Supervised Learning Project

Domain: Banking

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Context:

This case is about a bank (Thera Bank) whose 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 with minimal budget.

Approach:

The file Bank.xls 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. We will implement Classification algorithms to differentiate people who will buy loans vs the who will not.

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

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 UniversalBank

Import the necessary libraries

In [138]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from scipy import stats
from sklearn import preprocessing

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB

# calculate accuracy measures and confusion matrix
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix,f1_score,
from sklearn.metrics import confusion_matrix,precision_score
```

Reading Data from csv file and understanding its data

In [3]:
```
data=pd.read_csv('Bank_Personal_Loan_Modelling.csv')
```

In [4]:
```
data.head(6)
```

Out[4]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Secu Ac
0	1	25	1	49	91107	4	1.6	1	0	0	
1	2	45	19	34	90089	3	1.5	1	0	0	
2	3	39	15	11	94720	1	1.0	1	0	0	
3	4	35	9	100	94112	1	2.7	2	0	0	
4	5	35	8	45	91330	4	1.0	2	0	0	
5	6	37	13	29	92121	4	0.4	2	155	0	

In [5]:
```
data.shape
```

Out[5]:
```
(5000, 14)
```

There are 5000 rows and 14 column in our dataset

There is no duplicate data present in our dataset

1. Read the column description and ensure you understand each attribute well

In [6]:
```
data.info()
```

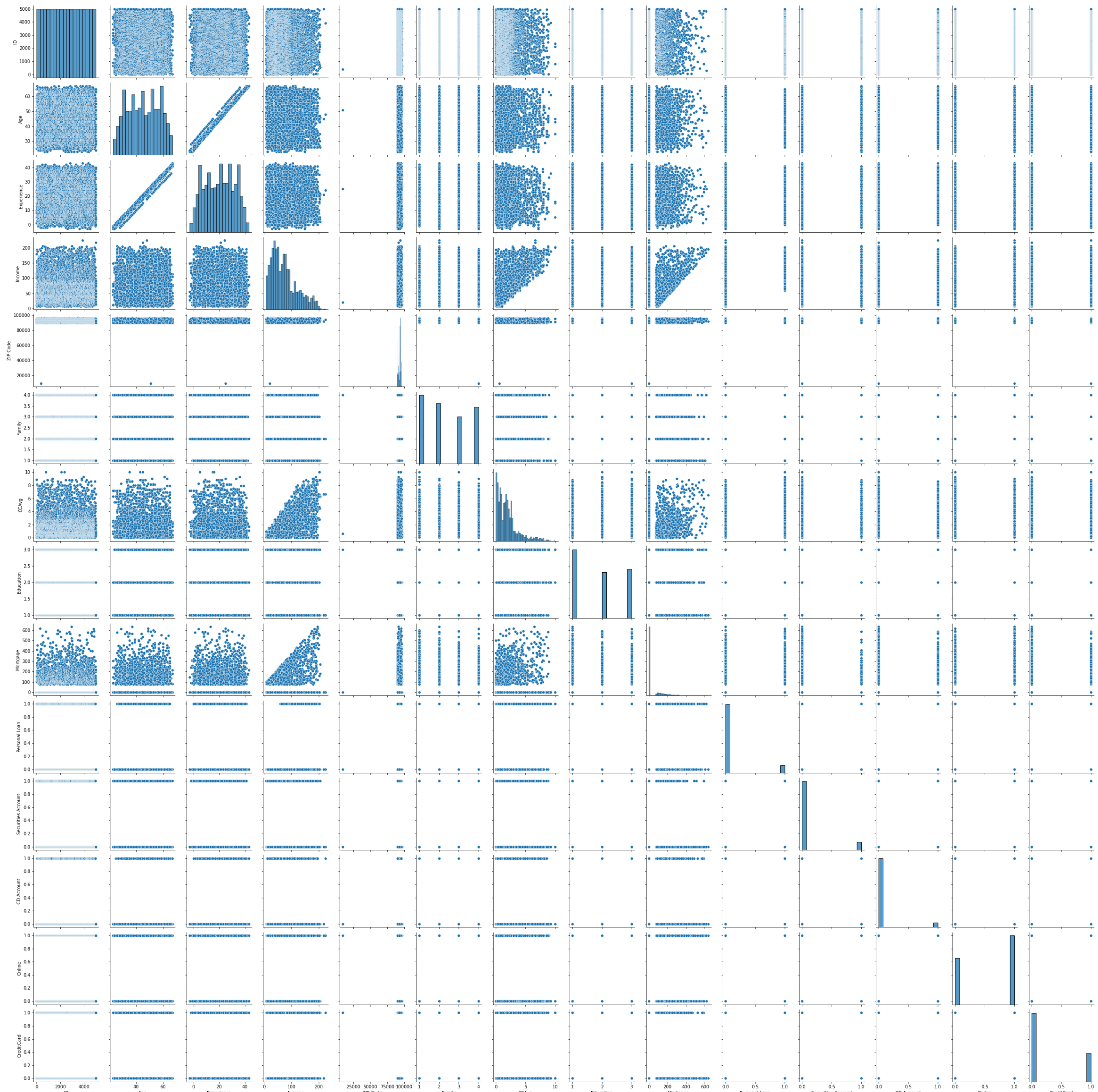
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   ID                  5000 non-null   int64  
 1   Age                 5000 non-null   int64  
 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
```

