# Project - Supervised Learning

## Name: Panagam Mohitha

**Domain:** Banking

**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.

**Data Description:** 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.

**Attribute Information:**

- **ID** : Customer ID
- **Age** : Customer's age in completed years
- **Experience** : #years of professional experience
- **Income** : Annual income of the customer
- **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.
- **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

**Objective:** We will implement Classification algorithms to differentiate people who will buy loans vs the who will not.

## 1. Read the column description and ensure you

## understand each attribute well

## Importing the library:

In [459…
```
import warnings
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib import pyplot
import seaborn as sns
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn import metrics
from sklearn import preprocessing
from sklearn.metrics import average_precision_score, confusion_matrix, accuracy_sc
import math as m
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.linear_model import LinearRegression
```

In [460…
```
warnings.filterwarnings('ignore')
pd.options.display.max_columns = None
pd.options.display.float_format = '{:.5f}'.format
pd.options.display.max_rows = None
```

## Read data as Data frame:

In [461…
```
cust_data = pd.read_csv('C:\\Users\\Mohitha Panagam\\Downloads\\Project\\Bank_Pers
```

In [462…
```
cust_data.head()
```

Out[462]:

| | ID | Age | Experience | Income | ZIP Code | Family | CCAvg | Education | Mortgage | Personal_Loan |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 25 | 1 | 49 | 91107 | 4 | 1.60000 | 1 | 0 | 0 |
| **1** | 2 | 45 | 19 | 34 | 90089 | 3 | 1.50000 | 1 | 0 | 0 |
| **2** | 3 | 39 | 15 | 11 | 94720 | 1 | 1.00000 | 1 | 0 | 0 |
| **3** | 4 | 35 | 9 | 100 | 94112 | 1 | 2.70000 | 2 | 0 | 0 |
| **4** | 5 | 35 | 8 | 45 | 91330 | 4 | 1.00000 | 2 | 0 | 0 |

## Shape of the data

In [463…
```
cust_data.shape
```

Out[463]:
```
(5000, 14)
```

**Inference:**

- There are 5000 Observations / Rows and 14 Attributes / Columns.

## Data type of each attribute

In [464…
```
cust_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
```

**Inference:**

- Except CCAvg other attributes are integers.

## 5 point summary of attributes

In [465…
```
cust_data.describe()
```

Out[465]:

| | ID | Age | Experience | Income | ZIP Code | Family | CCAvg | Edu |
|---|---|---|---|---|---|---|---|---|
| **count** | 5000.00000 | 5000.00000 | 5000.00000 | 5000.00000 | 5000.00000 | 5000.00000 | 5000.00000 | 5000 |
| **mean** | 2500.50000 | 45.33840 | 20.10460 | 73.77420 | 93152.50300 | 2.39640 | 1.93794 | 1 |
| **std** | 1443.52000 | 11.46317 | 11.46795 | 46.03373 | 2121.85220 | 1.14766 | 1.74766 | 0 |
| **min** | 1.00000 | 23.00000 | -3.00000 | 8.00000 | 9307.00000 | 1.00000 | 0.00000 | 1 |
| **25%** | 1250.75000 | 35.00000 | 10.00000 | 39.00000 | 91911.00000 | 1.00000 | 0.70000 | 1 |
| **50%** | 2500.50000 | 45.00000 | 20.00000 | 64.00000 | 93437.00000 | 2.00000 | 1.50000 | 2 |
| **75%** | 3750.25000 | 55.00000 | 30.00000 | 98.00000 | 94608.00000 | 3.00000 | 2.50000 | 3 |
| **max** | 5000.00000 | 67.00000 | 43.00000 | 224.00000 | 96651.00000 | 4.00000 | 10.00000 | 3 |

**Inference:**

- It is observed that the minimum value of Experience in negative value which is not possible.
- Assuming the minus symbol as error in data entry.

In [466…
```
cust_data['Experience'] = cust_data['Experience'].abs()
cust_data.describe().transpose()
```

Out[466]:

| | count | mean | std | min | 25% | 50% |
|---|---|---|---|---|---|---|
| **ID** | 5000.00000 | 2500.50000 | 1443.52000 | 1.00000 | 1250.75000 | 2500.50000 |
| **Age** | 5000.00000 | 45.33840 | 11.46317 | 23.00000 | 35.00000 | 45.00000 |
| **Experience** | 5000.00000 | 20.13460 | 11.41519 | 0.00000 | 10.00000 | 20.00000 |
| **Income** | 5000.00000 | 73.77420 | 46.03373 | 8.00000 | 39.00000 | 64.00000 |
| **ZIP Code** | 5000.00000 | 93152.50300 | 2121.85220 | 9307.00000 | 91911.00000 | 93437.00000 |
| **Family** | 5000.00000 | 2.39640 | 1.14766 | 1.00000 | 1.00000 | 2.00000 |
| **CCAvg** | 5000.00000 | 1.93794 | 1.74766 | 0.00000 | 0.70000 | 1.50000 |
| **Education** | 5000.00000 | 1.88100 | 0.83987 | 1.00000 | 1.00000 | 2.00000 |
| **Mortgage** | 5000.00000 | 56.49880 | 101.71380 | 0.00000 | 0.00000 | 0.00000 |
| **Personal_Loan** | 5000.00000 | 0.09600 | 0.29462 | 0.00000 | 0.00000 | 0.00000 |
| **Securities_Account** | 5000.00000 | 0.10440 | 0.30581 | 0.00000 | 0.00000 | 0.00000 |
| **CD_Account** | 5000.00000 | 0.06040 | 0.23825 | 0.00000 | 0.00000 | 0.00000 |
| **Online** | 5000.00000 | 0.59680 | 0.49059 | 0.00000 | 0.00000 | 1.00000 |
| **CreditCard** | 5000.00000 | 0.29400 | 0.45564 | 0.00000 | 0.00000 | 0.00000 |

**Inference:**

- Using abs() function to make all the negative values of the experience into positive values therefore the minimum value of experience has corrected to zero.

