IMPORTING LIBRARIES AND DATASET

In [ ]:

```
# IMPORTING LIBRARIES

import pandas as pd
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn import preprocessing
```

In [ ]:

```
df = pd.read_excel("Bank_Personal_Loan_Modelling.xlsx")
```

In [ ]:

```
df.head()
```

Out[ ]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account	CD Account	Online	CreditCa
0	1	25	1	49	91107	4	1.6	1	0	0	1	0	0	
1	2	45	19	34	90089	3	1.5	1	0	0	1	0	0	
2	3	39	15	11	94720	1	1.0	1	0	0	0	0	0	
3	4	35	9	100	94112	1	2.7	2	0	0	0	0	0	
4	5	35	8	45	91330	4	1.0	2	0	0	0	0	0	

In [ ]:

```
# RENAMING THE COLUMNS SO AS TO REMOVE THE WHITESPACES PRESENT BETWEEN SOME OF THEM
df.columns = ["ID","Age","Experience","Income","ZIPCode","Family","CCAvg","Education","M
ortgage","PersonalLoan","SecuritiesAccount","CDAccount","Online","CreditCard"]
df.head()
```

Out[ ]:

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

In [ ]:

```
# SIZE OF THE DATASET (ROW,COLUMNS)
df.shape
```

Out[ ]:

```
(5000, 14)
```

In [ ]:

```
# THERE ARE NO NULL VALUES PRESENT IN THE DATASET
df.isnull().values.any()
```

Out[ ]:

```
False
```

In [ ]:

```
df[['Family','Education','PersonalLoan','SecuritiesAccount','CDAccount','Online','CreditCard']]=df[['Family','Education','PersonalLoan','SecuritiesAccount','CDAccount','Online','CreditCard']].astype('int')
```

In [ ]:

```
# DATATYPES OF EACH COLUMN OF THE DATASET
df.dtypes
```

Out[ ]:

```
ID                      int64
Age                     int64
Experience              int64
Income                  int64
ZIPCode                 int64
Family                  int64
CCAvg                 float64
Education               int64
Mortgage                int64
PersonalLoan            int64
SecuritiesAccount       int64
CDAccount               int64
Online                  int64
CreditCard              int64
dtype: object
```

In [ ]:

```
# STATISTICAL SUMMARY OF THE DATASET
df.describe()
```

Out[ ]:

	ID	Age	Experience	Income	ZIPCode	Family	CCAvg	Education	Mortgage
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.00000
mean	2500.500000	45.338400	20.104600	73.774200	93152.503000	2.396400	1.937913	1.881000	56.49880
std	1443.520003	11.463166	11.467954	46.033729	2121.852197	1.147663	1.747666	0.839869	101.71380
min	1.000000	23.000000	-3.000000	8.000000	9307.000000	1.000000	0.000000	1.000000	0.00000
25%	1250.750000	35.000000	10.000000	39.000000	91911.000000	1.000000	0.700000	1.000000	0.00000
50%	2500.500000	45.000000	20.000000	64.000000	93437.000000	2.000000	1.500000	2.000000	0.00000
75%	3750.250000	55.000000	30.000000	98.000000	94608.000000	3.000000	2.500000	3.000000	101.00000
max	5000.000000	67.000000	43.000000	224.000000	96651.000000	4.000000	10.000000	3.000000	635.00000

CLEANING THE DATASET

In [ ]:

```
# AS WE CAN SEE ABOVE THAT THE MINIMUM EXPERIENCE LEVEL IS -3, WHICH SHOULD BE REMOVED AS EXPERIENCE CANNOT BE NEGATIVE

neg = df.Experience < 0
neg.value_counts()
```

Out[ ]:

```
False    4948
True       52
Name: Experience, dtype: int64
```

In [ ]:

```
# THERE ARE 52 NEGATIVE VALUES, WHICH IS AN ERROR
# THEREFORE REPLACING THESE VALUES BY ABSOLUTE VALUE

df['Experience'] = abs(df['Experience'])
```

In [ ]:

```
df['Experience'].describe()
```

Out[ ]:

```
count    5000.000000
mean       20.134600
std        11.415189
min         0.000000
25%        10.000000
50%        20.000000
75%        30.000000
max        43.000000
Name: Experience, dtype: float64
```

EXPLORATORY DATA ANALYSIS(EDA)

In [ ]:

```
# NUMBER OF UNIQUES IN EACH COLUMN

df.nunique()
```

Out[ ]:

```
ID                     5000
Age                      45
Experience               44
Income                  162
ZIPCode                 467
Family                    4
CCAvg                   108
Education                 3
Mortgage                347
PersonalLoan              2
SecuritiesAccount         2
CDAccount                 2
Online                    2
CreditCard                2
dtype: int64
```

In [ ]:

```
# DROPPING THE ID, ZIPCode COLUMNs AS THEY DOEN'T CONTRIBUTE ANYTHING TO OUR DATA ANALYSI
S

df.drop(['ID'],inplace=True,axis=1)
df.drop(['ZIPCode'],inplace=True,axis=1)
df
```

Out[ ]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	PersonalLoan	SecuritiesAccount	CDAccount	Online
0	25	1	49	4	1.6	1	0	0	1	0	0
1	45	19	34	3	1.5	1	0	0	1	0	0

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	PersonalLoan	SecuritiesAccount	CDAccount	Online
2	39	15	11	1	1.0	1	0	0	0	0	0
3	35	9	100	1	2.7	2	0	0	0	0	0
4	35	8	45	4	1.0	2	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
4995	29	3	40	1	1.9	3	0	0	0	0	1
4996	30	4	15	4	0.4	1	85	0	0	0	1
4997	63	39	24	2	0.3	3	0	0	0	0	0
4998	65	40	49	3	0.5	2	0	0	0	0	1
4999	28	4	83	3	0.8	1	0	0	0	0	1

5000 rows × 12 columns

In [ ]:

```
# NUMBER OF CUSTOMERS WITH 0 MORTGAGE

df['Mortgage'].isin([0]).sum()
```