All the columns have 5000 non-null values.

Only one value is float all other are integer type.

In [7]:
```
sns.pairplot(data)
```

Out[7]: <seaborn.axisgrid.PairGrid at 0x21a24fc3190>



In [8]:
```
data.Experience.describe()
```

Out[8]:
```
count    5000.000000
mean       20.104600
std        11.467954
min        -3.000000
25%        10.000000
50%        20.000000
75%        30.000000
max        43.000000
Name: Experience, dtype: float64
```

There are negative values present in dataset as min value is negative -3.

In [9]:
```
# Total records of negative experience
data[data['Experience'] < 0]['Experience'].count()
```

Out[9]:
```
52
```

It shows that there are 52 negative Value of expereince that we have to handle

Firstly we will replace negative values to null values

In [10]:
```
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 )
```

In [11]:
```
 #Now checking Total records of negative experience
data[data['Experience'] < 0]['Experience'].count()
```

Out[11]:
```
0
```

Now there is no negative value in experience column

Now there are 52 null values in experience as we have replaced them so now we will replace them to median

In [12]:
```
data['Experience'].fillna(data['Experience'].median(),inplace=True)
```

In [13]:
```
#Quick overview of Experience column
data.Experience.describe()
```

Out[13]:
```
count    5000.000000
mean       20.327600
std        11.253035
min         0.000000
25%        11.000000
50%        20.000000
75%        30.000000
max        43.000000
Name: Experience, dtype: float64
```

In [14]:
```
data.isnull().sum()
```

Out[14]:
```
ID                    0
Age                   0
Experience            0
Income                0
ZIP Code              0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal Loan         0
Securities Account    0
CD Account            0
Online                0
CreditCard            0
dtype: int64
```

Now we can see that null values count is 0 in the dataframe.

In [15]:
```
 #Now again Total records of negative experience
data[data['Experience'] < 0]['Experience'].count()
```

Out[15]:
```
0
```

Thus all the negative values are handled and converted into positive

In [16]:
```
data.describe().transpose()     #Look at the data distribution
```

Out[16]:

	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	20.327600	11.253035	0.0	11.00	20.0	30.00	43.0
Income	5000.0	73.774200	46.033729	8.0	39.00	64.0	98.00	224.0
ZIP Code	5000.0	93152.503000	2121.852197	9307.0	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

In [17]:
```
data_temp=pd.DataFrame(data) #creating temporary data
data_temp
```

Out[17]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan
0	1	25	1.0	49	91107	4	1.6	1	0	0
1	2	45	19.0	34	90089	3	1.5	1	0	0
2	3	39	15.0	11	94720	1	1.0	1	0	0
3	4	35	9.0	100	94112	1	2.7	2	0	0
4	5	35	8.0	45	91330	4	1.0	2	0	0
...	...	...	...	...	...	...	...	...	...	...
4995	4996	29	3.0	40	92697	1	1.9	3	0	0
4996	4997	30	4.0	15	92037	4	0.4	1	85	0
4997	4998	63	39.0	24	93023	2	0.3	3	0	0
4998	4999	65	40.0	49	90034	3	0.5	2	0	0
4999	5000	28	4.0	83	92612	3	0.8	1	0	0

5000 rows × 14 columns

2. Perform univariate analysis of each and every attribute - use an appropriate plot for a given attribute and mention your insights

