In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from scipy.stats import zscore
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.impute import SimpleImputer
```

In [2]:

```
bank =pd.read_csv("Bank_Personal_Loan_Modelling.csv")
```

In [3]:

```
bank.shape
```

Out[3]:

```
(5000, 14)
```

In [4]:

```
bank.head()
```

Out[4]:

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

In [5]:

```
bank.isnull().values.any()
```

Out[5]:

```
False
```

In [6]:

```
bank.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
```

Data distribution in each attribute

In [7]:

```
bank.describe()
```

Out[7]:

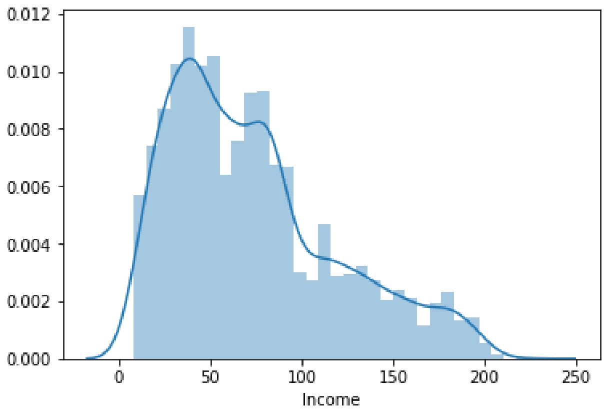
	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Pers
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.0(
mean	2500.500000	45.338400	20.104600	73.774200	93152.503000	2.396400	1.937938	1.881000	56.498800	0.09
std	1443.520003	11.463166	11.467954	46.033729	2121.852197	1.147663	1.747659	0.839869	101.713802	0.29
min	1.000000	23.000000	-3.000000	8.000000	9307.000000	1.000000	0.000000	1.000000	0.000000	0.0(
25%	1250.750000	35.000000	10.000000	39.000000	91911.000000	1.000000	0.700000	1.000000	0.000000	0.0(
50%	2500.500000	45.000000	20.000000	64.000000	93437.000000	2.000000	1.500000	2.000000	0.000000	0.0(
75%	3750.250000	55.000000	30.000000	98.000000	94608.000000	3.000000	2.500000	3.000000	101.000000	0.0(
max	5000.000000	67.000000	43.000000	224.000000	96651.000000	4.000000	10.000000	3.000000	635.000000	1.0(

In [8]:

```
sns.distplot(bank["Income"])
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4214c88>
```

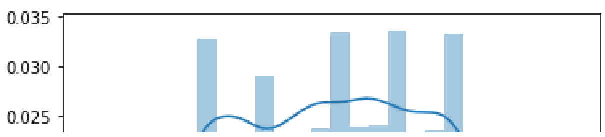


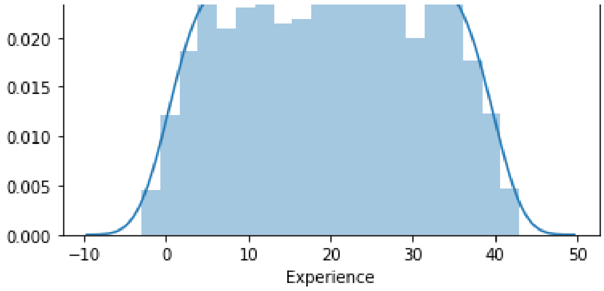
In [9]:

```
sns.distplot(bank["Experience"])
```

Out[9]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfb454a6c8>
```



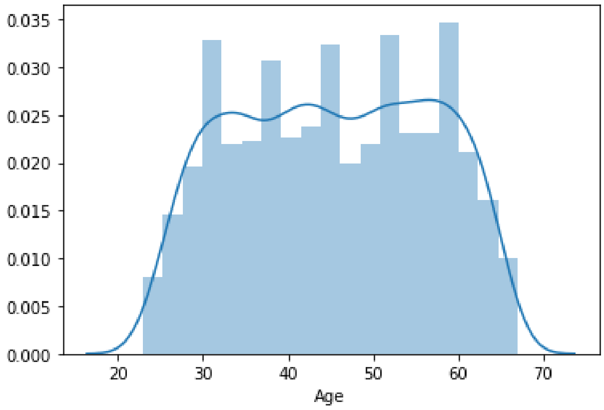


In [10]:

```
sns.distplot(bank["Age"])
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4662888>
```

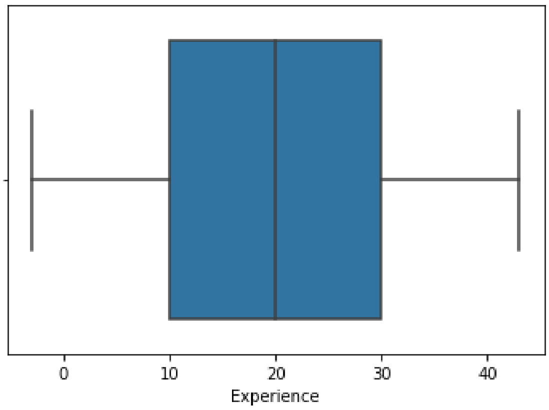


In [11]:

```
sns.boxplot(bank["Experience"])
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4709b48>
```

