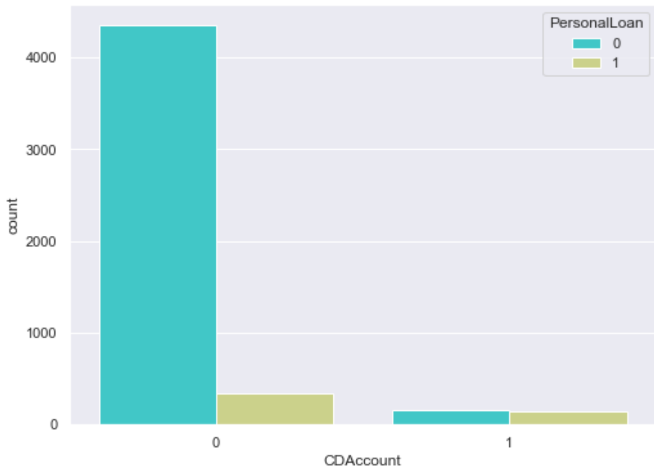
Feature : **SecuritiesAccount**



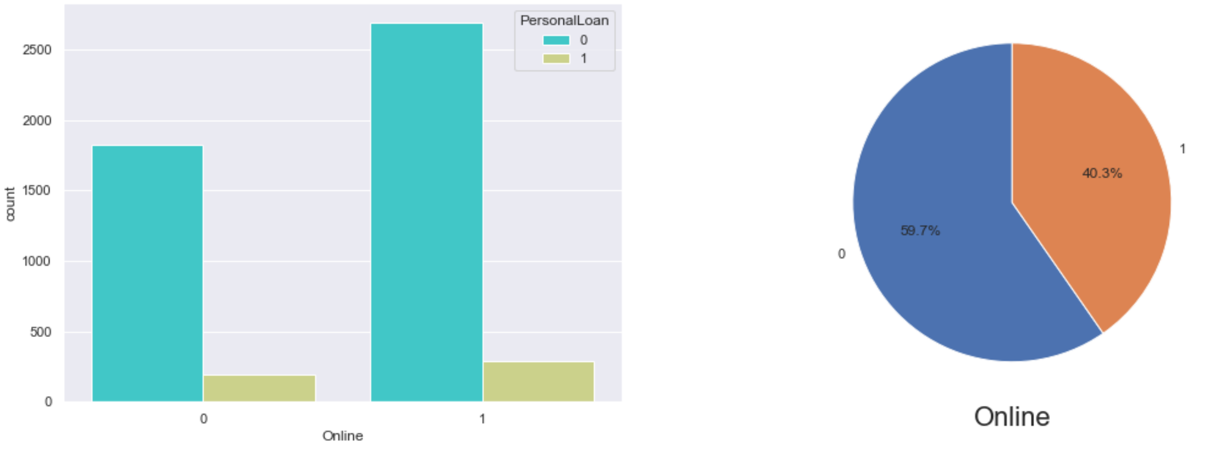


Feature : **CDAccount**

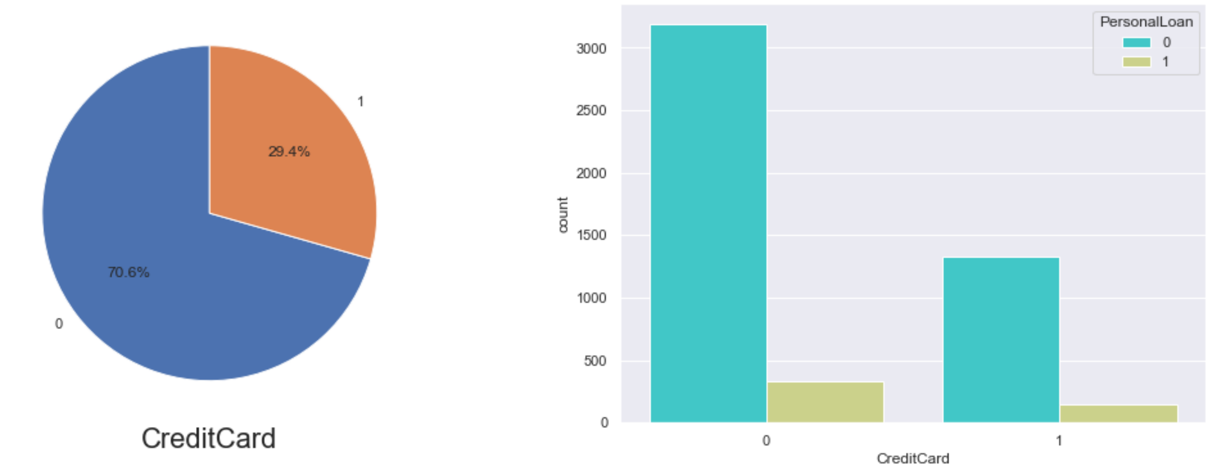




Feature : **Online**




```
----------------------------------------------------------------------------------------------------------------------------------------------------------------
Feature : CreditCard
----------------------------------------------------------------------------------------------------------------------------------------------------------------
```



Observation :

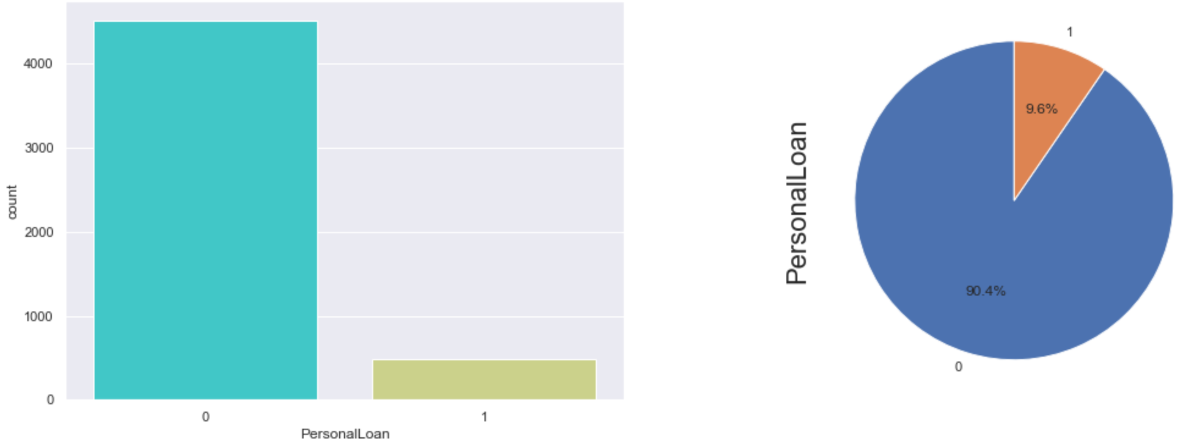
- Majority of customers who does not have loan have securities account
- Family size does not have any impact in personal loan. But it seems families with size of 3 are more likely to take loan. When considering future campaign this might be good association.
- Customers who does not have CD account , does not have loan as well. This seems to be majority. But almost all customers who has CD account has loan as well

Analyzing target feature

In [37]:

```
# Create subplots figure
fig, axes = plt.subplots(1, 2, figsize=(18, 6))

target = "PersonalLoan"

# Plot countplot of feature with respect to target
sns.countplot(x = target, data = data, ax = axes[0], palette='rainbow')

# Plot pie chart to show distribution of feature

labels = data[target].unique()

axes[1].pie(categorical_data[target].value_counts().values, labels = labels, autopct
axes[1].set_ylabel(target, size=22)
```