Continuous variable

In [18]:
```
data.nunique()
```

Out[18]:
```
ID                    5000
Age                     45
Experience              44
Income                 162
ZIP Code               467
Family                   4
CCAvg                  108
Education                3
Mortgage               347
Personal Loan            2
Securities Account       2
CD Account               2
Online                   2
CreditCard               2
dtype: int64
```

On the basis of number of unique values we can separate the continuous and categorical data

In [19]:
```
categorical_variables=[col for col in data.columns if data[col].nunique()<=5]
print(categorical_variables)
continuous_variables=[col for col in data.columns if data[col].nunique()>5]
print(continuous_variables)
```

```
['Family', 'Education', 'Personal Loan', 'Securities Account', 'CD Accoun
t', 'Online', 'CreditCard']
['ID', 'Age', 'Experience', 'Income', 'ZIP Code', 'CCAvg', 'Mortgage']
```

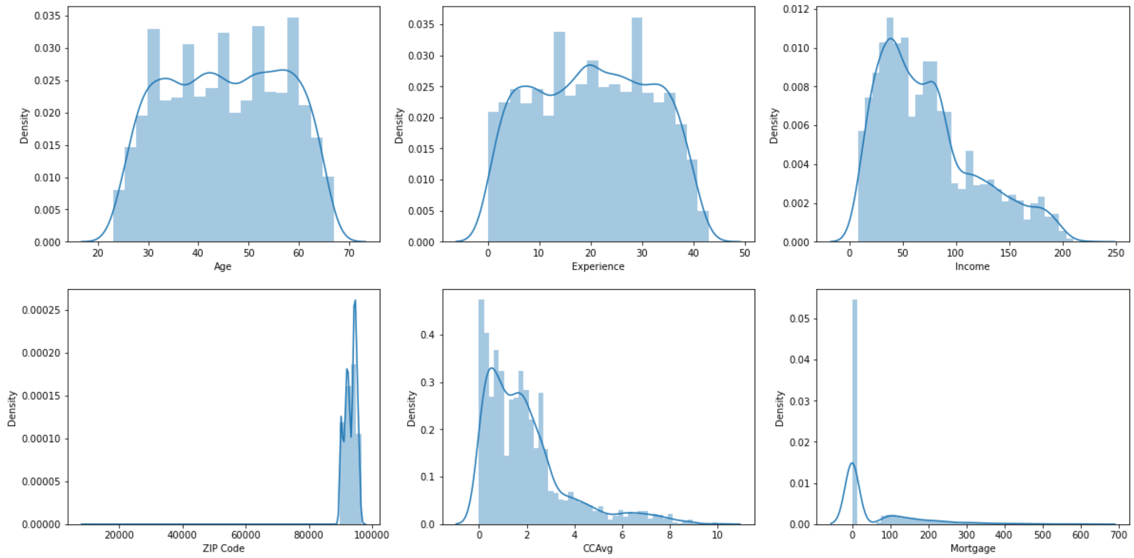
In [20]:
```
categorical_variables.remove("Personal Loan")
print(categorical_variables)
continuous_variables.remove("ID")
print(continuous_variables)
```

```
['Family', 'Education', 'Securities Account', 'CD Account', 'Online', 'Cred
itCard']
['Age', 'Experience', 'Income', 'ZIP Code', 'CCAvg', 'Mortgage']
```