## Checking the presence of missing values

In [467…
```
missing_values = cust_data.isnull().sum()

print(missing_values)
```

```
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
```

**Inference:**

- 'isnull' function used to check missing values in dataframe.
- No missing and null value present in the dataframe.

## Checking the unique values

In [468…
```
cust_data.apply(lambda x: len(x.unique()))
```

Out[468]:
```
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
```

**Inference:**

- It is observed that last 5 attributes have 2 unique values (0 and 1)
- Education attribute have 3 unique values (1: Undergrad; 2: Graduate; 3: Advanced/Professional)

In [469…
```
# Customer 'ID' is not required for further analysis. Therefore, it is removed.
cols_to_drop = ['ID']
cust_data = cust_data.drop(cols_to_drop, axis=1)
```

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

In [470…
```
cust_data[cust_data['Mortgage']==0].shape[0]
```

Out[470]: 3462

**Inference:**

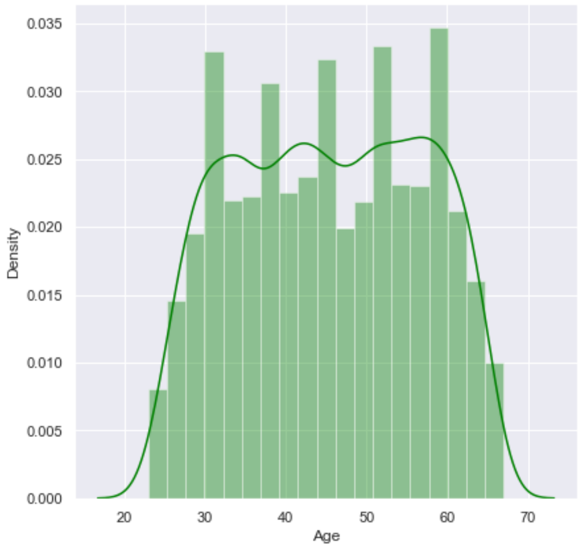
- There are more than half customers with no mortgage.
- The count of people having home mortgage as zero is 3462 which is like most of the people do not have mortgage.

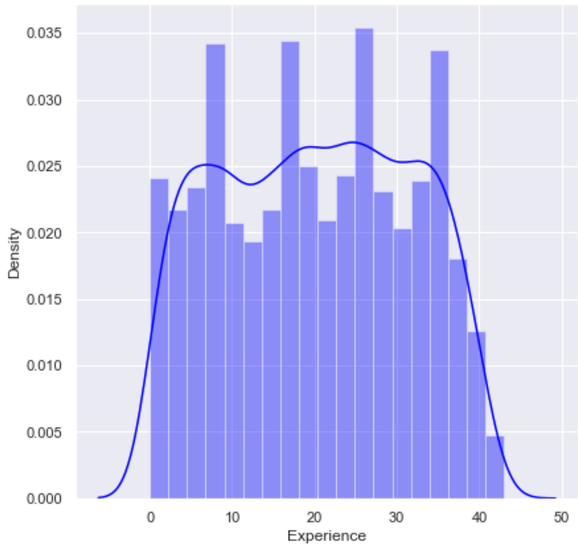
In [471…

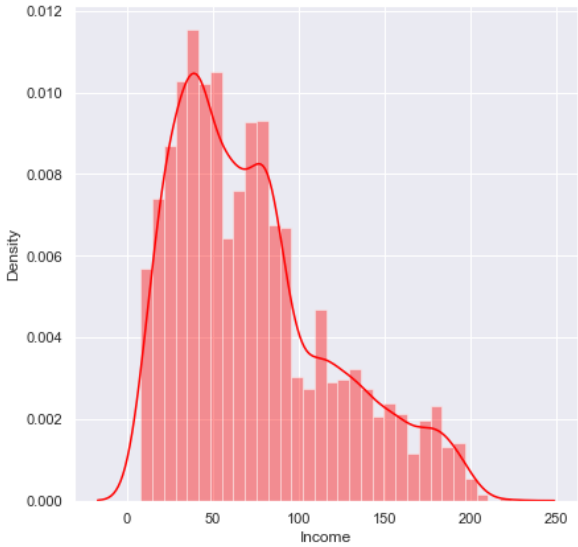
```
sns.set()
fig, axes = plt.subplots(5, 2, figsize=(15, 40))
sns.distplot(cust_data['Age'], color='green', ax=axes[0,0])
sns.distplot(cust_data['Experience'],color='blue', ax=axes[0,1])
sns.distplot(cust_data['Income'], color='red',ax=axes[1,0])
sns.countplot(cust_data['Education'], ax=axes[1,1])
sns.countplot(cust_data['Personal_Loan'], ax=axes[2,0])
sns.countplot(cust_data['Securities_Account'],ax=axes[2,1])
sns.countplot(cust_data['CD_Account'], ax=axes[3,0])
sns.countplot(cust_data['CreditCard'], ax=axes[3,1])
sns.countplot(cust_data['Family'], ax=axes[4,0])
sns.countplot(cust_data['Online'], ax=axes[4,1])
```

