Introduction

Ever wondered how internet provides search results about the topic of interest?

Let's say you searched for "movie automatic shoe laces" and it brings up "Back to the future".

Has the search engine watched the movie? No, but it knows from lots of other searches what people are probably looking for.

And it calculates that probability using Bayes' Theorem.

Bayes' Theorem describes the probability of an event, based on prior knowledge of conditions that might be related to the event.

Problem Statement

- **USA Leading Bank**, provides **Multiple products and services** to its customers.
- Bank having corpus balance and they wanted to scale **Personal loan business** to boost their Assets base.
- **Bank is running the campaign to reach out the existing saleried customers with Personal Loan Product offering.**
- As of now only **9.60% customer** have accepted the offer. Response to the campaign is below expectations.
- Bank targeting the customers who have already cosuming the Asset product like **Credit Cards and Mortgage loans.**
- Bank is also targeting customers who have not taken any loans but having banking relationship and using othe product like **Securities Account & CD Account.**
- Looking after below par response to the campaign bank wanted to **analyse key factors to improve personal loan business and make this campaign successful.**
- Below are the features provided for the analysis.

Personal Loan - Did this customer accept the personal loan offered in the last campaign? **This is our target variable**

Securities Account - Customer have a securities account with the bank

CD Account - Customer have a certificate of deposit (CD) account with the bank

Online - Customer using internet banking facilities

Credit Card - Customer using a credit card issued by Bank

Age - Age of the customer

Experience - Years of experience

Income - Annual income in dollars

CCAvg - Average credit card spending

Mortage - Value of House Mortgage

Family - Family size of the customer

Education - Education level of the customer

Importing Libraries

```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib  inline
import seaborn as sns
import warnings
import warnings
warnings.filterwarnings("ignore")
```

Data Acquisition & Description

```
df_loan= pd.read_csv("https://raw.githubusercontent.com/ajaykini25/PersonalLoanPrediction/mai
df_loan.shape
```

```
(5000, 14)
```

```
df_loan.head()
```

```
df_loan.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
```

```
df_loan.describe().T
```

	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	20.104600	11.467954	-3.0	10.00	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

Observations:

- The experience column is having minimum values in range of -1,-2-3. This needs to be checked and process.
- Mortgage is positively skewed.

Data Pre-Processing

Data Cleaning

```
# Dropping the redudant columns which are not much significance.
df_loan.drop(['ID','ZIP Code'], axis=1, inplace=True)
```

```
df_loan.isnull().sum()
```

```
Age                   0
Experience            0
Income                0
Family                0
CCAvg                 0
Education             0
Mortgage              0
Personal Loan         0
Securities Account    0
CD Account            0
Online                0
CreditCard            0
dtype: int64
```

There are some negative values in the "Experience" column.

```
df_loan[df_loan['Experience']<0]
```

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Personal Loan	Securiti Accou
89	25	-1	113	4	2.30	3	0	0	
226	24	-1	39	2	1.70	2	0	0	
315	24	-2	51	3	0.30	3	0	0	
451	28	-2	48	2	1.75	3	89	0	
524	24	-1	75	4	0.20	1	0	0	
536	25	-1	43	3	2.40	2	176	0	
540	25	-1	109	4	2.30	3	314	0	
576	25	-1	48	3	0.30	3	0	0	
583	24	-1	38	2	1.70	2	0	0	
597	24	-2	125	2	7.20	1	0	0	
649	25	-1	82	4	2.10	3	0	0	
670	23	-1	61	4	2.60	1	239	0	
686	24	-1	38	4	0.60	2	0	0	
793	24	-2	150	2	2.00	1	0	0	
889	24	-2	82	2	1.60	3	0	0	
909	23	-1	149	1	6.33	1	305	0	
1173	24	-1	35	2	1.70	2	0	0	
1428	25	-1	21	4	0.40	1	90	0	
1522	25	-1	101	4	2.30	3	256	0	
1905	25	-1	112	2	2.00	1	241	0	
2102	25	-1	81	2	1.60	3	0	0	
2430	23	-1	73	4	2.60	1	0	0	
2466	24	-2	80	2	1.60	3	0	0	
2545	25	-1	39	3	2.40	2	0	0	

Since Income vs Experience is critical factor while making any credit decision. Hence checking the mean of the negative values in Experience before treating the negative values

```
df_loan.groupby(by= 'Experience' )['Income'].mean()
```

```
Experience
-3    68.250000
```

```
-2     82.466667
-1     64.454545
 0     69.651515
 1     74.472973
 2     80.258824
 3     82.449612
 4     74.000000
 5     76.527397
 6     78.159664
 7     72.148760
 8     75.050420
 9     75.959184
 10    72.576271
 11    71.525862
 12    82.303922
 13    77.452991
 14    68.921260
 15    76.352941
 16    74.047244
 17    76.800000
 18    75.715328
 19    74.762963
 20    89.182432
 21    80.292035
 22    83.790323
 23    71.590278
 24    72.236641
 25    68.063380
 26    73.753731
 27    67.472000
 28    72.514493
 29    68.201613
 30    67.896825
 31    67.884615
 32    66.285714
 33    69.333333
 34    62.824000
 35    70.265734
 36    72.289474
 37    68.663793
 38    75.363636
 39    73.694118
 40    74.754386
 41    85.418605
 42    50.125000
 43    75.000000
Name: Income, dtype: float64
```

```
df_loan['Experience'][df_loan['Experience'] <0]= df_loan['Experience'].median(0)
```

For the Experience Feature:

Mean= 20.10 and Median= 20

Mean value Experience vs Income is:

-1 64.454545

-2 82.466667

-3 68.250000

Mean value of Income is 73.774200

I have replaced the -1,-2 & -3 values in the experience column with the Median, because as per above observation we can notice that mean of negative values are closest to range of mean value to Income feature

```
df_loan.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Age	5000.0	45.338400	11.463166	23.0	35.0	45.0	55.0	67.0
Experience	5000.0	20.327600	11.253035	0.0	11.0	20.0	30.0	43.0
Income	5000.0	73.774200	46.033729	8.0	39.0	64.0	98.0	224.0
Family	5000.0	2.396400	1.147663	1.0	1.0	2.0	3.0	4.0
CCAvg	5000.0	1.937938	1.747659	0.0	0.7	1.5	2.5	10.0
Education	5000.0	1.881000	0.839869	1.0	1.0	2.0	3.0	3.0
Mortgage	5000.0	56.498800	101.713802	0.0	0.0	0.0	101.0	635.0
Personal Loan	5000.0	0.096000	0.294621	0.0	0.0	0.0	0.0	1.0
Securities Account	5000.0	0.104400	0.305809	0.0	0.0	0.0	0.0	1.0
CD Account	5000.0	0.060400	0.238250	0.0	0.0	0.0	0.0	1.0
Online	5000.0	0.596800	0.490589	0.0	0.0	1.0	1.0	1.0
CreditCard	5000.0	0.294000	0.455637	0.0	0.0	0.0	1.0	1.0

- Checked for the missing values in the dataset if there any.
- As we have treated the experience column now data looks clean.

```
df_loan.skew()
```

```
Age                  -0.029341
Experience           -0.014100
Income                0.841339
Family                0.155221
CCAvg                 1.598443
Education             0.227093
```

```
Mortgage              2.104002
Personal Loan         2.743607
Securities Account    2.588268
CD Account            3.691714
Online               -0.394785
CreditCard            0.904589
dtype: float64
```

A skewness value greater than 1 or less than -1 indicates a highly skewed distribution. A value between 0.5 and 1 or -0.5 and -1 is moderately skewed. A value between -0.5 and 0.5 indicates that the distribution is fairly symmetrical.

Observations

- **From the above distribution plot and quantile range study we can illustrate that Income,family,CCAvg,Education,Mortgage,Personal Loan,Securities Account,CD Account,Credit Card are Positively skewed**.
- **Age,Experience,ZIP Code,Online columns are Negative skewed**

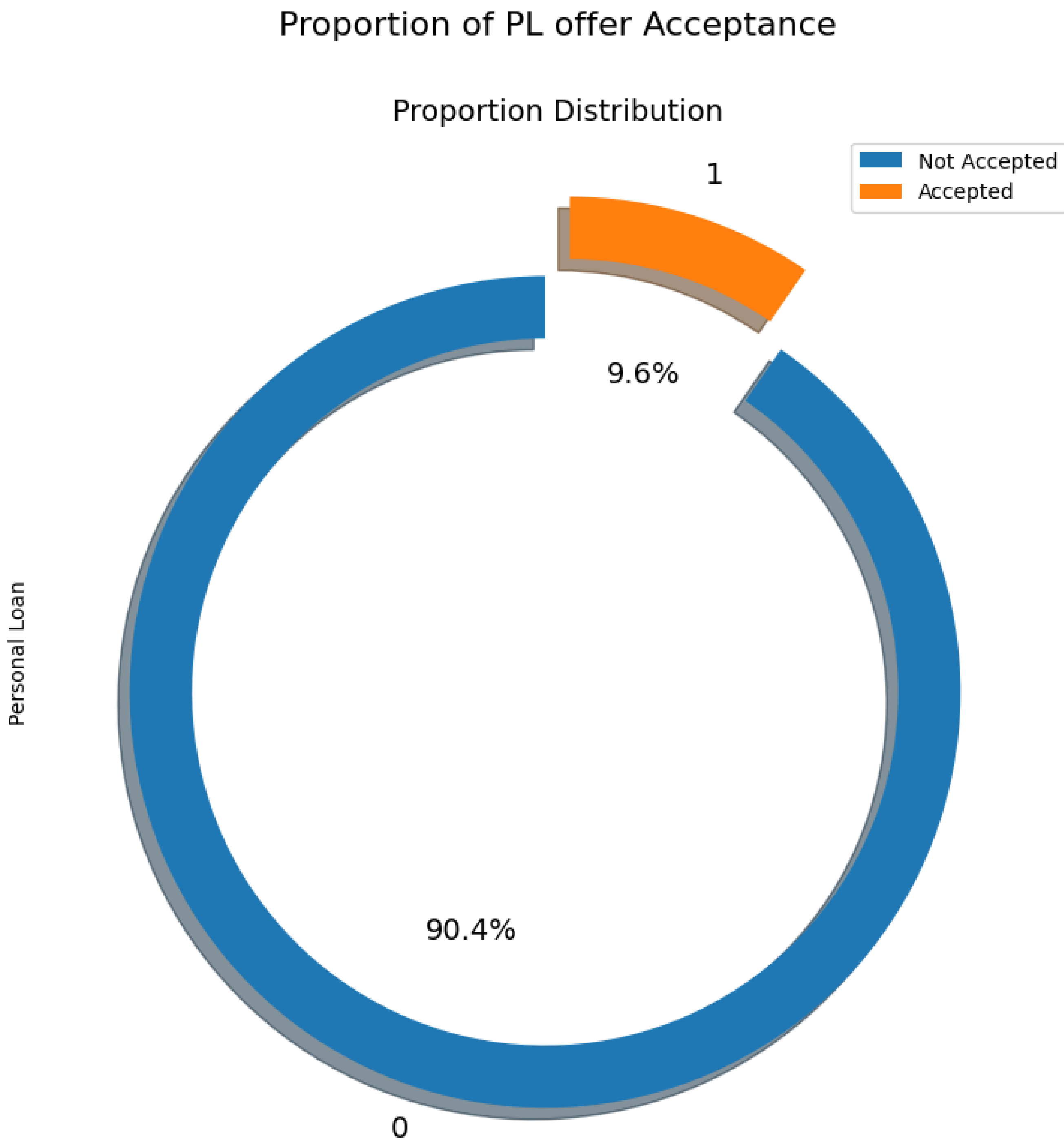
Exploaratory Data analysis

What is the distribution of the target variable ?