In [21]:

```
fig=plt.figure(figsize=(20,10))
#fig.subplots_adjust(wspace=0.4,hspace=0.4)
for i,col in enumerate(continuous_variables):
    ax=fig.add_subplot(2,3,i+1)
    sns.distplot(data[col])
```

```
C:\Users\PRIYA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\PRIYA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\PRIYA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\PRIYA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\PRIYA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\PRIYA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



We can see that Age and Experience are uniformaly distributed and show a good similarities in distribution.

Income, CCAvg, Mortgage are positive Skew

Most of the customer doesn't have Securities Account, CD Account and CreditCard

More number of customer use internet banking facilities.

3. Perform correlation analysis among all the variables - you can use Pairplot and Correlation coefficients of every attribute with every other attribute

In [22]:

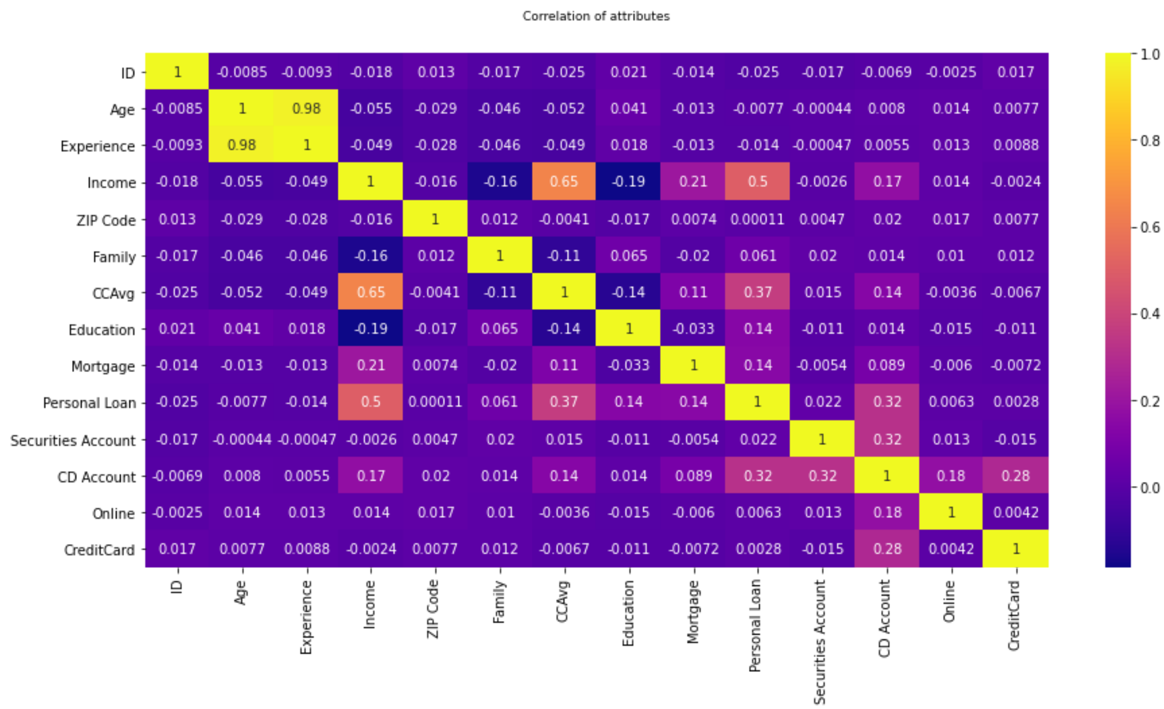
```
cor=data.corr()
cor
```

Out[22]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Educ
ID	1.000000	-0.008473	-0.009339	-0.017695	0.013432	-0.016797	-0.024675	0.02
Age	-0.008473	1.000000	0.977182	-0.055269	-0.029216	-0.046418	-0.052012	0.04
Experience	-0.009339	0.977182	1.000000	-0.049046	-0.028492	-0.045528	-0.048718	0.0
Income	-0.017695	-0.055269	-0.049046	1.000000	-0.016410	-0.157501	0.645984	-0.18
ZIP Code	0.013432	-0.029216	-0.028492	-0.016410	1.000000	0.011778	-0.004061	-0.0
Family	-0.016797	-0.046418	-0.045528	-0.157501	0.011778	1.000000	-0.109275	0.06
CCAvg	-0.024675	-0.052012	-0.048718	0.645984	-0.004061	-0.109275	1.000000	-0.13
Education	0.021463	0.041334	0.018074	-0.187524	-0.017377	0.064929	-0.136124	1.00
Mortgage	-0.013920	-0.012539	-0.013365	0.206806	0.007383	-0.020445	0.109905	-0.03
Personal Loan	-0.024801	-0.007726	-0.014013	0.502462	0.000107	0.061367	0.366889	0.13
Securities Account	-0.016972	-0.000436	-0.000465	-0.002616	0.004704	0.019994	0.015086	-0.0
CD Account	-0.006909	0.008043	0.005526	0.169738	0.019972	0.014110	0.136534	0.0
Online	-0.002528	0.013702	0.013459	0.014206	0.016990	0.010354	-0.003611	-0.0
CreditCard	0.017028	0.007681	0.008834	-0.002385	0.007691	0.011588	-0.006689	-0.0

In [23]:
```
plt.figure(figsize=(15,7))
plt.title("Correlation of attributes",y=1.05,size=9)
sns.heatmap(data.corr(),cmap='plasma',annot=True)
```

Out[23]: <AxesSubplot:title={'center':'Correlation of attributes'}>



Age and Experience are highly correlated and correlation of almost 1.

'Income' and CCAvg are moderately correlated.

4. One hot encode the Education variable

In [24]:
```
#one hot encoding of coloumn B
one_hot=pd.get_dummies(data_temp['Education'])

#Drop column Education as it is now encoded
data_temp=data_temp.drop('Education',axis=1)

#join the encoded Dataset
data_temp=data_temp.join(one_hot)
data_temp
```

Out[24]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Mortgage	Personal Loan	Securities Account
0	1	25	1.0	49	91107	4	1.6	0	0	1
1	2	45	19.0	34	90089	3	1.5	0	0	1
2	3	39	15.0	11	94720	1	1.0	0	0	0
3	4	35	9.0	100	94112	1	2.7	0	0	0
4	5	35	8.0	45	91330	4	1.0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
4995	4996	29	3.0	40	92697	1	1.9	0	0	0
4996	4997	30	4.0	15	92037	4	0.4	85	0	0
4997	4998	63	39.0	24	93023	2	0.3	0	0	0
4998	4999	65	40.0	49	90034	3	0.5	0	0	0
4999	5000	28	4.0	83	92612	3	0.8	0	0	0

5000 rows × 16 columns

One hot encoding allows the representation of categorical data to be more expressive

5. Separate the data into dependant and independent variables and create training and test sets out of them (X_train, y_train, X_test, y_test)

In [25]:
```
X=data_temp.drop('Personal Loan',axis=1)
y=data_temp['Personal Loan']
```

In [26]:
```
X_train,y_train,X_test,y_test=train_test_split(X,y,train_size=0.7,test_size=0
```

In [27]:
```
X_train.head()
```

Out[27]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Mortgage	Securities Account	CD Account
1334	1335	47	22.0	35	94304	2	1.3	0	0	0
4768	4769	38	14.0	39	93118	1	2.0	0	0	0
65	66	59	35.0	131	91360	1	3.8	0	0	0
177	178	29	3.0	65	94132	4	1.8	244	0	0
4489	4490	39	13.0	21	95518	3	0.2	0	0	0

6. Use StandardScaler( ) from sklearn, to transform the training and test data into scaled values (fit the StandardScaler object to the train data and transform train and test data using this object, making sure that the test set does not influence the values of the train set)

In [28]:
```
scaler=StandardScaler()
```

In [29]:
```
scaled_data=scaler.fit_transform(data.drop('Personal Loan',axis=1))
```

In [30]:
```
scaled_data=pd.DataFrame(scaled_data)
```

In [31]:
```
scaled_data.columns=data.drop('Personal Loan',axis=1).columns
scaled_data.head()
```

Out[31]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mo
0	-1.731704	-1.774417	-1.717717	-0.538229	-0.964114	1.397414	-0.193385	-1.049078	-0.
1	-1.731012	-0.029524	-0.117989	-0.864109	-1.443932	0.525991	-0.250611	-1.049078	-0.
2	-1.730319	-0.552992	-0.473484	-1.363793	0.738814	-1.216855	-0.536736	-1.049078	-0.
3	-1.729626	-0.901970	-1.006727	0.569765	0.452243	-1.216855	0.436091	0.141703	-0.
4	-1.728933	-0.901970	-1.095601	-0.625130	-0.859007	1.397414	-0.536736	0.141703	-0.

7. Write a function which takes a model, X_train, X_test, y_train and y_test as input and returns the accuracy, recall, precision, specificity,

f1_score of the model trained on the train set and evaluated on the test set

8. Employ multiple Classification models (Logistic, K-NN, Naïve Bayes etc) and use the function from step 7 to train and get the metrics of the model

9. Create a dataframe with the columns - “Model”, “accuracy”, “recall”, “precision”, “specificity”, “f1_score”.Populate the dataframe accordingly

In [115]:
```
X=scaled_data
y=data['Personal Loan']
```

In [116]:
```
x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state
```

LogisticRegression

In [117]:
```
model_list.append('LogisticRegression')
lm=LogisticRegression()
```

In [118]:
```
lm.fit(x_train,y_train)
yhat_lm=lm.predict(x_test)
```

In [119]:
```
lm_score=f1_score(y_test,yhat_lm)
print("F1_score of LogisticRegression is")
lm_score
```

```
F1_score of LogisticRegression is
```

Out[119]:
```
0.6692015209125476
```

In [120]:
```
lm_accuracy=accuracy_score(y_test,yhat_lm)
print("accuracy of LogisticRegression is")
lm_accuracy
```

```
accuracy of LogisticRegression is
```

Out[120]:
```
0.942
```

In [121]:
```
lm_precision=precision_score(y_test,yhat_lm)
print("precision of LogisticRegression is")
lm_precision
```

```
precision of LogisticRegression is
```

Out[121]:
```
0.8380952380952381
```

In [122]:
```
print(classification_report(y_test,yhat_lm))
```

```
              precision    recall  f1-score   support

           0       0.95      0.99      0.97      1342
           1       0.84      0.56      0.67       158

    accuracy                           0.94      1500
   macro avg       0.89      0.77      0.82      1500
weighted avg       0.94      0.94      0.94      1500
```

In [123]:
```
print(confusion_matrix(y_test,yhat_lm))
```

```
[[1325   17]
 [  70   88]]
```

SVC

In [124]:
```
model_list.append('SVC')
svc=SVC()
```

In [125]:
```
svc.fit(x_train,y_train)
yhat_svc=svc.predict(x_test)
```

In [126]:
```
svc_score=f1_score(y_test,yhat_svc)
print("f1_score of SVC is")
svc_score
```

```
f1_score of SVC is
```

Out[126]:
```
0.7927272727272728
```

In [127]:
```
svc_accuracy=accuracy_score(y_test,yhat_svc)
print("accuracy of SVC is")
svc_accuracy
```

```
accuracy of SVC is
```

Out[127]:
```
0.962
```

In [128]:
```
svc_precision=precision_score(y_test,yhat_svc)
print("precision of SVC is")
svc_precision
```

```
precision of SVC is
```

Out[128]:
```
0.9316239316239316
```

In [129]:
```
print(classification_report(y_test,yhat_svc))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.98      1342
           1       0.93      0.69      0.79       158

    accuracy                           0.96      1500
   macro avg       0.95      0.84      0.89      1500
weighted avg       0.96      0.96      0.96      1500
```

In [130]:
```
print(confusion_matrix(y_test,yhat_svc))
```

```
[[1334    8]
 [  49  109]]
```

KNeighborsClassifier

In [131]:
```
model_list.append('KNeighborsClassifier')
neighbour=KNeighborsClassifier()
```

In [132]:
```
neighbour.fit(x_train,y_train)
yhat_neighbour=neighbour.predict(x_test)
```

In [133]:
```
neighbour_score=f1_score(y_test,yhat_neighbour)
print("f1_score of KNeighborsClassifier is")
neighbour_score
```

```
f1_score of KNeighborsClassifier is
```

Out[133]:
```
0.6363636363636364
```

In [134]:
```
neighbour_accuracy=accuracy_score(y_test,yhat_neighbour)
print("accuracy of KNeighborsClassifier is")
neighbour_accuracy
```

```
accuracy of KNeighborsClassifier is
```

Out[134]:
```
0.9413333333333334
```

In [135]:
```
neighbour_precision=precision_score(y_test,yhat_neighbour)
print("precision of KNeighborsClassifier is")
neighbour_precision
```

```
precision of KNeighborsClassifier is
```

Out[135]:
```
0.9166666666666666
```

In [136]:
```
print(classification_report(y_test,yhat_neighbour))
```

```
              precision    recall  f1-score   support

           0       0.94      0.99      0.97      1342
           1       0.92      0.49      0.64       158

    accuracy                           0.94      1500
   macro avg       0.93      0.74      0.80      1500
weighted avg       0.94      0.94      0.93      1500
```

In [137]:
```
print(confusion_matrix(y_test,yhat_neighbour))
```

```
[[1335    7]
 [  81   77]]
```

Among the 5 models that we have implemented DecisionTreeClassifier and RandomForestClassifier gives the same and

best F1 Score and accuracy score with almost accuracy of 98% and F1-Score

Thus all the feature of every model is converted into a dataframe and are propogated.

It is clear seen that accuracy of RandonForestClassifier and DecisionTreeClassifier is more as compare to other models

Also precision of RandonForestClassifier is maximum

10. Give your reasoning on which is the best model in this case

Among the 5 models that we have implemented DecisionTreeClassifier and RandomForestClassifier gives the same and best F1 Score and accuracy score with almost accuracy of 98% and F1-Score of 91%

From the accuracy scores , it seems like "KNN" algorithm have the highest accuracy and stability.

But we can use SVM also as all the Kernels have good accuracy as well.

The logistic Regression model is the best as the accuracy of the train and test set is almost similar and also the precision and recall accuracy is good.