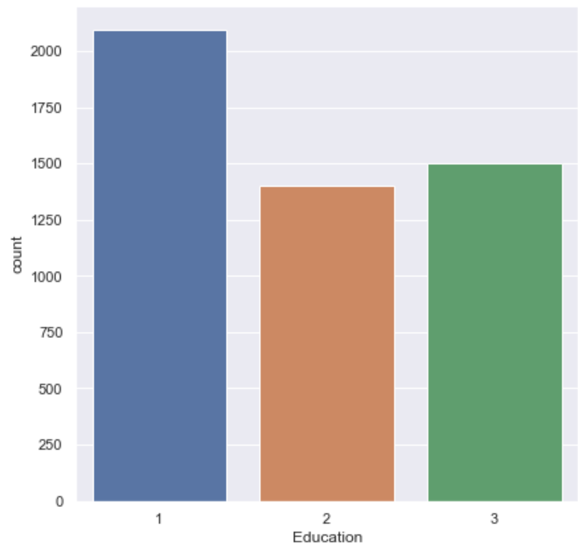
Out[471]:

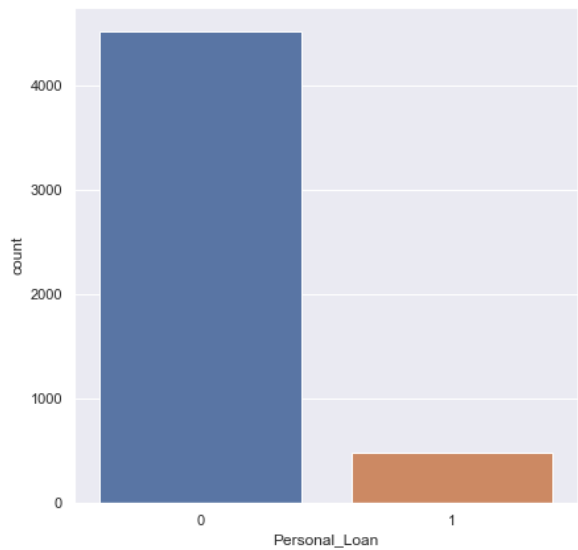
```
<AxesSubplot:xlabel='Online', ylabel='count'>
```

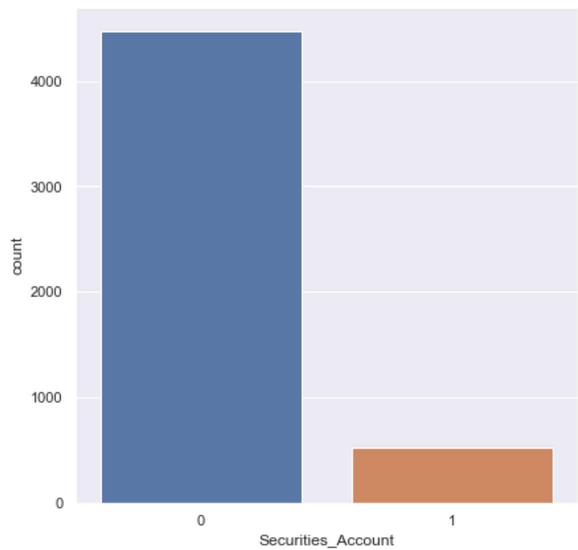

Density
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
20
30
40
50
60
70
Age

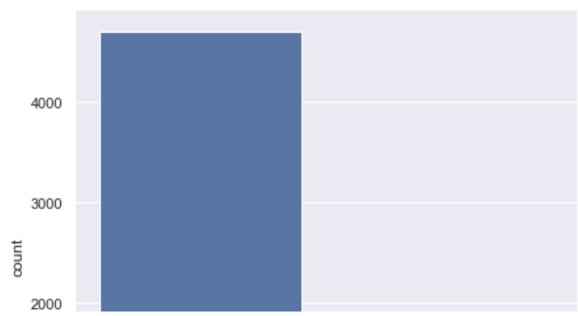

Density
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0
10
20
30
40
50
Experience

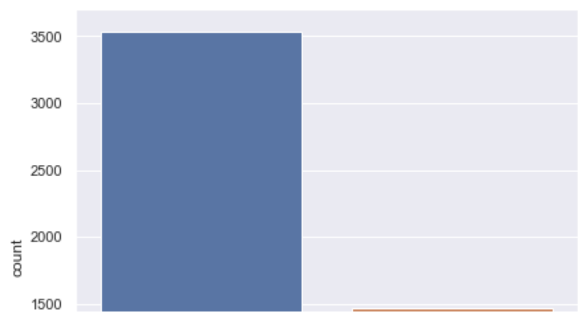

Density
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0
50
100
150
200
250
Income