```
df_loan['Personal Loan'].value_counts()
```

```
0    4520
1     480
Name: Personal Loan, dtype: int64
```

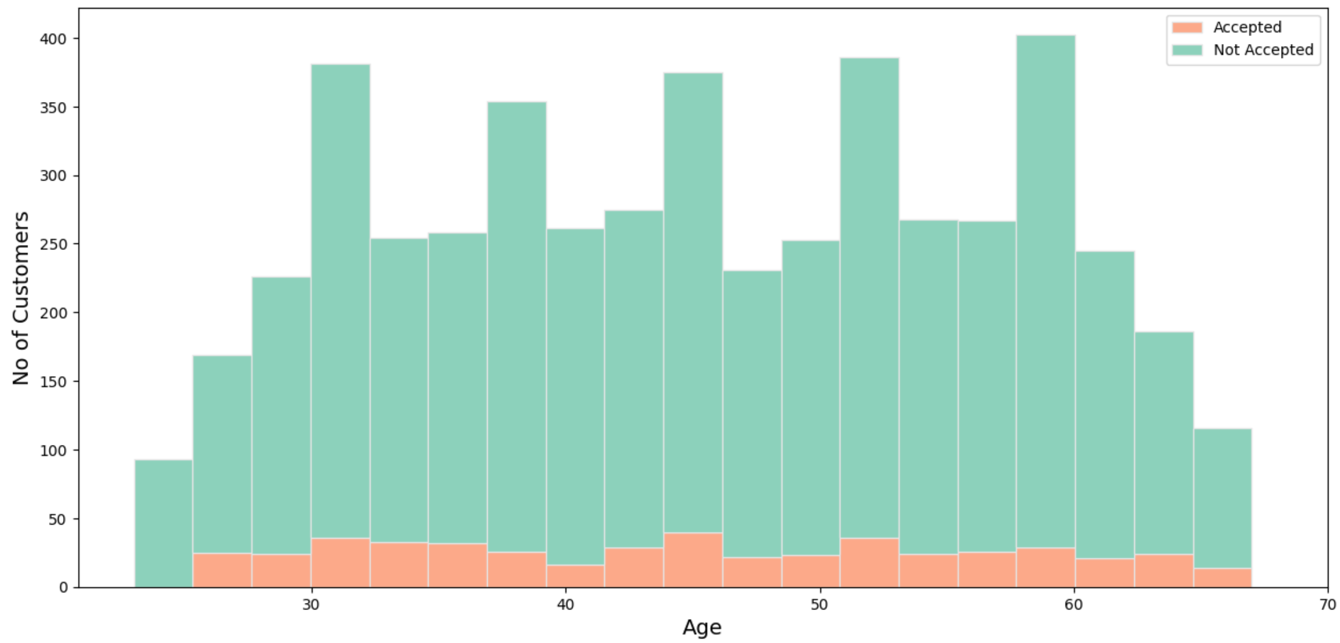
```
fig = plt.figure(figsize = [15, 8])

space = np.ones(2)/10

df_loan['Personal Loan'].value_counts().plot(kind = 'pie',explode = space, fontsize = 14, aut
                                       shadow = True, startangle = 90, legend = True,)
plt.legend(['Not Accepted', 'Accepted'])
plt.title(label = 'Proportion Distribution', size = 14)
plt.tight_layout(pad = 3.0)
plt.suptitle(t = 'Proportion of PL offer Acceptance', y = 1.02, size = 16)
plt.show()
```



Let's check the distribution of independent variables distribution with respect to Target Variable

```
figure = plt.figure(figsize=[15, 7])
sns.histplot(df_loan,x="Age", hue="Personal Loan", multiple="stack",
             palette="Set2", edgecolor=".9",linewidth=.9)
plt.xlabel(xlabel='Age', size = 14)
plt.ylabel(ylabel='No of Customers', size = 14)
```

```
plt.xticks(ticks= np.arange(30,80,10))
plt.legend(['Accepted', 'Not Accepted'])
plt.show()
```

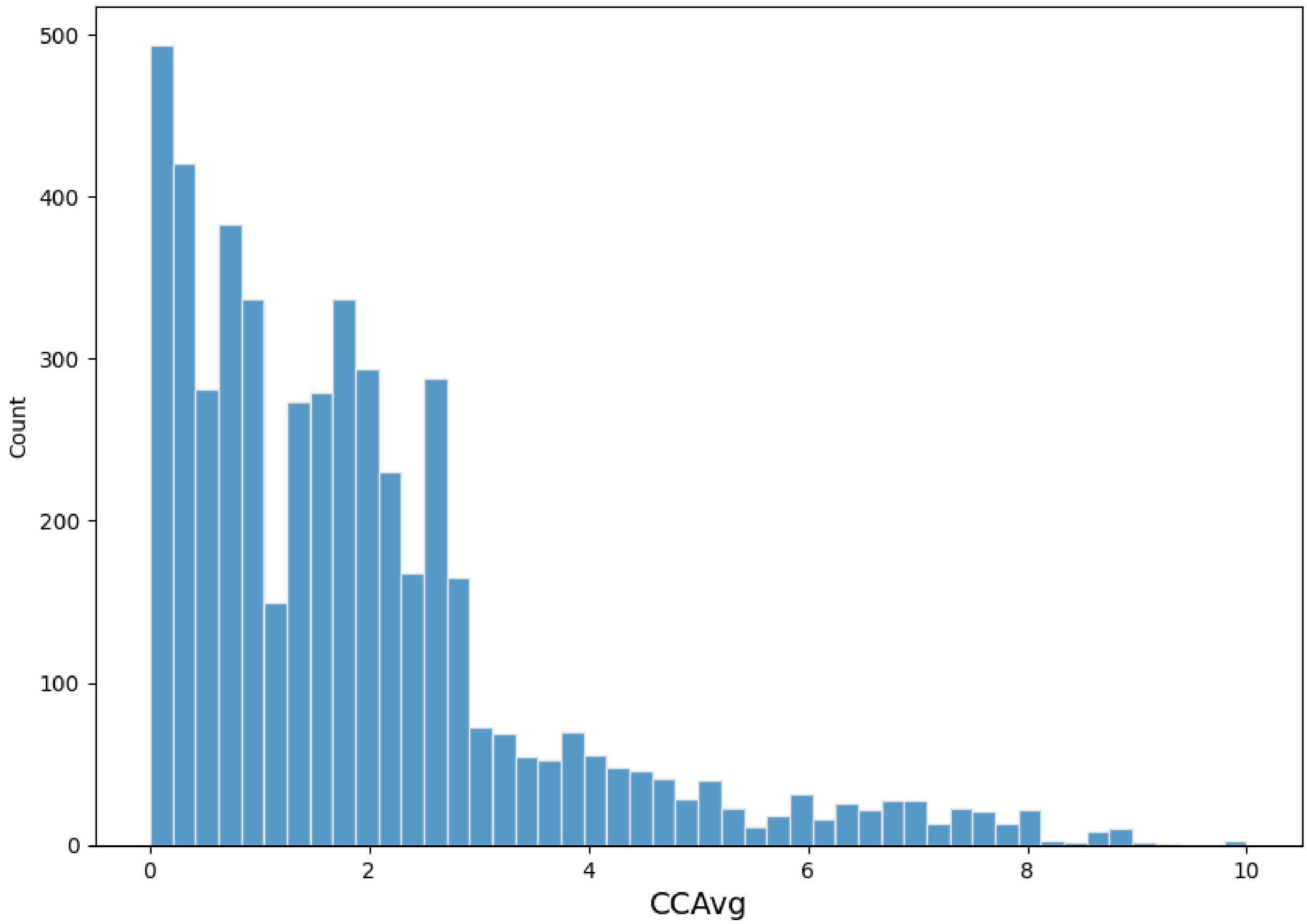