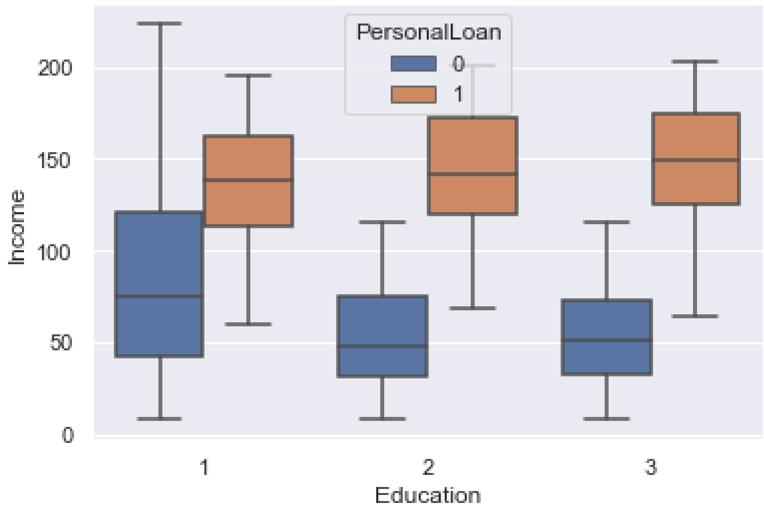
```
# Save plot
fig.savefig('plots/target_feature.png')

# Show all plots
plt.show()
```



Influence of income and education on personal loan

In [38]:
```
sns.boxplot(x='Education',y='Income',hue='PersonalLoan',data = data)
```

Out[38]: <AxesSubplot:xlabel='Education', ylabel='Income'>

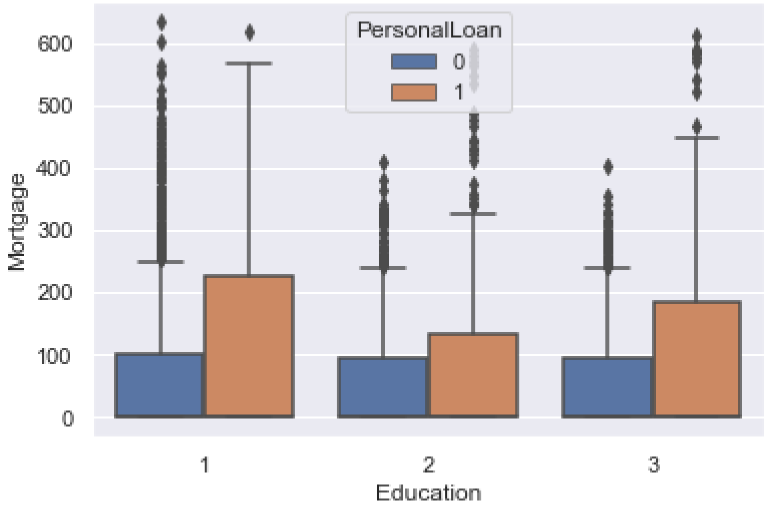


Observation : It seems the customers whose education level is 1 is having more income. However customers who has taken the personal loan have the same income levels

Influence of Mortage and education on personal loan

In [39]:
```
sns.boxplot(x = "Education", y = 'Mortgage', hue = "PersonalLoan", data = data)
```

Out[39]: <AxesSubplot:xlabel='Education', ylabel='Mortgage'>



Inference : From the above chart it seems that customers having personal loan have high mortgage

Chi-squared Test

The Chi-Squared test is a statistical hypothesis test that assumes (the null hypothesis) that two categorical features are dependent. It checkes if two categorical variables are independent or not.

We can interpret the test statistic in the context of the chi-squared distribution with the requisite number of degress of freedom as follows:

```
- If Statistic >= Critical Value: significant result, reject null
hypothesis (H0), dependent.
- If Statistic < Critical Value: not significant result, fail to
reject null hypothesis (H0), independent.
```

The degrees of freedom for the chi-squared distribution is calculated based on the size of the contingency table as

-

Degree's of Freedom = (rows - 1) * (cols - 1)

-

In terms of a p-value and a chosen significance level (alpha), the test can be interpreted as follows:

```
- If p-value <= alpha: significant result, reject null hypothesis
(H0), dependent.
- If p-value > alpha: not significant result, fail to reject null
hypothesis (H0), independent.
```

In [40]:

```
from scipy.stats import chi2_contingency

# Function to perform Chi-squared Test
def perform_chisquared_test(data, features, alpha = 0.05):
    chi_test = pd.DataFrame()
    dependent_feature, independent_features = [], []
```

```python
    for feature in features:
        for f in features:
            if feature == f:
                chi_test.loc[feature, f] = 1
                continue
            stat, p, dof, expected = chi2_contingency(pd.crosstab(categorical_data[f
            chi_test.loc[feature, f] = p

            if p <= alpha:
                if (f, feature) not in dependent_feature:
                    dependent_feature.append((feature, f))
            else:
                if (f, feature) not in independent_features:
                    independent_features.append((feature, f))

    return chi_test, dependent_feature, independent_features
```

In [41]:

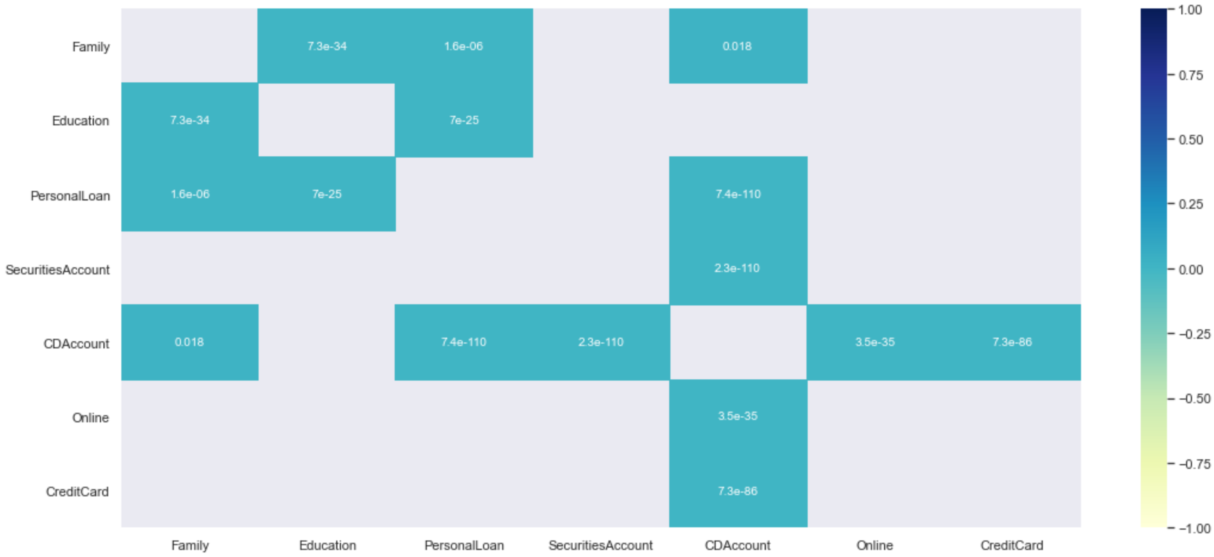
```python
# perform test

alpha = 0.05
chi_test, dependent_feature, independent_features = perform_chisquared_test(categori
chi_test
```