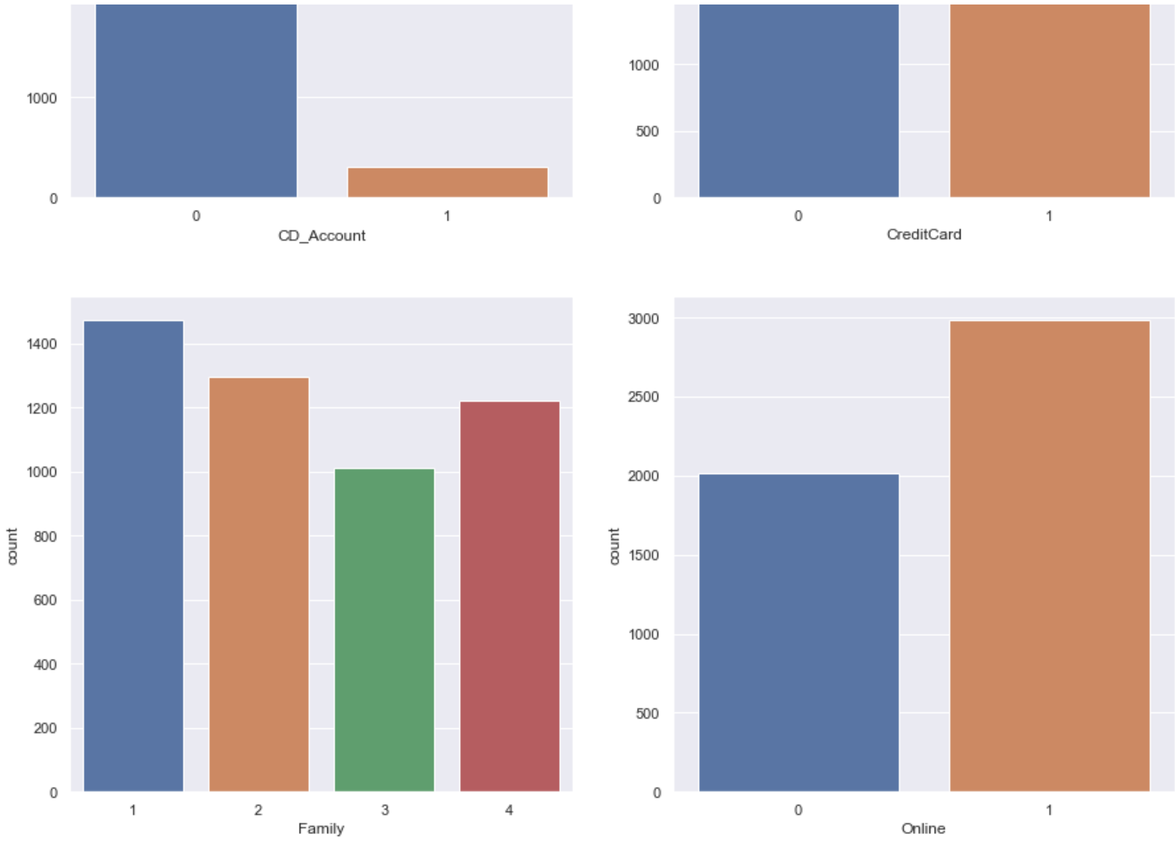

count
0
250
500
750
1000
1250
1500
1750
2000
1
2
3
Education


count
0
1000
2000
3000
4000
0
1
Personal_Loan


count
0
1000
2000
3000
4000
0
1
Securities_Account


count
2000
3000
4000


count
1500
2000
2500
3000
3500




**Inference:**

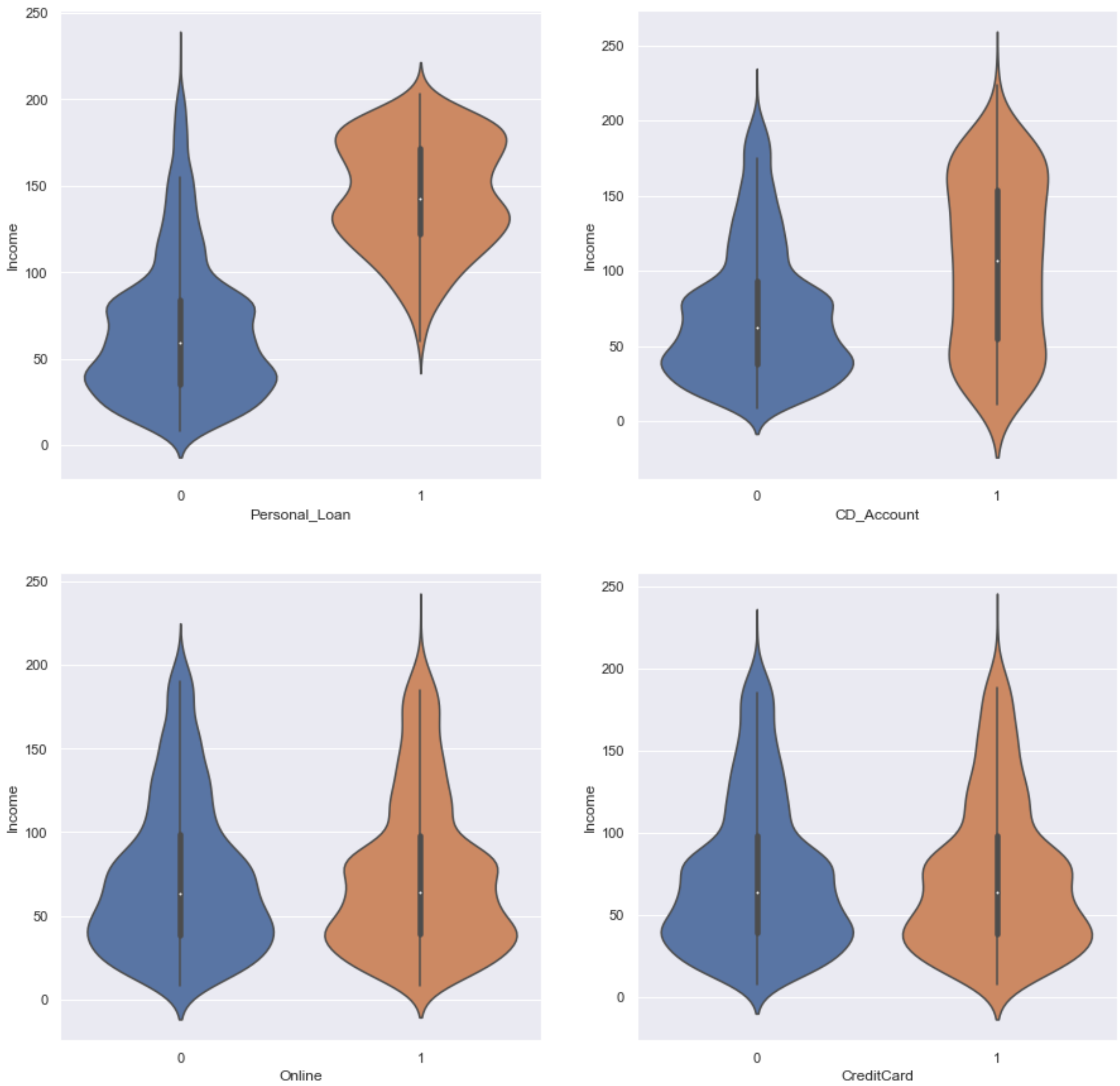
- The distribution of each attribute is found.
- It is found in the income distribution plot that it is left-skewed.
- The distribution plot of age and experience is evenly distributed.
- Regarding Education level of customers, Undergrads has major share.
- Graduates and Advanced/Professional has almost equal share but less than undergrads.
- People taking personal loans are very less.
- People prefer online mode.
- Most of the people in the given data don't have a credit card.
- People with securities account and CD account are low in the given data.

In [472…

```
sns.set()
fig, axes = plt.subplots(2, 2, figsize=(15, 15))
sns.violinplot(y='Income', x='Personal_Loan', data=cust_data, split=True, ax=axes[(
sns.violinplot(y='Income', x='CD_Account', data=cust_data, split=True, ax=axes[0,1
sns.violinplot(y='Income', x='Online', data=cust_data, split=True, ax=axes[1,0])
sns.violinplot(y='Income', x='CreditCard', data=cust_data, split=True, ax=axes[1,1
```

Out[472]:

```
<AxesSubplot:xlabel='CreditCard', ylabel='Income'>
```

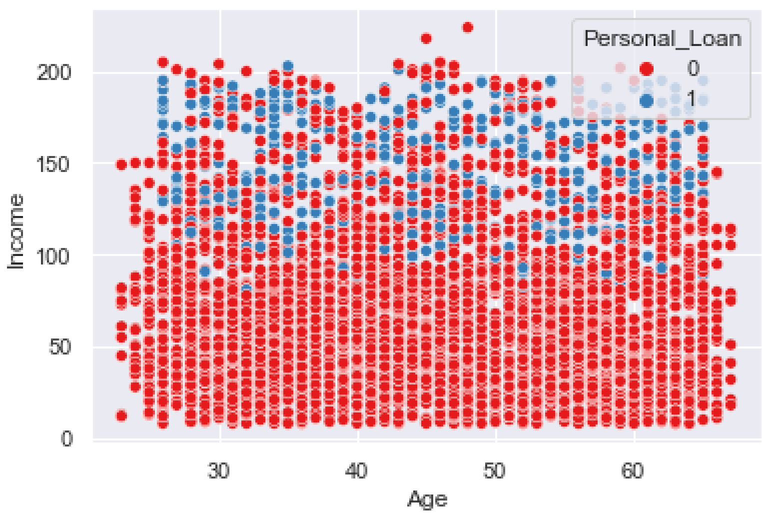



In [473…

```
sns.scatterplot(cust_data['Age'], cust_data['Income'], hue=cust_data['Personal_Loa
```

Out[473]:

```
<AxesSubplot:xlabel='Age', ylabel='Income'>
```

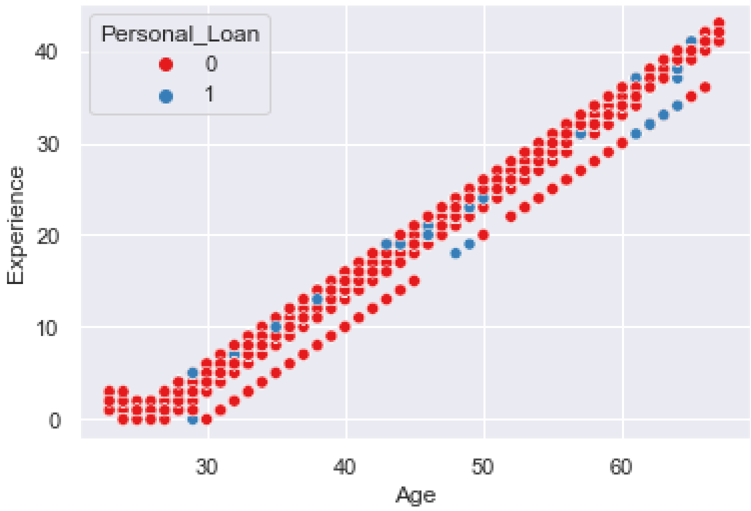



In [474…

```
sns.scatterplot(cust_data['Age'], cust_data['Experience'], hue=cust_data['Personal_
```