Out[ ]:

```
3462
```

In [ ]:

```
# NUMBER OF CUSTOMERS WITH ZERO CREDIT CARD SPENDINGS PER MONTH

df['CCAvg'].isin([0]).sum()
```

Out[ ]:

```
106
```

In [ ]:

```
# Value counts of all categorical columns.

print(df.Online.value_counts())
print('\n')
print(df.PersonalLoan.value_counts())
print('\n')
print(df.SecuritiesAccount.value_counts())
print('\n')
print(df.CDAccount.value_counts())
print('\n')
print(df.CreditCard.value_counts())
print('\n')
print(df.Family.value_counts())
print('\n')
print(df.Education.value_counts())
```

```
1    2984
0    2016
Name: Online, dtype: int64


0    4520
1     480
Name: PersonalLoan, dtype: int64


0    4478
1     522
Name: SecuritiesAccount, dtype: int64


0    4698
```

```
1     302
Name: CDAccount, dtype: int64


0    3530
1    1470
Name: CreditCard, dtype: int64


1    1472
2    1296
4    1222
3    1010
Name: Family, dtype: int64


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

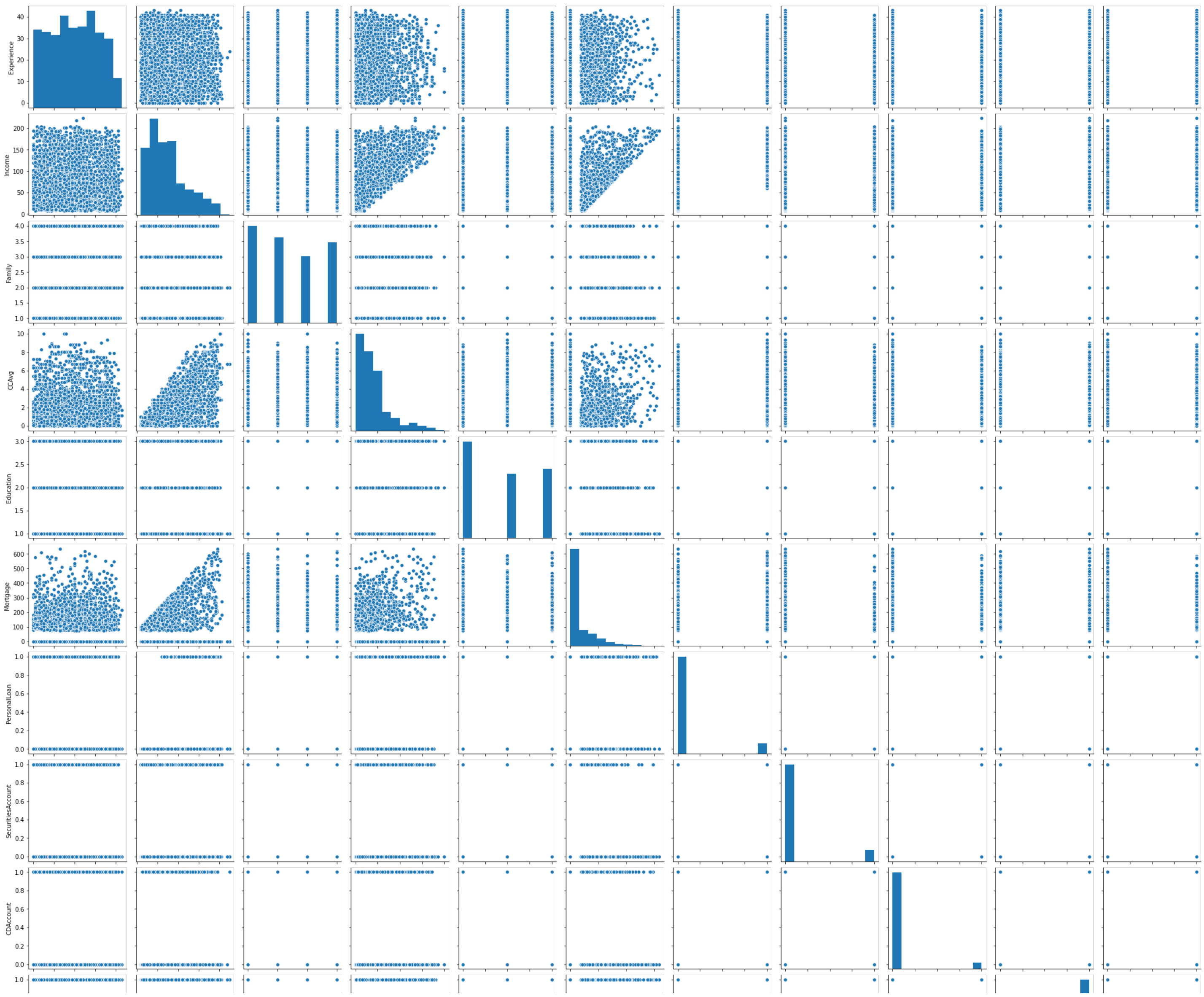
In [ ]:

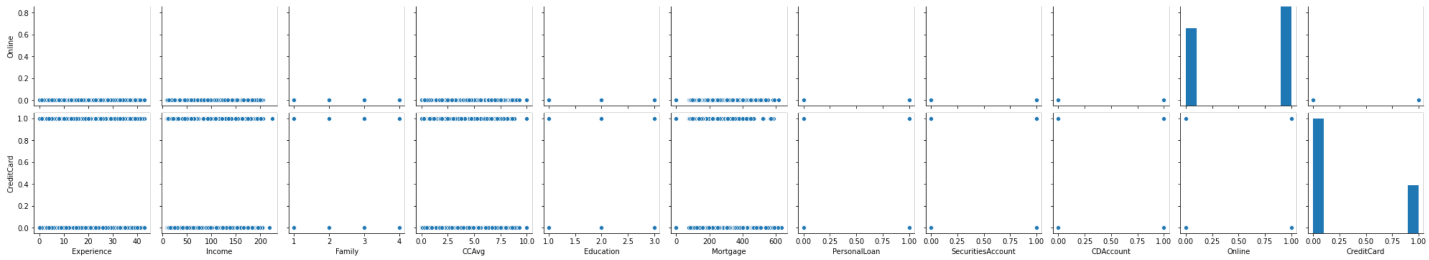
```
# UNIVARIATE AND BIVARIATE ANALYSIS.
# THIS SHOWS THE CORELATION BETWEEN EACH AND EVERY COLUMN PAIR OF THE DATASET, SOME OF TH
E ARE USEFUL.
# EXAMPLE INCOME AND EDUCATION HAVE A LINEAR RELATIONSHIP.

sns.pairplot(df.iloc[:,1:])
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7f14e10b3be0>
```





In [ ]:

```
# THIS OVERLAPS PERSONAL LOAN GRAPHS, SHOWS THE INTERSECTION OF PERSONAL LOAN WITH OTHER COLUMNS
sns.pairplot(df.iloc[:,1:],hue ='PersonalLoan')
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7f14de3f84e0>
```

In [ ]:

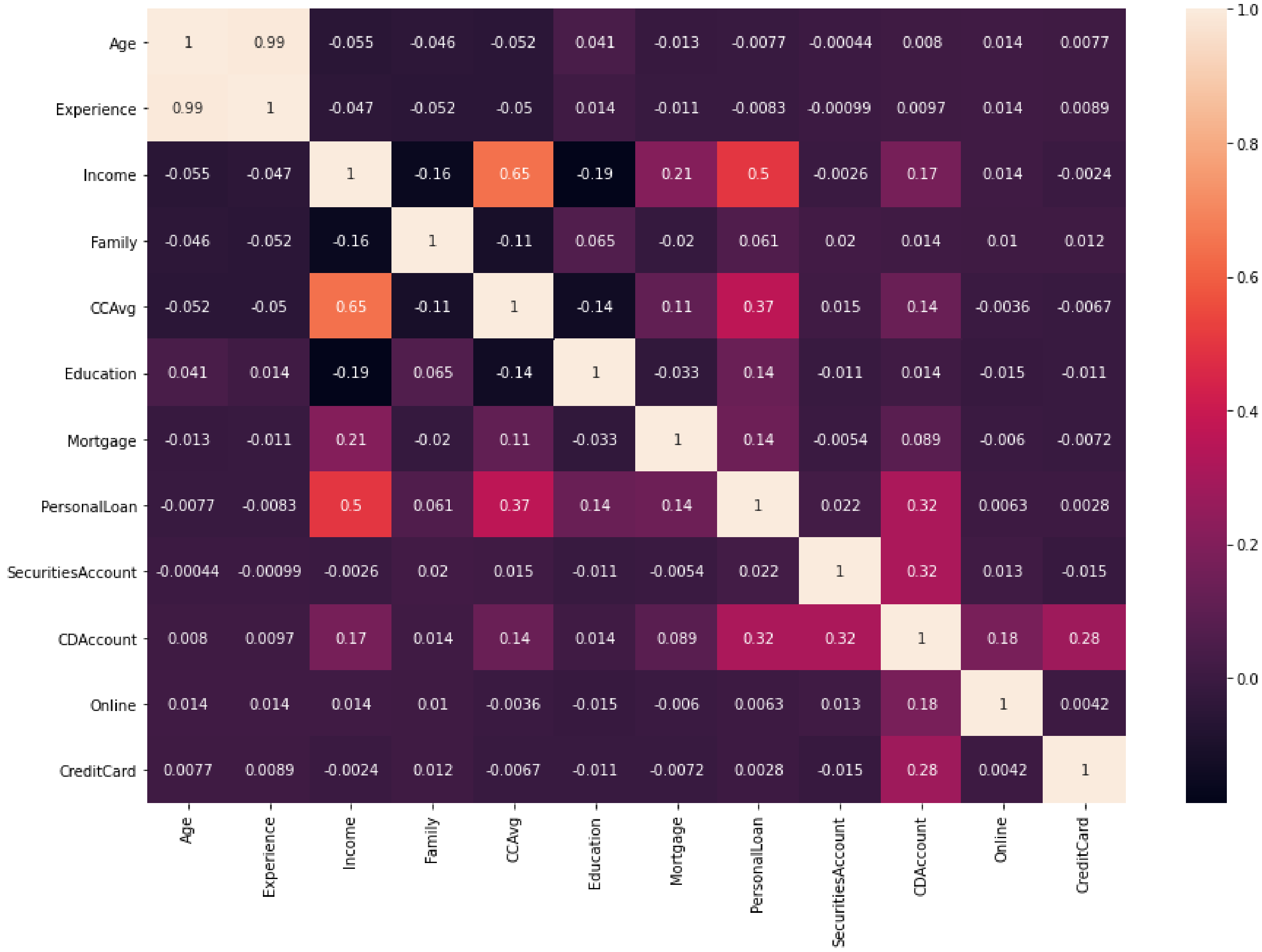
```
# Income and CCAvg is moderately correlated
# Age and Experience is highly correlated
# Also there is a moderate correlation b/w Income and Loan

corr=df.corr()
```

```
plt.subplots(figsize =(15, 10))
sns.heatmap(corr,annot=True)
```

Out[ ]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f14da9b4fd0>



In [ ]:

```
# SINCE AGE AND EXPERIENCE ARE HIGHLY CORRELATED, THEREFORE CONSIDERING ONLY ONE OF THEM
IN OUR PREDICTIONS

df.drop(['Experience'],inplace=True,axis=1)
df
```

Out[ ]:

	Age	Income	Family	CCAvg	Education	Mortgage	PersonalLoan	SecuritiesAccount	CDAccount	Online	CreditCard
0	25	49	4	1.6	1	0	0	1	0	0	0
1	45	34	3	1.5	1	0	0	1	0	0	0
2	39	11	1	1.0	1	0	0	0	0	0	0
3	35	100	1	2.7	2	0	0	0	0	0	0
4	35	45	4	1.0	2	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...	...	...
4995	29	40	1	1.9	3	0	0	0	0	1	0
4996	30	15	4	0.4	1	85	0	0	0	1	0
4997	63	24	2	0.3	3	0	0	0	0	0	0
4998	65	49	3	0.5	2	0	0	0	0	1	0
4999	28	83	3	0.8	1	0	0	0	0	1	1

5000 rows × 11 columns

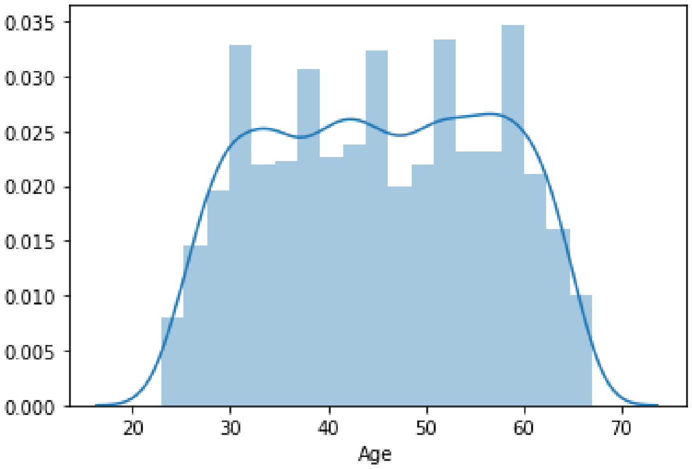
UNIVARIATE ANALYSIS

In [ ]:

```
sns.distplot(df.Age)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d94c8320>
```

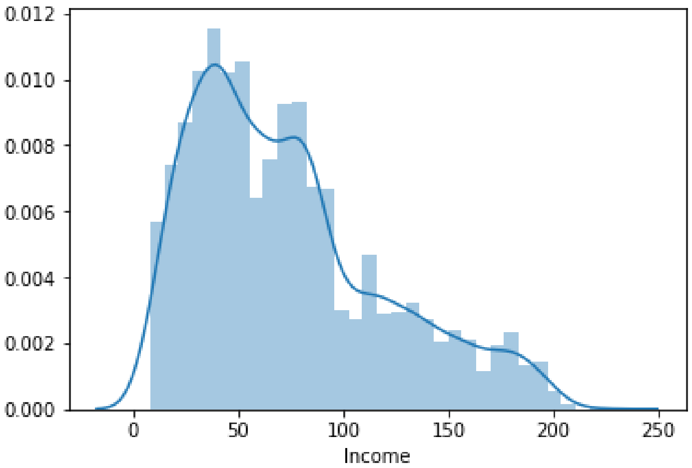


In [ ]:

```
sns.distplot(df.Income)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d92fc358>
```

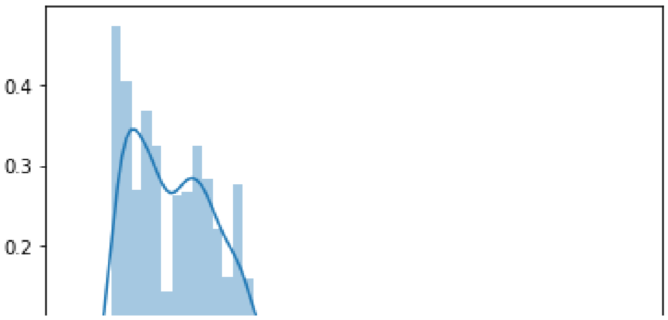


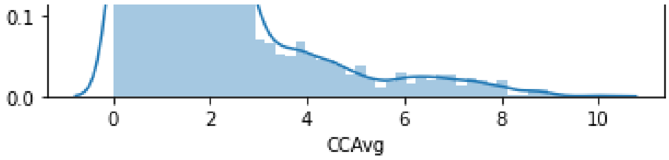
In [ ]:

```
sns.distplot(df.CCAvg)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d92e8f60>
```



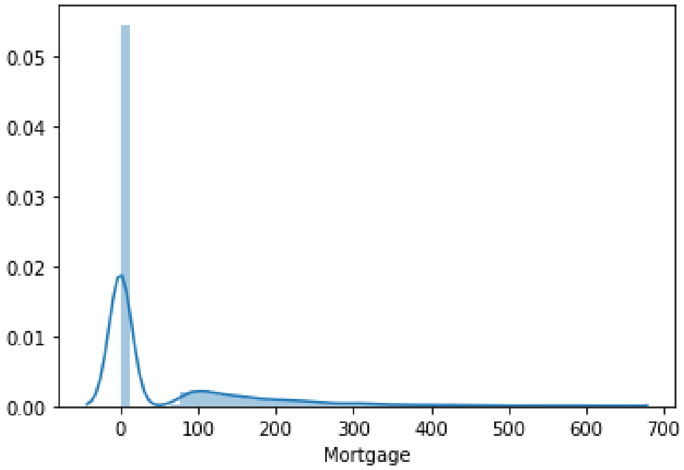


In [ ]:

```
sns.distplot(df.Mortgage)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d91888d0>
```



CONCLUSION : THE MORTGAGE, INCOME AND CCAVG PLOTS ARE RIGHT SKEWED, WHICH NEEDS TO BE IMPROVED.

BIVARIATE AND MULTIVARIATE ANALYSIS

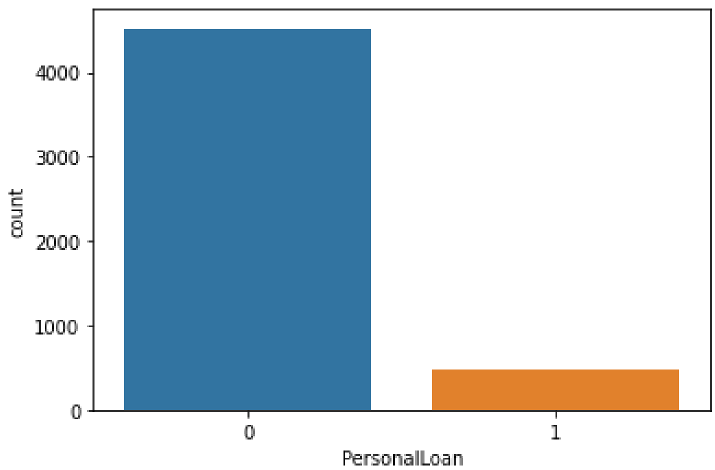
In [ ]:

```
# SHOW COUNT OF PEOPLE WHO HAVE TAKEN A LOAN and WHO HAVEN'T

sns.countplot(x='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d91a9ef0>
```

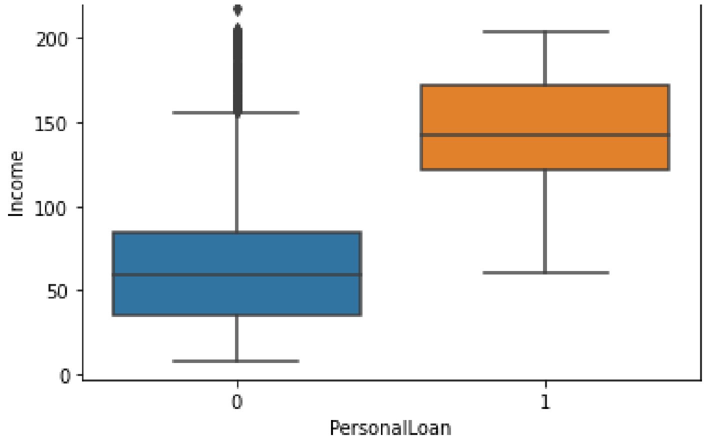


In [ ]:

```
sns.boxplot(x='PersonalLoan',y='Income',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d9039518>
```



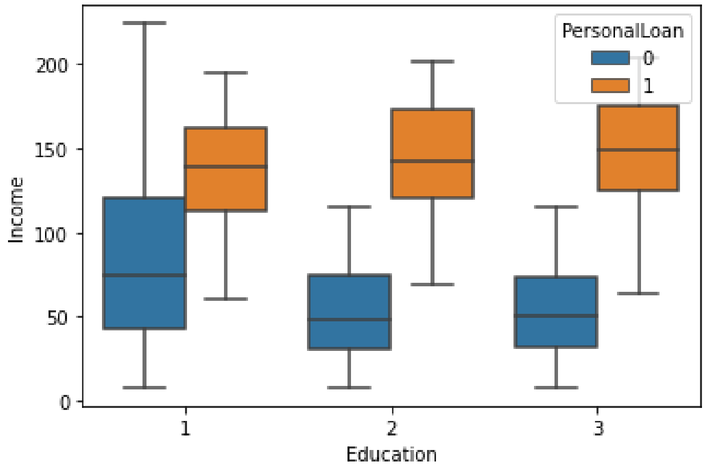
In [ ]:

```
# NO SPECIFIC CORRELATION BETWEEN AGE AND PERSONAL LOAN, AS ALL AGE GROUPS HAVE PEOPLE WH
O HAVE TAKEN LOAN AND WHO HAVE NOT TAKEN LOAN.
# PEOPLE WHO HAVE TAKEN LOANS BELONG TO A PARTICULAR INCOME LEVEL.

sns.boxplot(x='Education',y='Income',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d9024358>
```



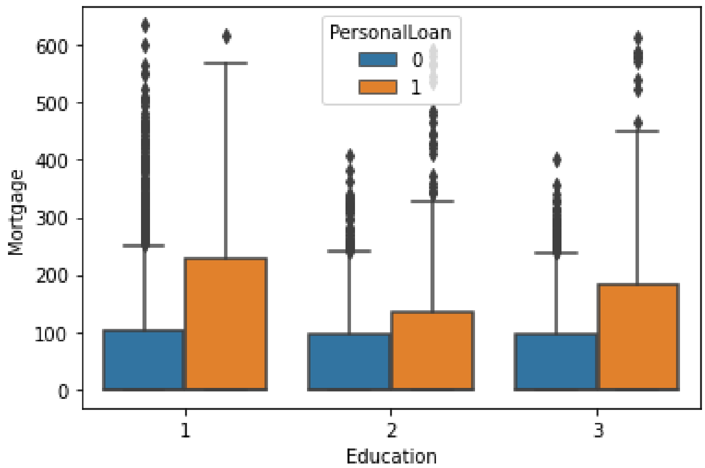
In [ ]:

```
# CUSTOMERS WITH AND WITHOUT PERSONAL LOANS, BOTH HAVE HIGH MORTGAGES
# THEREFORE, MORTGAGE IS NOT A VERY GOOD VARIABLE FOR PREDICTIONS.

sns.boxplot(x="Education", y='Mortgage', hue="PersonalLoan",data = df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8f6aa58>
```



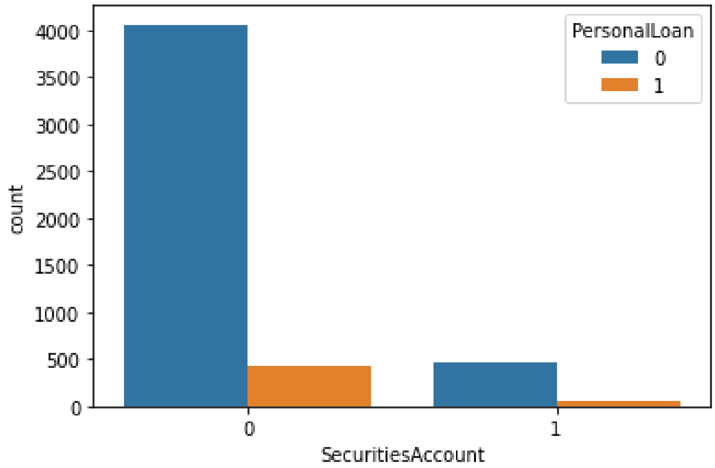
In [ ]:

```
# MAJORITY OF CUSTOMERS, WHO TAKE LOAN, DO NOT HAVE A SECURITY ACCOUNT

sns.countplot(x='SecuritiesAccount',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8ea6048>
```

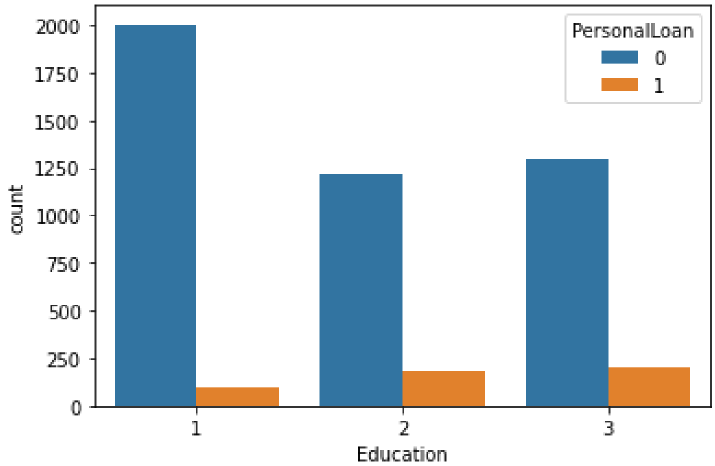


In [ ]:

```
# MAJORITY OF CUSTOMERS WITH EDUCATION LEVEL 1 DON'T TAKE LOANS
sns.countplot(x='Education',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8e2d240>
```

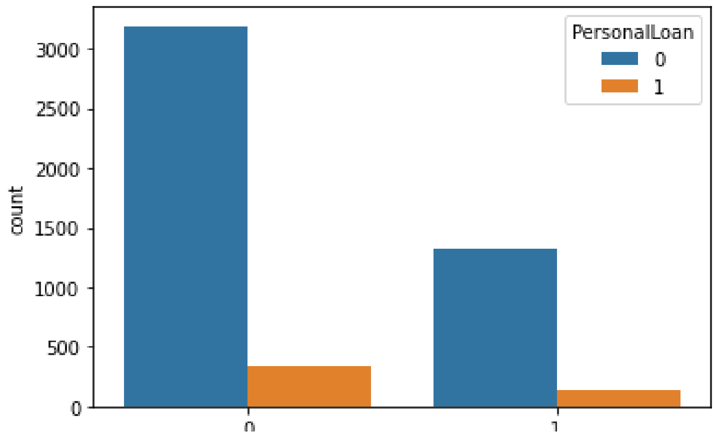


In [ ]:

```
# CUSTOMERS WITH NO CREDIT CARDS ARE LESS LIKELY TO TAKE LOANS.
sns.countplot(x='CreditCard',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8d8b898>
```



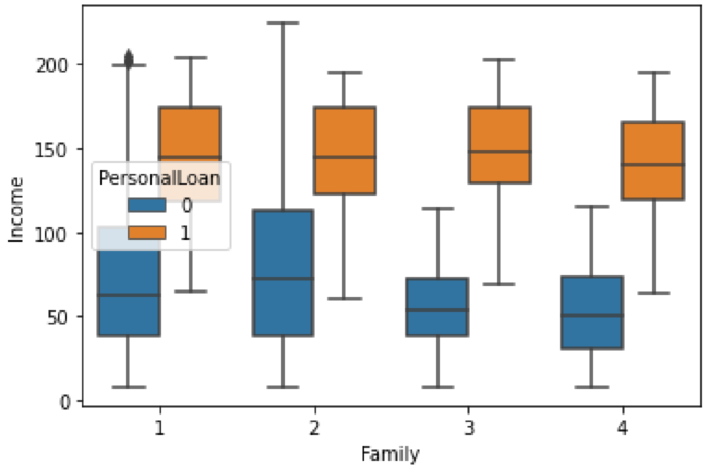
CreditCard

In [ ]:

```
#FAMILIES WITH HIGHER INCOME ARE MORE LIKELY TO TAKE LOANS.
sns.boxplot(x='Family',y='Income',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8d6d390>
```

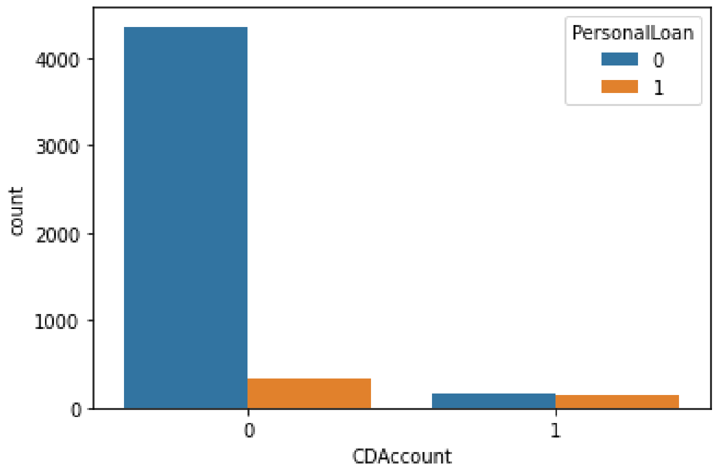


In [ ]:

```
# CUSTOMERS WITH A CDACCOUNT TEND TO TAKE LOAN.
sns.countplot(x='CDAccount',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8e0df28>
```

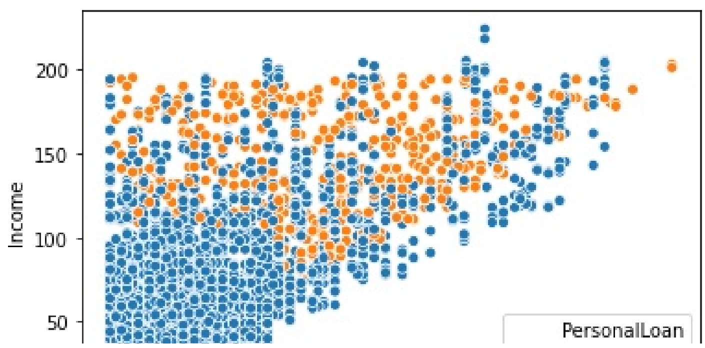


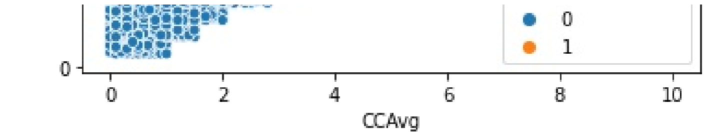
In [ ]:

```
# With the increase in income, ccavg also increases, and people tend to take more loans.
sns.scatterplot(x='CCAvg',y='Income',hue = 'PersonalLoan',data = df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8bb5240>
```



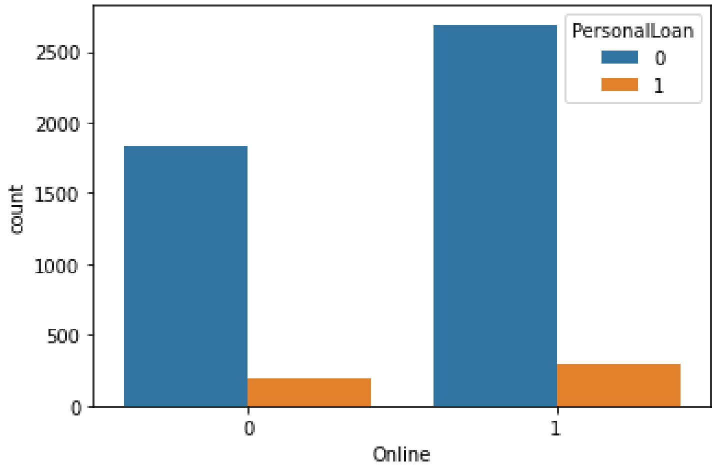


In [ ]:

```
# NO CORRELATION BETWEEN A CUSTOMER USING INTERNET BANKING FACILITIES AND TAKING A PERSON
AL LOAN.
sns.countplot(x='Online',hue='PersonalLoan',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8e1d7b8>
```

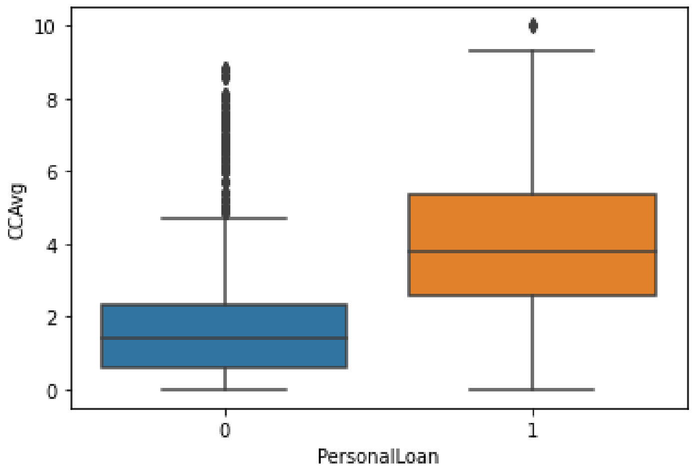


In [ ]:

```
sns.boxplot(x='PersonalLoan',y='CCAvg',data=df)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8b10438>
```



NECESSARY TRANSFORMATIONS FOR FEATURE VARIABLES

In [ ]:

```
y=df['PersonalLoan']
x=df.drop(['PersonalLoan'],axis=1)
```

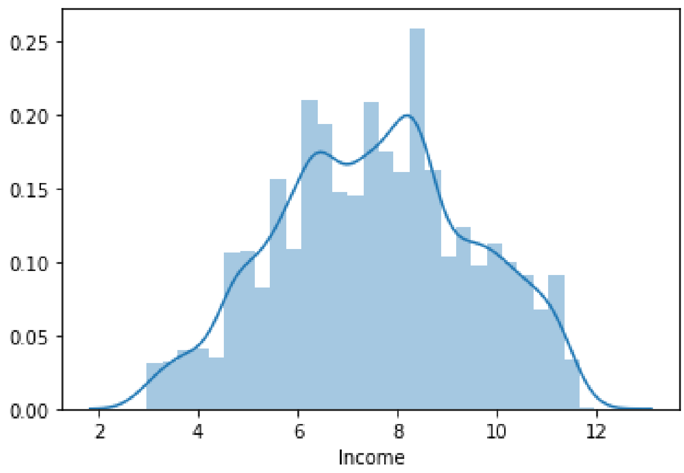
In [ ]:

```
from sklearn.preprocessing import PowerTransformer
pt = PowerTransformer(method = "yeo-johnson", standardize = False)
pt.fit(x['Income'].values.reshape(-1,1))
```

```
x['Income'] = pt.transform(x['Income'].values.reshape(-1,1))
sns.distplot(x.Income)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d8a8ac18>
```

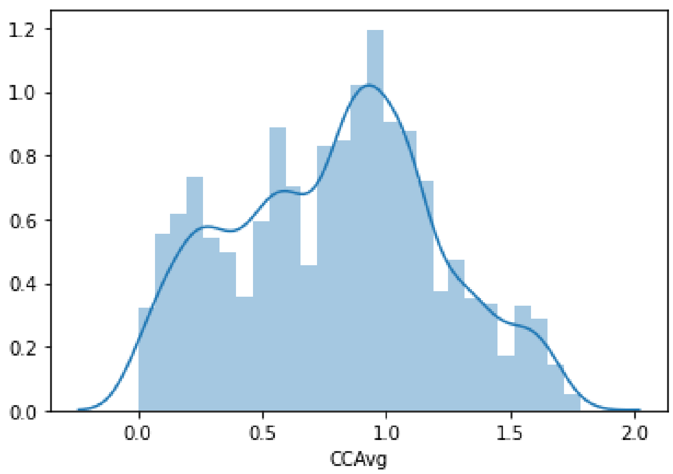


In [ ]:

```
pt = PowerTransformer(method = "yeo-johnson", standardize = False)
pt.fit(x['CCAvg'].values.reshape(-1,1))
x['CCAvg'] = pt.transform(x['CCAvg'].values.reshape(-1,1))
sns.distplot(x.CCAvg)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d89fd438>
```

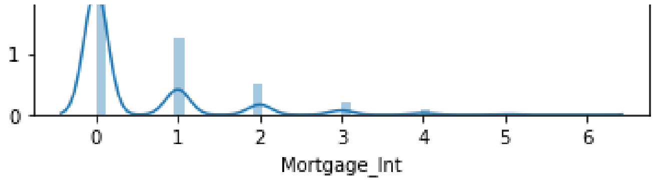


In [ ]:

```
x['Mortgage_Int'] = pd.cut(x['Mortgage'],
                           bins = [0,100,200,300,400,500,600,700],
                           labels = [0,1,2,3,4,5,6],
                           include_lowest = True)
x.drop('Mortgage',axis = 1, inplace = True)
sns.distplot(x.Mortgage_Int)
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14d88f2940>
```



CONCLUSION : THE SKEWNESS HAS BEEN REMOVED FROM THE FEATURE VARIABLES AND NOW THEY ARE NORMALLY DISTRIBUTED.

STANDARDIZING AND SPLITTING DATA

In [ ]:

```
def standardization(X_train,X_test):
    scaler=preprocessing.StandardScaler()
    X_train=scaler.fit_transform(X_train)
    X_test=scaler.transform(X_test)
    return X_train,X_test
```

In [ ]:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30,stratify = y ,r
andom_state=42)
x_train,x_test = standardization(x_train,x_test)
```

PREDICTION MODELS

LOGISTIC REGRESSION MODEL

In [ ]:

```
from sklearn.linear_model import LogisticRegression
lrmodel = LogisticRegression()
lrmodel.fit(x_train,y_train)
y_pred = lrmodel.predict(x_test)
```

In [ ]:

```
from sklearn.metrics import accuracy_score
score = accuracy_score(y_train,lrmodel.predict(x_train), normalize=True)
print(" TRAINING Accuracy :",int(score*100),end='%')
```

```
 TRAINING Accuracy : 95%
```

In [ ]:

```
from sklearn.metrics import accuracy_score
score = accuracy_score(y_test, y_pred, normalize=True)
print(" TESTING Accuracy :",int(score*100),end='%')
```

```
 TESTING Accuracy : 95%
```

In [ ]:

```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred)
```

Out[ ]:

```
array([[1339,   17],
       [  45,   99]])
```

In [ ]:

```
from sklearn import metrics

  print("The Classification report is")
  print(metrics.classification_report(y_test, y_pred))
  roc=metrics.roc_auc_score(y_test, y_pred)
  print("ROC value for logistic model is "+ str(roc*100) + "%")
```

```
The Classification report is
              precision    recall  f1-score   support

           0       0.97      0.99      0.98      1356
           1       0.85      0.69      0.76       144

    accuracy                           0.96      1500
   macro avg       0.91      0.84      0.87      1500
weighted avg       0.96      0.96      0.96      1500

ROC value for logistic model is 83.7481563421829%
```

NAIVE BAYES

In [ ]:

```
from sklearn.naive_bayes import GaussianNB
nbmodel = GaussianNB()
nbmodel.fit(x_train,y_train)
y_pred = nbmodel.predict(x_test)
```

In [ ]:

```
score = nbmodel.score(x_train,y_train)
print(" TRAINING Accuracy :",int(score*100),end='%')
```

```
 TRAINING Accuracy : 90%
```

In [ ]:

```
score = nbmodel.score(x_test,y_test)
print(" TESTING Accuracy :",int(score*100),end='%')
```

```
 TESTING Accuracy : 90%
```

In [ ]:

```
confusion_matrix(y_test,y_pred)
```

Out[ ]:

```
array([[1287,   69],
       [  69,   75]])
```

In [ ]:

```
print("The Classification report is")
  print(metrics.classification_report(y_test, y_pred))
  roc=metrics.roc_auc_score(y_test, y_pred)
  print("ROC value for naive bayes model is "+ str(roc*100) + "%")
```

```
The Classification report is
              precision    recall  f1-score   support

           0       0.95      0.95      0.95      1356
           1       0.52      0.52      0.52       144

    accuracy                           0.91      1500
   macro avg       0.73      0.73      0.73      1500
weighted avg       0.91      0.91      0.91      1500

ROC value for naive bayes model is 73.49741887905606%
```

KNN MODEL

In [ ]:

```
from sklearn.neighbors import KNeighborsClassifier
knnmodel = KNeighborsClassifier()
knnmodel.fit(x_train,y_train)
y_pred = knnmodel.predict(x_test)
```

In [ ]:

```
score = knnmodel.score(x_train,y_train)
print(" TRAINING Accuracy :",int(score*100),end='%')
```

```
 TRAINING Accuracy : 96%
```

In [ ]:

```
score = knnmodel.score(x_test,y_test)
print(" TESTING Accuracy :",int(score*100),end='%')
```

```
 TESTING Accuracy : 95%
```

In [ ]:

```
confusion_matrix(y_test,y_pred)
```

Out[ ]:

```
array([[1350,    6],
       [  55,   89]])
```

In [ ]:

```
print("The Classification report is")
  print(metrics.classification_report(y_test, y_pred))
  roc=metrics.roc_auc_score(y_test, y_pred)
  print("ROC value for knn model is "+ str(roc*100) + "%")
```

```
The Classification report is
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      1356
           1       0.94      0.62      0.74       144

    accuracy                           0.96      1500
   macro avg       0.95      0.81      0.86      1500
weighted avg       0.96      0.96      0.96      1500

ROC value for knn model is 80.68153883972468%
```

DECISION TREE MODEL

In [ ]:

```
from sklearn.tree import DecisionTreeClassifier
dtmodel = DecisionTreeClassifier(max_depth = 5, random_state=1)
dtmodel.fit(x_train,y_train)
y_pred = dtmodel.predict(x_test)
```

In [ ]:

```
score = dtmodel.score(x_train,y_train)
print(" TRAINING Accuracy :",int(score*100),end='%')
```

```
 TRAINING Accuracy : 98%
```

In [ ]:

```
score = dtmodel.score(x_test,y_test)
```

```
print(" TESTING Accuracy :",int(score*100),end='%')
```

```
 TESTING Accuracy : 98%
```

In [ ]:

```
confusion_matrix(y_test,y_pred)
```

Out[ ]:

```
array([[1339,   17],
       [   7,  137]])
```

In [ ]:

```
print("The Classification report is")
print(metrics.classification_report(y_test, y_pred))
roc=metrics.roc_auc_score(y_test, y_pred)
print("ROC value for decision tree model is "+ str(roc*100) + "%")
```

```
The Classification report is
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1356
           1       0.89      0.95      0.92       144

    accuracy                           0.98      1500
   macro avg       0.94      0.97      0.96      1500
weighted avg       0.98      0.98      0.98      1500

ROC value for decision tree model is 96.94260078662734%
```

RANDOM FOREST CLASSIFIER MODEL

In [ ]:

```
from sklearn.ensemble import RandomForestClassifier
rfcmodel = RandomForestClassifier(max_depth=5, random_state=42)
rfcmodel.fit(x_train,y_train)
rfcmodel.predict(x_test)
```

Out[ ]:

```
array([0, 0, 0, ..., 0, 0, 0])
```

In [ ]:

```
score = rfcmodel.score(x_train,y_train)
print(" TRAINING Accuracy :",int(score*100),end='%')
```

```
 TRAINING Accuracy : 98%
```

In [ ]:

```
score = rfcmodel.score(x_test,y_test)
print(" TESTING Accuracy :",int(score*100),end='%')
```

```
 TESTING Accuracy : 97%
```

In [ ]:

```
confusion_matrix(y_test,y_pred)
```

Out[ ]:

```
array([[1339,   17],
       [   7,  137]])
```

In [ ]:

```
print("The Classification report is")
```

```
print(metrics.classification_report(y_test, y_pred))
roc=metrics.roc_auc_score(y_test, y_pred)
print("ROC value for random forest classifier model is "+ str(roc*100) + "%")
```

```
The Classification report is
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1356
           1       0.89      0.95      0.92       144

    accuracy                           0.98      1500
   macro avg       0.94      0.97      0.96      1500
weighted avg       0.98      0.98      0.98      1500

ROC value for random forest classifier model is 96.94260078662734%
```

GRADIENT BOOSTING CLASSIFIER MODEL

In [ ]:

```
from sklearn.ensemble import GradientBoostingClassifier
gbmodel = GradientBoostingClassifier(random_state=42)
gbmodel.fit(x_train,y_train)
y_pred = gbmodel.predict(x_test)
```

In [ ]:

```
score = gbmodel.score(x_train,y_train)
print(" TRAINING Accuracy :",int(score*100),end='%')
```

```
 TRAINING Accuracy : 99%
```

In [ ]:

```
score = gbmodel.score(x_test,y_test)
print(" TESTING Accuracy :",int(score*100),end='%')
```

```
 TESTING Accuracy : 99%
```

In [ ]:

```
confusion_matrix(y_test,y_pred)
```

Out[ ]:

```
array([[1348,    8],
       [   7,  137]])
```

In [ ]:

```
print("The Classification report is")
print(metrics.classification_report(y_test, y_pred))
roc=metrics.roc_auc_score(y_test, y_pred)
print("ROC value for gradient boosting classifier model is "+ str(roc*100) + "%")
```

```
The Classification report is
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1356
           1       0.94      0.95      0.95       144

    accuracy                           0.99      1500
   macro avg       0.97      0.97      0.97      1500
weighted avg       0.99      0.99      0.99      1500

ROC value for gradient boosting classifier model is 97.27445919370699%
```

COMPARISON BETWEEN DIFFERENT MODELS

The models are listed in the increasing order of their performance :-

Model Name	Trainig Accuracy	Testing Accuracy	Sensitivity*	ROC Value
Naive Bayes	90	90	52	73
KNN	96	96	63	81
Logistic Regression	95	95	69	82
Decision Tree	98	98	95	96
Random Forest	98	98	94	96
Gradient Boosting	99	98	94	96

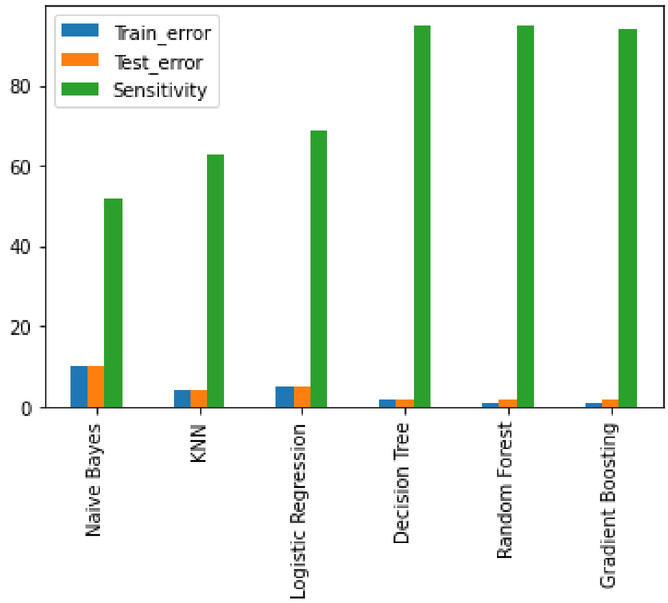
Sensitivity represents when the customer has actually taken the loan, and how often the model predicts that the customer will take a loan.

In [ ]:

```
sensitivity = [52,63,69,95,95,94]
train_error = [10,4,5,2,1,1]
test_error = [10,4,5,2,2,2]
ROC = [73,81,82,96,96,96]
col = {'Train_error' : train_error, 'Test_error' : test_error, 'Sensitivity' : sensitivi
ty}
models = ['Naive Bayes','KNN','Logistic Regression','Decision Tree','Random Forest','Gra
dient Boosting']
data =  pd.DataFrame(data = col, index = models)
data.plot(kind='bar')
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f14e11296a0>
```



Decision Tree, Random Forest and Gradient Boosting Classifier are close in terms of Accuracy, but the best predictions here, are made by Decision Tree model.

Therefore, Decision Tree Model is best for this data !

BUSINESS UNDERSATNDING

Here are some key takeaways from this model :

- **Income plays a major role in predicting whether a customer will take loan or not. Usually people with Income between 120K - 170K dollars, tend to take loans.**
- **Customers with education level 2 and 3 are more likely to take loans as compared to the customers with**

education level 1.

- Customers with credit cards are also more likely to take a loan.
- Customers with certificate of deposit accounts are more likely to take a loan.
- Customers without securites account, are more likely to take a loan.
- Customers with average credit card spending between 3k - 5k dollars per month are more likely to take a loan.
- The Decision Tree model predicts 137 customers out of 144 who have actually taken the loan. Therefore this will help us to predict customers who are willing to take a loan from the bank. Also, the Random Forest Classifier Model and Gradient Boosting Classifier Model work good enough !