Out[41]:

	Family	Education	PersonalLoan	SecuritiesAccount	CDAccount	
Family	1.000000e+00	7.287679e-34	1.614412e-06	5.445135e-01	1.816763e-02	3.97
Education	7.287679e-34	1.000000e+00	6.991474e-25	6.799513e-01	5.799550e-01	1.69
PersonalLoan	1.614412e-06	6.991474e-25	1.000000e+00	1.405150e-01	7.398298e-110	6.92
SecuritiesAccount	5.445135e-01	6.799513e-01	1.405150e-01	1.000000e+00	2.328904e-110	3.97
CDAccount	1.816763e-02	5.799550e-01	7.398298e-110	2.328904e-110	1.000000e+00	3.52
Online	3.973556e-01	1.697842e-01	6.928600e-01	3.976891e-01	3.520986e-35	1.00
CreditCard	2.793896e-01	5.376533e-01	8.843861e-01	3.115835e-01	7.325271e-86	7.90

In [42]:

```python
# Plot heatmap
plt.figure(figsize = (18,8))

sns.heatmap(chi_test[(chi_test <= alpha)], cmap='YlGnBu', vmax=1.0, vmin=-1.0,
            annot=True, annot_kws={"size": 10})

# Save the plot
plt.savefig("plots/Chi-squared Test.png")

# Show the plot
```



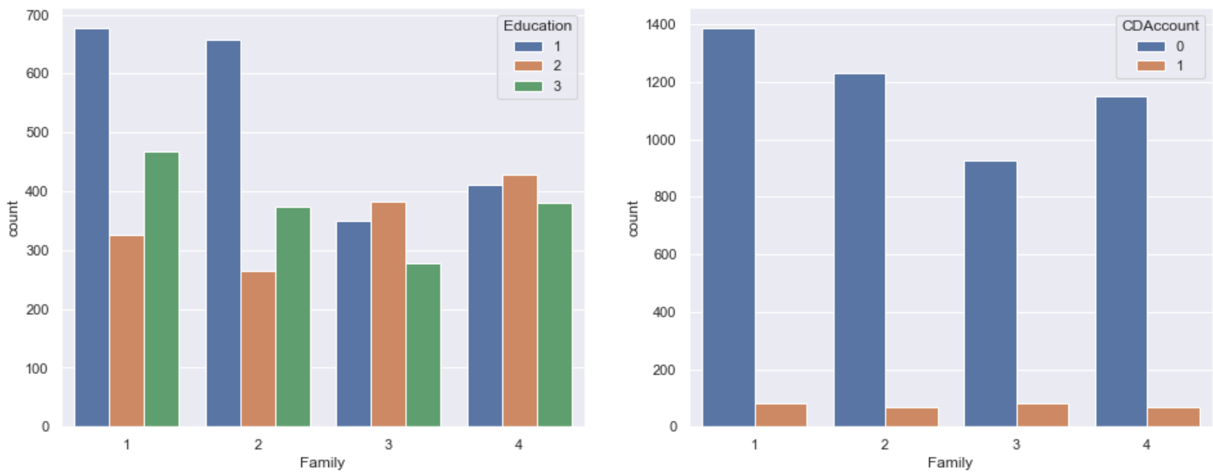
In [43]:
```
print("Dependent Features", dependent_feature)
```

```
Dependent Features [('Family', 'Education'), ('Family', 'PersonalLoan'), ('Family',
'CDAccount'), ('Education', 'PersonalLoan'), ('PersonalLoan', 'CDAccount'), ('Securi
tiesAccount', 'CDAccount'), ('CDAccount', 'Online'), ('CDAccount', 'CreditCard')]
```

Let's explore each dependency

In [44]:
```
fig, ax = plt.subplots(1, 2, figsize = (16,6))
sns.countplot(x='Family',data=data,hue='Education', ax = ax[0])
sns.countplot(x='Family',data=data,hue='CDAccount', ax = ax[1])
```

Out[44]: `<AxesSubplot:xlabel='Family', ylabel='count'>`

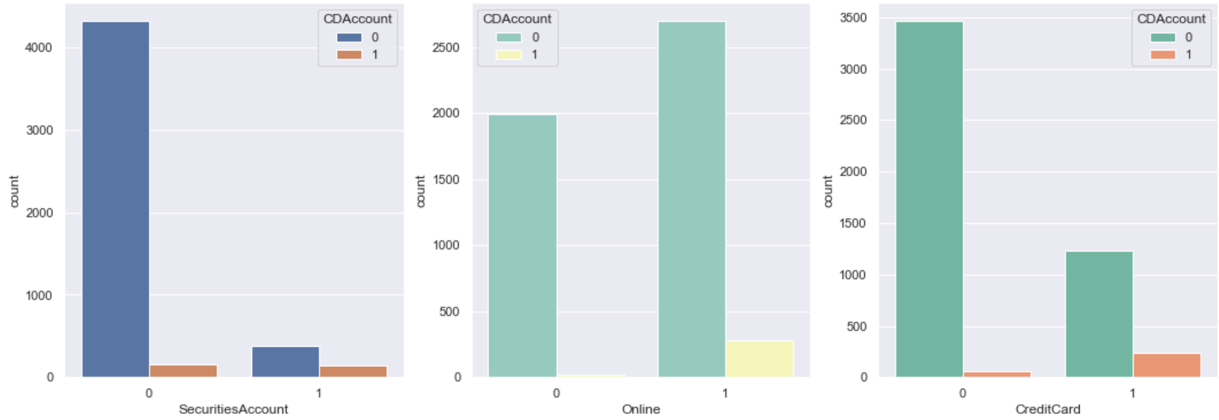


Observations

- Generally, as family size increase we can see that the education qualification decrease. Family with more number of members don't opte for higher studies.
- Additionaly, Larger familes prefer to have a certificate of deposit (CD) account with the bank

In [45]:
```
fig, ax = plt.subplots(1, 3, figsize = (18,6))
sns.countplot(x='SecuritiesAccount', data=data, hue ='CDAccount', ax = ax[0])
sns.countplot(x='Online', data=data, hue ='CDAccount', ax = ax[1], palette='Set3')
sns.countplot(x='CreditCard', data=data, hue ='CDAccount', ax = ax[2], palette='Set2
```

Out[45]: `<AxesSubplot:xlabel='CreditCard', ylabel='count'>`



Observation

- Generally, customers use a internet banking facilities have a certificate of deposit (CD) account with the bank
- Customers using a credit card don't opt for a certificate of deposit account with the bank
- It is clear that majority of customers not having a Securities Account don't have CD Account

4.3. Data Transformation

...goto toc

In [47]:

```
final_data = pd.concat([numeric_data, categorical_data], axis = 1)
final_data.head()
```

Out[47]:

	Age	Income	CCAvg	Mortgage	Family	Education	PersonalLoan	SecuritiesAccount	CDAccount
0	25	49	1.6	0	4	1	0	1	0
1	45	34	1.5	0	3	1	0	1	0
2	39	11	1.0	0	1	1	0	0	0
3	35	100	2.7	0	1	2	0	0	0
4	35	45	1.0	0	4	2	0	0	0

4.3.1 Label Encoding Categorical Features

Label Encoding is a popular encoding technique for handling categorical variables. In this technique, each label is assigned a unique integer based on alphabetical ordering.

...goto toc

In [48]:

```
# Perform label encoding
for feature in categorical_features:
        # Initialize the label encoder
        label_encoder = LabelEncoder()

        # Encode labels in column
        final_data[feature] = label_encoder.fit_transform(final_data[feature])

final_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Age                5000 non-null   int64  
 1   Income             5000 non-null   int64  
 2   CCAvg              5000 non-null   float64
 3   Mortgage           5000 non-null   int64  
 4   Family             5000 non-null   int64  
 5   Education          5000 non-null   int64  
 6   PersonalLoan       5000 non-null   int64  
 7   SecuritiesAccount  5000 non-null   int64  
 8   CDAccount          5000 non-null   int64  
 9   Online             5000 non-null   int64  
 10  CreditCard         5000 non-null   int64  
dtypes: float64(1), int64(10)
memory usage: 429.8 KB
```

In [49]:

```
# Get independent features
x = final_data.drop('PersonalLoan', axis = 1)

# Get target feature
y = final_data['PersonalLoan']
```

4.3.2 Normalization

Normalization is used to scale the data of an attribute so that it falls in a smaller range, such as -1.0 to 1.0 or 0.0 to 1.0. It is generally useful for classification algorithms.

We will use *Standard Scaler* to perform normalization.

...goto toc

In [50]:

```
# Initilize scaler
scaler = StandardScaler()

# fit the scaler
scaler.fit(x)
```

Out[50]:

```
StandardScaler()
```

In [51]:

```
# Transform the dataset
X = scaler.transform(x)
```

4.4.2. Split dataset

We will be splitting the dataset into train and test set with **80-20** split

...goto toc

In [52]:

```
# let us now split the dataset into train & test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_st

# print the shape of 'x_train'
print("X_train : ",X_train.shape)
```

```
# print the shape of 'x_test'
print("X_test : ",X_test.shape)

# print the shape of 'y_train'
print("y_train : ",y_train.shape)

# print the shape of 'y_test'
print("y_test : ",y_test.shape)
```

```
X_train :  (4000, 10)
X_test :  (1000, 10)
y_train :  (4000,)
y_test :  (1000,)
```

5. Model Development

We will be training different classification model and choose the one with best performance

...goto toc

Evaluation Metric

The problem we are working on is Imbalanced Classification Problem because our target feature is imbalanced. We shouldn't use accuracy as a metric for imbalanced problems.

Since we care equally about positive and negative classes we will be using

- Confusion Matrix
- Precision Recall AUC Score
- Precision
- Recall
- F1 Score - F1 score is calculated from Precision and Recall

In [53]:

```
# Tabulate the result

# create a list of column names
cols = ['Model', "PR-AUC Score", 'Precision Score', 'Recall Score', 'f1-score']

# creating an empty dataframe of the colums
result_tabulation = pd.DataFrame(columns = cols)
```

5.1 Logistic Regression

Training a logistic regression classifier

...goto toc

In [54]:

```
# Initialize the regressor
logistic = LogisticRegression()
```

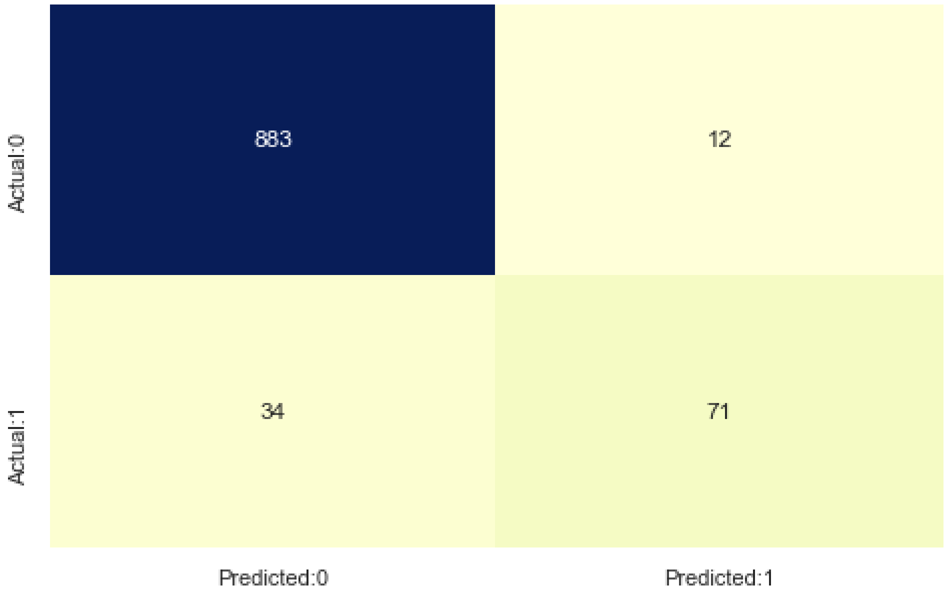
In [55]:

```
# Fit the model on training set
logistic.fit(X_train,y_train)
```

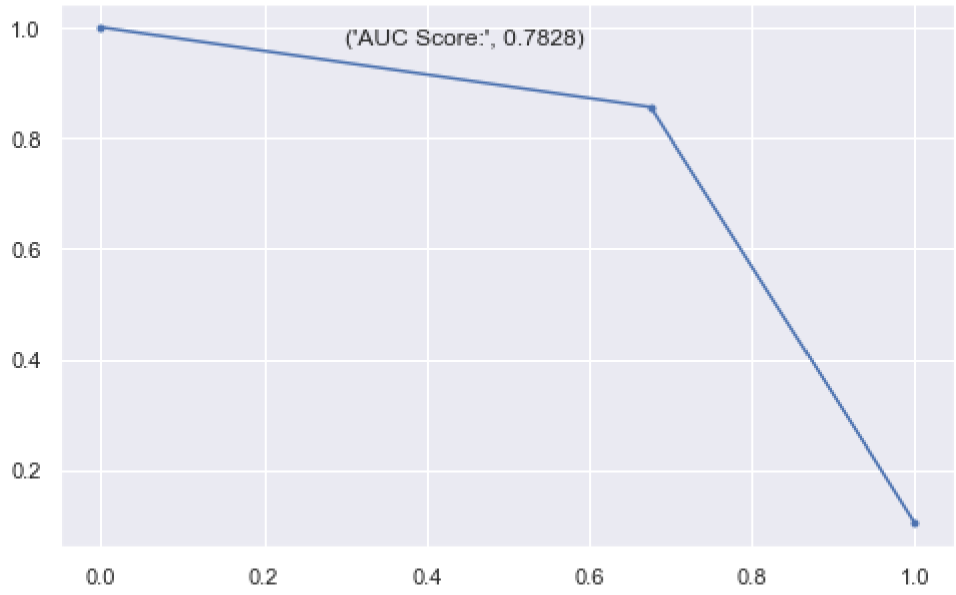
Out[55]: LogisticRegression()

In [56]:
```
# predict the values
y_pred = logistic.predict(X_test)
```

In [57]:
```
# Compute the accuracy

# compute the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# label the confusion matrix
conf_matrix = pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Act

# set sizeof the plot
plt.figure(figsize = (8,5))

# plot a heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="YlGnBu", cbar=False)
plt.show()
```



In [58]:
```
# Calculate precision and recall
precision, recall, thresholds = precision_recall_curve(y_test, y_pred)

# Calcaulte AUC Score
auc_precision_recall = auc(recall, precision)

# set the figure size
plt.figure(figsize = (8,5))

# plot the ROC curve
plt.plot(recall, precision, marker='.')

# add the AUC score
plt.text(x = 0.3, y = 0.97, s =('AUC Score:', round(auc_precision_recall,4)))

plt.show()
```



In [59]:

```
# compiling the required information
logistic_regression_estimator = pd.Series({'Model': "Logistic Regression",
                     'PR-AUC Score' : auc_precision_recall,
                 'Precision Score': metrics.precision_score(y_test, y_pred),
                 'Recall Score': metrics.recall_score(y_test, y_pred),
                  'f1-score':metrics.f1_score(y_test, y_pred)})



# appending our result table
result_tabulation = result_tabulation.append(logistic_regression_estimator , ignore_

# view the result table
result_tabulation
```

Out[59]:

	Model	PR-AUC Score	Precision Score	Recall Score	f1-score
0	Logistic Regression	0.782806	0.855422	0.67619	0.755319

5.2 Naive Bayes

...goto toc

In [60]:

```
# build the model
GNB = GaussianNB()

# fit the model
GNB.fit(X_train, y_train)
```

Out[60]: GaussianNB()

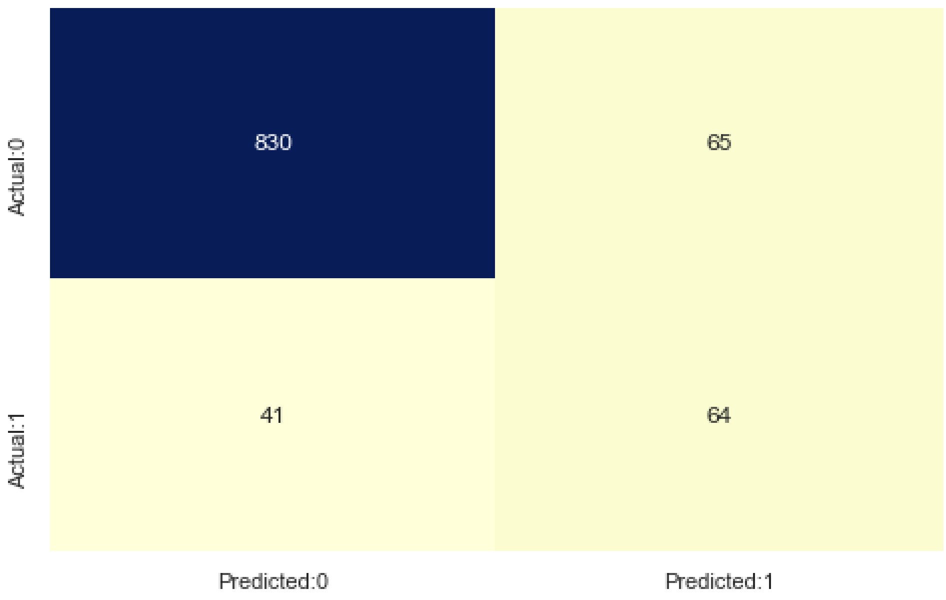
In [61]:

```
# predict the values
y_pred_GNB  = GNB.predict(X_test)
```

In [62]:

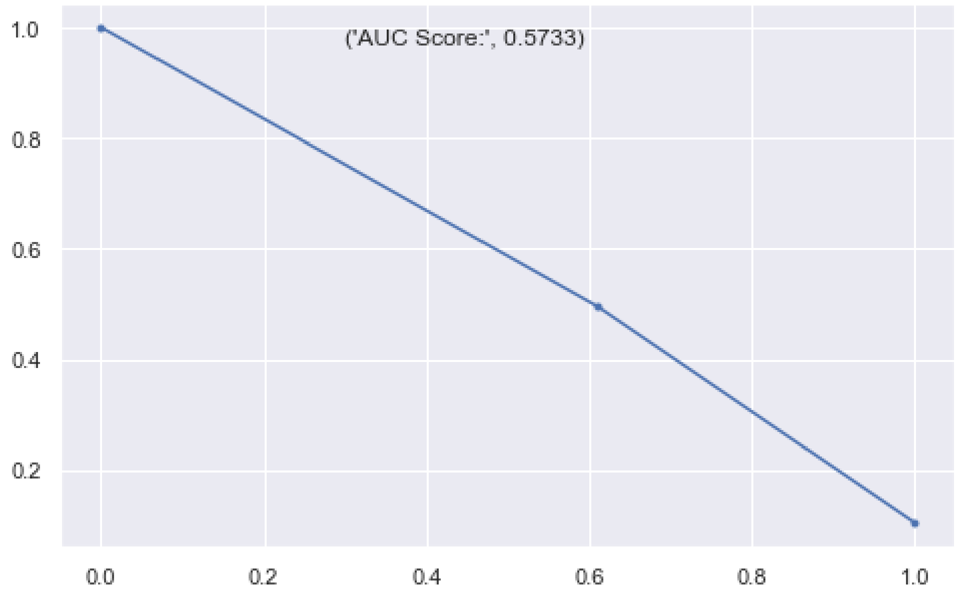
```
# compute the confusion matrix
cm = confusion_matrix(y_test, y_pred_GNB)
```

```
# label the confusion matrix
conf_matrix = pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Act

# set sizeof the plot
plt.figure(figsize = (8,5))

# plot a heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="YlGnBu", cbar=False)
plt.show()
```



In [63]:

```
# Calculate precision and recall
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_GNB)

# Calcaulte AUC Score
auc_precision_recall = auc(recall, precision)

# set the figure size
plt.figure(figsize = (8,5))

# plot the ROC curve
plt.plot(recall, precision, marker='.')

# add the AUC score
plt.text(x = 0.3, y = 0.97, s =('AUC Score:', round(auc_precision_recall,4)))

plt.show()
```



In [64]:

```
# compiling the required information
GNB_metrices = pd.Series({'Model': "Gaussian Naive Bayes",
                     'PR-AUC Score' : auc_precision_recall,
                 'Precision Score': metrics.precision_score(y_test, y_pred_GNB),
                 'Recall Score': metrics.recall_score(y_test, y_pred_GNB),
                  'f1-score':metrics.f1_score(y_test, y_pred_GNB)})


# appending our result table
result_tabulation = result_tabulation.append(GNB_metrices , ignore_index = True)

# view the result table
result_tabulation
```

Out[64]:

	Model	PR-AUC Score	Precision Score	Recall Score	f1-score
0	Logistic Regression	0.782806	0.855422	0.676190	0.755319
1	Gaussian Naive Bayes	0.573324	0.496124	0.609524	0.547009

5.3. Support Vector Machine

We will be using Radial Basis Function (RBF) kernel of SVM for our classification task. The reson behind using RBF is that it works well when the data is not linearly seperable.