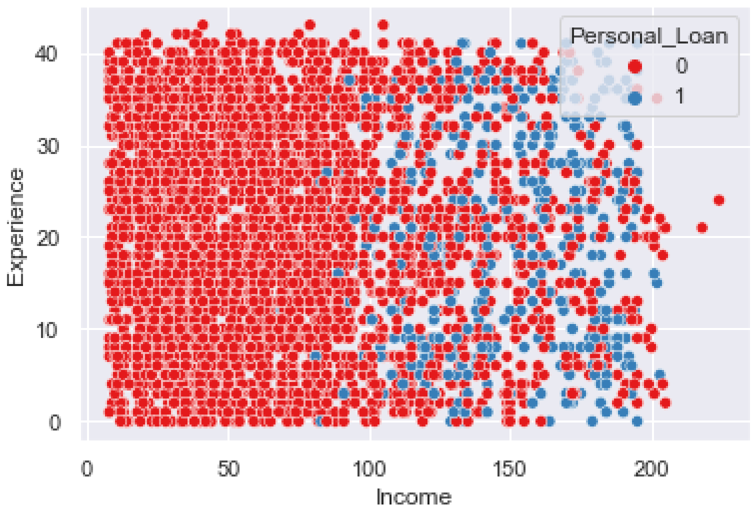
Out[474]:

```
<AxesSubplot:xlabel='Age', ylabel='Experience'>
```




```
In [475…  sns.scatterplot(cust_data['Income'], cust_data['Experience'], hue=cust_data['Perso
```

```
Out[475]: <AxesSubplot:xlabel='Income', ylabel='Experience'>
```




**Inference:**

- Age and Experience forms almost a straight line.
- Personal loan has been accepted to different age group customers.
- Only customers with Income more than 100 has likely get the personal loan.

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

```
In [476…  corr_data = cust_data.corr()
```

```
In [477…  corr_data
```

Out[477]:

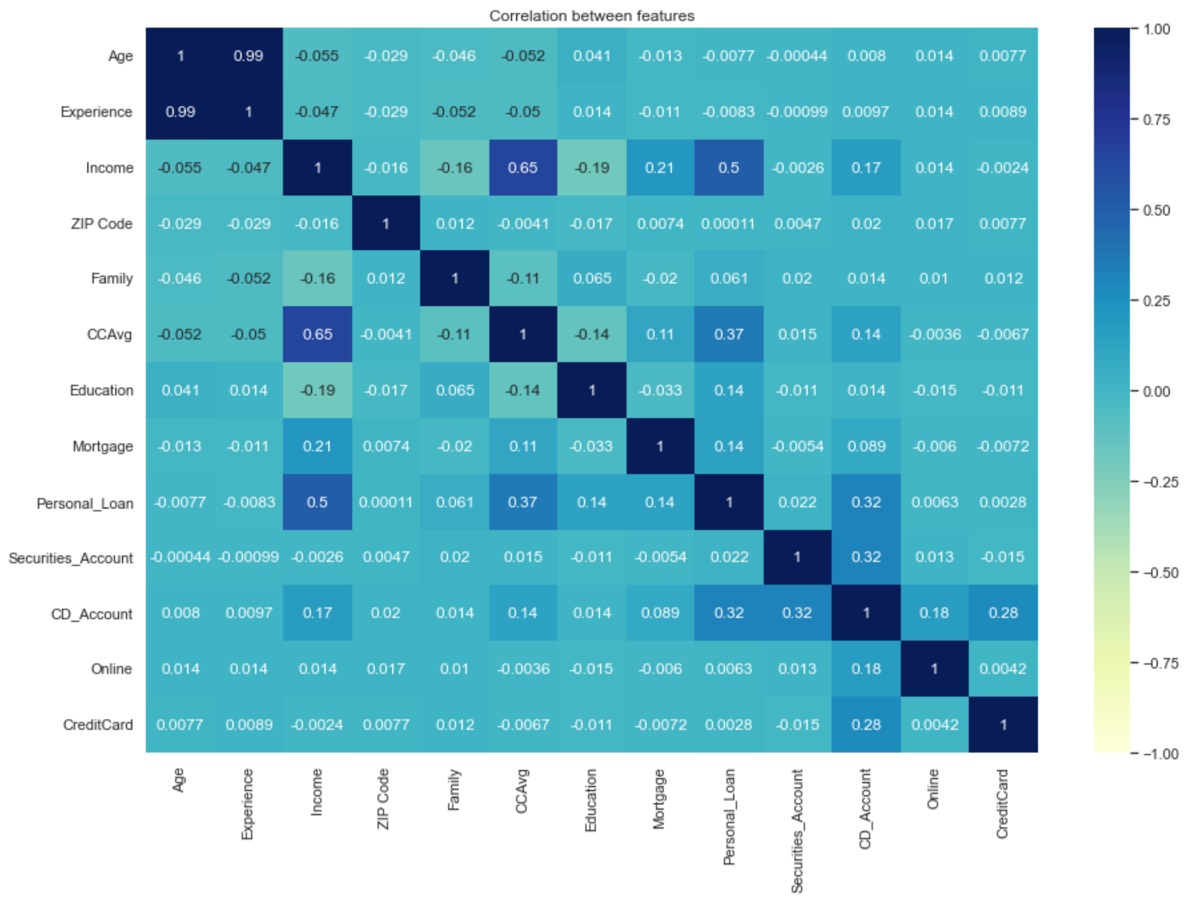
| | Age | Experience | Income | ZIP Code | Family | CCAvg | Education | Mortg |
|---|---|---|---|---|---|---|---|---|
| **Age** | 1.00000 | 0.99399 | -0.05527 | -0.02922 | -0.04642 | -0.05201 | 0.04133 | -0.0 |
| **Experience** | 0.99399 | 1.00000 | -0.04688 | -0.02894 | -0.05185 | -0.04974 | 0.01392 | -0.0 |
| **Income** | -0.05527 | -0.04688 | 1.00000 | -0.01641 | -0.15750 | 0.64598 | -0.18752 | 0.2 |
| **ZIP Code** | -0.02922 | -0.02894 | -0.01641 | 1.00000 | 0.01178 | -0.00406 | -0.01738 | 0.0 |
| **Family** | -0.04642 | -0.05185 | -0.15750 | 0.01178 | 1.00000 | -0.10927 | 0.06493 | -0.0 |
| **CCAvg** | -0.05201 | -0.04974 | 0.64598 | -0.00406 | -0.10927 | 1.00000 | -0.13612 | 0.1 |
| **Education** | 0.04133 | 0.01392 | -0.18752 | -0.01738 | 0.06493 | -0.13612 | 1.00000 | -0.0 |
| **Mortgage** | -0.01254 | -0.01110 | 0.20681 | 0.00738 | -0.02044 | 0.10990 | -0.03333 | 1.0 |
| **Personal_Loan** | -0.00773 | -0.00830 | 0.50246 | 0.00011 | 0.06137 | 0.36689 | 0.13672 | 0.1 |
| **Securities_Account** | -0.00044 | -0.00099 | -0.00262 | 0.00470 | 0.01999 | 0.01509 | -0.01081 | -0.0 |
| **CD_Account** | 0.00804 | 0.00973 | 0.16974 | 0.01997 | 0.01411 | 0.13653 | 0.01393 | 0.0 |
| **Online** | 0.01370 | 0.01405 | 0.01421 | 0.01699 | 0.01035 | -0.00361 | -0.01500 | -0.0 |
| **CreditCard** | 0.00768 | 0.00885 | -0.00239 | 0.00769 | 0.01159 | -0.00669 | -0.01101 | -0.0 |