```
# Slicing data with Not_accepted status
Not_accepted = df_loan['Income'][df_loan['Personal Loan'] == 0]

# Slicing data with accepted transactions
accepted = df_loan['Income'][df_loan['Personal Loan'] == 1]

# Plotting the distribution of the sliced data
fig, (ax1, ax2) = plt.subplots(nrows = 2, ncols = 1, sharex = True, figsize = (20, 7))
sns.distplot(a = Not_accepted, bins = 50, ax = ax1, color = 'green')
ax1.set_title(label = 'Distribution of Income Vs Not accepted', size = 14)
ax1.set_xlabel(xlabel = '')
sns.distplot(a = accepted, bins = 50, ax = ax2, color = 'red')
ax2.set_title(label = 'Distribution of Income Vs Accepted', size = 14)
plt.show()
```

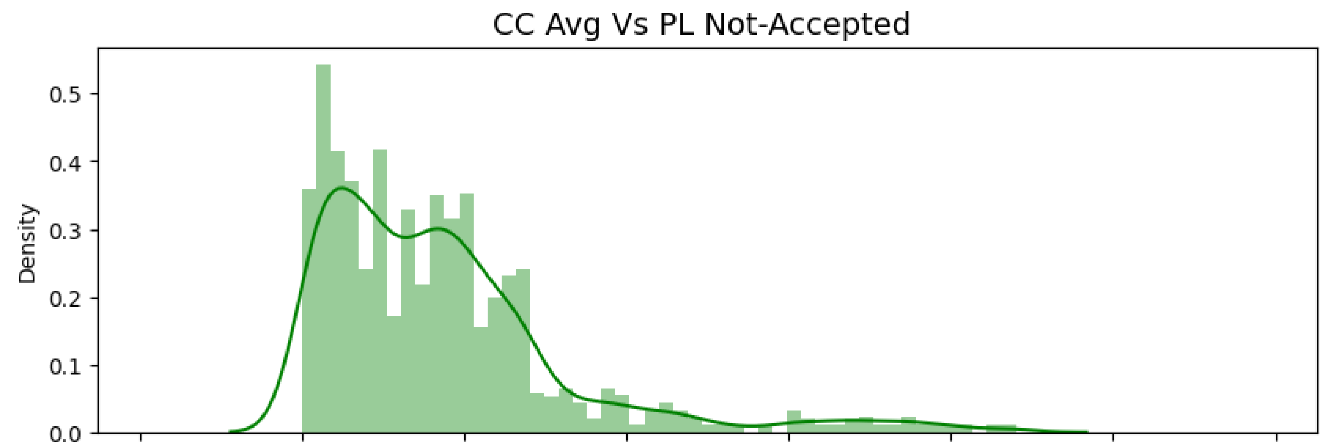

```
df_loan['CCAvg'].unique()
```

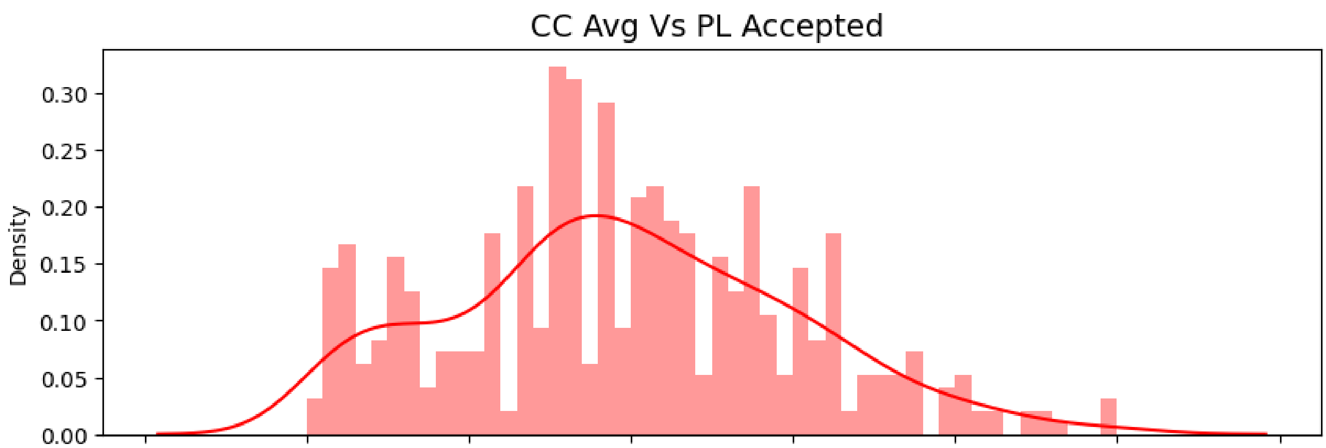
```
array([ 1.6 ,  1.5 ,  1.  ,  2.7 ,  0.4 ,  0.3 ,  0.6 ,  8.9 ,  2.4 ,
        0.1 ,  3.8 ,  2.5 ,  2.  ,  4.7 ,  8.1 ,  0.5 ,  0.9 ,  1.2 ,
        0.7 ,  3.9 ,  0.2 ,  2.2 ,  3.3 ,  1.8 ,  2.9 ,  1.4 ,  5.  ,
        2.3 ,  1.1 ,  5.7 ,  4.5 ,  2.1 ,  8.  ,  1.7 ,  0.  ,  2.8 ,
        3.5 ,  4.  ,  2.6 ,  1.3 ,  5.6 ,  5.2 ,  3.  ,  4.6 ,  3.6 ,
        7.2 ,  1.75,  7.4 ,  2.67,  7.5 ,  6.5 ,  7.8 ,  7.9 ,  4.1 ,
        1.9 ,  4.3 ,  6.8 ,  5.1 ,  3.1 ,  0.8 ,  3.7 ,  6.2 ,  0.75,
        2.33,  4.9 ,  0.67,  3.2 ,  5.5 ,  6.9 ,  4.33,  7.3 ,  4.2 ,
        4.4 ,  6.1 ,  6.33,  6.6 ,  5.3 ,  3.4 ,  7.  ,  6.3 ,  8.3 ,
        6.  ,  1.67,  8.6 ,  7.6 ,  6.4 , 10.  ,  5.9 ,  5.4 ,  8.8 ,
        1.33,  9.  ,  6.7 ,  4.25,  6.67,  5.8 ,  4.8 ,  3.25,  5.67,
        8.5 ,  4.75,  4.67,  3.67,  8.2 ,  3.33,  5.33,  9.3 ,  2.75])
```

```
figure = plt.figure(figsize=[10, 7])
sns.histplot(df_loan,x="CCAvg", multiple="stack",
             palette="Set2", edgecolor=".9",linewidth=.9)
plt.xlabel(xlabel='CCAvg', size = 14)
plt.show()
```

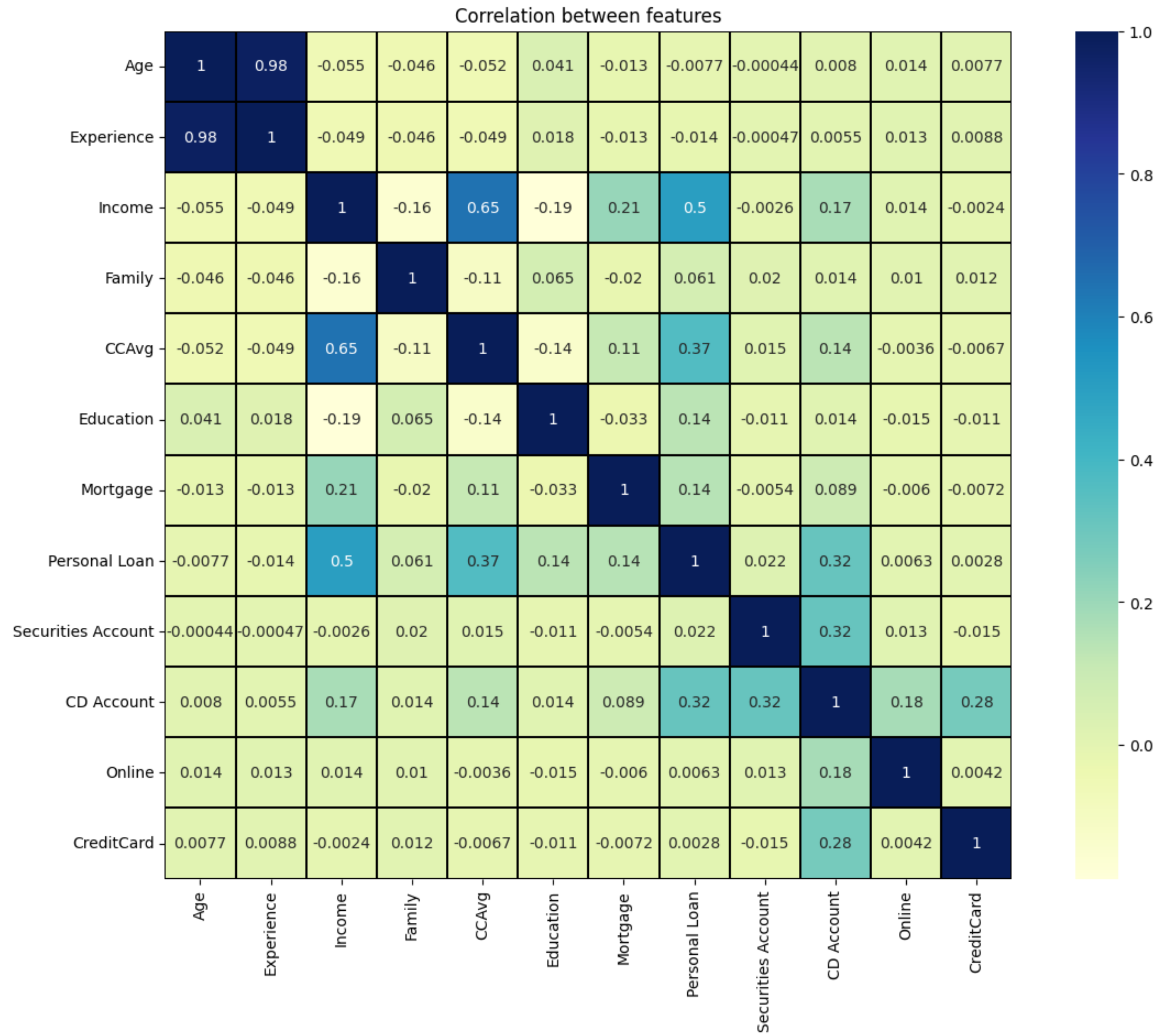



```
# Slicing data with respect to loan not accepted when cust not having mortgage facility
Not_accepted = df_loan[df_loan['Personal Loan'] == 0]['CCAvg']

# Slicing data with respect to loan accepted when customer not having mortgage facility
accepted = df_loan[df_loan['Personal Loan'] == 1]['CCAvg']

# Plotting the distribution of the sliced data
fig, (ax1, ax2) = plt.subplots(nrows = 2, ncols = 1, sharex = True, figsize = (10, 7))
sns.distplot(a = Not_accepted, bins = 50, ax = ax1, color = 'green')
ax1.set_title(label = 'CC Avg Vs PL Not-Accepted ', size = 14)
ax1.set_xlabel(xlabel = '')
sns.distplot(a = accepted, bins = 50, ax = ax2, color = 'red')
ax2.set_title(label = 'CC Avg Vs PL Accepted ', size = 14)
plt.show()
```






```
# Lets check co-relation between the features
plt.figure(figsize=(15,10))
sns.heatmap(data=df_loan.corr(), cmap="YlGnBu", annot=True, square=True,linewidth=.01,
           linecolor='black')
plt.title("Correlation between features")
plt.show()
```



EDA Observations:

- The age group of customers opting for loan is between 25-65 years
- Income distribution of the customers is slightly right skewed. The range of income is between $8-224$
- The low income group have not opted for personal loan, Whereas density for the liability customers is more in higher income group
- **Customer with family of 4 members have higher chances of opting for personal loan**
- The avg CC spending of the customers who have not opted for personal loan is high in $ 0-5 range
- **The customers with no credit card have slightly more chances of opting for personal loan**
- **Customers with credit card who have high avg spending per month, have more chances of opting persona loan**

- **The count of customers, who are post graduate and who have applied for personal loan is more compared to rest of the graduates. This shows education can impact outcome of customers opting for personal loan**
- The liability customers seem to have no security account with the bank and still have opted for more personal loan

Comapred to asset customers

- Count of customers having Mortgage not opted for loan is 1370, opted for loan 168
- Count of customers not having Mortgage not opted for loan 312, opted for loan 3150
- Customers with Certificate of deposit opting for personal loan is less compared to customers with no CD.
- Customers with online netbanking facility have more chances of opting for personal loan
- **Experience has a strong linear relationship with Age**

Post Data Processing & Feature Selection

X, y split

```
X = df_loan.drop('Personal Loan', axis=1)
X.shape
```

```
(5000, 11)
```

```
y = df_loan['Personal Loan']
y.shape
```

```
(5000,)
```

Train Test Split

- Now we will split our data in training and testing part for further development.

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.20, random_state=42)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((4000, 11), (1000, 11), (4000,), (1000,))
```

Standard Scaling

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train_sc = sc.fit_transform(X_train)

X_test_sc = sc.transform(X_test)
```

Model Development & Evaluation

Naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem.

It follows strong (naïve) independence assumptions between the features.

Before diving further let's get to know some important concepts that are realted to Naive Bayes.

```
from sklearn.tree import DecisionTreeClassifier
DTC=DecisionTreeClassifier()
```

```
DTC.fit(X_train,y_train)
DTC
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

```
y_pred_test = DTC.predict(X_test)
y_pred_train = DTC.predict(X_train)
```

```
from sklearn.metrics import accuracy_score
accuracy_score(y_train, y_pred_train)
```

```
1.0
```

```
accuracy_score(y_test, y_pred_test)
```

```
0.985
```

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
```

```
rfc.fit(X_train, y_train)
rfc
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
yrfc_pred_test = rfc.predict(X_test)
yrfc_pred_train = rfc.predict(X_train)
accuracy_score(y_train,yrfc_pred_train)
```

```
1.0
```

```
accuracy_score(y_test,yrfc_pred_test)
```

```
0.989
```

```
from sklearn.naive_bayes import GaussianNB

naive = GaussianNB()
```

```
naive.fit(X_train, y_train)
```

```
▾ GaussianNB
GaussianNB()
```

```
ygnb_train_pred = naive.predict(X_train)
ygnb_test_pred = naive.predict(X_test)
```

```
accuracy_score(y_train,ygnb_train_pred)
```

```
0.8805
```

```
accuracy_score(y_test, ygnb_test_pred)
```

```
0.894
```

Model 2

```
from sklearn.feature_selection import SelectFromModel

selector = SelectFromModel(RandomForestClassifier (n_estimators=100, random_state=42 ,n_jobs=

selector.fit(X,y)
```

```
▸ SelectFromModel
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

```
X = df_loan.drop('Personal Loan', axis=1)
```

```
selector.get_support()
```

```
array([False, False,  True,  True,  True,  True, False, False, False,
       False, False])
```

```
X.columns[selector.get_support()]
```

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

```
#Converting it to a list
X.columns[selector.get_support()].tolist()
```

```
['Income', 'Family', 'CCAvg', 'Education']
```

```
features_selected = X.columns[selector.get_support()].tolist()
features_selected
len(features_selected)
```

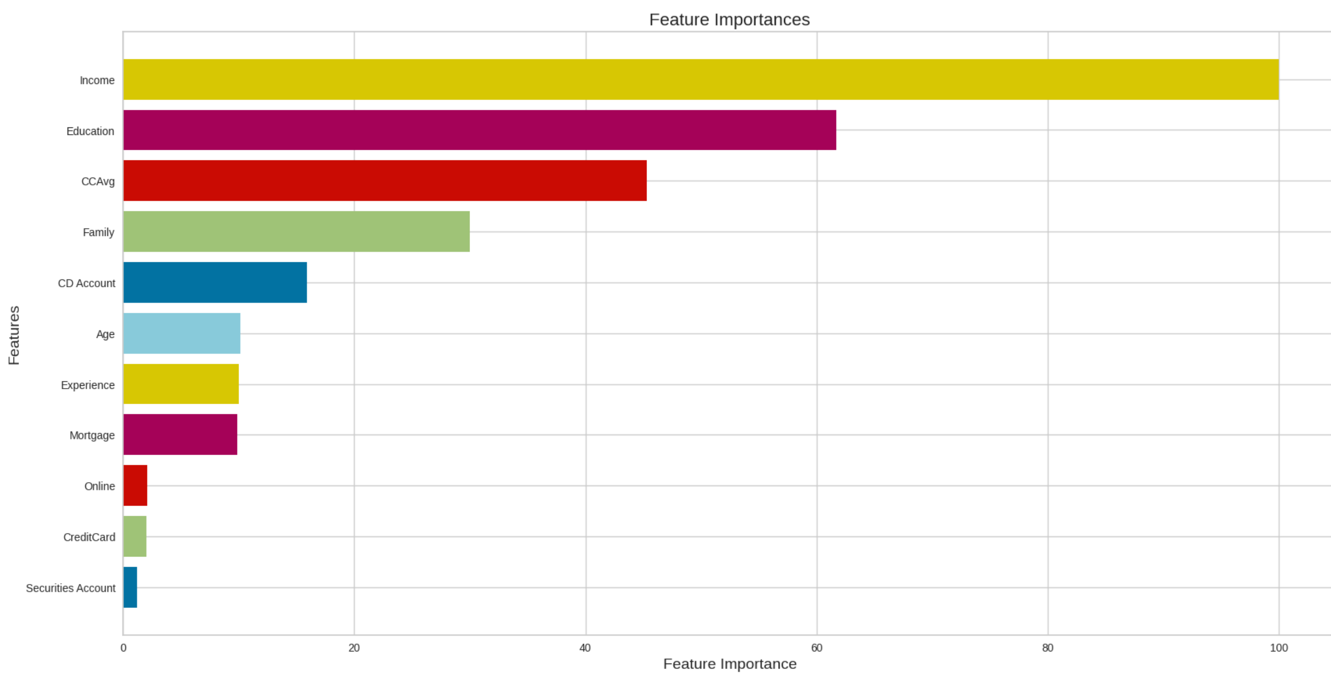
```
4
```

```
!pip install yellowbrick
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Requirement already satisfied: yellowbrick in /usr/local/lib/python3.10/dist-packages (1
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in /usr/local/lib/python3.10/di
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: scikit-learn>=1.0.0 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: cycler>=0.10.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-package
```

```
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (fron
```

```python
from yellowbrick.model_selection import FeatureImportances

figure = plt.figure(figsize=(20,10))

viz = FeatureImportances(selector.estimator)
viz.fit(X,y)
plt.xlabel('Feature Importance', size = 14)
plt.ylabel('Features', size = 14)
plt.title(label = 'Feature Importances', size = 16)
plt.show()
```



X , y split will be done again basis the feature selected

```
X = X[features_selected]
y= df_loan['Personal Loan']
X.shape, y.shape
```

```
((5000, 4), (5000,))
```

```
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_state=100)
```

```
from sklearn.naive_bayes import GaussianNB

naive = GaussianNB()

naive.fit(X_train, y_train)
```

```
▾ GaussianNB
GaussianNB()
```

```
y_train_pred = naive.predict(X_train)
y_test_pred = naive.predict(X_test)
```

```
accuracy_score(y_train, y_train_pred)
```

```
0.914
```

```
accuracy_score(y_test, y_test_pred)
```

```
0.9073333333333333
```

Linear Regrssion Model

Lets create two dataframes for dependent and independent features.

Considering 'CCAvg' as X

```
X = df_loan.drop('CCAvg', axis =1)
y= df_loan['CCAvg']
X.shape, y.shape
```

```
((5000, 11), (5000,))
```

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25, random_state=1)
```

```
sc = StandardScaler()

X_train_sc = sc.fit_transform(X_train)

X_test_sc = sc.transform(X_test)
```

```
linreg = LinearRegression()
linreg.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
print ('Intercept:',linreg.intercept_)
print ('Coefficients:',linreg.coef_)
```

```
Intercept: 0.4776454511397479
Coefficients: [ 0.00096418 -0.00477071  0.02272166 -0.02288476 -0.05462    -0.00064605
  0.4773906   0.07798804  0.17285337 -0.03993274 -0.0289868 ]
```

```
df_loan.columns
```

```
Index(['Age', 'Experience', 'Income', 'Family', 'CCAvg', 'Education',
       'Mortgage', 'Personal Loan', 'Securities Account', 'CD Account',
       'Online', 'CreditCard'],
      dtype='object')
```

```
feature_cols = (['Age', 'Experience', 'Income', 'Family', 'Education',
       'Mortgage', 'Personal Loan', 'Securities Account', 'CD Account',
       'Online', 'CreditCard'])
```

```
feature_cols.insert(0, 'Intercept')
feature_cols
```

```
['Intercept',
 'Age',
 'Experience',
 'Income',
 'Family',
 'Education',
 'Mortgage',
 'Personal Loan',
 'Securities Account',
 'CD Account',
```

```
       'Online',
       'CreditCard']
```

```
coef = linreg.coef_.tolist()
coef
```

```
[0.00096417506682247,
 -0.0047707094165927305,
 0.022721662387098312,
 -0.022884760266992564,
 -0.05461999695813479,
 -0.0006460451338220569,
 0.47739059958298374,
 0.07798804433469804,
 0.17285337130293799,
 -0.03993273530785397,
 -0.02898679774410351]
```

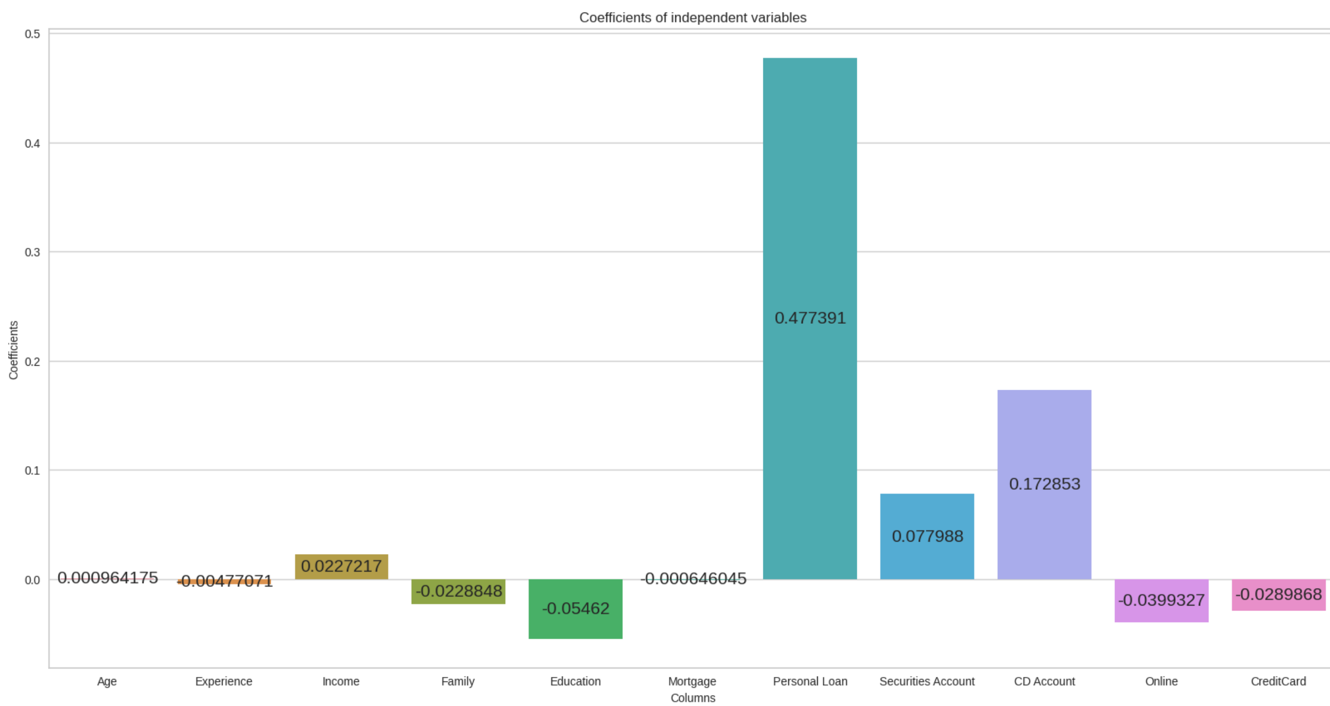
```
coef.insert(0, linreg.intercept_)
coef
```

```
[0.4776454511397479,
 0.00096417506682247,
 -0.0047707094165927305,
 0.022721662387098312,
 -0.022884760266992564,
 -0.05461999695813479,
 -0.0006460451338220569,
 0.47739059958298374,
 0.07798804433469804,
 0.17285337130293799,
 -0.03993273530785397,
 -0.02898679774410351]
```

```
eq1 = zip(feature_cols, coef)

for c1,c2 in eq1:
    print(c1,c2)
```

```
Intercept 0.4776454511397479
Age 0.00096417506682247
Experience -0.0047707094165927305
Income 0.022721662387098312
Family -0.022884760266992564
Education -0.05461999695813479
Mortgage -0.0006460451338220569
Personal Loan 0.47739059958298374
Securities Account 0.07798804433469804
CD Account 0.17285337130293799
Online -0.03993273530785397
CreditCard -0.02898679774410351
```

```
column_names = X.columns
column_coef = pd.DataFrame({"columns" : column_names,
             "coef_": linreg.coef_ })

plt.figure(figsize = (20,10))

viz = sns.barplot(data = column_coef, x = "columns", y = "coef_")

plt.bar_label(viz.containers[0],size=15,label_type="center")

plt.xticks(size = 10)
plt.yticks(size = 10)
plt.xlabel("Columns",size = 10)
plt.ylabel("Coefficients",size = 10)
plt.title("Coefficients of independent variables")
plt.show()
```



Model Development & Evaluation

```
y_pred_train = linreg.predict(X_train)
y_pred_test = linreg.predict(X_test)
```

```
from sklearn import metrics
#Computing the MAE for our Sales predictions
MAE_train = metrics.mean_absolute_error(y_train, y_pred_train)
MAE_test = metrics.mean_absolute_error(y_test, y_pred_test)
```

```
print ('Mae for the training is {}'.format(MAE_train))
print("-"*50)
print ('Mae for the test is {}'.format(MAE_test))
```

```
Mae for the training is 0.9541733933655965
--------------------------------------------------
Mae for the test is 0.9736315658810832
```

```
# Computing the MSE for our Sales predictions
MSE_train = metrics.mean_squared_error(y_train, y_pred_train)
MSE_test = metrics.mean_squared_error(y_test, y_pred_test)
print ('MSE for the training is{}'.format(MSE_train))
print("-"*50)
print ('MSE for the test is{}'.format(MSE_test))
```

```
MSE for the training is1.7376113484730769
--------------------------------------------------
MSE for the test is1.8466110640439424
```

```
# Computing the RMSE for our Sales predictions
RMSE_train = np.sqrt( metrics.mean_squared_error(y_train, y_pred_train))
RMSE_test = np.sqrt( metrics.mean_squared_error(y_test, y_pred_test))
print('RMSE for the training is {}'.format(RMSE_train))
print("-"*50)
print('RMSE for the test is {}'.format(RMSE_test))
```

```
RMSE for the training is 1.3181848688530289
--------------------------------------------------
RMSE for the test is 1.3589006821853988
```

Model Evaluation using R-squared and Adjusted R-squared value

```
r2_train = metrics.r2_score(y_train, y_pred_train)
r2_test = metrics.r2_score(y_test, y_pred_test)

print ('R2 score for training is {}'.format(r2_train))
```

```
print("-"*50)
print ('R2 score for test is {}'.format(r2_test))
```

```
R2 score for training is 0.4250181115590582
--------------------------------------------------
R2 score for test is 0.41331220976517624
```

```
adj_r2_train = 1 - (1-r2_train)*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1)
adj_r2_test = 1 - (1-r2_test)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)

print('Adjusted R2 for training is {}'.format(adj_r2_train))
print("-"*50)
print('Adjusted R2 for test is {}'.format(adj_r2_test))
```

```
Adjusted R2 for training is 0.4233260835299383
--------------------------------------------------
Adjusted R2 for test is 0.4080993134060623
```

Conclusion By using Descion Tree Regressor we are getting below scores:

RMSE for the training is 1.31

RMSE for the test is 1.35

R2 score for the training is 0.42

R2 score for the test is 0.41

AdjR2 score for the training is 0.42

AdjR2 score for the test is 0.40