...goto toc

In [65]:

```
# Initialize svm and kernel as linear
svclassifier = SVC(kernel = 'rbf')

# fit the model
svclassifier.fit(X_train, y_train)
```

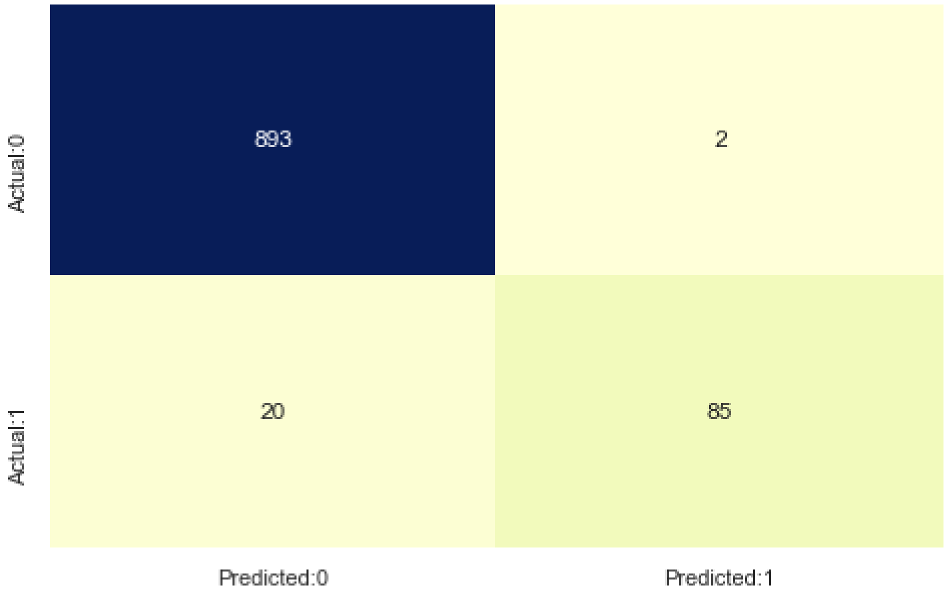
Out[65]: SVC()

In [66]:

```
# predict the values
y_pred_SVC  = svclassifier.predict(X_test)
```

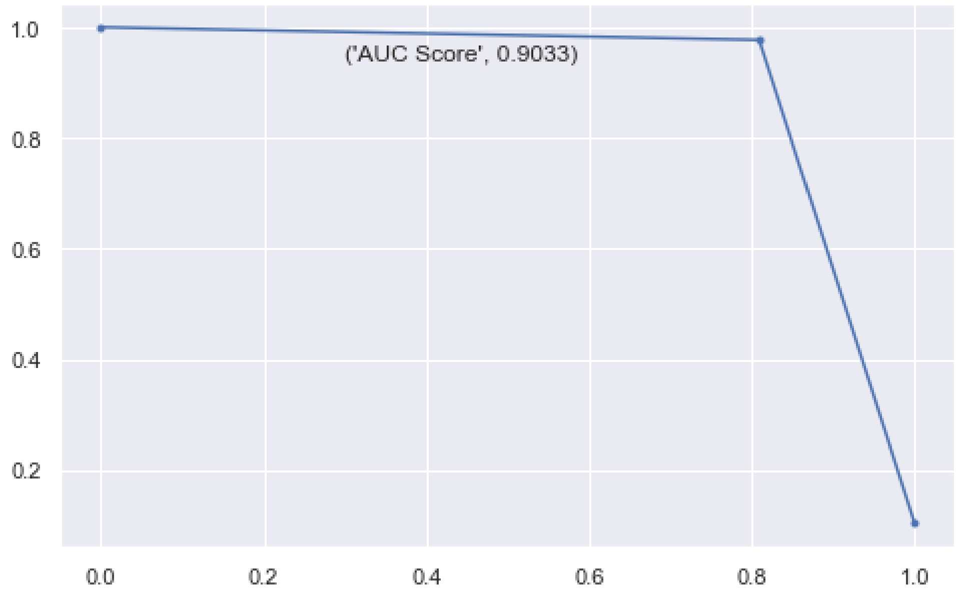
In [67]:

```
# compute the confusion matrix
cm = confusion_matrix(y_test, y_pred_SVC)

# label the confusion matrix
conf_matrix = pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Act

# set sizeof the plot
plt.figure(figsize = (8,5))

# plot a heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="YlGnBu", cbar=False)
plt.show()
```



In [68]:

```
# Calculate precision and recall
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_SVC)

# Calcaulte AUC Score
auc_precision_recall = auc(recall, precision)

# set the figure size
plt.figure(figsize = (8,5))

# plot the ROC curve
plt.plot(recall, precision, marker='.')

# add the AUC score
plt.text(x = 0.3, y = 0.94, s =('AUC Score', round(auc_precision_recall,4)))

plt.show()
```



In [69]:

```
# create the result table for all scores
SVM_metrices = pd.Series({'Model': "Support Vector Machine",
                     'PR-AUC Score' : auc_precision_recall,
                 'Precision Score': metrics.precision_score(y_test, y_pred_SVC),
                 'Recall Score': metrics.recall_score(y_test, y_pred_SVC),
                  'f1-score':metrics.f1_score(y_test, y_pred_SVC)})



# appending our result table
result_tabulation = result_tabulation.append(SVM_metrices , ignore_index = True)

# view the result table
result_tabulation
```

Out[69]:

	Model	PR-AUC Score	Precision Score	Recall Score	f1-score
0	Logistic Regression	0.782806	0.855422	0.676190	0.755319
1	Gaussian Naive Bayes	0.573324	0.496124	0.609524	0.547009
2	Support Vector Machine	0.903268	0.977011	0.809524	0.885417

5.4 Random Forest

We will perform Hyperparameter tunning to find optimal parameters of random forest classifier

...goto toc

In [70]:

```
# Fitting Random Forest Classification to the Training set
random_classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy',
random_classifier.fit(X_train, y_train)
```

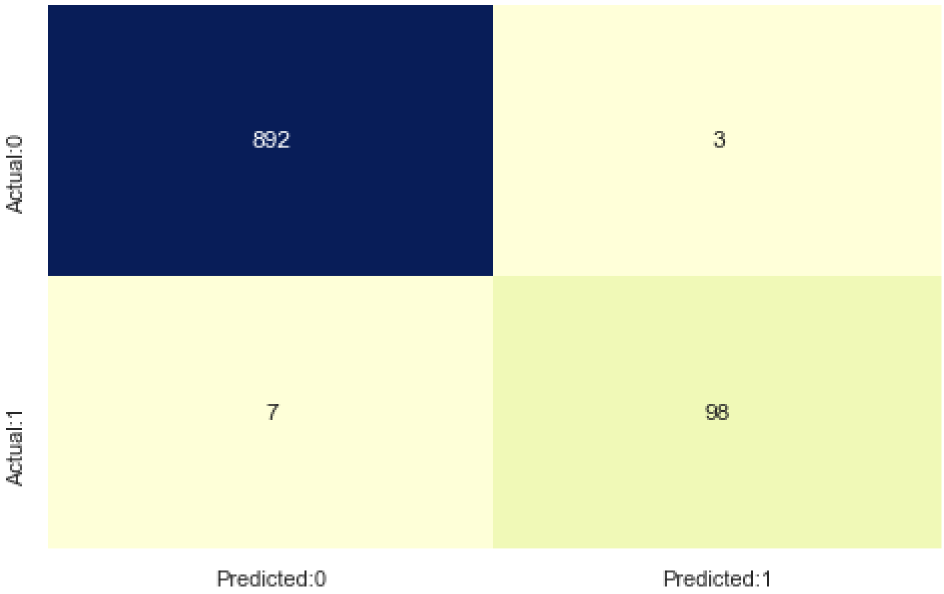
Out[70]: `RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=42)`

In [71]:

```
# Predicting the Test set results
y_pred_random = random_classifier.predict(X_test)
```