In [478…

```
corr = cust_data.iloc[:, :13].corr()
plt.figure(figsize=(15, 10))

sns.heatmap(corr, cmap='YlGnBu', vmax=1.0, vmin=-1.0, annot = True, annot_kws={"si

plt.title('Correlation between features')
plt.show()
```



**Inference:**

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

In [432…

```
sns.pairplot(cust_data,hue="Personal_Loan");
```


**Inference:**

- The above plot show with experience and age have a positive correlation. As experience increase age also increases.

## Changing the datatype of attributes

In [479…

```
cust_data.dtypes
```

Out[479]:
```
Age                    int64
Experience             int64
Income                 int64
ZIP Code               int64
Family                 int64
CCAvg                float64
Education              int64
Mortgage               int64
Personal_Loan          int64
Securities_Account     int64
CD_Account             int64
Online                 int64
CreditCard             int64
dtype: object
```

In [480…
```
cust_data.Education = cust_data.Education.astype('object')
cust_data.Personal_Loan = cust_data.Personal_Loan.astype('bool')
cust_data.Securities_Account = cust_data.Securities_Account.astype('bool')
cust_data.CD_Account = cust_data.CD_Account.astype('bool')
cust_data.Online = cust_data.Online.astype('bool')
cust_data.CreditCard = cust_data.CreditCard.astype('bool')
```

In [481…
```
cust_data.dtypes
```

Out[481]:
```
Age                    int64
Experience             int64
Income                 int64
ZIP Code               int64
Family                 int64
CCAvg                float64
Education             object
Mortgage               int64
Personal_Loan           bool
Securities_Account      bool
CD_Account              bool
Online                  bool
CreditCard              bool
dtype: object
```

**Inference:**

- As the Personal_Loan, Securities_Account, CD_Account, Online, CreditCard attributes are bool type attributes. Therefore, it has been converted into boolean datatype.
- Education attribute has been typecasted to object data type since it has different categories.

In [482…
```
cols_to_drop = ['ZIP Code','Experience']
cust_data = cust_data.drop(cols_to_drop, axis=1)
```

**Inference:**

- ZIP Code is irrelevant to the analysis as the correlation is less than 0.01 with most of the attributes.
- Experience attribute is highly correlated with age. Therefore, these columns are dropped from the dataframe for further analysis.

## 4. One hot encode the Education variable

In [483…
```
cust_data.describe(include=object)
```

Out[483]:

| | Education |
|---|---|
| **count** | 5000 |
| **unique** | 3 |
| **top** | 1 |
| **freq** | 2096 |

In [484…

```
print(cust_data['Education'].unique())
cust_data['Education'].value_counts()
```

```
[1 2 3]
```

Out[484]:

```
1    2096
3    1501
2    1403
Name: Education, dtype: int64
```

In [485…

```
# Numerical attributes
cust_data_numeric_features = cust_data.select_dtypes(include=[np.number])
cust_data_numeric_features.columns
```

Out[485]:

```
Index(['Age', 'Income', 'Family', 'CCAvg', 'Mortgage'], dtype='object')
```

In [486…

```
# Categorical attributes
cust_data_categorical_features = cust_data.select_dtypes(include=[np.object])
cust_data_categorical_features.columns
```

Out[486]:

```
Index(['Education'], dtype='object')
```

In [487…

```
for col in cust_data_categorical_features.columns.values:
    dummy_encoded_variables = pd.get_dummies(cust_data_categorical_features[col], 
    cust_data_categorical_features = pd.concat([cust_data_categorical_features, du
    cust_data_categorical_features.drop([col], axis=1, inplace=True)
```

In [488…

```
 # concats two dataframes
cust_data_dummy = pd.concat([cust_data_numeric_features, cust_data_categorical_fea
```

In [489…

```
cust_data_dummy.head()
```

Out[489]:

| | Age | Income | Family | CCAvg | Mortgage | Education_2 | Education_3 |
|---|---|---|---|---|---|---|---|
| **0** | 25 | 49 | 4 | 1.60000 | 0 | 0 | 0 |
| **1** | 45 | 34 | 3 | 1.50000 | 0 | 0 | 0 |
| **2** | 39 | 11 | 1 | 1.00000 | 0 | 0 | 0 |
| **3** | 35 | 100 | 1 | 2.70000 | 0 | 1 | 0 |
| **4** | 35 | 45 | 4 | 1.00000 | 0 | 1 | 0 |

**Inference:**

- One-Hot-Encoding helps us to create dummy variables to replace the categories in a categorical variable into features of each category and represent it using 1 or 0 based on the presence or absence of the categorical value in the record.
- Education attribute has different categories as 1: Undergrad; 2: Graduate; 3: Advanced/Professional

- This function does One-Hot-Encoding on categorical text and convert the array into a dataframe. Specifically, one hot encoded dataframe

# 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 [490…
```
# Independent vs target variable
y = cust_data['Personal_Loan']
X = cust_data[['Age','Income','Family','CCAvg','Education','Mortgage',
               'Securities_Account','CD_Account','Online','CreditCard']]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.30, random_st
```

# 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 StandardScaler method, we convert variables with different scales of measurements into a single scale which normalizes the data.

In [491…
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_sd = scaler.fit_transform(X_train)
X_test_sd = scaler.transform(X_test)


y_train.replace({0: 'Rejected the loan', 1:'Accepeted the loan'}, inplace=True)
y_test.replace({0: 'Rejected the loan', 1:'Accepeted the loan'}, inplace = True)
```

# 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

In [492…
```
def fit_n_print(model, X_train, X_test, y_train, y_test):

    from sklearn.metrics import precision_score, recall_score, f1_score

    model.fit(X_train, y_train)

    test_accuracy = model.score(X_test, y_test)
    train_accuracy = model.score(X_train, y_train)
```

```
    pred = model.predict(X_test)
    precision = precision_score(y_test, pred)
    recall = recall_score(y_test, pred)
    specificity = recall_score(y_test, pred, pos_label=0)
    f1_score = f1_score(y_test, pred)

    return test_accuracy, train_accuracy, recall, precision, specificity, f1_score
```

## 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

In [493…

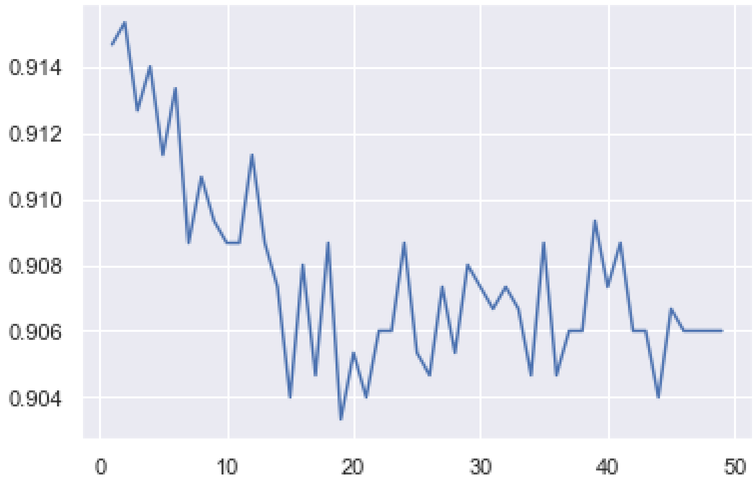
```
knn_scores =[]
for k in range(1,50):
    NNH = KNeighborsClassifier(n_neighbors = k, weights = 'distance' )
    NNH.fit(X_train, y_train)
    knn_scores.append(NNH.score(X_test, y_test))
```

In [494…

```
plt.plot(range(1,50),knn_scores)
```

Out[494]:

```
[<matplotlib.lines.Line2D at 0x2c7b297ed00>]
```




- For KNN model iterate through some range of values and check the train and test score.
- A Range of 0 to 20 for n_neighbors has been checked and to find the optimal value of k.
- From the above graph, the line is in its highest at the k=3

In [495…

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression()

from sklearn.naive_bayes import GaussianNB
NB = GaussianNB()

from sklearn.svm import SVC
SVM = SVC()

from sklearn.neighbors import KNeighborsClassifier
KNN = KNeighborsClassifier(n_neighbors=3)
# Therefore, optimal neighbours are used.
```

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

In [496…
```
result = pd.DataFrame(columns=['test_accuracy', 'train_accuracy', 'recall', 'preci

for name, model in zip(['Logistic Regression', 'Naive Bayes', 'SVM','KNN'], [LR, NI

    result.loc[name,:] = fit_n_print(model, X_train_sd, X_test_sd, y_train, y_test
```

In [497…
```
result
```

Out[497]:

| | test_accuracy | train_accuracy | recall | precision | specificity | f1_score |
|---|---|---|---|---|---|---|
| **Logistic Regression** | 0.94267 | 0.95429 | 0.56329 | 0.83962 | 0.98733 | 0.67424 |
| **Naive Bayes** | 0.88400 | 0.88457 | 0.60759 | 0.46154 | 0.91654 | 0.52459 |
| **SVM** | 0.96467 | 0.98229 | 0.71519 | 0.93388 | 0.99404 | 0.81004 |
| **KNN** | 0.96067 | 0.98000 | 0.67089 | 0.93805 | 0.99478 | 0.78229 |

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

- SVM is the best model as it has highest values in all columns except Precision, specificity.
- It gives 0.964 as output of accuracy. However, care should be taken while using accuracy as a metric because it gives biased results for data with unbalanced classes.
- SVM is the best model among other models since the best value of these scores is 1.
- Following SVM, KNN has second best and specificity, Precision values are better than the SVM model. In all other columns the values are nearer to SVM Model.
- Following KNN, Logistic model has the third position compared to other model values.
- Naive Bayes is the worst model in this case. Even though it has 0.884 accuarcy but the precision is not even 50%. Therefore, it is not the best model among other ones.