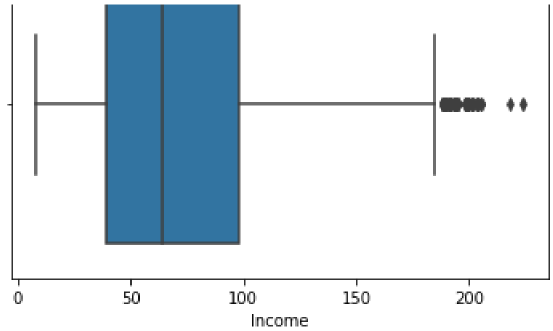


In [12]:

```
sns.boxplot(bank["Income"])
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4689ec8>
```

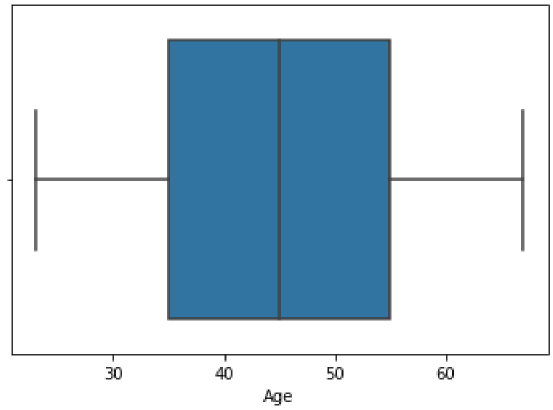


In [13]:

```
sns.boxplot(bank["Age"])
```

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb47f3d88>

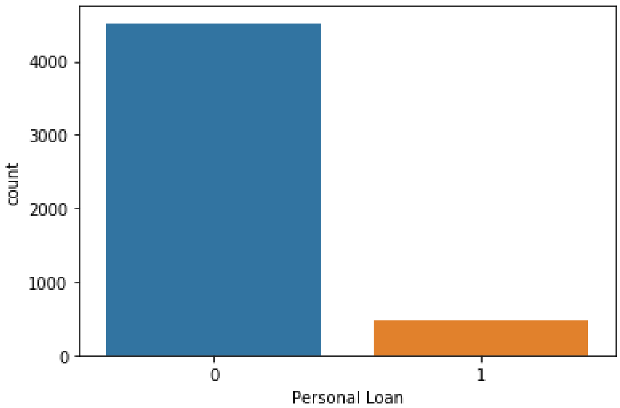


In [14]:

```
sns.countplot(bank["Personal Loan"])
```

Out[14]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4853d88>

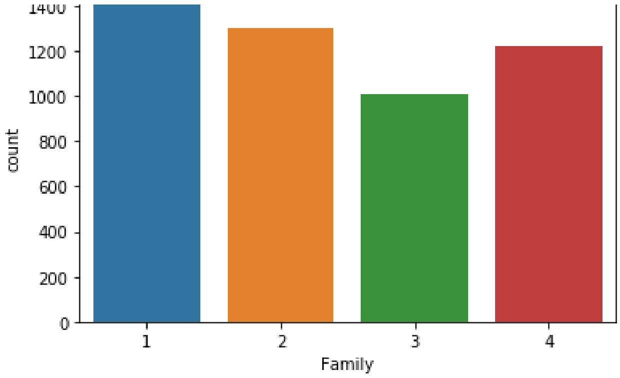


In [15]:

```
sns.countplot(bank["Family"])
```

Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4898f08>

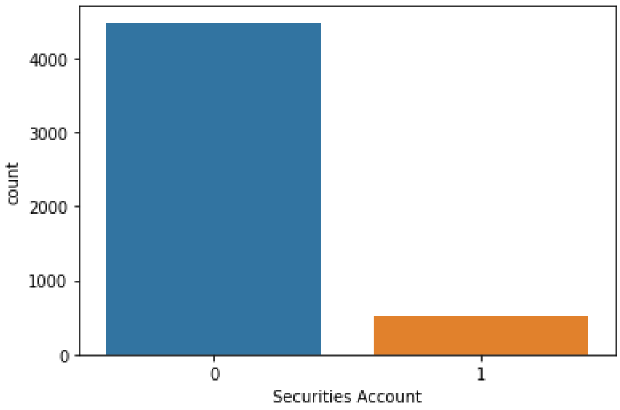


In [16]:

```
sns.countplot(bank["Securities Account"])
```

Out[16]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb49209c8>

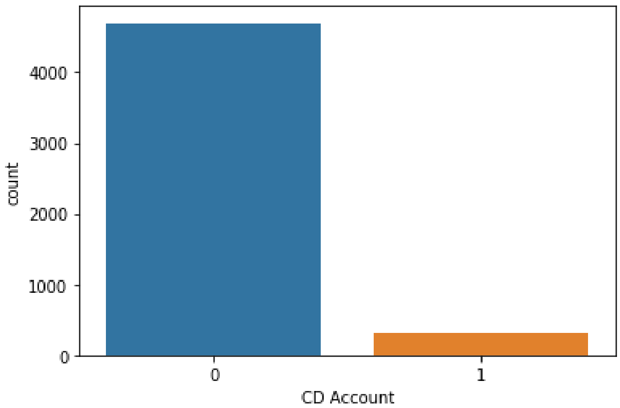


In [17]:

```
sns.countplot(bank["CD Account"])
```

Out[17]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4969808>

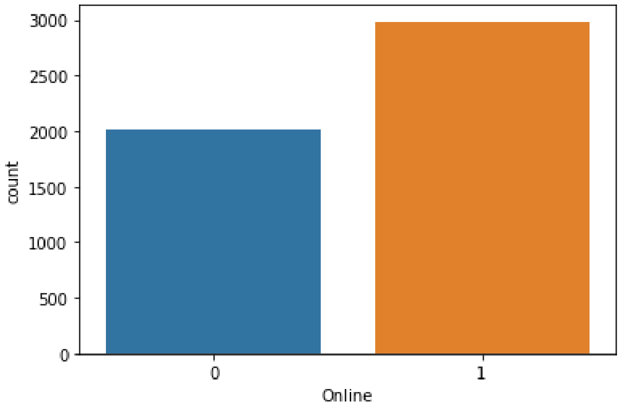


In [18]:

```
sns.countplot(bank["Online"])
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb49ab908>

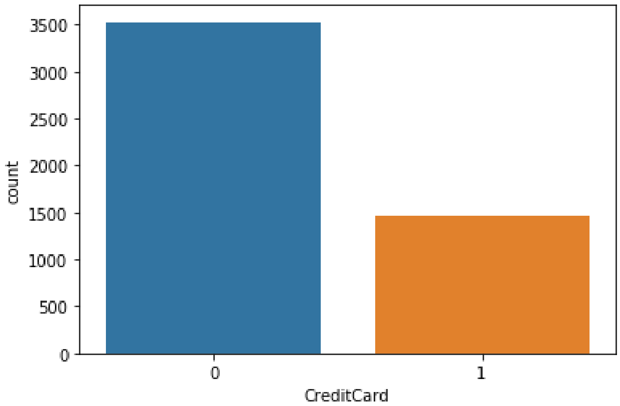


In [19]:

```
sns.countplot(bank["CreditCard"])
```

Out[19]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfb4a1da48>

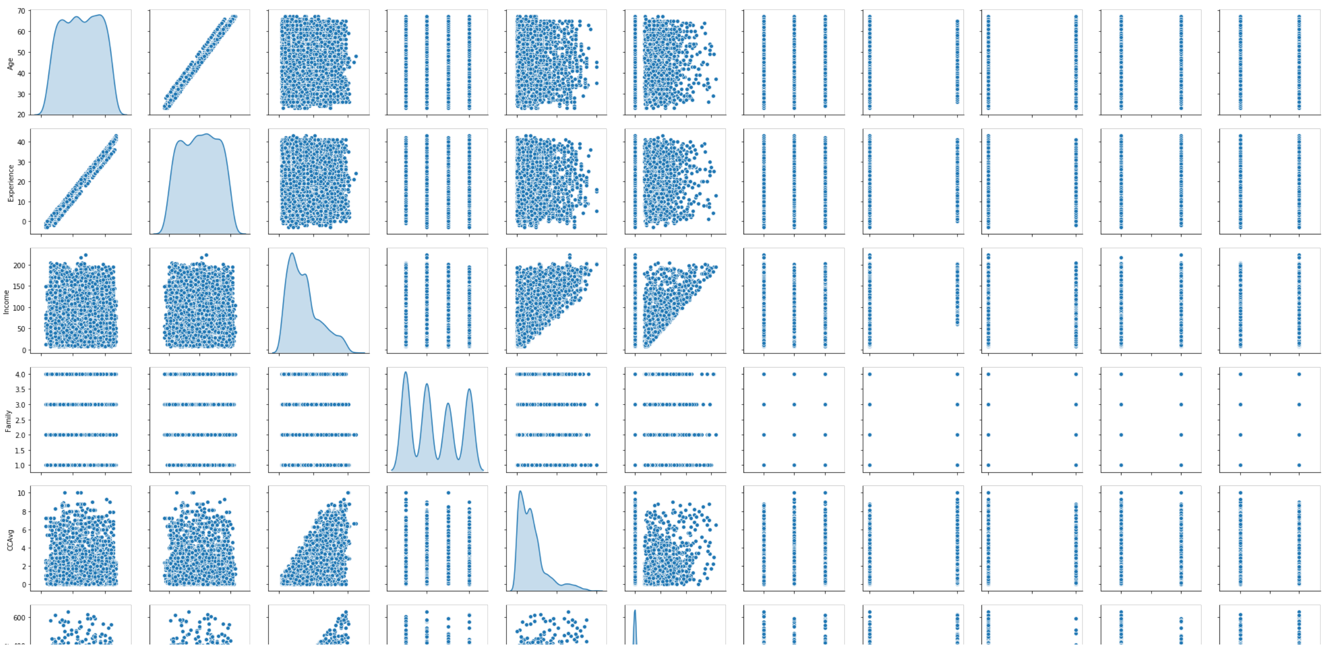


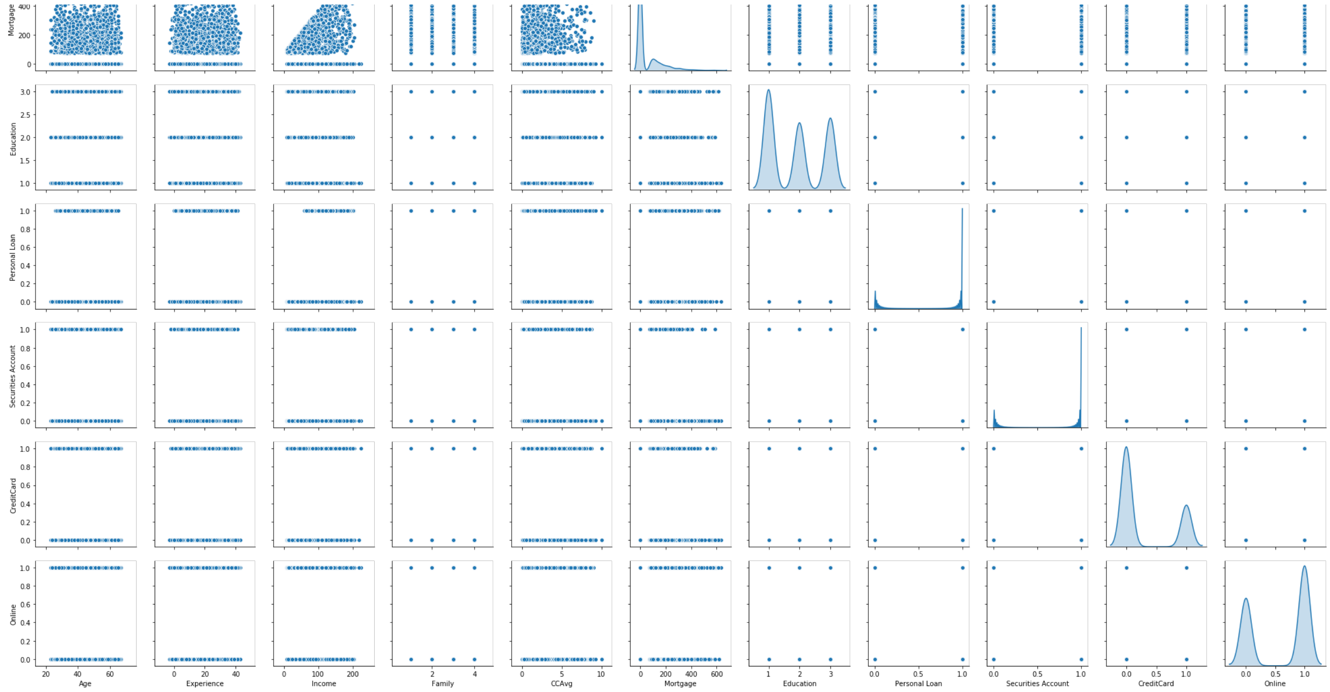
In [20]:

```
sns.pairplot(bank[["Age","Experience","Income","Family","CCAvg","Mortgage","Education","Personal Loan","Securities Account","CreditCard","Online"]], diag_kind='kde')
```

Out[20]:

<seaborn.axisgrid.PairGrid at 0x1dfb4a73f88>





In [21]:

```
corre=bank.corr()
bank.corr()
```

Out[21]:

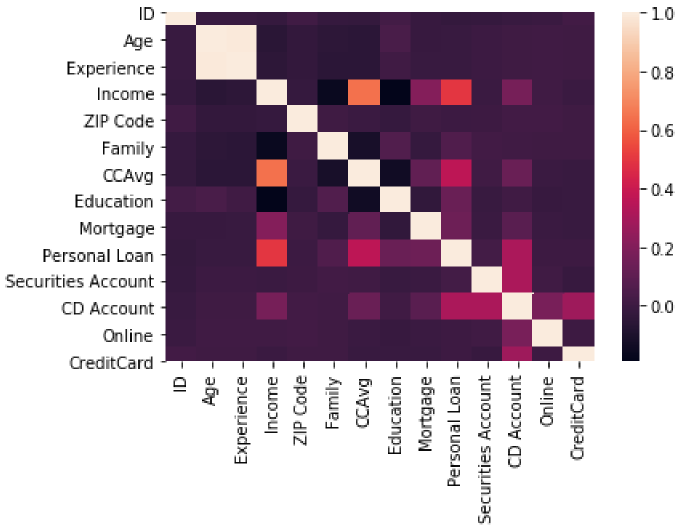
	ID	Age	Experience	Income	ZIP Code	Family	CCAvg	Education	Mortgage	Personal Loan	Securities Account	C Accou
ID	1.000000	-0.008473	-0.008326	-0.017695	0.013432	-0.016797	-0.024675	0.021463	-0.013920	-0.024801	-0.016972	0.00690
Age	-0.008473	1.000000	0.994215	-0.055269	-0.029216	-0.046418	-0.052012	0.041334	-0.012539	-0.007726	-0.000436	0.00804
Experience	-0.008326	0.994215	1.000000	-0.046574	-0.028626	-0.052563	-0.050077	0.013152	-0.010582	-0.007413	-0.001232	0.01035
Income	-0.017695	-0.055269	-0.046574	1.000000	-0.016410	-0.157501	0.645984	-0.187524	0.206806	0.502462	-0.002616	0.16973
ZIP Code	0.013432	-0.029216	-0.028626	-0.016410	1.000000	0.011778	-0.004061	-0.017377	0.007383	0.000107	0.004704	0.01997
Family	-0.016797	-0.046418	-0.052563	-0.157501	0.011778	1.000000	-0.109275	0.064929	-0.020445	0.061367	0.019994	0.01411
CCAvg	-0.024675	-0.052012	-0.050077	0.645984	-0.004061	-0.109275	1.000000	-0.136124	0.109905	0.366889	0.015086	0.13653
Education	0.021463	0.041334	0.013152	-0.187524	-0.017377	0.064929	-0.136124	1.000000	-0.033327	0.136722	-0.010812	0.01393
Mortgage	-0.013920	-0.012539	-0.010582	0.206806	0.007383	-0.020445	0.109905	-0.033327	1.000000	0.142095	-0.005411	0.08931
Personal Loan	-0.024801	-0.007726	-0.007413	0.502462	0.000107	0.061367	0.366889	0.136722	0.142095	1.000000	0.021954	0.31635
Securities Account	-0.016972	-0.000436	-0.001232	-0.002616	0.004704	0.019994	0.015086	-0.010812	-0.005411	0.021954	1.000000	0.31703
CD Account	-0.006909	0.008043	0.010353	0.169738	0.019972	0.014110	0.136534	0.013934	0.089311	0.316355	0.317034	1.00000
Online	-0.002528	0.013702	0.013898	0.014206	0.016990	0.010354	-0.003611	-0.015004	-0.005995	0.006278	0.012627	0.17588
CreditCard	0.017028	0.007681	0.008967	-0.002385	0.007691	0.011588	-0.006689	-0.011014	-0.007231	0.002802	-0.015028	0.27864

In [22]:

```
sns.heatmap(corre)
```

Out[22]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfba27d548>



Findings

1. The distribution of each attribute is found.
2. It is found that outliers are present in income while no outlier is present in age & experience attributes.
3. It is found in the income distribution plot that it is left-skewed.
4. The mean, median, minimum,25%,50%,75% and maximum value of each attribute is found out.

Inference from count table.

1. People taking personal loans are very less.
2. People prefer online mode.
3. Most of the people in the given data don't have a credit card.
4. People with securities account and CD account are low in the given data.

In [23]:

```
bank["Personal Loan"].describe()
```

Out[23]:

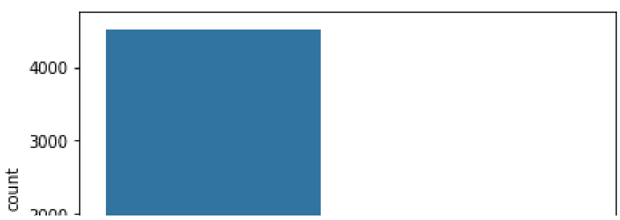
```
count    5000.000000
mean        0.096000
std         0.294621
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000
Name: Personal Loan, dtype: float64
```

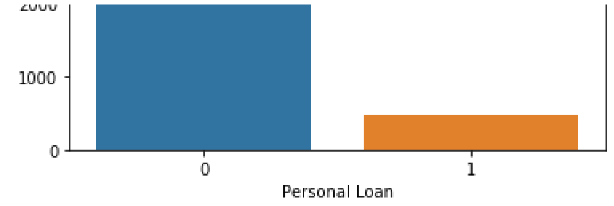
In [24]:

```
sns.countplot(bank["Personal Loan"])
```

Out[24]:

<matplotlib.axes._subplots.AxesSubplot at 0x1dfbc458c48>





Logistic Regression.

In [25]:

```
bank=bank.drop(["ID","ZIP Code"],axis=1)
```

In [26]:

```
X = bank.drop('Personal Loan',axis=1)
Y = bank['Personal Loan']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=42)
x_train.head()
```

Out[26]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Securities Account	CD Account	Online	CreditCard
1840	55	25	23	4	0.4	3	88	0	0	0	0
2115	57	31	30	3	1.4	1	0	0	0	0	0
4437	63	38	63	2	1.5	1	0	0	0	1	0
1146	31	7	71	1	0.1	1	78	1	0	0	0
2486	61	36	130	1	1.3	1	257	0	0	0	0

In [27]:

```
a=(len(x_train)/len(bank.index)) * 100
print(a,"% data is in training set")
b=(len(x_test)/len(bank.index)) * 100
print(b,"% data is in test set")
```

```
70.0 % data is in training set
30.0 % data is in test set
```

In [28]:

```
c=(len(bank.loc[bank['Personal Loan'] == 1]))
c1=(len(bank.loc[bank['Personal Loan'] == 1])/len(bank.index)) * 100
print("Original Personal loans True Values    : ",c,"(",c1,"%)")
d=len(bank.loc[bank['Personal Loan'] == 0]),
d1=(len(bank.loc[bank['Personal Loan'] == 0])/len(bank.index)) * 100
print("Original Personal loans False Values   : ",d,"(",d1,"%)")
e=len(y_train[y_train[:] == 1])
e1=(len(y_train[y_train[:] == 1])/len(y_train)) * 100
print("Training Personal loans True Values    :",e,"(",e1,"%)")
f=len(y_train[y_train[:] == 0])
f1=(len(y_train[y_train[:] == 0])/len(y_train)) * 100
print("Training Personal loans False Values   : ",f,"(",f1,"%)")
g=len(y_test[y_test[:] == 1])
g1=(len(y_test[y_test[:] == 1])/len(y_test)) * 100
print("Test Personal loans True Values        :  ",g,"(",g1,"%)")
h=len(y_test[y_test[:] == 0])
h1=(len(y_test[y_test[:] == 0])/len(y_test)) * 100
print("Test Personal loans False Values       :  ",h,"(",h1,"%)")
```

```
Original Personal loans True Values     :  480 ( 9.6 %)
Original Personal loans False Values    :  (4520,) ( 90.4 %)
Training Personal loans True Values     : 323 ( 9.22857142857143 %)
Training Personal loans False Values    :  3177 ( 90.77142857142857 %)
Test Personal loans True Values         :   157 ( 10.466666666666667 %)
```

```
Test Personal loans False Values       :   1343 ( 89.53333333333333 %)
```

In [29]:

```python
rep_0 = SimpleImputer(missing_values=0, strategy="mean")
cols=x_train.columns
x_train = pd.DataFrame(rep_0.fit_transform(x_train))
x_test = pd.DataFrame(rep_0.fit_transform(x_test))

x_train.columns = cols
x_test.columns = cols

x_train.head()
```

Out[29]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Securities Account	CD Account	Online	CreditCard
0	55.0	25.0	23.0	4.0	0.4	3.0	88.000000	1.0	1.0	1.0	1.0
1	57.0	31.0	30.0	3.0	1.4	1.0	187.162162	1.0	1.0	1.0	1.0
2	63.0	38.0	63.0	2.0	1.5	1.0	187.162162	1.0	1.0	1.0	1.0
3	31.0	7.0	71.0	1.0	0.1	1.0	78.000000	1.0	1.0	1.0	1.0
4	61.0	36.0	130.0	1.0	1.3	1.0	257.000000	1.0	1.0	1.0	1.0

In [30]:

```python
model = LogisticRegression(solver="liblinear")
model.fit(x_train, y_train)
y_predict = model.predict(x_test)
coef_df = pd.DataFrame(model.coef_)
coef_df['intercept'] = model.intercept_
print(coef_df)
```

```
          0         1         2         3         4         5         6  \
0 -0.058191  0.070155  0.050494  0.629828  0.092142  1.469759  0.000718

          7         8         9        10  intercept
0 -2.256718 -2.256718 -2.256718 -2.256718  -2.256718
```

In [31]:

```python
model_score = model.score(x_test, y_test)
print(model_score)
```

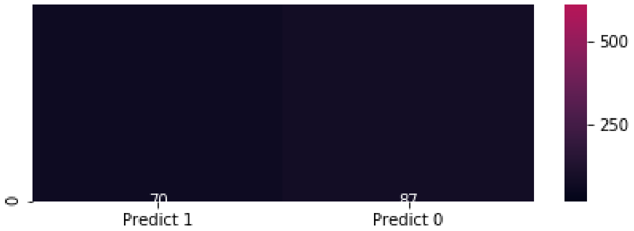
```
0.9386666666666666
```

In [58]:

```python
lrm=metrics.confusion_matrix(y_test, y_predict)
lr_m = pd.DataFrame(lrm, index = [i for i in ["1","0"]],columns = [i for i in ["Predict 1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(lr_m,annot=True)
```

Out[58]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfbc978988>
```



In [33]:

```
print("Classification Report")
print(metrics.classification_report(y_test, y_predict, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.80      0.55      0.65       157
           0       0.95      0.98      0.97      1343

    accuracy                           0.94      1500
   macro avg       0.87      0.77      0.81      1500
weighted avg       0.93      0.94      0.93      1500
```

Result

It is found that the model accuracy of **Logistic Regression** is **94%**.

This means the model gives correct result 94% of the time.

KNN Classifier

In [34]:

```
bank.groupby(["Personal Loan"]).count()
```

Out[34]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Securities Account	CD Account	Online	CreditCard
Personal Loan											
0	4520	4520	4520	4520	4520	4520	4520	4520	4520	4520	4520
1	480	480	480	480	480	480	480	480	480	480	480

In [35]:

```
XScaled  = X.apply(zscore)
XScaled.describe()
```

Out[35]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Securities Account	CD Accoun
count	5.000000e+03	5.000000e+03	5.000000e+03	5.000000e+03	5.000000e+03	5.000000e+03	5.000000e+03	5.000000e+03	5.000000e+0
mean	2.478018e-17	-1.693312e-16	1.939449e-16	7.850609e-16	-2.078338e-17	-6.315837e-16	2.810197e-16	5.092149e-16	4.426903e-1
std	1.000100e+00	1.000100e+00	1.000100e+00	1.000100e+00	1.000100e+00	1.000100e+00	1.000100e+00	1.000100e+00	1.000100e+0
min	-1.948906e+00	-2.014911e+00	-1.428969e+00	-1.216855e+00	-1.108987e+00	-1.049078e+00	-5.555239e-01	-3.414233e-01	-2.535403e-0
25%	-9.019702e-01	-8.812043e-01	-7.554825e-01	-1.216855e+00	-7.084116e-01	-1.049078e+00	-5.555239e-01	-3.414233e-01	-2.535403e-0
50%	-2.952359e-02	-9.121982e-03	-2.123482e-01	-3.454321e-01	-2.506106e-01	1.417029e-01	-5.555239e-01	-3.414233e-01	-2.535403e-0

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Securities Account	CD Account
75%	8.429230[illegible]	8.[illegible]	5.263[illegible]	5.2599[illegible]	3.2164[illegible]	1.33[illegible]	4.37[illegible]	-3[illegible]	-2.535403e[illegible]
max	1.889859e+00	1.996667e+00	3.263712e+00	1.397414e+00	4.613525e+00	1.332484e+00	5.688108e+00	2.928915e+00	3.944146e+0[illegible]

In [36]:

```
X_train, X_test, y_train, y_test = train_test_split(XScaled, Y, test_size=0.30, random_state=42)
```

In [37]:

```
NNH = KNeighborsClassifier(n_neighbors= 5 , weights = 'distance' )
```

In [38]:

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

Out[38]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='distance')
```

In [39]:

```
predicted_labels = NNH.predict(X_test)
NNH.score(X_test, y_test)
```

Out[39]:

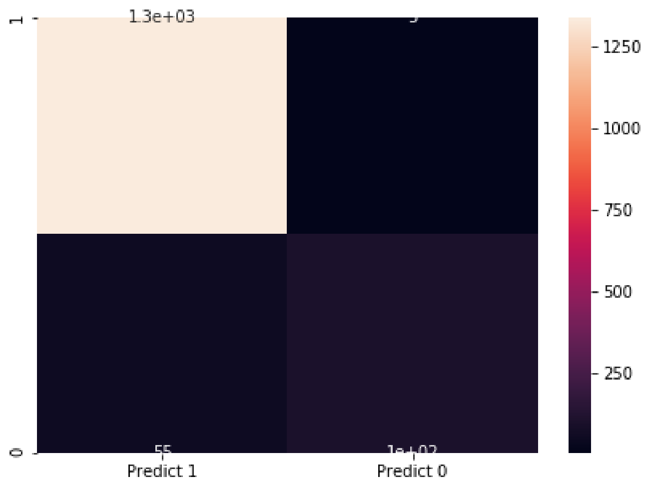
```
0.96
```

In [52]:

```
knnm=metrics.confusion_matrix(y_test, predicted_labels)
knn_m = pd.DataFrame(knnm, index = [i for i in ["1","0"]],columns = [i for i in ["Predict
1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(knn_m, annot=True)
```

Out[52]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfbc7656c8>
```



In [41]:

```
print("Classification Report")
print(metrics.classification_report(y_test, predicted_labels, labels=[1, 0]))
```

```
Classification Report
```

```
              precision    recall  f1-score   support

           1       0.95      0.65      0.77       157
           0       0.96      1.00      0.98      1343

    accuracy                           0.96      1500
   macro avg       0.96      0.82      0.88      1500
weighted avg       0.96      0.96      0.96      1500
```

Result

The model accuracy of **KNN Classifier** is **96%**.