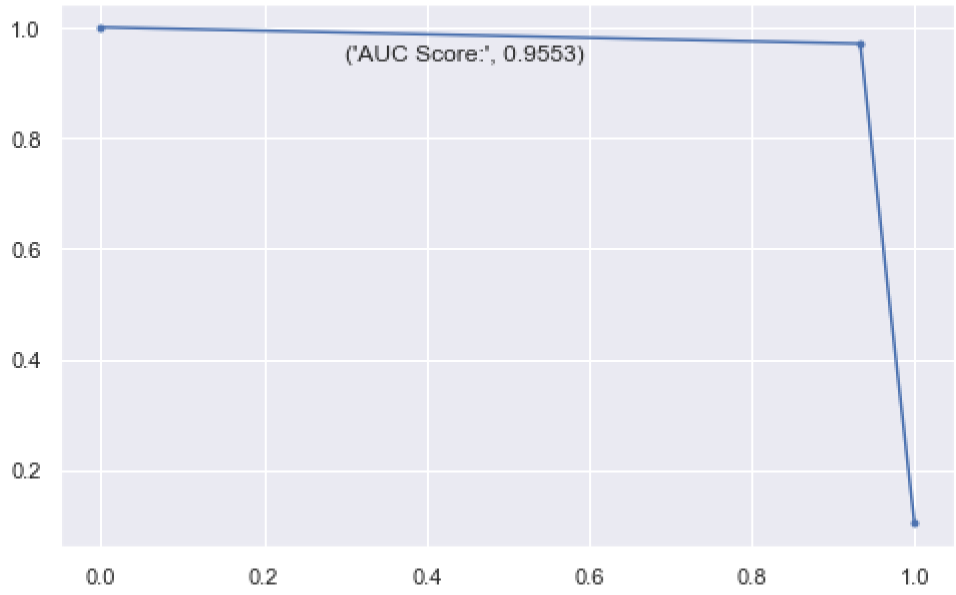
In [72]:

```
# compute the confusion matrix
cm = confusion_matrix(y_test, y_pred_random)

# label the confusion matrix
conf_matrix = pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Act

# set sizeof the plot
plt.figure(figsize = (8,5))

# plot a heatmap
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="YlGnBu", cbar=False)
plt.show()
```



In [73]:

```
# Calculate precision and recall
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_random)

# Calcaulte AUC Score
auc_precision_recall = auc(recall, precision)

# set the figure size
plt.figure(figsize = (8,5))

# plot the ROC curve
plt.plot(recall, precision, marker = '.')

# add the AUC score
plt.text(x = 0.3, y = 0.94, s =('AUC Score:', round(auc_precision_recall,4)))

plt.show()
```



In [74]:

```
# create the result table for all scores
random_forest_metrics = pd.Series({'Model': "Random Forest",
                                   'PR-AUC Score' : auc_precision_recall,
                 'Precision Score': metrics.precision_score(y_test, y_pred_random),
                 'Recall Score': metrics.recall_score(y_test, y_pred_random),
                  'f1-score':metrics.f1_score(y_test, y_pred_random)})



# appending our result table
result_tabulation = result_tabulation.append(random_forest_metrics , ignore_index =

# view the result table
result_tabulation
```

Out[74]:

	Model	PR-AUC Score	Precision Score	Recall Score	f1-score
0	Logistic Regression	0.782806	0.855422	0.676190	0.755319
1	Gaussian Naive Bayes	0.573324	0.496124	0.609524	0.547009
2	Support Vector Machine	0.903268	0.977011	0.809524	0.885417
3	Random Forest	0.955315	0.970297	0.933333	0.951456

6. Model Comparision

...goto toc

In [76]:

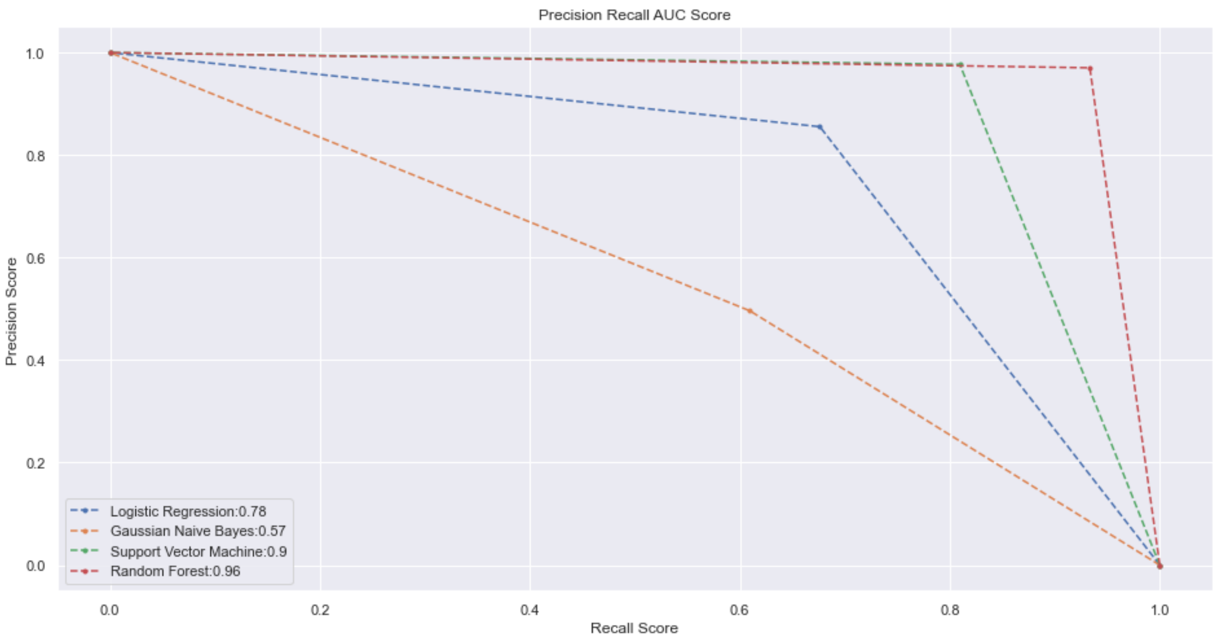
```
result_tabulation
```

Out[76]:

	Model	PR-AUC Score	Precision Score	Recall Score	f1-score
0	Logistic Regression	0.782806	0.855422	0.676190	0.755319
1	Gaussian Naive Bayes	0.573324	0.496124	0.609524	0.547009
2	Support Vector Machine	0.903268	0.977011	0.809524	0.885417
3	Random Forest	0.955315	0.970297	0.933333	0.951456

In [75]:

```
# Create a empty list to save legend
legend = []

# set the figure size
plt.figure(figsize = (16,8))

# Iterate over each row
for i in range(result_tabulation.shape[0]):
    # plot the ROC curve
    plt.plot([1.0, result_tabulation.iloc[i,3], 0.], [0., result_tabulation.iloc[i,2

    # append legend name to list
    legend.append(f'{result_tabulation.iloc[i,0]}:{round(result_tabulation.iloc[i,1]


# Add title
plt.title("Precision Recall AUC Score")

# Add x-axis
plt.xlabel("Recall Score")

# Add y-axis
plt.ylabel("Precision Score")

# Add the legend
plt.legend(legend)

# Save figure
plt.savefig("model/models_roc_plot.png")

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



From the above graph, it seems like **Random Forest Classifier** have the highest Precision Recall AUC Score of **0.96** and we will choose that as our final model.

In [77]:

```
# Best Model
best_model = random_classifier
```

In [78]:

```
# Create a dataframe to store importance of features
```

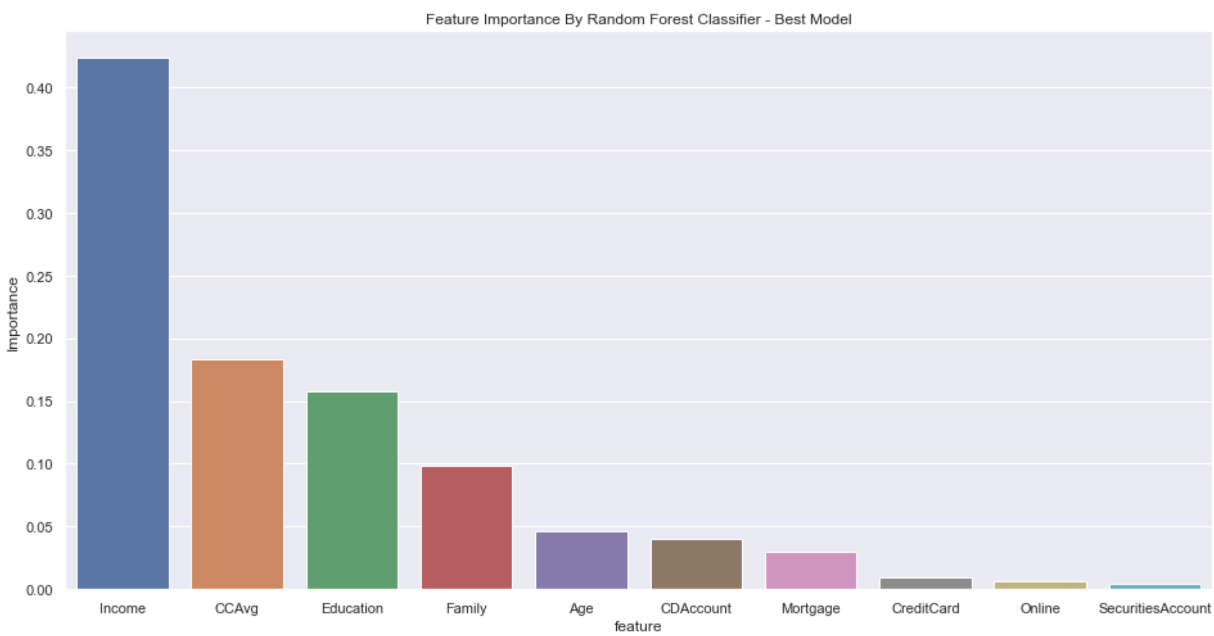
```python
feature_importance = pd.DataFrame()
feature_importance['feature'] = x.columns.values.tolist()
feature_importance['Importance'] = best_model.feature_importances_

# Sort in decreasing order
feature_importance = feature_importance.sort_values(ascending = False, by = 'Importa
feature_importance
```

Out[78]:

	feature	Importance
0	Income	0.423407
1	CCAvg	0.182815
2	Education	0.158168
3	Family	0.098733
4	Age	0.046204
5	CDAccount	0.040623
6	Mortgage	0.029997
7	CreditCard	0.009090
8	Online	0.006348
9	SecuritiesAccount	0.004615

In [79]:

```python
# Plot feature importance
fig, ax = plt.subplots(figsize = (16,8))

# Barplot
sns.barplot(x = 'feature' , y = 'Importance', data = feature_importance, ax = ax)

# Add title
ax.set_title("Feature Importance By Random Forest Classifier - Best Model")

# Save the plot
fig.savefig('model/Feature_importance.png')

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



Observations

From the above plot it can see that target feature heavily depends on

- Income
- CCAvg
- Education
- Family
- Age

Save the model

In [80]:
```
# Save the model as a pickle in a file
joblib.dump(best_model, 'model/model.pkl')
```

Out[80]:
```
['model/model.pkl']
```

...goto toc

Final Report

Number of Instances	Number of Attributes	Numeric Features	Categorical Features	Target Feature	Missing Values
5000	12	5	7	PersonalLoan	Null

Data Types

Sr.No.	Column	Data type
1	Age	int64
2	Experience	int64
3	Income	int64
4	Family	category
5	CCAvg	float64
6	Education	category
7	Mortgage	int64
8	PersonalLoan	category
9	SecuritiesAccount	category
10	CDAccount	category
11	Online	category
12	CreditCard	category

Exploratory Data Analysis

Numeric Features

- **Age** feature is normally distributed with majority of customers falling between **30 years and 60 years** of age. We can confirm this by looking at the describe statement above, which shows mean is almost equal to median

- **Experience** is normally distributed with more customer having experience starting from **8 years**. Here the mean is equal to median. There are negative values in the Experience.

    - This could be a data input error as in general it is not possible to measure negative years of experience. We will replace with the negeative records with median of entries having save age as age and experience are related to each other.
- Additionally, scatter plot of **Age** and **experience** indicated that they are positively correlated. As experience increase age also increases.

- **Income** is positively skewed. Majority of the customers have income between **45K** and **55K**. We can confirm this by saying the mean is greater than the median

- **CCAvg** is also a positively skewed variable and average spending is between **0K to 10K** and majority spends less than **2.5K**

- Customers having a personal loan have a higher credit card average. Average credit card spending with a median of **3800** dollar indicates a **higher probability** of personal loan. Lower credit card spending with a median of **1400** dollars is less likely to take a loan.

- **70%** of the individuals have a **mortgage** of less than **40K**. However the max value is **635K**.

- **Income** and **CCAvg** are moderately correlated

- **Age** and **Experience** are highly correlated

Categorical Features

- Majority of customers who does not have loan have securities account

- Family size does not have any impact in personal loan. But it seems families with size of 3 are more likely to take loan. When considering future campaign this might be good association.

- Customers who does not have CD account , does not have loan as well. This seems to be majority. But almost all customers who has CD account has loan as well.

- The customers whose education level is 1 is having more income. However customers who has taken the personal loan have the same income levels.

- Additionally, Customers having personal loan have high mortgage

- Generally, as family size increase we can see that the education qualification decrease. Family with more number of members don't opte for higher studies.

- Generally, Larger familes prefer to have a certificate of deposit (CD) account with the bank. And majority of customers not having a Securities Account don't have CD Account

- Customers using a credit card don't opt for a certificate of deposit account with the bank also the one using a internet banking facilities have a certificate of deposit (CD) account with the bank.

Conclusion

The aim of the universal bank is to convert there liability customers into loan customers. They want to set up a new marketing campaign; hence, they need information about the connection between the variables given in the data.

In this study four classification algorithms (Logistic Regression, Naive Bayes, Support Vector Machine and Random Forest) were trained. Precision Recall AUC Score and F1-Score are used as evaluation metrics for our study. Out of all trained classifier **Random Forest** outperformed with **PR AUC Score** of **0.95** and **F1-score** of **0.95**.

According to random forest classifier, target feature heavily depends on

- **Income** - Annual income of the customer
- **CCAvg** - Avg. spending on credit cards per month
- **Education** - Education Level of the customer {1 : Undergrad, 2 : Graduate, 3 : Advanced/Professional}
- **Family** - Family size of the customer
- **Age** - Customer's age in completed years

Trained Models

Model	PR-AUC Score	Precision Score	Recall Score	f1-score
Random Forest	0.955315	0.970297	0.933333	0.951456
Logistic Regression	0.782806	0.855422	0.676190	0.755319
Naive Bayes	0.573324	0.496124	0.609524	0.547009
Support Vector Machine	0.903268	0.977011	0.809524	0.885417
