Project-Personal-Loan-Modelling

October 18, 2019

1 Data Description

The file `Bank_Personal_Loan_Modelling.csv` contains data on 5000 customers. The data include customer demographic information (age, income, etc.), the customer's relationship with the bank (mortgage, securities account, etc.), and the customer response to the last personal loan campaign (Personal Loan). Among these 5000 customers, only 480 (= 9.6%) accepted the personal loan that was offered to them in the earlier campaign.

2 Domain

Banking

3 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.

4 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. ($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?
- **`CreditCard`** : Does the customer use a credit card issued by `UniversalBank`?

5 Learning Outcomes

- Exploratory Data Analysis
- Preparing the data to train a model
- Training and making predictions using a classification model
- Model evaluation

6 Objective

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

7 Steps and tasks

1. Read the column description and ensure you understand each attribute well
2. Study the data distribution in each attribute, share your findings
3. Get the target column distribution. Your comments
4. Split the data into training and test set in the ratio of 70:30 respectively
5. Use different classification models (Logistic, K-NN and Naïve Bayes) to predict the likelihood of a liability customer buying personal loans
6. Print the confusion matrix for all the above models
7. Give your reasoning on which is the best model in this case and why it performs better?

8 References

1. Data analytics use cases in Banking
2. Machine Learning for Financial Marketing

8.0.1 Step 0: Import Modules

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
%matplotlib inline
```

[148]:
```
# Supress warnings
import warnings
warnings.filterwarnings("ignore")
```

8.0.2 Step 1: Read data from file

[2]:
```
bankData = pd.read_csv("Bank_Personal_Loan_Modelling.csv")
```

[3]:
```
bankData.head()
```

[3]:
```
   ID  Age  Experience  Income  ZIP Code  Family  CCAvg  Education  Mortgage  \
0   1   25           1      49     91107       4    1.6          1         0
```

```
1   2   45          19     34     90089      3    1.5          1          0
2   3   39          15     11     94720      1    1.0          1          0
3   4   35           9    100     94112      1    2.7          2          0
4   5   35           8     45     91330      4    1.0          2          0

   Personal Loan  Securities Account  CD Account  Online  CreditCard
0              0                   1           0       0           0
1              0                   1           0       0           0
2              0                   0           0       0           0
3              0                   0           0       0           0
4              0                   0           0       0           1
```

We can refer to Section 4 to understand the meaning of each column.

Key Findings

1. Since every user is going to have a separate `ID`, it's not going to add any significant value to the model, so we can remove that.
2. Age can provide us information regarding the likelihood of a user accepting the personal loan based on the age group he/she lies in.
3. We can get similar information based on Experience, Income, etc.
4. ZIP Code can give information regarding the effect of the personal loan on the likelihood of a person opting for personal loan.
5. Education, because it has 3 levels, serves as a categorical variable and provides information regarding the education of the user.
6. Personal Loan, Securities Account, CD Account, Online and CredictCard are also categorical variables with only 2 levels and provide the relevant user attributes.
7. All the columns except **`ID`** and **`Personal Loan`** can be used as independent variables.
8. The target variable/column is **`Personal Loan`**.

8.0.3 Step 2: Study the data distribution

[10]:
```
bankData.shape
```

[10]:
```
(5000, 14)
```

[12]:
```
bankData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
ID                    5000 non-null int64
Age                   5000 non-null int64
Experience            5000 non-null int64
Income                5000 non-null int64
ZIP Code              5000 non-null int64
Family                5000 non-null int64
CCAvg                 5000 non-null float64
Education             5000 non-null int64
Mortgage              5000 non-null int64
```

```
Personal Loan         5000 non-null int64
Securities Account    5000 non-null int64
CD Account            5000 non-null int64
Online                5000 non-null int64
CreditCard            5000 non-null int64
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

As we can see, there are no null values in the data. Also, the data types of the variables are already correct so we won't have to change the data types.

[16]:
```
bankData.describe(percentiles=[0.10,0.25,0.50,0.75,0.90]).T
```

[16]:

	count	mean	std	min	10%
ID	5000.0	2500.500000	1443.520003	1.0	500.9
Age	5000.0	45.338400	11.463166	23.0	30.0
Experience	5000.0	20.104600	11.467954	-3.0	4.0
Income	5000.0	73.774200	46.033729	8.0	22.0
ZIP Code	5000.0	93152.503000	2121.852197	9307.0	90275.0
Family	5000.0	2.396400	1.147663	1.0	1.0
CCAvg	5000.0	1.937938	1.747659	0.0	0.3
Education	5000.0	1.881000	0.839869	1.0	1.0
Mortgage	5000.0	56.498800	101.713802	0.0	0.0
Personal Loan	5000.0	0.096000	0.294621	0.0	0.0
Securities Account	5000.0	0.104400	0.305809	0.0	0.0
CD Account	5000.0	0.060400	0.238250	0.0	0.0
Online	5000.0	0.596800	0.490589	0.0	0.0
CreditCard	5000.0	0.294000	0.455637	0.0	0.0

	25%	50%	75%	90%	max
ID	1250.75	2500.5	3750.25	4500.1	5000.0
Age	35.00	45.0	55.00	61.0	67.0
Experience	10.00	20.0	30.00	36.0	43.0
Income	39.00	64.0	98.00	145.0	224.0
ZIP Code	91911.00	93437.0	94608.00	95138.0	96651.0
Family	1.00	2.0	3.00	4.0	4.0
CCAvg	0.70	1.5	2.50	4.3	10.0
Education	1.00	2.0	3.00	3.0	3.0
Mortgage	0.00	0.0	101.00	200.0	635.0
Personal Loan	0.00	0.0	0.00	0.0	1.0
Securities Account	0.00	0.0	0.00	1.0	1.0
CD Account	0.00	0.0	0.00	0.0	1.0
Online	0.00	1.0	1.00	1.0	1.0
CreditCard	0.00	0.0	1.00	1.0	1.0

If we refer to the distribution above, we can come up with the following findings:

1. `Income` variable has some potential outliers on the higher end and the lower end. This can be seen because of the sudden jump in `min` and `10%` percentile. Similar jump is present in `75%` and `90%` and between `90%` and `max`.

2. `ZIP Code` being a **nominal variable**, the description doesn't convey any meaning.
3. `CCAvg` has some potential outliers on the higher end. This can be seen because of a sudden jump between `90%` and `max` value.
4. `Mortgage` description shows that at least 50% entries don't have any mortgage. There's also a potential outlier on the higher end. This can be seen because of the sudden jump in `90%` and `max` value.

[18]:
```
bankData.apply(lambda x: len(x.unique()))
```

[18]:
```
ID                    5000
Age                     45
Experience              47
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
```

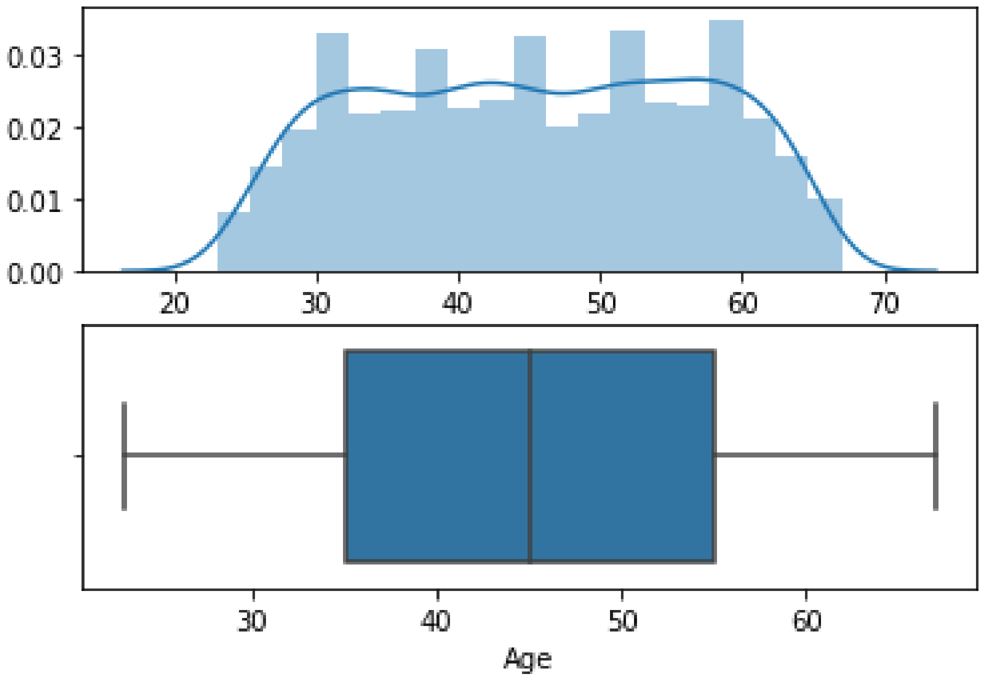
The number of unique elements for `Family`, `Education`, `Personal Loan`, `Securities Account`, `CD Account`, `Online` and `CreditCard` variables show that they are categorical variables.

8.0.4 Step 2.1: Unilateral Analysis

Next, let's start carrying out **Unilateral Analysis**.

[30]:
```
def unilateralAnalysis(variable, categorical=False):
    # For categorical attributes, plot a countplot
    if categorical:
        sns.countplot(bankData[variable])
        plt.show()
    else:
        plt.subplot(2,1,1)
        # Distribution Plot
        sns.distplot(bankData[variable])
        plt.subplot(2,1,2)
        # Boxplot
        sns.boxplot(bankData[variable])
        plt.show()
        print("Mean: {:.2f}".format(bankData[variable].mean()))
```

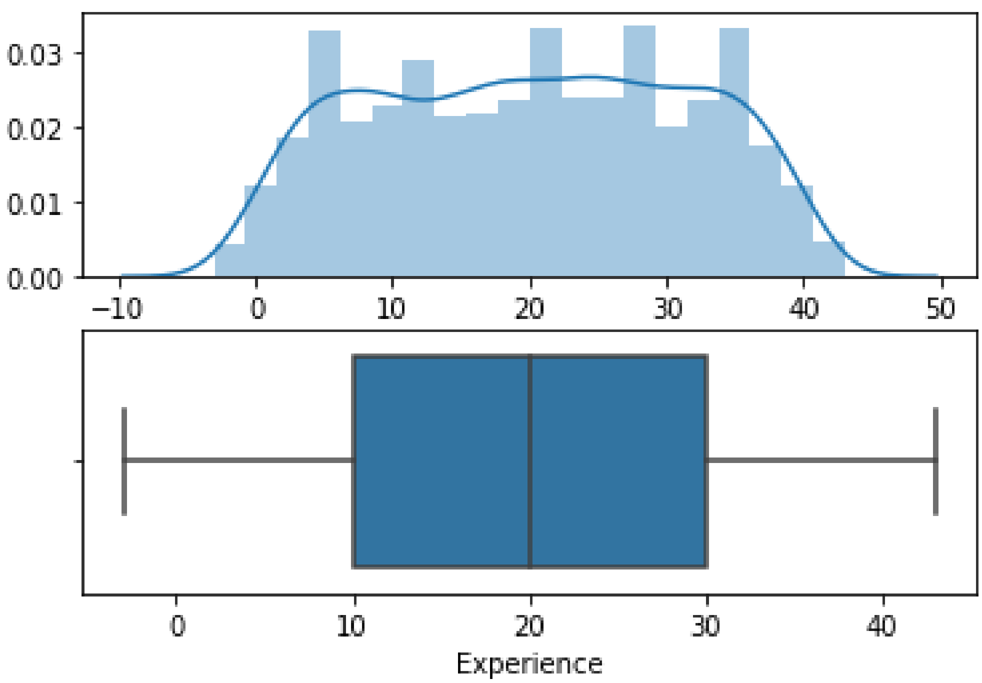
[31]:
```
unilateralAnalysis("Age")
```




```
Mean: 45.34
```

Age follows an approximately normal distribution. The mean and median are same.

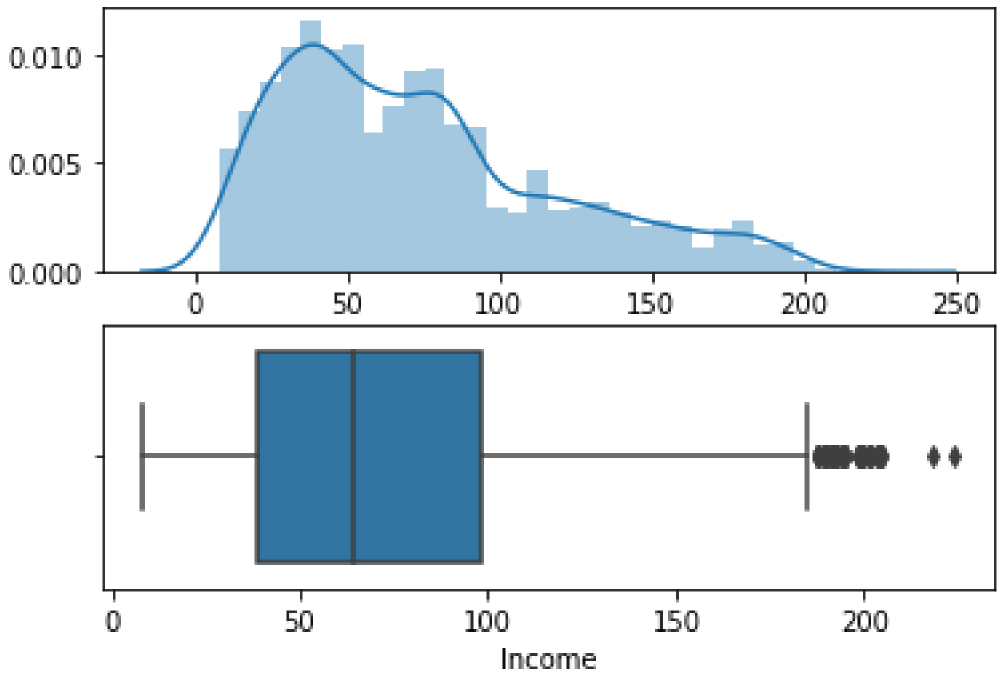
[32]:
```
unilateralAnalysis("Experience")
```



```
Mean: 20.10
```

Experience also follows an approximately normal distribution. Also note that there are some entries with negative experience which should be removed.

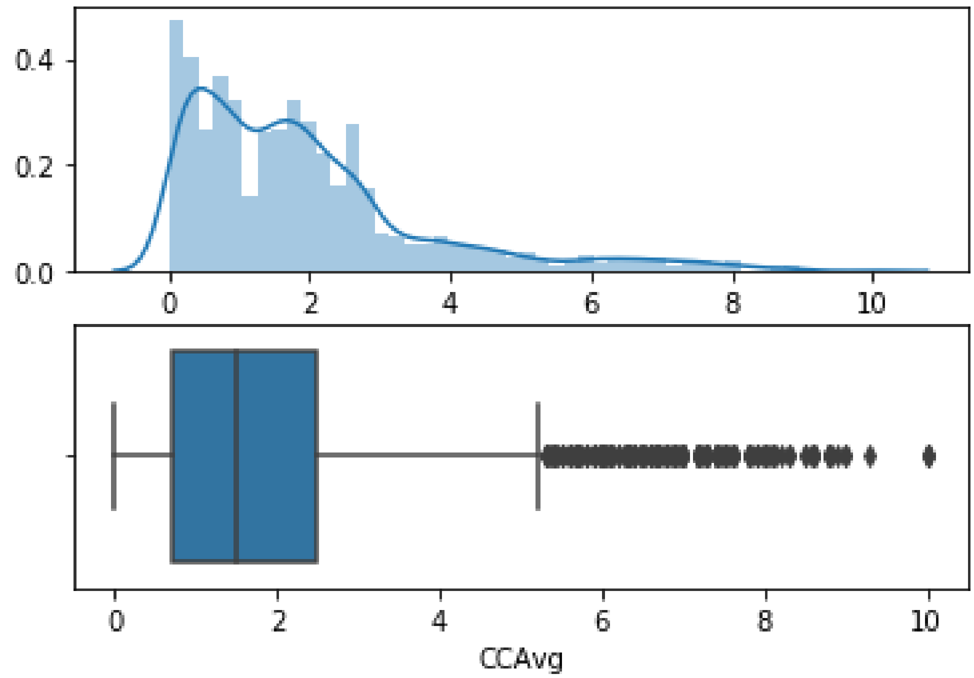
[33]:
```
unilateralAnalysis("Income")
```




```
Mean: 73.77
```

As we had mentioned before, Income has some outliers which need to be removed. Also, it can be seen that Income is positively skewed (Mean is greater than median).

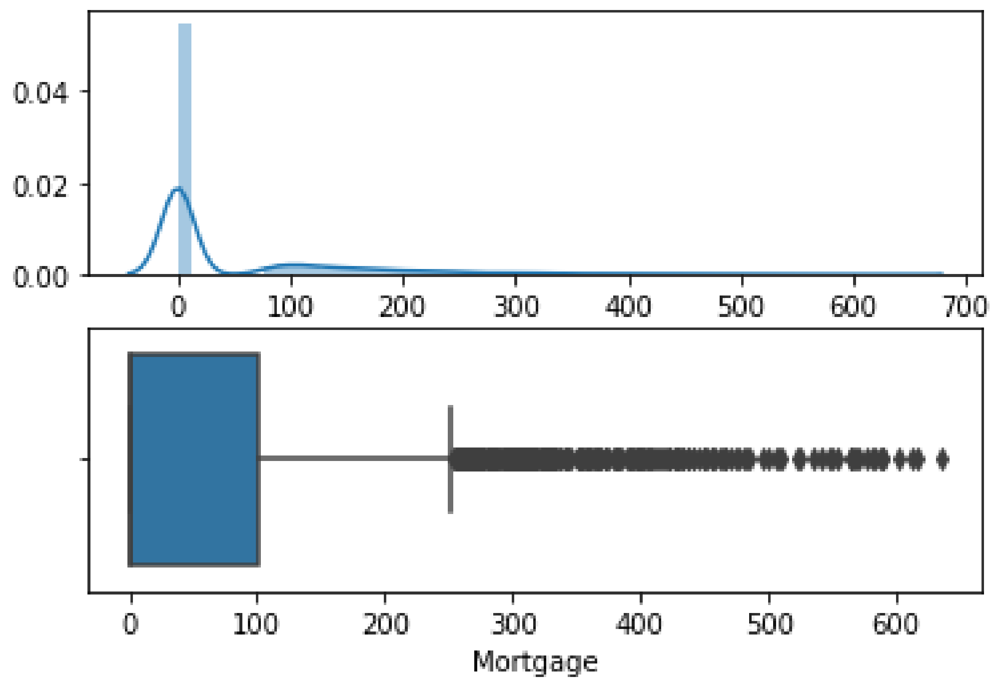
[35]:
```
unilateralAnalysis("CCAvg")
```




```
Mean: 1.94
```

CCAvg is also positively skewed and has some outliers that can be removed.

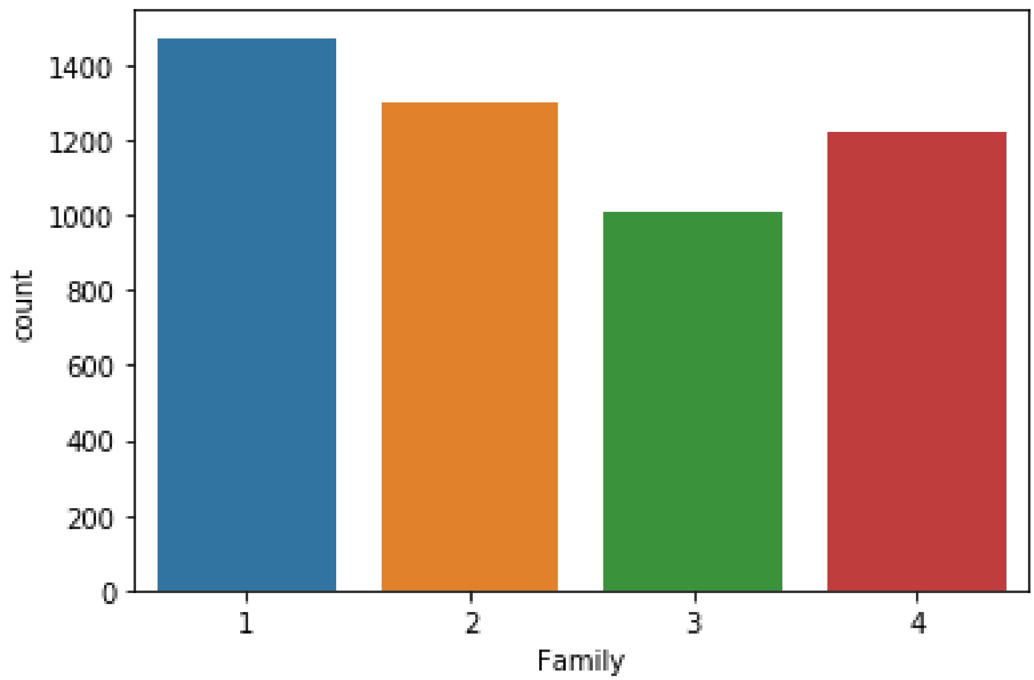
[36]:
```
unilateralAnalysis("Mortgage")
```



```
Mean: 56.50
```

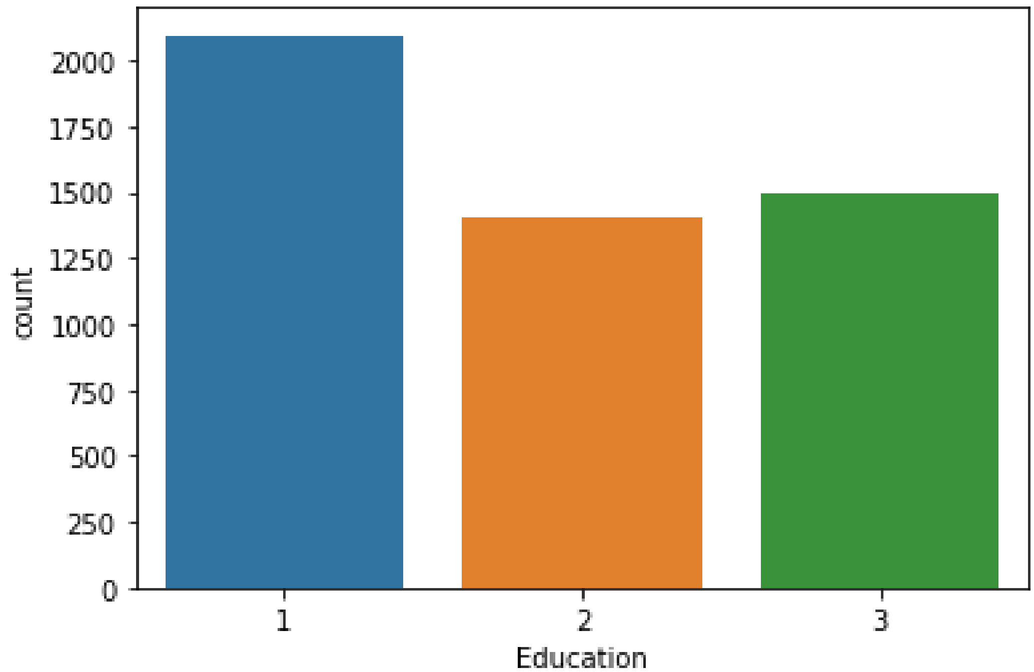
As can be seen from the above plots, majority of customers don't have a mortgage and the maximum mortgage is very high and can be removed.

[34]:
```
unilateralAnalysis("Family",True)
```



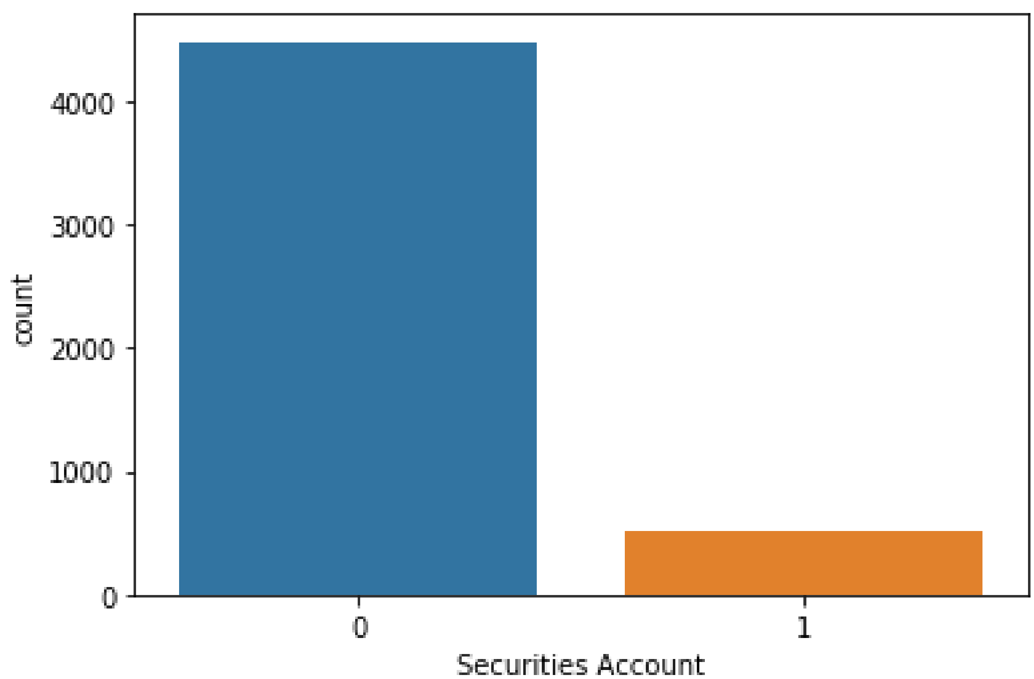
Family variable is evenly distributed.

[41]:
```
unilateralAnalysis("Education",True)
```



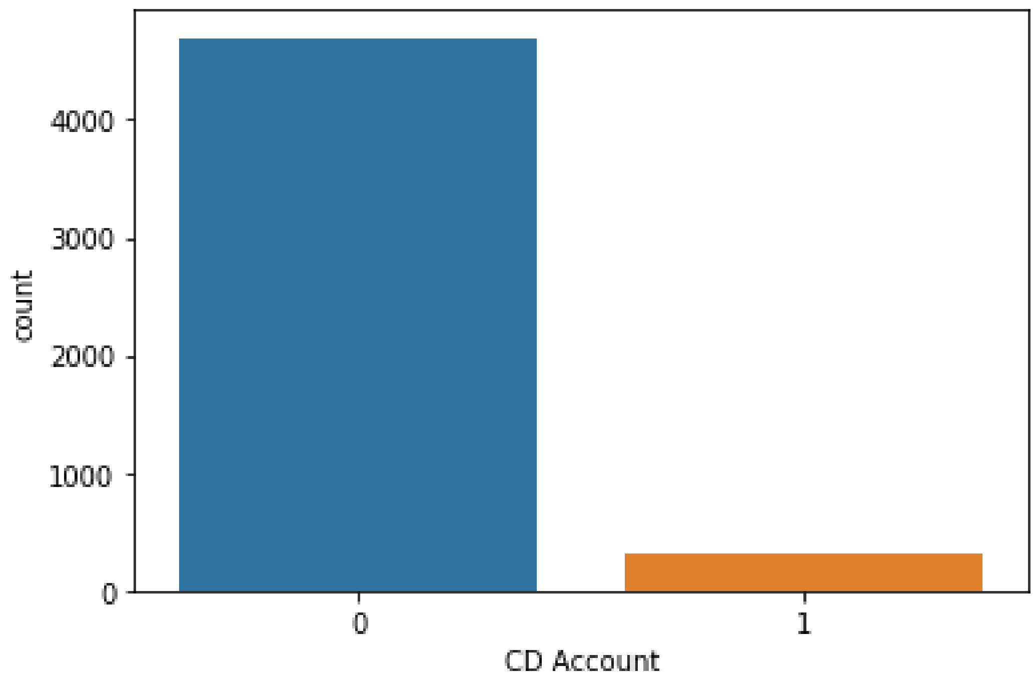
The data for Education is evenly distributed to a large extent. Most customers hold an unergrad level education.

[37]:
```
unilateralAnalysis("Securities Account",True)
```



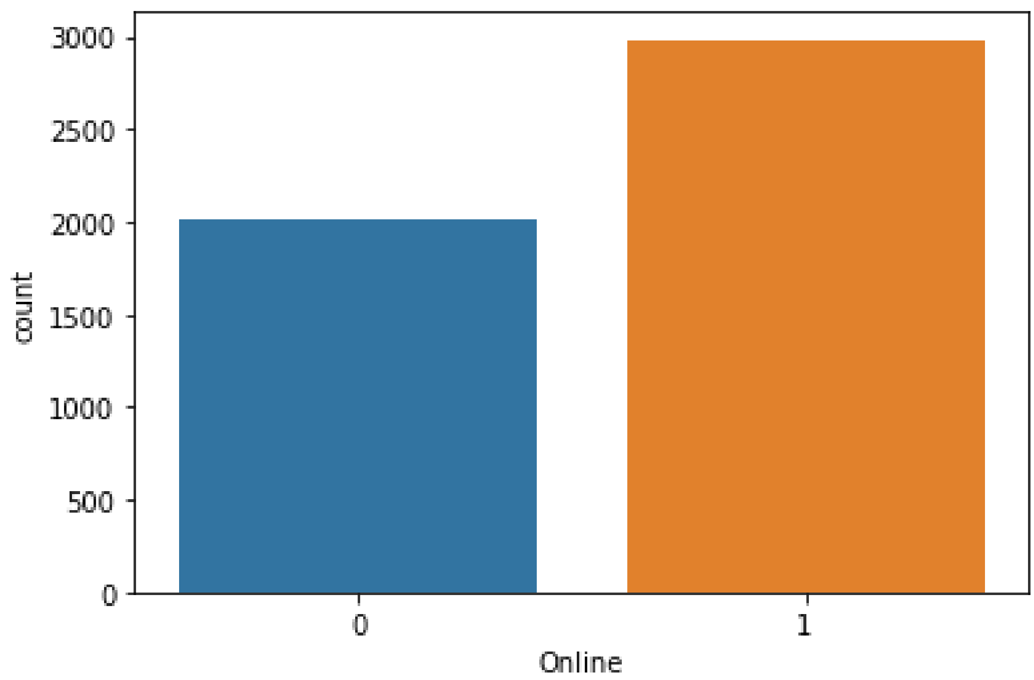
The data for Securities Account is unevenly distributed. Most people don't have a Securities Account.

[38]:
```
unilateralAnalysis("CD Account", True)
```

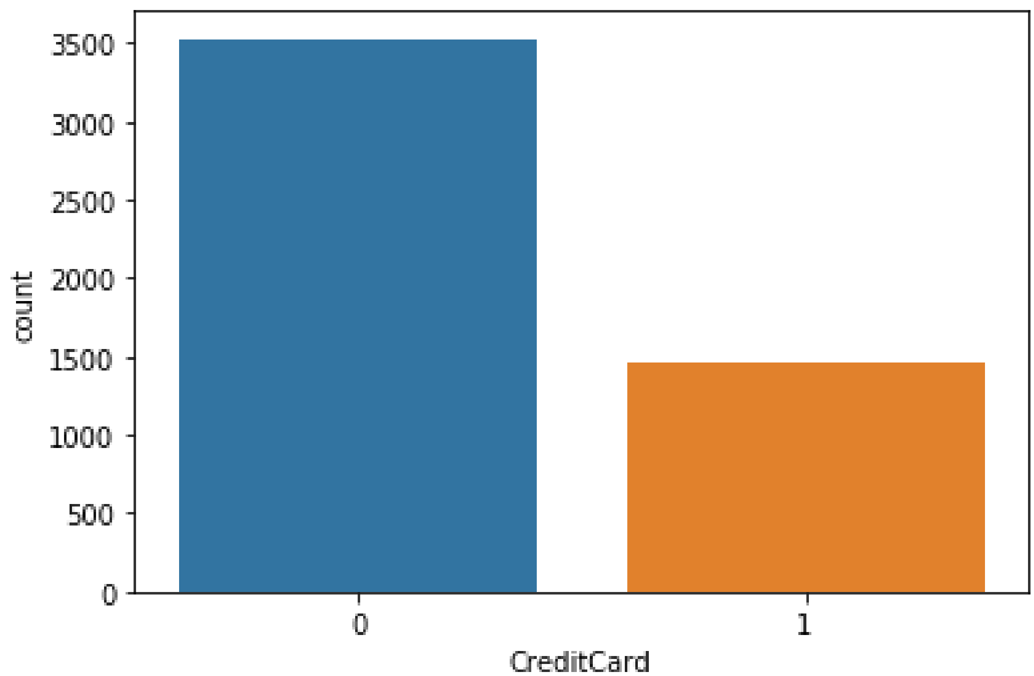


CD Account data is also unevenly distributed. Most people don't have a CD Account.

[39]:
```
unilateralAnalysis("Online",True)
```



[40]:
```
unilateralAnalysis("CreditCard",True)
```



For both Online and CreditCard, the data is slightly unevenly distributed.

8.0.5 Step 2.2: Data Cleaning

Now that we have performed unilateral analysis, let's perform some data cleaning based on our findings.

We will start off with treating the negative experience entries.

[42]:
```
sum(bankData["Experience"]<0)
```

[42]: 52

[44]:
```
sum(bankData["Experience"]<0)/len(bankData.index) * 100
```

[44]: 1.04

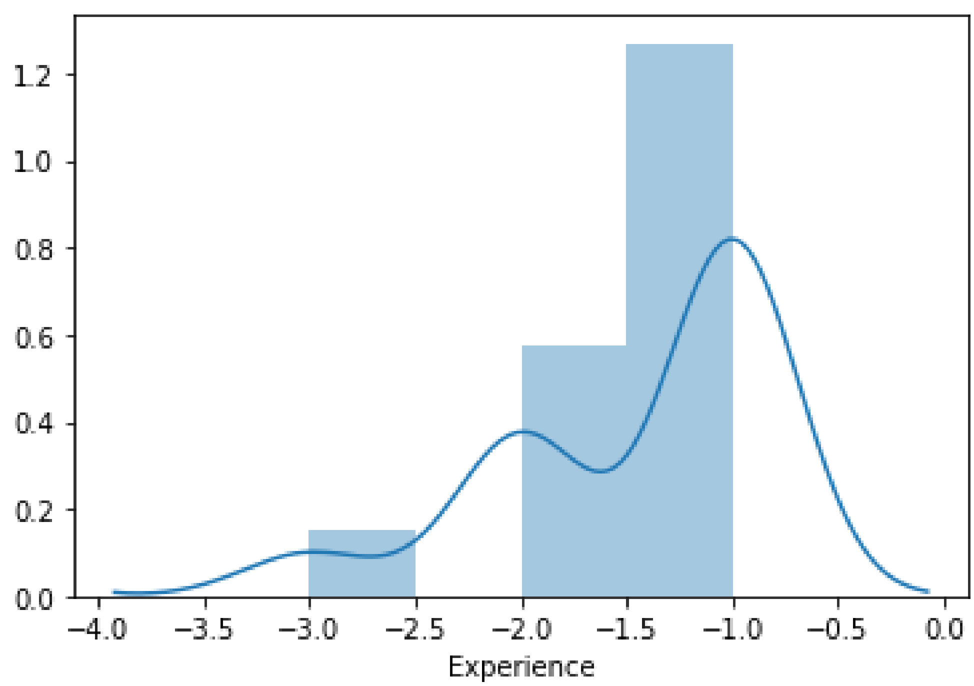
This means that 1.04% entries have negative experience. There are 2 main ways of treating with this data.

1. We can remove these entries. Since it's just 1.04%, we won't be losing any major amount of data.
2. We can replace these experience values with a different value.

Before we make the decision, let's have a look at the experience values.

[48]:
```
sns.distplot(bankData[bankData["Experience"] < 0]["Experience"])
```

[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7f35c64e6c50>



[49]:
```
bankData[bankData["Experience"]<0]
```

[49]:

	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	\
89	90	25	-1	113	94303	4	2.30	3	
226	227	24	-1	39	94085	2	1.70	2	
315	316	24	-2	51	90630	3	0.30	3	
451	452	28	-2	48	94132	2	1.75	3	
524	525	24	-1	75	93014	4	0.20	1	
536	537	25	-1	43	92173	3	2.40	2	
540	541	25	-1	109	94010	4	2.30	3	
576	577	25	-1	48	92870	3	0.30	3	
583	584	24	-1	38	95045	2	1.70	2	
597	598	24	-2	125	92835	2	7.20	1	
649	650	25	-1	82	92677	4	2.10	3	
670	671	23	-1	61	92374	4	2.60	1	
686	687	24	-1	38	92612	4	0.60	2	
793	794	24	-2	150	94720	2	2.00	1	
889	890	24	-2	82	91103	2	1.60	3	
909	910	23	-1	149	91709	1	6.33	1	
1173	1174	24	-1	35	94305	2	1.70	2	
1428	1429	25	-1	21	94583	4	0.40	1	
1522	1523	25	-1	101	94720	4	2.30	3	
1905	1906	25	-1	112	92507	2	2.00	1	
2102	2103	25	-1	81	92647	2	1.60	3	
2430	2431	23	-1	73	92120	4	2.60	1	
2466	2467	24	-2	80	94105	2	1.60	3	
2545	2546	25	-1	39	94720	3	2.40	2	
2618	2619	23	-3	55	92704	3	2.40	2	
2717	2718	23	-2	45	95422	4	0.60	2	
2848	2849	24	-1	78	94720	2	1.80	2	
2876	2877	24	-2	80	91107	2	1.60	3	
2962	2963	23	-2	81	91711	2	1.80	2	
2980	2981	25	-1	53	94305	3	2.40	2	
3076	3077	29	-1	62	92672	2	1.75	3	
3130	3131	23	-2	82	92152	2	1.80	2	
3157	3158	23	-1	13	94720	4	1.00	1	
3279	3280	26	-1	44	94901	1	2.00	2	
3284	3285	25	-1	101	95819	4	2.10	3	
3292	3293	25	-1	13	95616	4	0.40	1	
3394	3395	25	-1	113	90089	4	2.10	3	
3425	3426	23	-1	12	91605	4	1.00	1	
3626	3627	24	-3	28	90089	4	1.00	3	
3796	3797	24	-2	50	94920	3	2.40	2	
3824	3825	23	-1	12	95064	4	1.00	1	
3887	3888	24	-2	118	92634	2	7.20	1	
3946	3947	25	-1	40	93117	3	2.40	2	
4015	4016	25	-1	139	93106	2	2.00	1	
4088	4089	29	-1	71	94801	2	1.75	3	
4116	4117	24	-2	135	90065	2	7.20	1	

4285	4286	23	-3	149	93555	2	7.20	1
4411	4412	23	-2	75	90291	2	1.80	2
4481	4482	25	-2	35	95045	4	1.00	3
4514	4515	24	-3	41	91768	4	1.00	3
4582	4583	25	-1	69	92691	3	0.30	3
4957	4958	29	-1	50	95842	2	1.75	3

	Mortgage	Personal Loan	Securities Account	CD Account	Online	\
89	0	0	0	0	0	
226	0	0	0	0	0	
315	0	0	0	0	1	
451	89	0	0	0	1	
524	0	0	0	0	1	
536	176	0	0	0	1	
540	314	0	0	0	1	
576	0	0	0	0	0	
583	0	0	0	0	1	
597	0	0	1	0	0	
649	0	0	0	0	1	
670	239	0	0	0	1	
686	0	0	0	0	1	
793	0	0	0	0	1	
889	0	0	0	0	1	
909	305	0	0	0	0	
1173	0	0	0	0	0	
1428	90	0	0	0	1	
1522	256	0	0	0	0	
1905	241	0	0	0	1	
2102	0	0	0	0	1	
2430	0	0	0	0	1	
2466	0	0	0	0	1	
2545	0	0	0	0	1	
2618	145	0	0	0	1	
2717	0	0	0	0	1	
2848	0	0	0	0	0	
2876	238	0	0	0	0	
2962	0	0	0	0	0	
2980	0	0	0	0	0	
3076	0	0	0	0	0	
3130	0	0	1	0	0	
3157	84	0	0	0	1	
3279	0	0	0	0	0	
3284	0	0	0	0	0	
3292	0	0	1	0	0	
3394	0	0	0	0	1	
3425	90	0	0	0	1	
3626	0	0	0	0	0	

3796	0	0	1	0	0
3824	0	0	1	0	0
3887	0	0	1	0	1
3946	0	0	0	0	1
4015	0	0	0	0	0
4088	0	0	0	0	0
4116	0	0	0	0	1
4285	0	0	0	0	1
4411	0	0	0	0	1
4481	0	0	0	0	1
4514	0	0	0	0	1
4582	0	0	0	0	1
4957	0	0	0	0	0

	CreditCard
89	1
226	0
315	0
451	0
524	0
536	0
540	0
576	1
583	0
597	1
649	0
670	0
686	0
793	0
889	1
909	1
1173	0
1428	0
1522	1
1905	0
2102	1
2430	0
2466	0
2545	0
2618	0
2717	1
2848	0
2876	0
2962	0
2980	0
3076	1
3130	1

```
3157          0
3279          0
3284          1
3292          0
3394          0
3425          0
3626          0
3796          0
3824          1
3887          0
3946          0
4015          1
4088          0
4116          0
4285          0
4411          1
4481          0
4514          0
4582          0
4957          1
```

[50]:
```
bankData["Experience"].median()
```

[50]:
```
20.0
```

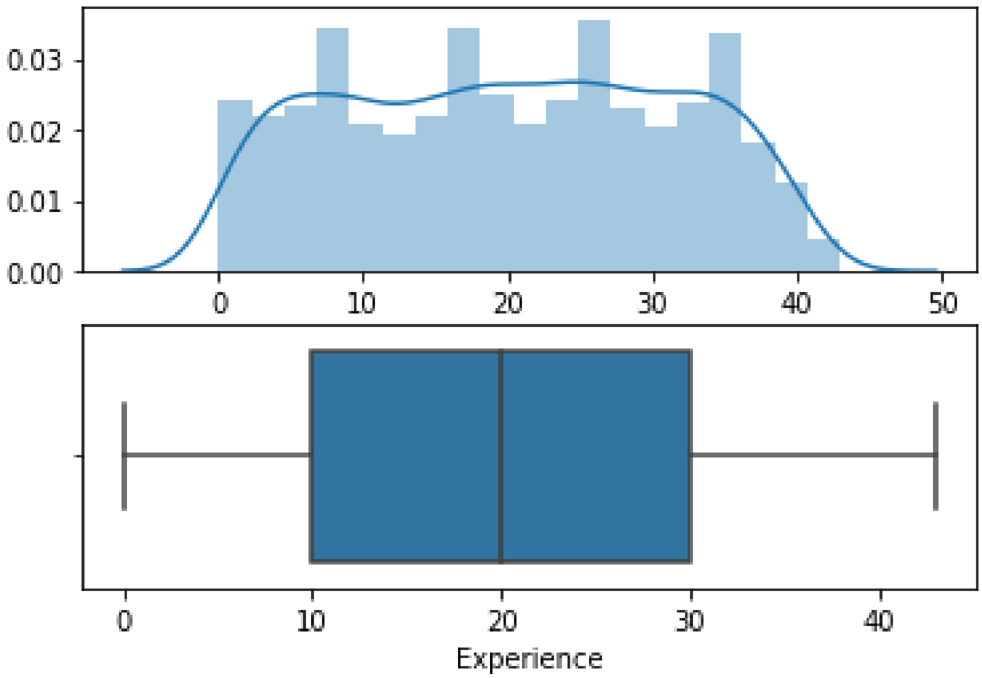
Instead of removing the data, it can be assumed that this was an error in manual entry of data because all the 52 entries have a stable income and a good education. If we replace these values with the median entry of 20 years, it will create a huge difference in the **magnitude** of experience for these values. That's why, I will replace these values with their magnitudes assuming that there was some error in entry. Since it's just 5000 entries of data, I don't want to lose any data unless until absolutely necessary.

[51]:
```
bankData["Experience"] = bankData["Experience"].apply(lambda x: abs(x))
```

[52]:
```
sum(bankData["Experience"] < 0)
```

[52]:
```
0
```

[53]:
```
unilateralAnalysis("Experience")
```




```
Mean: 20.13
```

[54]:
```
bankData["Experience"].median()
```

[54]:
```
20.0
```

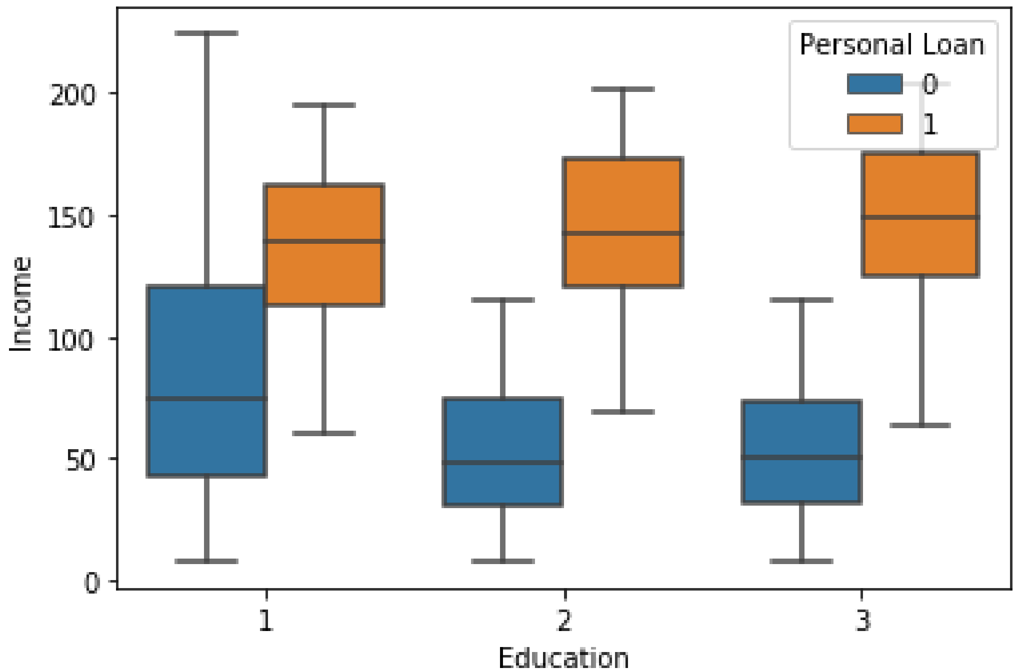
Good thing to note is that there is no significant change change in mean, median and distribution of Experience and we can safely continue using these values for model building.

8.0.6 Step 2.3: Further Analysis

Now that we have went over the distribution of each variable, let's continue to understand the effect they have on the target variable and their relationship between each other.

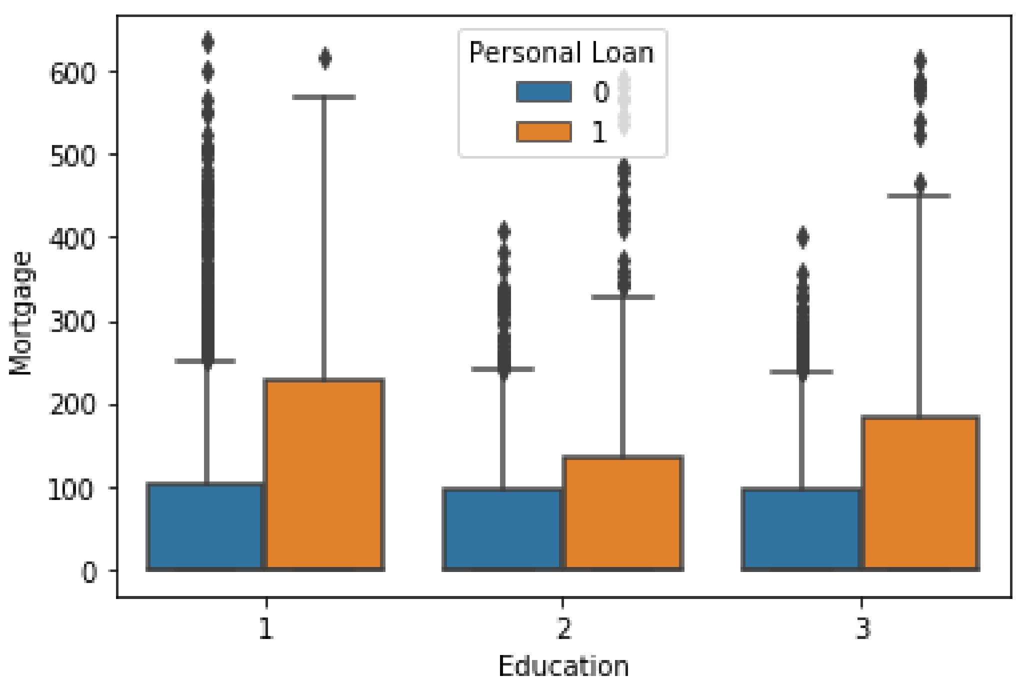
[69]:
```
def furtherAnalysisCategorical(variable, countplot=False, variable2 = None):
    if countplot:
        sns.countplot(x=variable,data=bankData,hue='Personal Loan')
        plt.show()
    else:
        # Boxplot
        sns.boxplot(x=variable,y=variable2,hue='Personal Loan',data=bankData)
        plt.show()
```

[70]:
```
furtherAnalysisCategorical("Education",False,"Income")
```



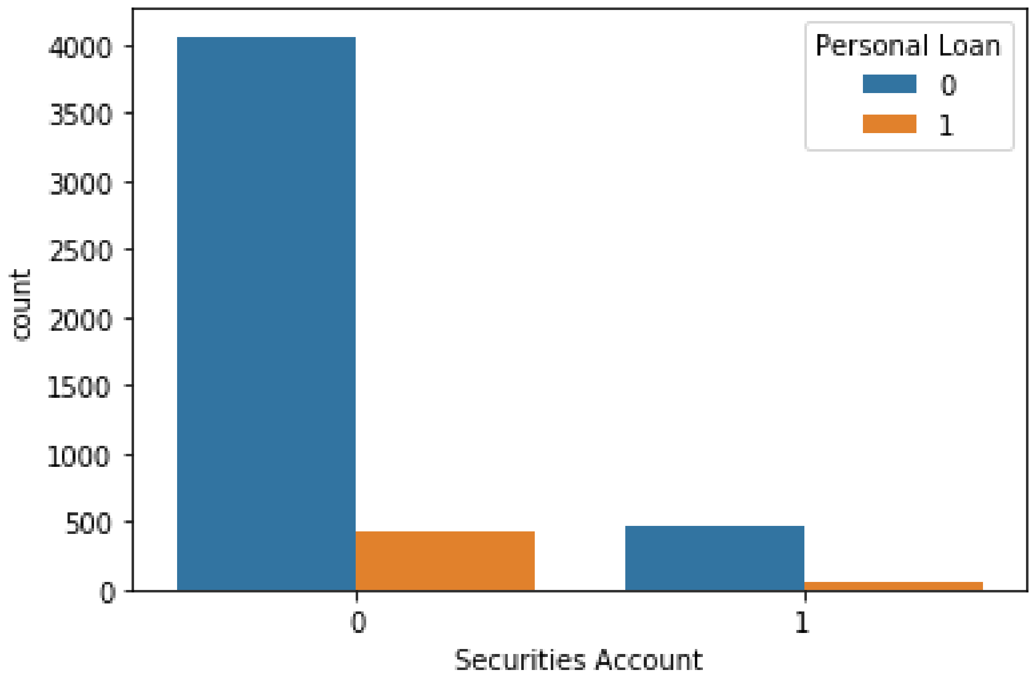
Note that as expected, people with higher income tend to go for the personal loan. The difference is larger as the education level increases from 1 to 3. Also note that the income levels for the people who opted for the loan have a similar income spread irrespective of their education level.

[71]:
```
furtherAnalysisCategorical("Education",False,"Mortgage")
```



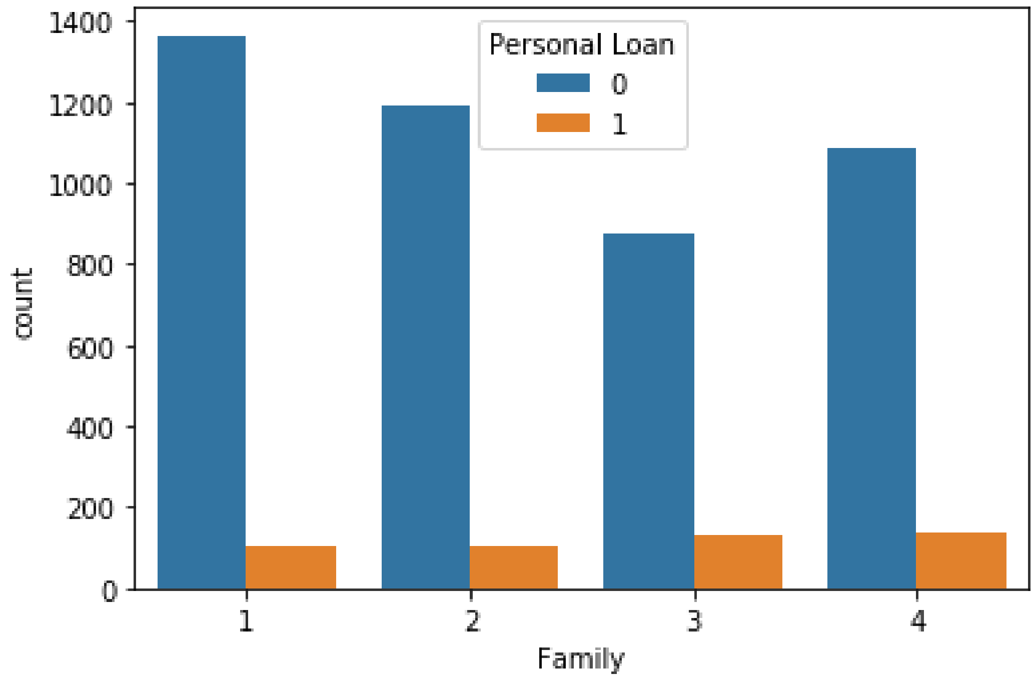
As expected, people with higher mortgage tend to go for a personal loan. The reason can be so that they can pay back the mortgage.

[72]:
```
furtherAnalysisCategorical("Securities Account",True)
```



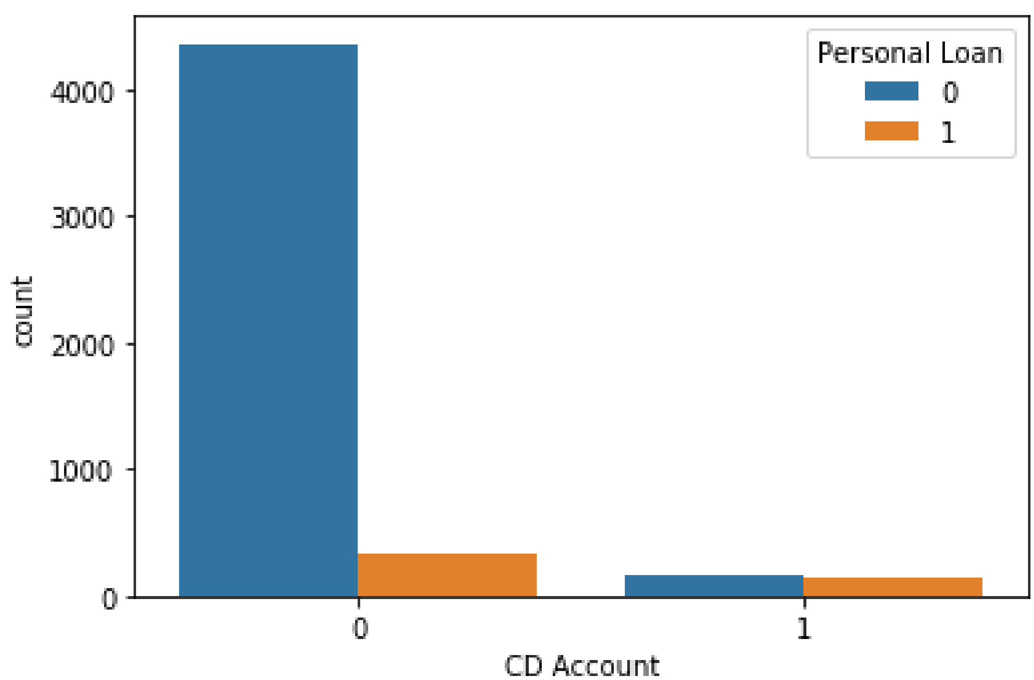
Compared to customers having a personal loan, more of those who don't have a personal loan have a securities account. But, the customers having a securities account is very low irrespective of whether they have taken a personal loan or not.

[73]:
```
furtherAnalysisCategorical("Family",True)
```



Number of family members doesn't seem to have any significant effect on the number of customers who opted for personal loan. But, if we focus on the ratio of people who didn't opt for the loan and those who opted for the loan, customers with family size 3 are most likely to opt for the loan.

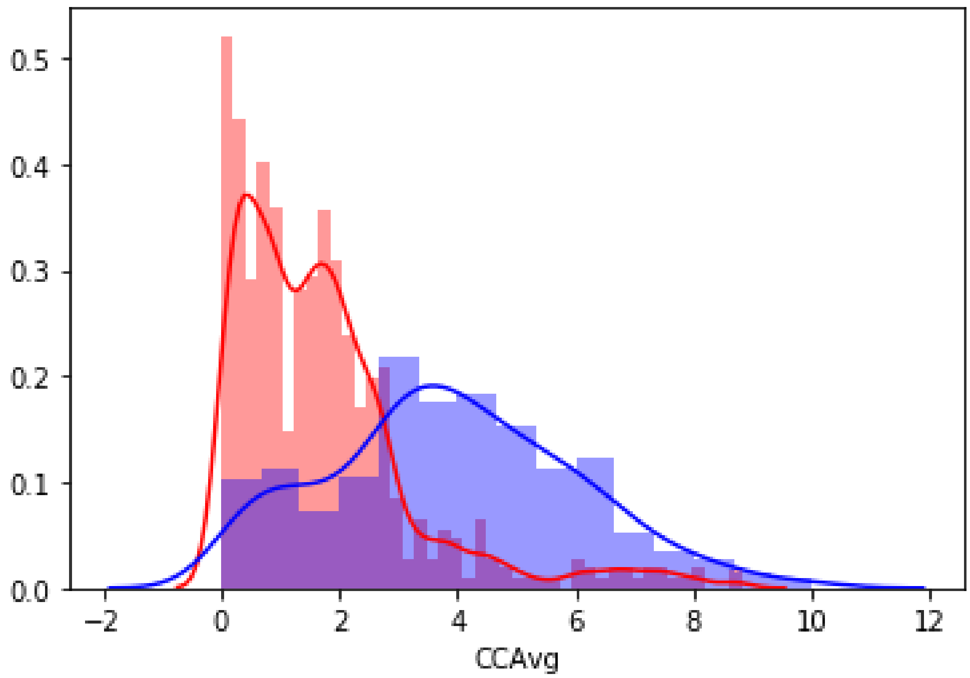
[74]:
```
furtherAnalysisCategorical("CD Account",True)
```



Almost all customers who have a CD Account have a personal loan whereas if a customer doesn't have a CD Account, the likelihood of the customer have a personal loan is very low.

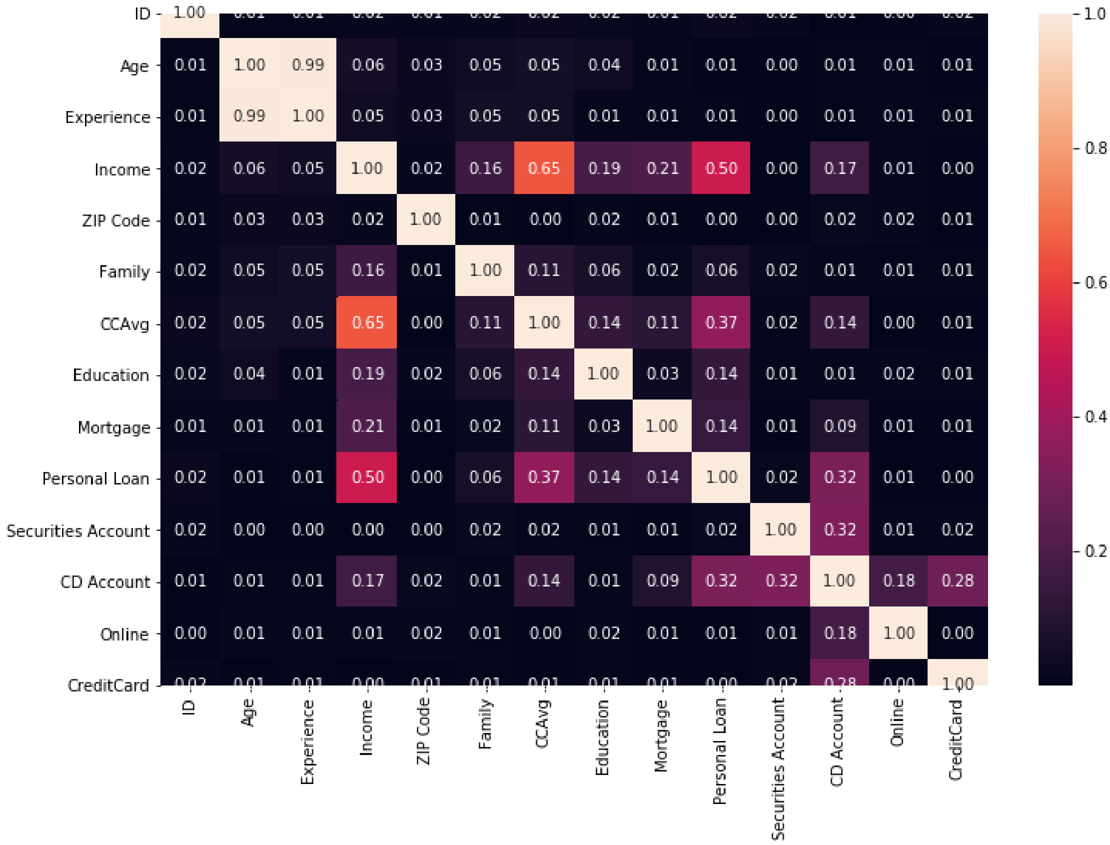
[77]:
```
sns.distplot( bankData[bankData["Personal Loan"] == 0]['CCAvg'], color='r')
sns.distplot( bankData[bankData["Personal Loan"] == 1]['CCAvg'], color='b')
```

[77]: <matplotlib.axes._subplots.AxesSubplot at 0x7f35c91a26d8>



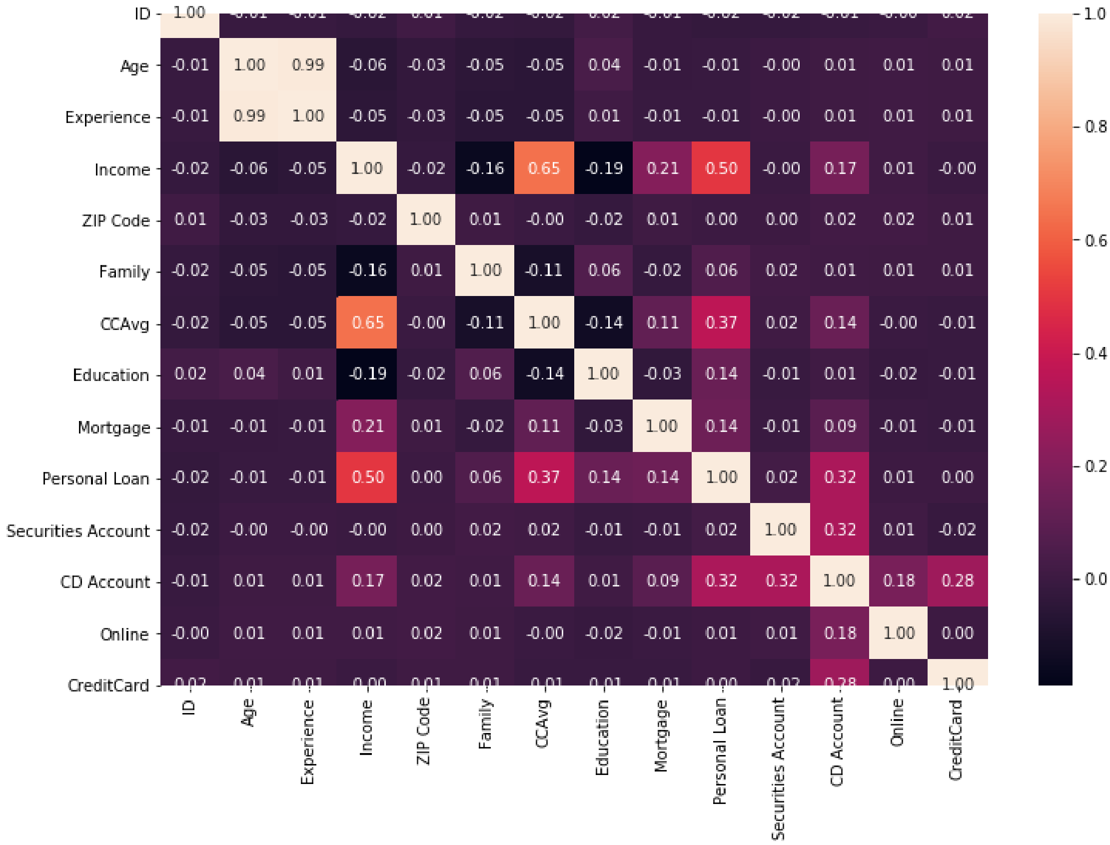
Customers with higher credit card average have a higher likelihood of having a personal loan. This can also be understood because a credit card is similar to a personal loan (one with a very short tenure) to a large extent. So if a customer is spending higher amount of money with a credit card, they have a higher chance to opt for a personal loan and pay the amount back later.

[82]:
```
# Heatmap of ABSOLUTE values of correlation
plt.figure(figsize=(12,8))
sns.heatmap(np.abs(bankData.corr()), annot=True, fmt=".2f")
plt.show()
```



From the heatmap of absolute values of correlation, we can see that **`Income`** and **`CC Avg`** are moderately correlated (corr = 0.65), **`Age`** and **`Experience`** are highly correlated.

[81]:
```
plt.figure(figsize=(12,8))
sns.heatmap(bankData.corr(), annot=True, fmt=".2f")
plt.show()
```



From the above heatmap, we can see that both **Age**, **Experience** and **Income**, **CC Avg** have a positive correlation.

I will drop **Experience** variable.

8.0.7 Step 3: Split the data into train and test

[83]:
```python
from sklearn.model_selection import train_test_split
```

[84]:
```python
# We want a 70:30 split
# Specify a random state so that the results can be generated again
train, test = train_test_split(bankData.drop(['ID','Experience'], axis=1),␣
↪test_size=0.3 , random_state=42)
```

[85]:
```python
X_train = train.drop("Personal Loan",axis=1)
y_train = train["Personal Loan"]
X_test = test.drop("Personal Loan",axis=1)
y_test = test["Personal Loan"]
```

[86]:
```python
X_train.shape, X_test.shape
```

[86]: ((3500, 11), (1500, 11))

[87]:
```python
y_train.shape, y_test.shape
```

[87]: ((3500,), (1500,))

Let's also normalize the values.

[88]:
```
from sklearn.preprocessing import StandardScaler
```

[89]:
```
scaler = StandardScaler()
```

[90]:
```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

8.0.8 Step 4: Model Building

8.0.9 Step 4.1: Logistic Regression

[91]:
```
from sklearn.linear_model import LogisticRegression
```

[115]:
```
from sklearn.metrics import confusion_matrix, classification_report
```

[92]:
```
lr = LogisticRegression()
```

[93]:
```
lr.fit(X_train, y_train)
```

```
/home/hp/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/logistic.py:432: FutureWarning: Default solver
will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

[93]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

[94]:
```
score = lr.score(X_test, y_test)
```

[95]:
```
score
```

[95]: 0.952

We obtained an accuracy of 95.2% on test set.

[96]:
```
score = lr.score(X_train, y_train)
score
```

[96]: 0.9528571428571428

And a similar accuracy on the train set. So we know that the model didn't overfit the data.

[114]:
```
confusion_matrix(y_test, lr.predict(X_test))
```

[114]:
```
array([[1325,   18],
       [  54,  103]])
```

[117]:
```
print(classification_report(y_test, lr.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.97      1343
           1       0.85      0.66      0.74       157

    accuracy                           0.95      1500
   macro avg       0.91      0.82      0.86      1500
weighted avg       0.95      0.95      0.95      1500
```

8.0.10 Step 4.2: K-NN Classifier

[97]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[101]:
```
from sklearn.metrics import accuracy_score
```

[118]:
```
knn = KNeighborsClassifier(n_neighbors=5)
```

[119]:
```
knn.fit(X_train,y_train)
```

[119]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

[120]:
```
y_pred = knn.predict(X_test)
acc = accuracy_score(y_pred, y_test)
acc
```

[120]:
```
0.9546666666666667
```

[121]:
```
y_pred = knn.predict(X_train)
acc = accuracy_score(y_pred, y_train)
acc
```

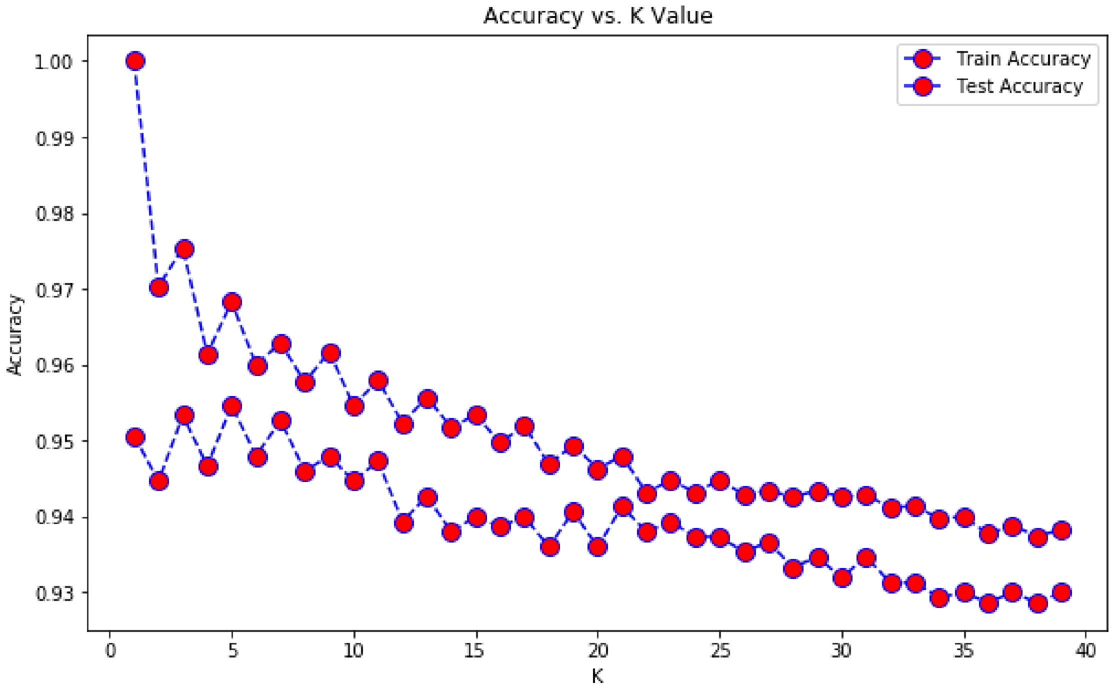
[121]:
```
0.9682857142857143
```

We obtain 96.83% accuracy on train data and 95.47% accuracy on test data using kNN classifier with n=5.

Let's use the Elbow Method to obtain the n_neighbors value

[111]:
```
test_accuracies = []
train_accuracies = []
# Might take some time
for i in range(1,40):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,y_train)
    pred_i = knn.predict(X_test)
    acc = accuracy_score(pred_i, y_test)
    test_accuracies.append(acc)
    pred_i = knn.predict(X_train)
    acc = accuracy_score(pred_i, y_train)
    train_accuracies.append(acc)
```

[112]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,40),train_accuracies,color='blue', linestyle='dashed',␣
 ↪marker='o',
         markerfacecolor='red', markersize=10, label="Train Accuracy")
plt.plot(range(1,40),test_accuracies,color='blue', linestyle='dashed',␣
 ↪marker='o',
         markerfacecolor='red', markersize=10, label="Test Accuracy")
plt.title('Accuracy vs. K Value')
plt.xlabel('K')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



As we can see from the graph above, we can continue using the initial choice of n_neighbors = 5

[122]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train,y_train)
```

[122]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

[123]:
```
confusion_matrix(y_test, knn.predict(X_test))
```

[123]:
```
array([[1337,    6],
       [  62,   95]])
```

[124]:
```
print(classification_report(y_test, knn.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      1343
           1       0.94      0.61      0.74       157

    accuracy                           0.95      1500
   macro avg       0.95      0.80      0.86      1500
weighted avg       0.95      0.95      0.95      1500
```

8.0.11 Step 4.3: Naive Bayes

[125]:
```
from sklearn.naive_bayes import GaussianNB
```

[126]:
```
nb = GaussianNB()
nb.fit(X_train, y_train)
```

[126]:
```
GaussianNB(priors=None, var_smoothing=1e-09)
```

[130]:
```
y_pred = nb.predict(X_test)
```

[135]:
```
nb.score(y_test.values.reshape(-1,1), y_pred.reshape(-1,1))
```

[135]:
```
0.8726666666666667
```

[136]:
```
y_pred = nb.predict(X_train)
nb.score(y_train.values.reshape(-1,1), y_pred.reshape(-1,1))
```

[136]:
```
0.8682857142857143
```

We obtained an accuracy of 86.83% on training set and 87.27% on testing set.

[137]:
```
confusion_matrix(y_test, nb.predict(X_test))
```

[137]:
```
array([[1245,   98],
       [  64,   93]])
```

[138]:
```
print(classification_report(y_test, nb.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.95      0.93      0.94      1343
           1       0.49      0.59      0.53       157

    accuracy                           0.89      1500
   macro avg       0.72      0.76      0.74      1500
weighted avg       0.90      0.89      0.90      1500
```

8.0.12 Step 5: Model Comparison

For final model comparison, we will use Cross Validation score.

[139]:
```
from sklearn.model_selection import KFold, cross_val_score
```

[152]:
```
models = [lr, knn, nb]
model_names = ["Logistic Regression", "K-NN Classifier", "Naive Bayes"]
results = []
kfold = KFold(n_splits = 10, random_state=42)
```

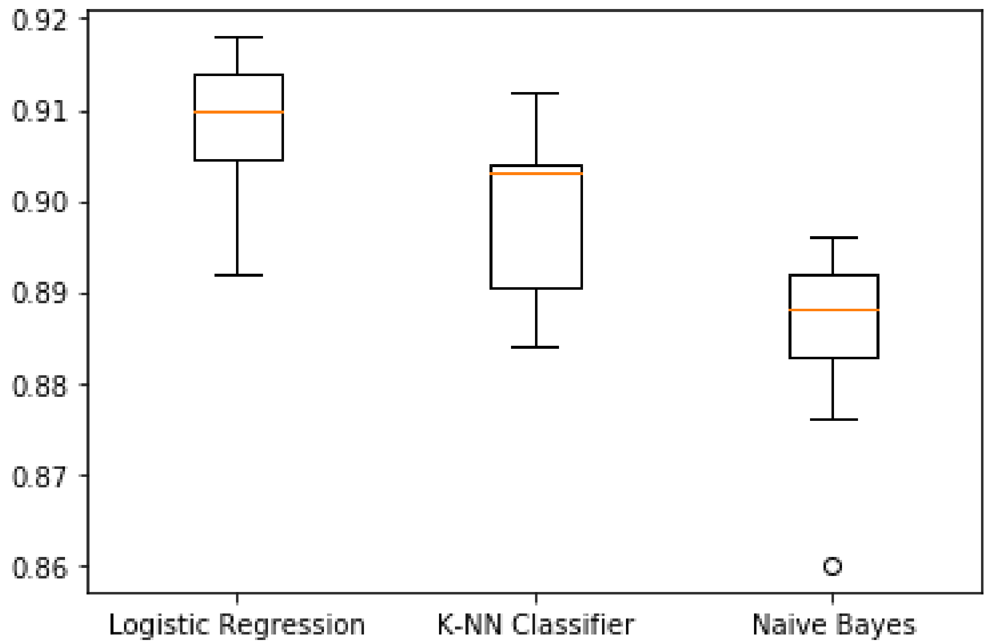
[153]:
```
X = bankData.drop(["ID","Experience","Personal Loan"],axis=1)
```

[154]:
```
y = bankData["Personal Loan"]
```

[155]:
```
for model,model_name in zip(models, model_names):
    cv_results = cross_val_score(model, X, y, cv=kfold, scoring = "accuracy")
    results.append(cv_results)
    print("Model: {}, Mean Accuracy: {}, Std: {}".format(model_name, cv_results.
 ↪mean(), cv_results.std()))
```

```
Model: Logistic Regression, Mean Accuracy: 0.9082000000000001, Std:
0.007871467461661777
Model: K-NN Classifier, Mean Accuracy: 0.8986000000000001, Std:
0.008901685233707162
Model: Naive Bayes, Mean Accuracy: 0.8855999999999999, Std: 0.010384603988597745
```

[156]:
```
fig = plt.figure()
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(model_names)
plt.show()
```



As we can see from the box plot above, **Logistic Regression** is the best model followed by K-NN Classifier and finally the Naive Bayes model.

Logistic Regression works best when there is a linearity in the model and the classes are cleanly distributed. As we saw in Steps 1 and 2, the target variable's dependence on the variables can be simply explained based on the values of the independent variables. In such a case, the decision tree classifier (CART) will also give a very good result which can be easily verified as shown below.

[157]:
```
from sklearn.tree import DecisionTreeClassifier
```

[158]:
```
dt=DecisionTreeClassifier(criterion = 'entropy',max_depth=3)
dt.fit(X_train,y_train)
```

[158]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

[159]:
```
dt.score(X_test , y_test)
```

[159]:
```
0.9826666666666667
```

[160]:
```
dt.score(X_train, y_train)
```

[160]:
```
0.9785714285714285
```

As we see, the Decision Tree classifier was able to obtain an accuracy of 98.27% on testing set and 97.86% on training set.