This means the model gives correct result 95% of time.

Naive Bayes classifier

In [42]:

```
X = bank.drop('Personal Loan',axis=1)
Y = bank['Personal Loan']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=42)
x_train.head()
```

Out[42]:

	Age	Experience	Income	Family	CCAvg	Education	Mortgage	Securities Account	CD Account	Online	CreditCard
1840	55	25	23	4	0.4	3	88	0	0	0	0
2115	57	31	30	3	1.4	1	0	0	0	0	0
4437	63	38	63	2	1.5	1	0	0	0	1	0
1146	31	7	71	1	0.1	1	78	1	0	0	0
2486	61	36	130	1	1.3	1	257	0	0	0	0

In [43]:

```
bank_model = GaussianNB()
bank_model.fit(x_train, y_train.ravel())
```

Out[43]:

```
GaussianNB(priors=None, var_smoothing=1e-09)
```

In [44]:

```
bank_train_predict = bank_model.predict(x_train)
print("Model Accuracy: ",(metrics.accuracy_score(y_train, bank_train_predict)))
print()
```

```
Model Accuracy:  0.8825714285714286
```

In [45]:

```
bank_test_predict = bank_model.predict(x_test)
print("Model Accuracy:",(metrics.accuracy_score(y_test,bank_test_predict)))
print()
```

```
Model Accuracy: 0.892
```

In [56]:

```
print("Confusion Matrix")
```

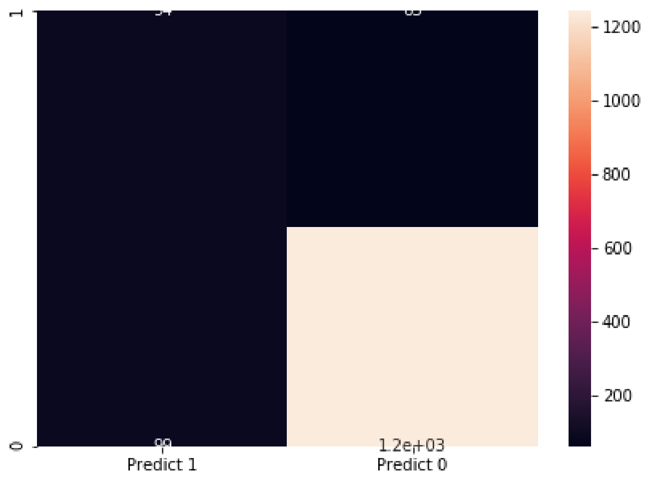
```
print("Confusion Matrix")
nbtm=metrics.confusion_matrix(y_test, bank_test_predict, labels=[1,0])

nbt_m = pd.DataFrame(nbtm, index = [i for i in ["1","0"]],
                  columns = [i for i in ["Predict 1","Predict 0"]])
plt.figure(figsize = (7,5))
sns.heatmap(nbt_m, annot=True)
```

```
Confusion Matrix
```

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dfbc8d5c48>
```



In [47]:

```
print("Classification Report")
print(metrics.classification_report(y_test, bank_test_predict, labels=[1, 0]))
```

```
Classification Report
              precision    recall  f1-score   support

           1       0.49      0.60      0.54       157
           0       0.95      0.93      0.94      1343

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

Confusion matrix of models

In [64]:

```
print("Confusion matrix of logistic regression")
print("")
print(lr_m)
print("")
print("Confusion matrix of KNN Clasifier")
print("")
print(knn_m)
print("")
print("Confusion matrix of Naive Bayes Theorem")
print("")
print(nbt_m)
print("")
```

```
Confusion matrix of logistic regression

   Predict 1  Predict 0
1       1321         22
0         70         87
```

```
Confusion matrix of KNN Clasifier

   Predict 1  Predict 0
1       1338          5
0         55        102

Confusion matrix of Naive Bayes Theorem

   Predict 1  Predict 0
1         94         63
0         99       1244
```

Result

The model accuracy of **Naive Bayes classifier** is **89**.

This means model gives correct result 89% of the time.

From the above model of Logistic regression, KNN, and Naive bayes.

- It is found out that the best model is KNN. As we can see that the\

  accuracy is 96 and the weighted average of recall is 96 which is more than\

  the other two models.

Reason for KNN being the best model.

- It doesn't make a prior assumption like naive bayes theorem.
- In logistic regression, assumption of linearity is used thus some

  points may be away from the line where as in KNN distance from nearby

  points are calculated thus more accuracy can be gained.

In [ ]: