Churn Prediction

March 24, 2020

1 Predicting churn for bank

Importing all the necessary libraries

[200]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import QuantileTransformer
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.feature_selection import SelectFromModel
```

[201]:
```
data = pd.read_csv("../input/predicting-churn-for-bank-customers/
↪Churn_Modelling.csv")
```

For checking correlation between features

[202]:
```
data.corr()
```

[202]:
```
                 RowNumber  CustomerId  CreditScore       Age   Tenure  \
RowNumber         1.000000    0.004202     0.005840  0.000783 -0.006495
CustomerId        0.004202    1.000000     0.005308  0.009497 -0.014883
CreditScore       0.005840    0.005308     1.000000 -0.003965  0.000842
Age               0.000783    0.009497    -0.003965  1.000000 -0.009997
Tenure           -0.006495   -0.014883     0.000842 -0.009997  1.000000
Balance          -0.009067   -0.012419     0.006268  0.028308 -0.012254
NumOfProducts     0.007246    0.016972     0.012238 -0.030680  0.013444
HasCrCard         0.000599   -0.014025    -0.005458 -0.011721  0.022583
IsActiveMember    0.012044    0.001665     0.025651  0.085472 -0.028362
EstimatedSalary  -0.005988    0.015271    -0.001384 -0.007201  0.007784
Exited           -0.016571   -0.006248    -0.027094  0.285323 -0.014001
```

```
                 Balance  NumOfProducts  HasCrCard  IsActiveMember  \
RowNumber      -0.009067       0.007246   0.000599        0.012044
CustomerId     -0.012419       0.016972  -0.014025        0.001665
CreditScore     0.006268       0.012238  -0.005458        0.025651
Age             0.028308      -0.030680  -0.011721        0.085472
Tenure         -0.012254       0.013444   0.022583       -0.028362
Balance         1.000000      -0.304180  -0.014858       -0.010084
NumOfProducts  -0.304180       1.000000   0.003183        0.009612
HasCrCard      -0.014858       0.003183   1.000000       -0.011866
IsActiveMember -0.010084       0.009612  -0.011866        1.000000
EstimatedSalary 0.012797       0.014204  -0.009933       -0.011421
Exited          0.118533      -0.047820  -0.007138       -0.156128

                EstimatedSalary    Exited
RowNumber             -0.005988 -0.016571
CustomerId             0.015271 -0.006248
CreditScore           -0.001384 -0.027094
Age                   -0.007201  0.285323
Tenure                 0.007784 -0.014001
Balance                0.012797  0.118533
NumOfProducts          0.014204 -0.047820
HasCrCard             -0.009933 -0.007138
IsActiveMember        -0.011421 -0.156128
EstimatedSalary        1.000000  0.012097
Exited                 0.012097  1.000000
```

[203]:
```
data.shape
```

[203]: (10000, 14)

Let's observer data

[204]:
```
data.head()
```

[204]:
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
0          1    15634602  Hargrave          619    France  Female   42
1          2    15647311      Hill          608     Spain  Female   41
2          3    15619304      Onio          502    France  Female   42
3          4    15701354      Boni          699    France  Female   39
4          5    15737888  Mitchell          850     Spain  Female   43

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
```

```
4       2  125510.82             1          1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

[205]:
```
data["Geography"].unique() #checking for unique values in Geography
```

[205]:
```
array(['France', 'Spain', 'Germany'], dtype=object)
```

[206]:
```
data.describe()
```

[206]:
```
         RowNumber    CustomerId   CreditScore           Age        Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000  10000.000000
mean    5000.50000  1.569094e+07    650.528800     38.921800      5.012800
std     2886.89568  7.193619e+04     96.653299     10.487806      2.892174
min        1.00000  1.556570e+07    350.000000     18.000000      0.000000
25%     2500.75000  1.562853e+07    584.000000     32.000000      3.000000
50%     5000.50000  1.569074e+07    652.000000     37.000000      5.000000
75%     7500.25000  1.575323e+07    718.000000     44.000000      7.000000
max    10000.00000  1.581569e+07    850.000000     92.000000     10.000000

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000
mean    76485.889288       1.530200      0.70550        0.515100
std     62397.405202       0.581654      0.45584        0.499797
min         0.000000       1.000000      0.00000        0.000000
25%         0.000000       1.000000      0.00000        0.000000
50%     97198.540000       1.000000      1.00000        1.000000
75%    127644.240000       2.000000      1.00000        1.000000
max    250898.090000       4.000000      1.00000        1.000000

       EstimatedSalary        Exited
count     10000.000000  10000.000000
mean     100090.239881      0.203700
std       57510.492818      0.402769
min          11.580000      0.000000
25%       51002.110000      0.000000
50%      100193.915000      0.000000
75%      149388.247500      0.000000
max      199992.480000      1.000000
```

[207]:
```
data.dtypes
```

[207]:
```
RowNumber             int64
CustomerId            int64
Surname              object
CreditScore           int64
Geography            object
Gender               object
Age                   int64
Tenure                int64
Balance             float64
NumOfProducts         int64
HasCrCard             int64
IsActiveMember        int64
EstimatedSalary     float64
Exited                int64
dtype: object
```

2 Data Visualization

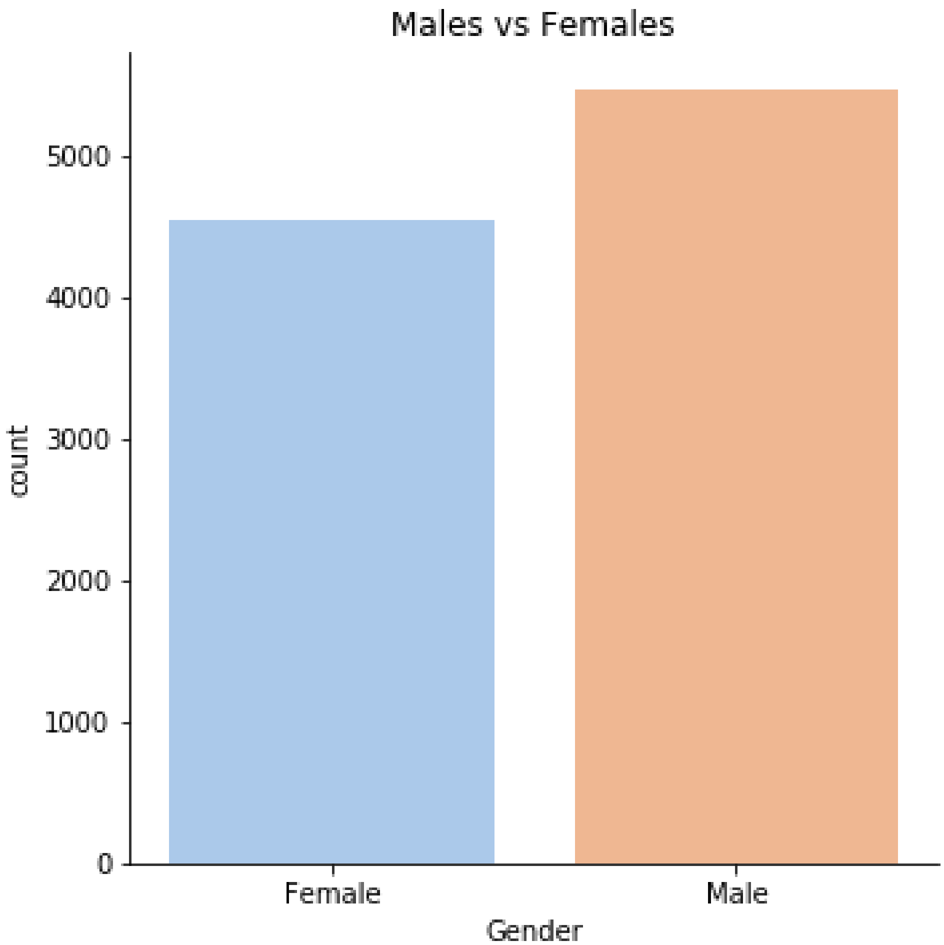
[208]:
```python
plt.figure(figsize = (15,15))
sns.catplot(x = 'Geography', kind = 'count', data = data, palette = 'pink')
plt.title('Customers distribution across Countries')
plt.show()
```

```
<Figure size 1080x1080 with 0 Axes>
```

Maximum customers from France

[209]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'Gender', kind = 'count', data = data, palette = 'pastel')
plt.title("Males vs Females")
plt.show()
```

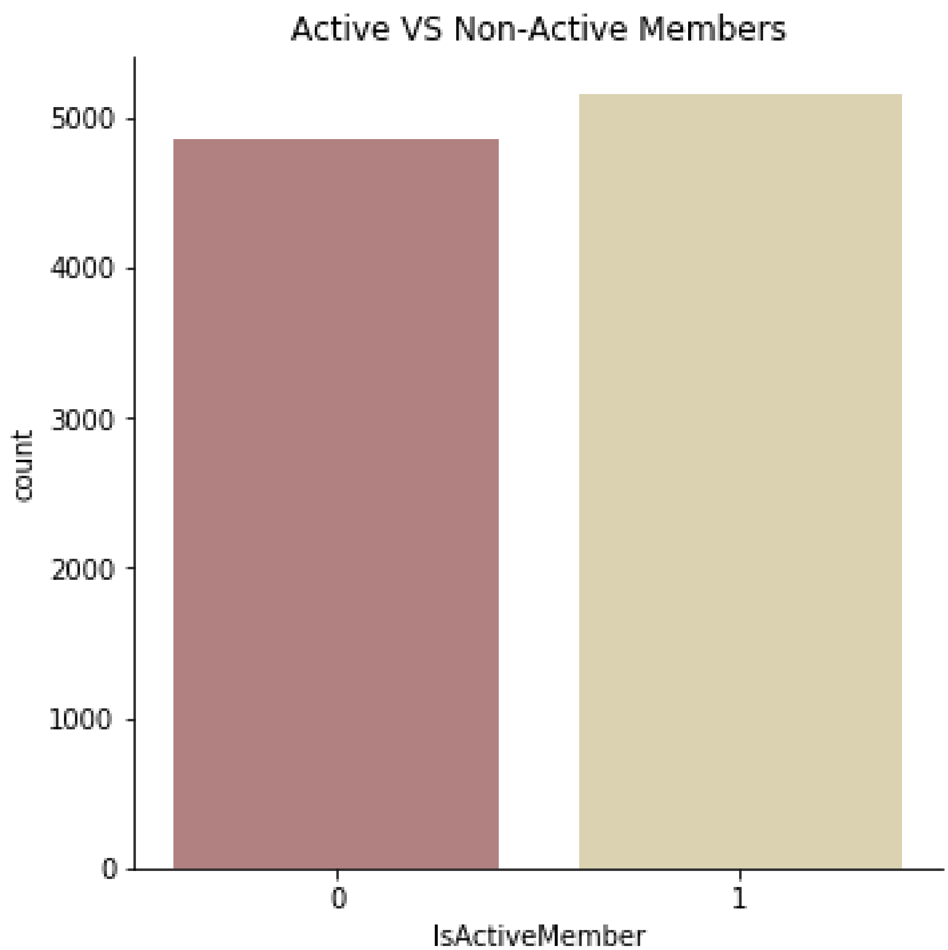
```
<Figure size 1080x1080 with 0 Axes>
```



We have more male customers

[210]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'IsActiveMember', kind = 'count', data = data, palette = 'pink')
plt.title("Active VS Non-Active Members")
plt.show()
```

```
<Figure size 1080x1080 with 0 Axes>
```



We have more active members

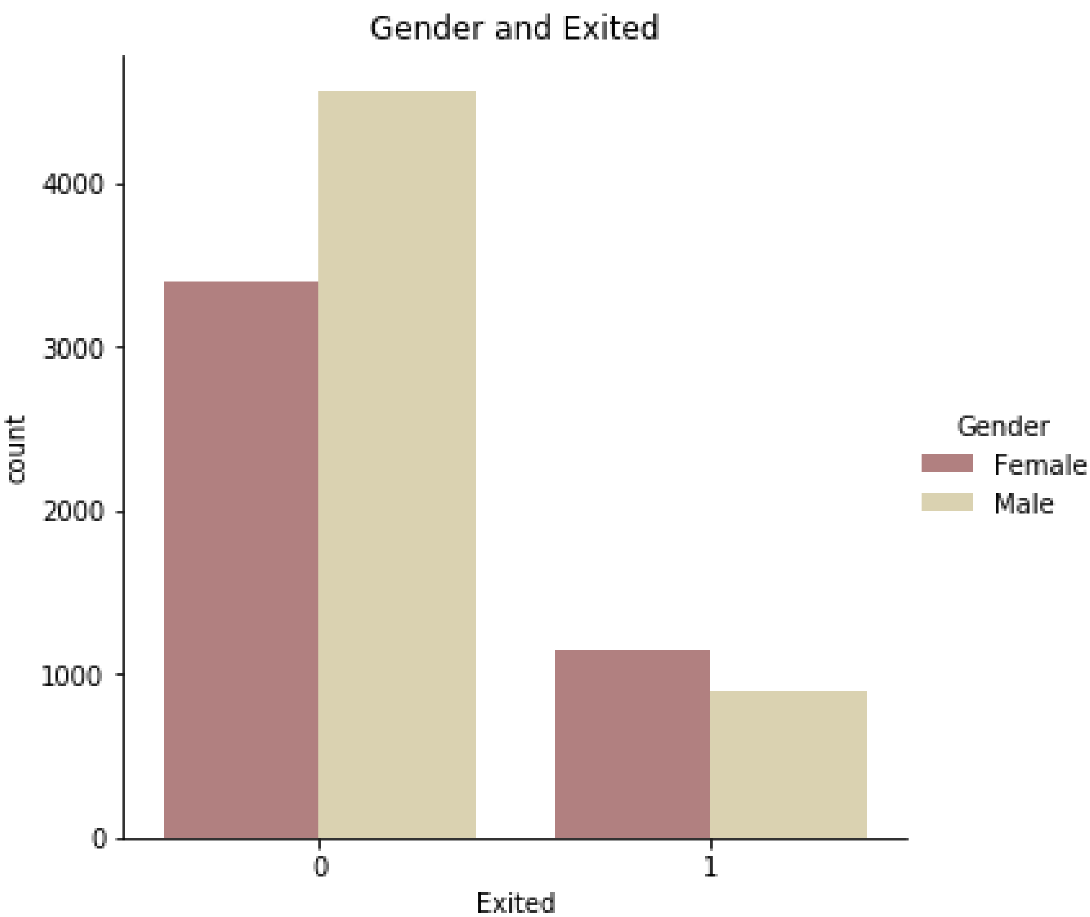
[211]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'HasCrCard', kind = 'count', palette = 'pastel', data = data)
plt.title("Credit Card VS No Credit Card")
plt.show()
```

```
<Figure size 1080x1080 with 0 Axes>
```

Most of the customers have credit card

[212]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'Exited', kind = 'count', hue = 'Gender', palette = 'pink',␣
 ↪data = data)
plt.title("Gender and Exited")
plt.show()
```

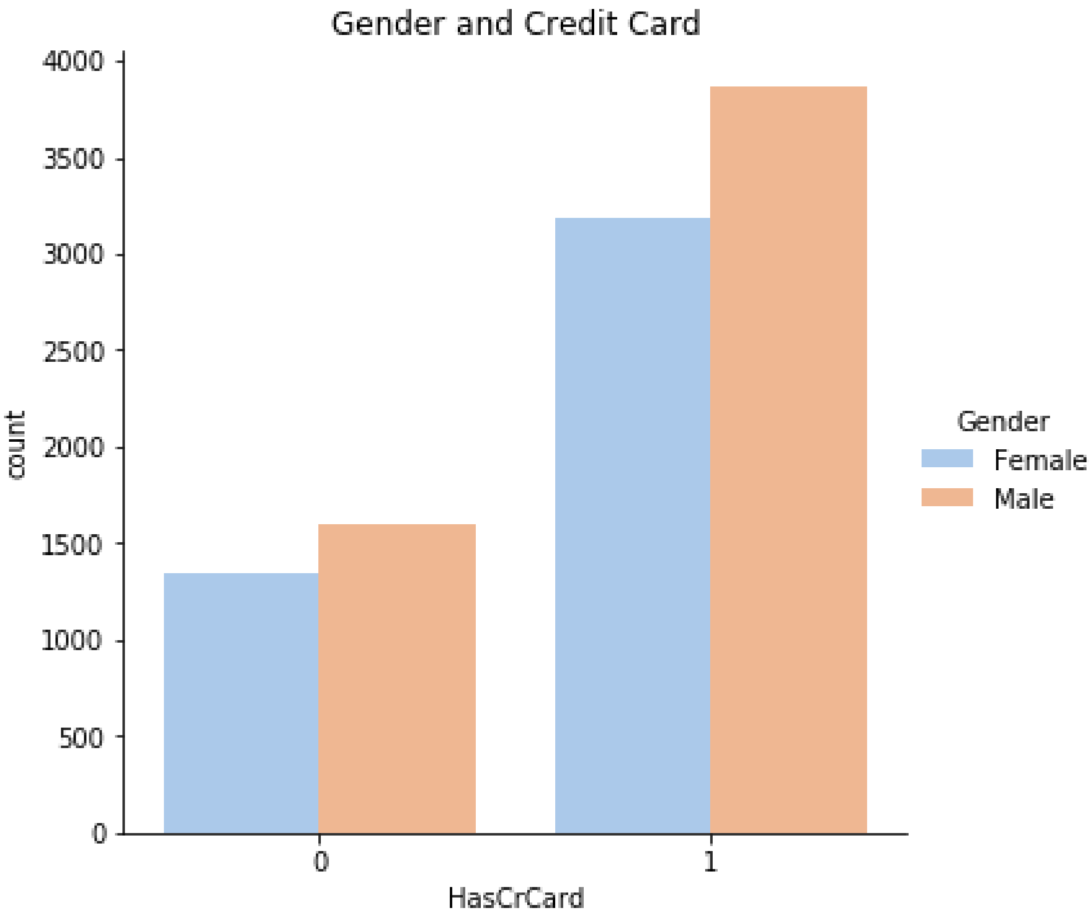
```
<Figure size 1080x1080 with 0 Axes>
```



Females are more likely to exit

[213]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'HasCrCard', kind = 'count', hue = 'Gender', palette =␣
↪'pastel', data = data)
plt.title("Gender and Credit Card")
plt.show()
```

```
<Figure size 1080x1080 with 0 Axes>
```

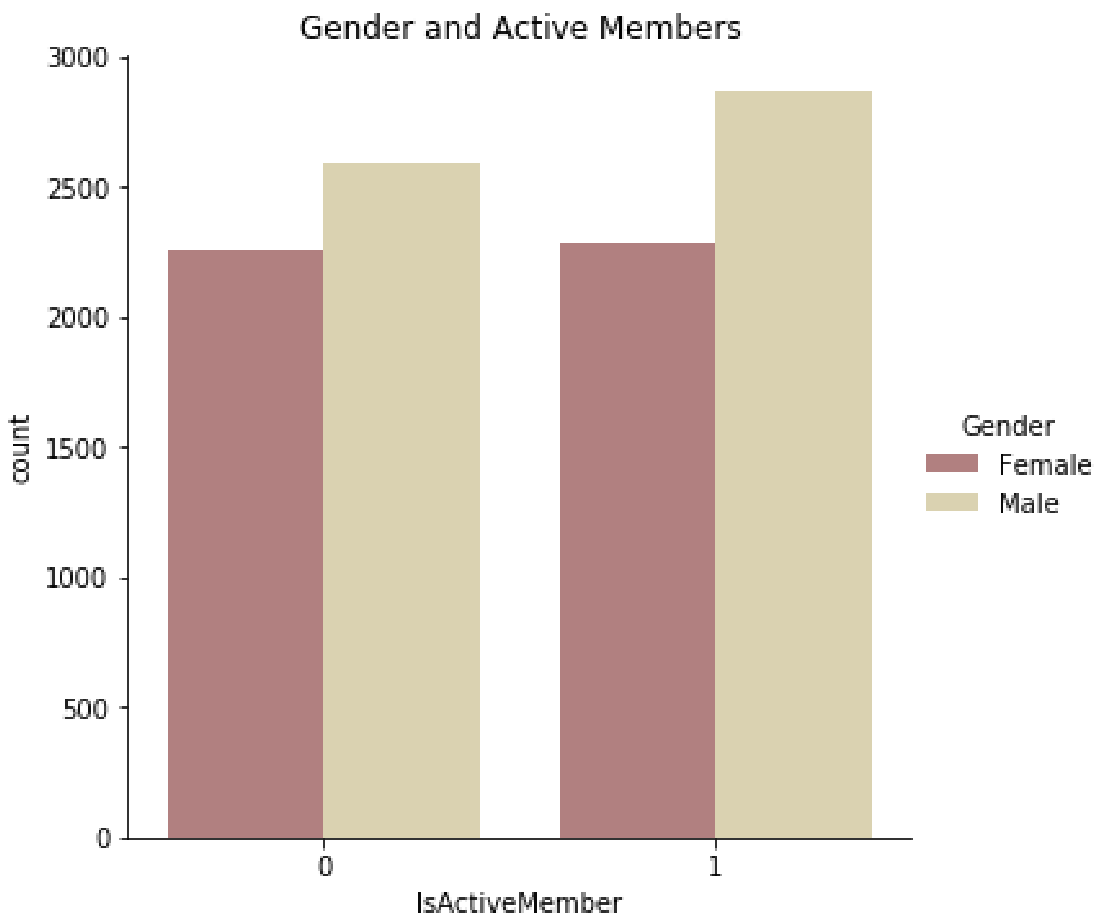


Males generally have credit card

But on other hand they are more likely not to have credit cards too

[214]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'IsActiveMember', kind = 'count', hue = 'Gender', palette =␣
↪'pink', data = data)
plt.title("Gender and Active Members")
plt.show()
```

```
<Figure size 1080x1080 with 0 Axes>
```

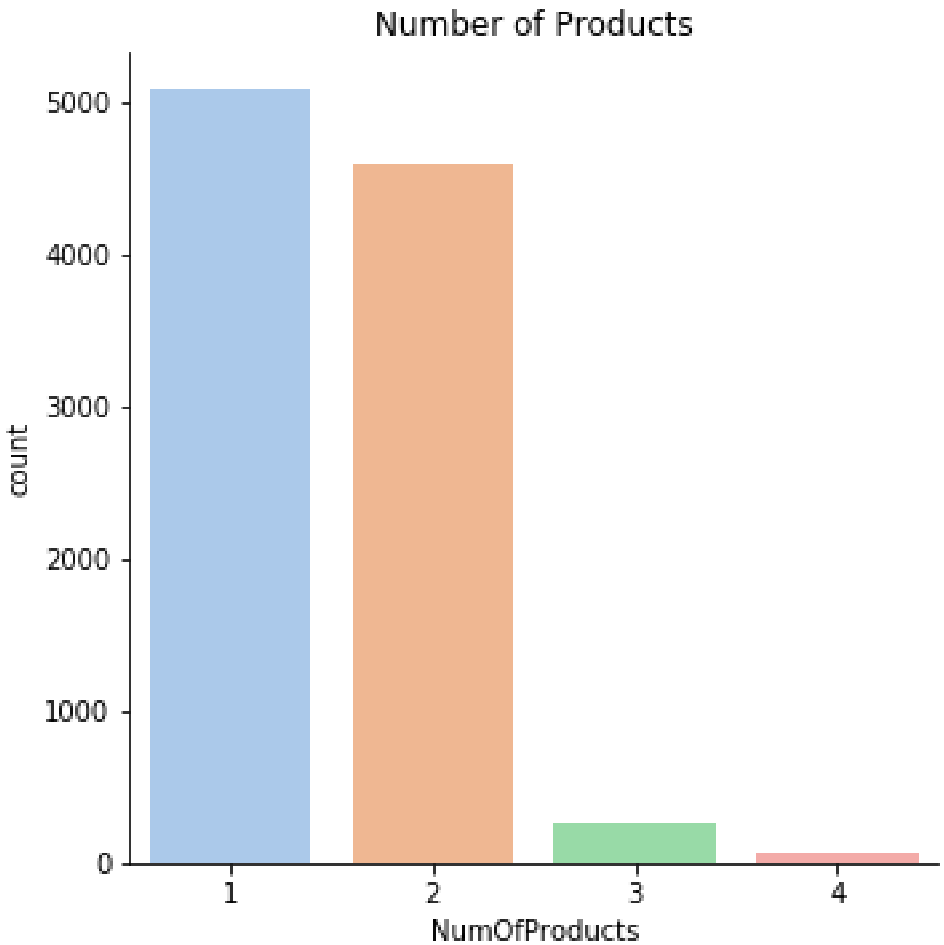


Males are more likely to be active members

But on other hand males are also likely to be non active members

[215]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = "NumOfProducts", kind = 'count', palette = 'pastel', data =␣
 ↪data )
plt.title('Number of Products')
plt.show()
```

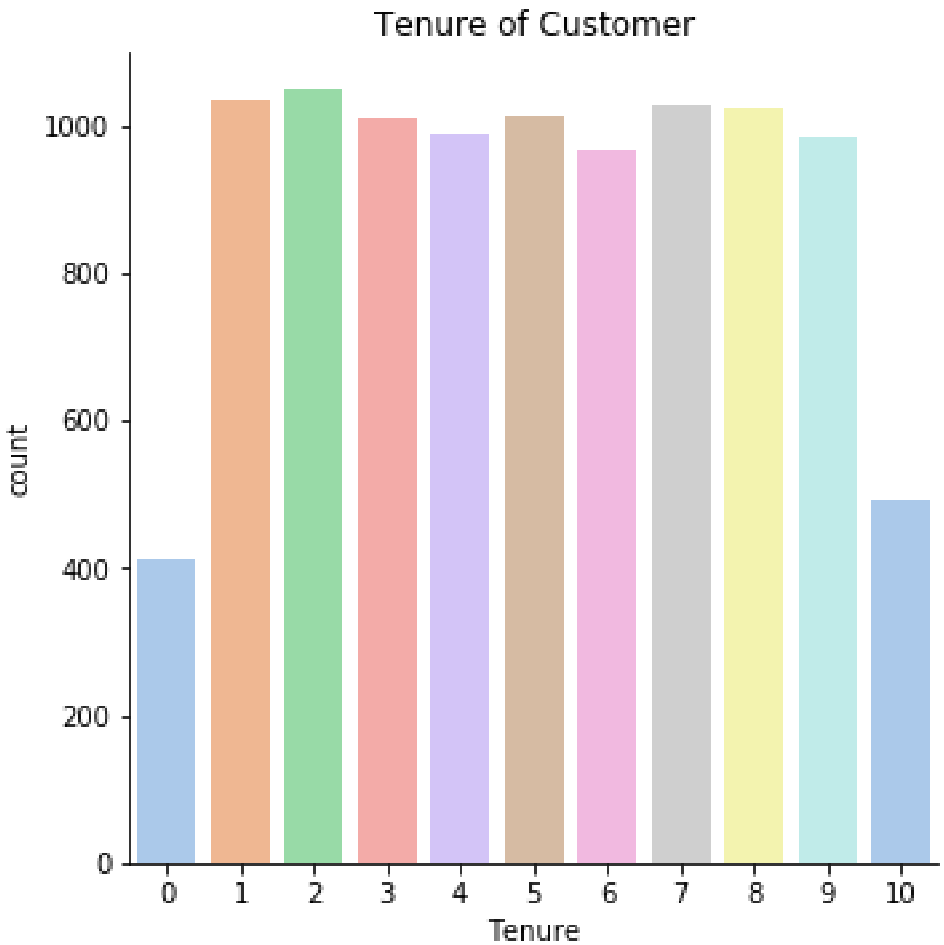
```
<Figure size 1080x1080 with 0 Axes>
```



Most of the customers have 1 or 2 products from bank

[216]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'Tenure', kind = 'count', palette = 'pastel', data = data)
plt.title("Tenure of Customer")
plt.show()
```

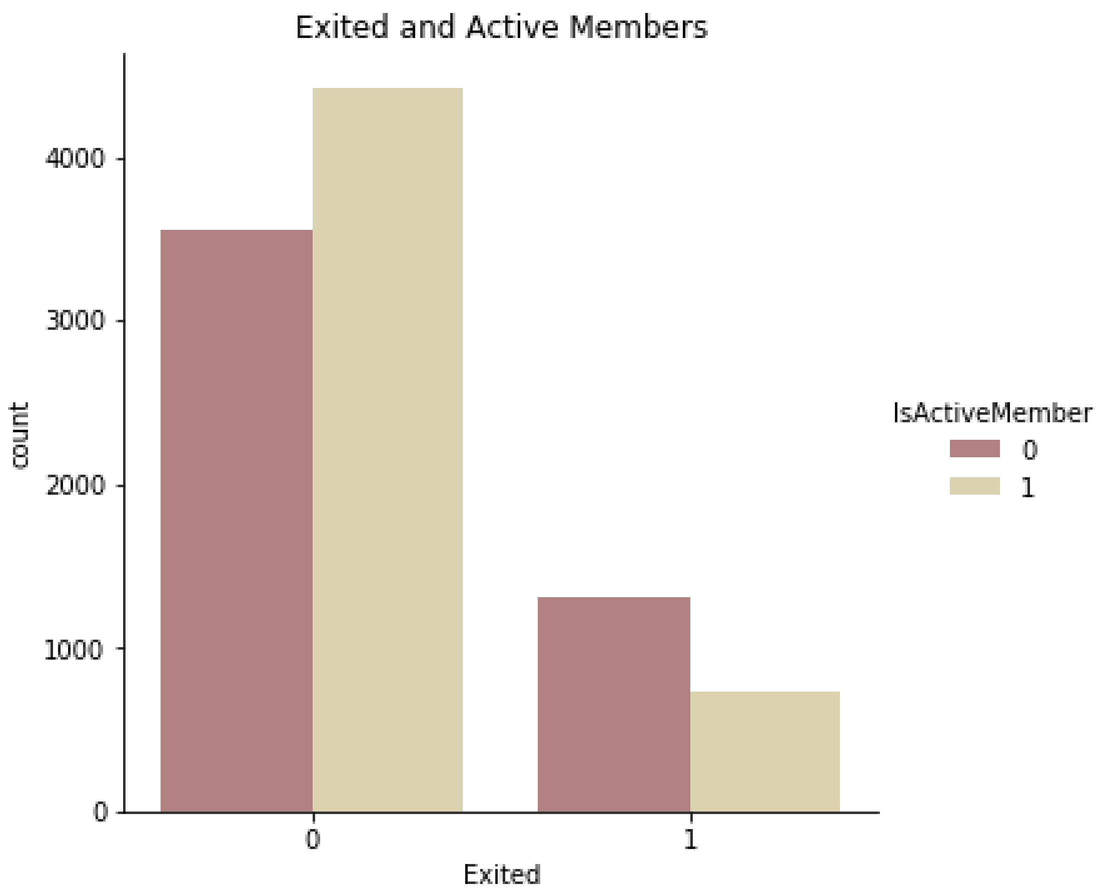
```
<Figure size 1080x1080 with 0 Axes>
```



Most customers have tenure of in between 1-8 years in bank

[217]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'Exited', kind = 'count', hue = 'IsActiveMember', palette =␣
↪'pink', data = data)
plt.title("Exited and Active Members")
plt.show()
```

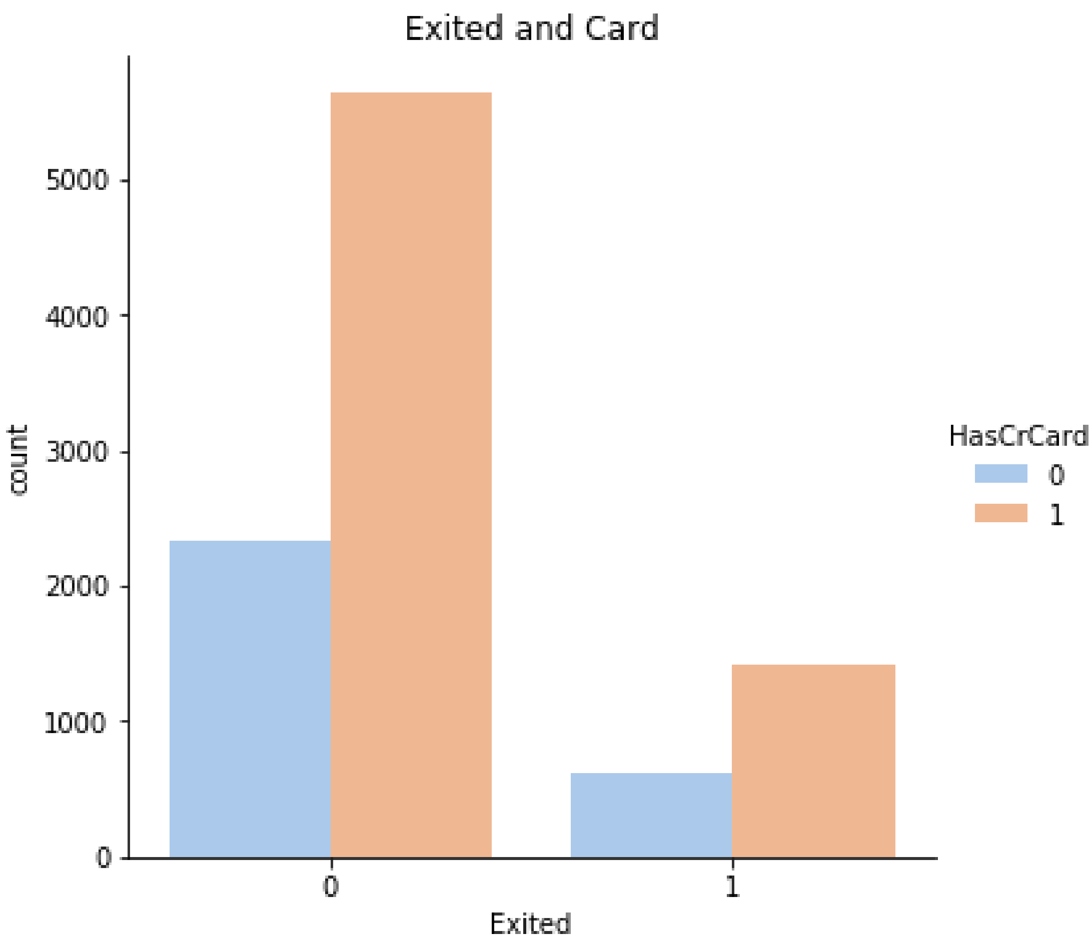
```
<Figure size 1080x1080 with 0 Axes>
```



Non active members are likely to exit more, quite understandable

[218]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'Exited', kind = 'count', hue = 'HasCrCard', palette =␣
↪'pastel', data = data)
plt.title("Exited and Card")
plt.show()
```

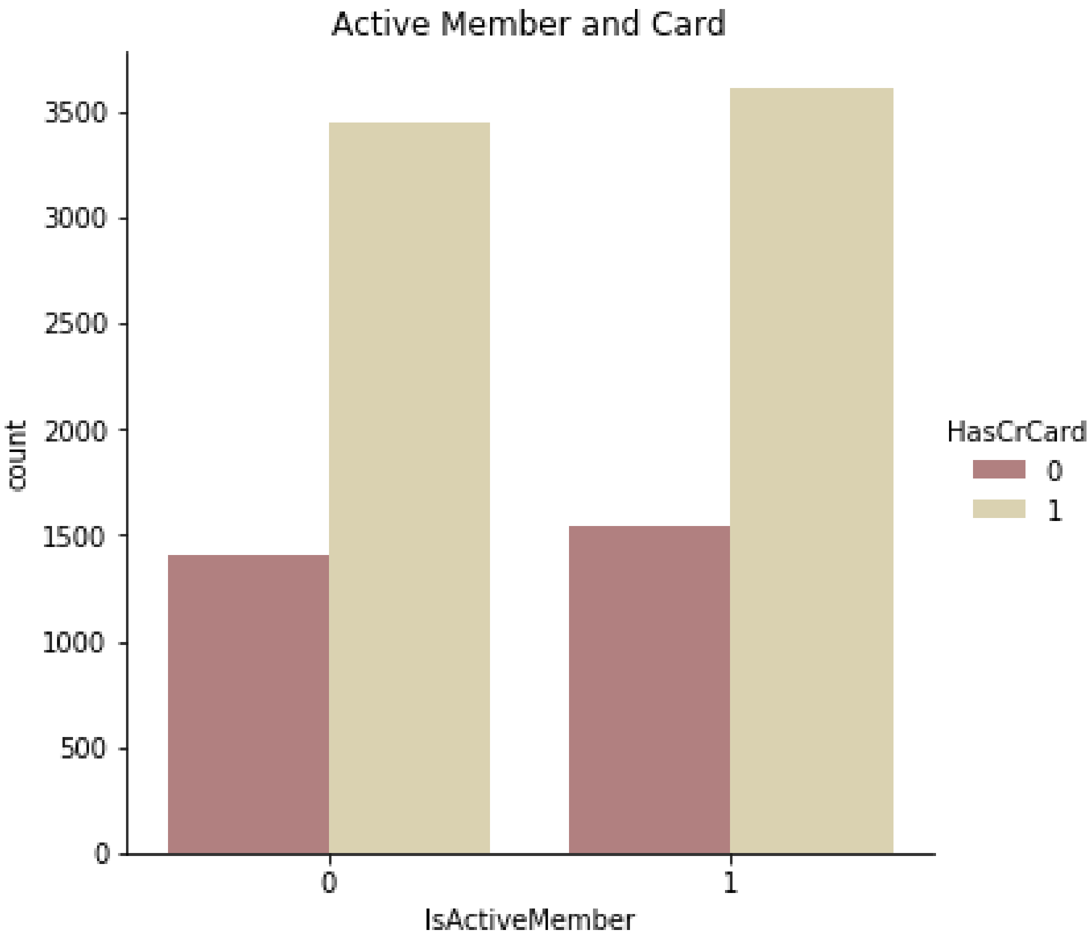
```
<Figure size 1080x1080 with 0 Axes>
```



Customers with credit card are likely to exit more

[219]:
```
plt.figure(figsize = (15,15))
sns.catplot(x = 'IsActiveMember', kind = 'count', hue = 'HasCrCard', palette =␣
 ↪'pink', data = data)
plt.title('Active Member and Card')
plt.show()
```

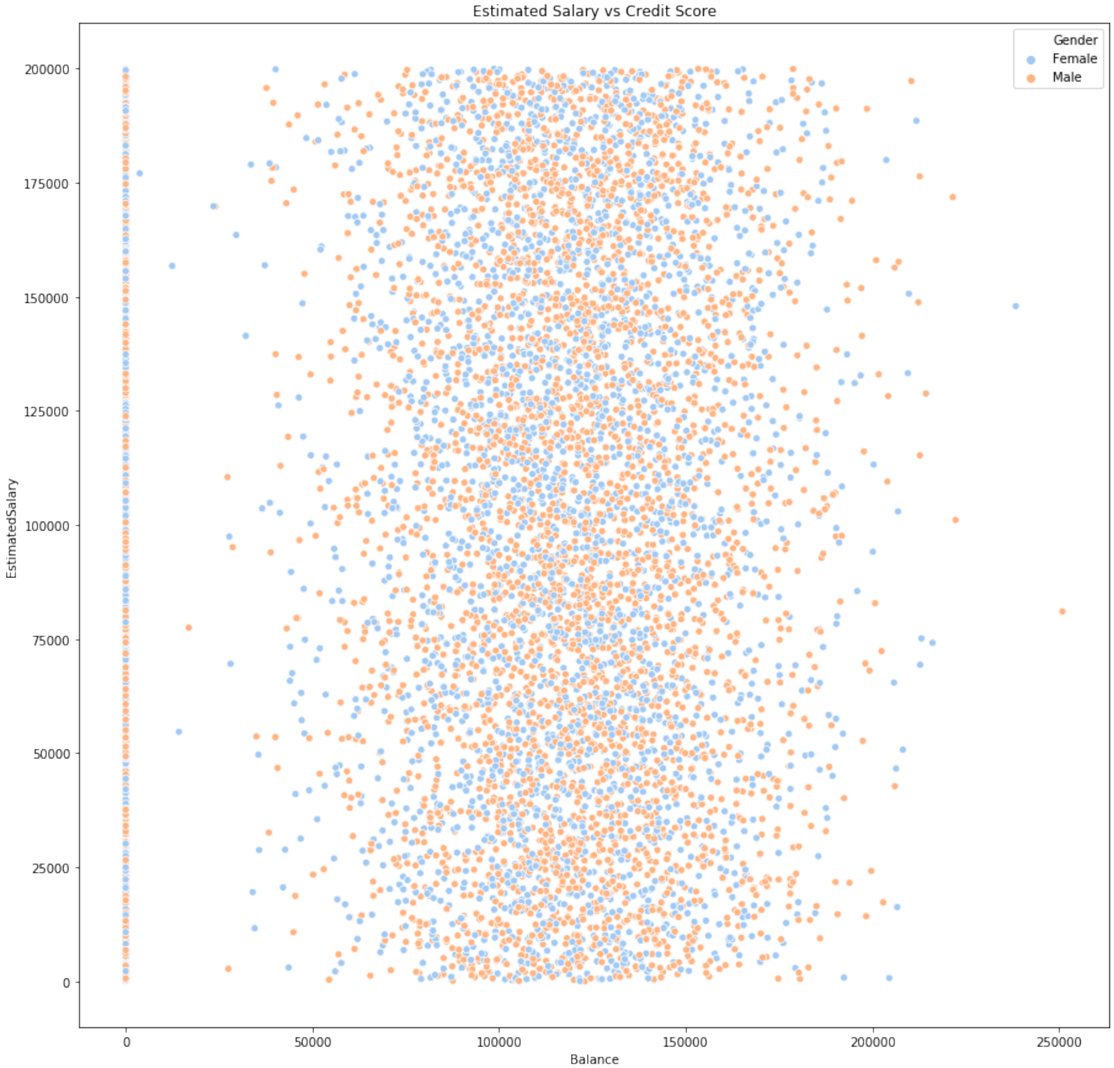
```
<Figure size 1080x1080 with 0 Axes>
```



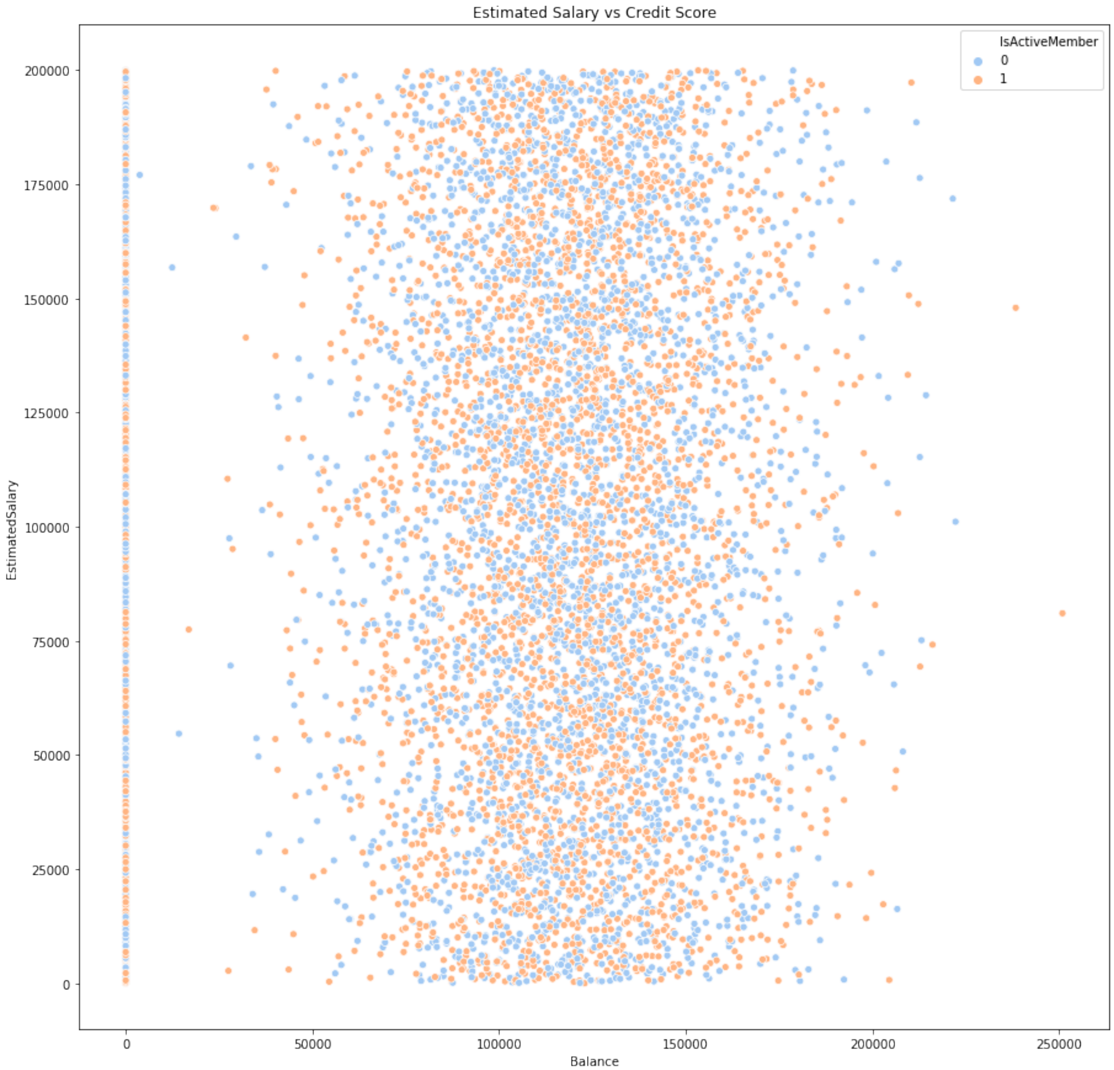
[220]:
```
plt.figure(figsize = (15,15))
sns.scatterplot(x = 'Balance', y = 'EstimatedSalary', hue = 'Exited',palette =␣
 ↪'pastel', data = data)
plt.title("Balance vs Estimated Salary")
plt.show()
```

[221]:
```
plt.figure(figsize = (15,15))
sns.scatterplot(x = 'Balance', y = 'CreditScore', hue = 'Exited',palette =␣
 ↪'pink', data = data)
plt.title("Balance vs Credit Score")
plt.show()
```

[222]:
```
plt.figure(figsize = (15,15))
sns.scatterplot(x = 'Balance', y = 'EstimatedSalary', hue = 'Gender',palette =␣
 ↪'pastel', data = data)
plt.title("Estimated Salary vs Credit Score")
plt.show()
```



[223]:
```
plt.figure(figsize = (15,15))
sns.scatterplot(x = 'Balance', y = 'EstimatedSalary', hue =␣
 ↪'IsActiveMember',palette = 'pastel', data = data)
plt.title("Estimated Salary vs Credit Score")
plt.show()
```



3 Data Preprocessing

[224]:
```
data.drop(['RowNumber', 'CustomerId', 'Surname'], axis = 1, inplace = True)
```

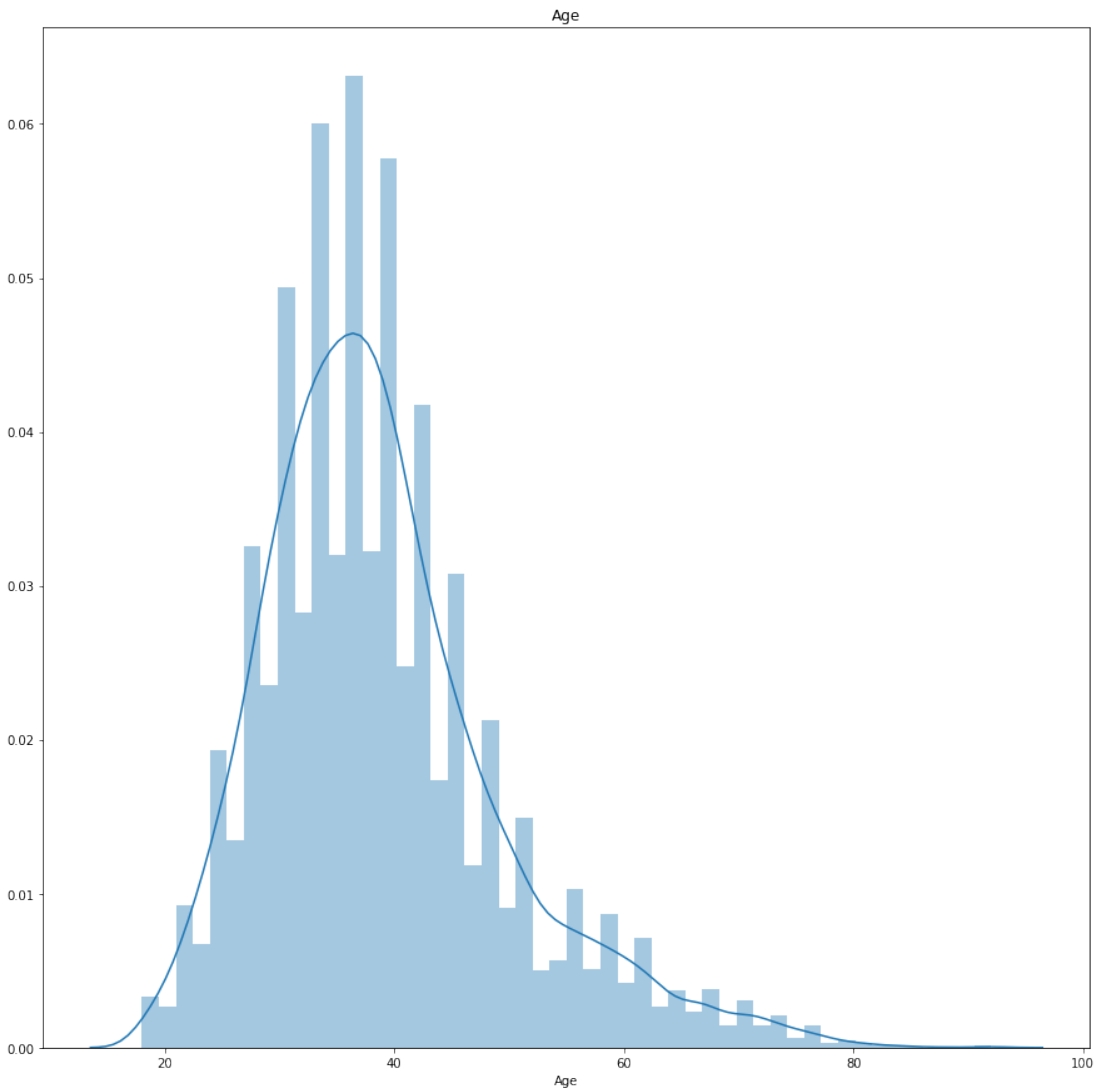
[225]:
```
data.isnull().sum() #checking for null values
```

[225]:
```
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
```

```
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

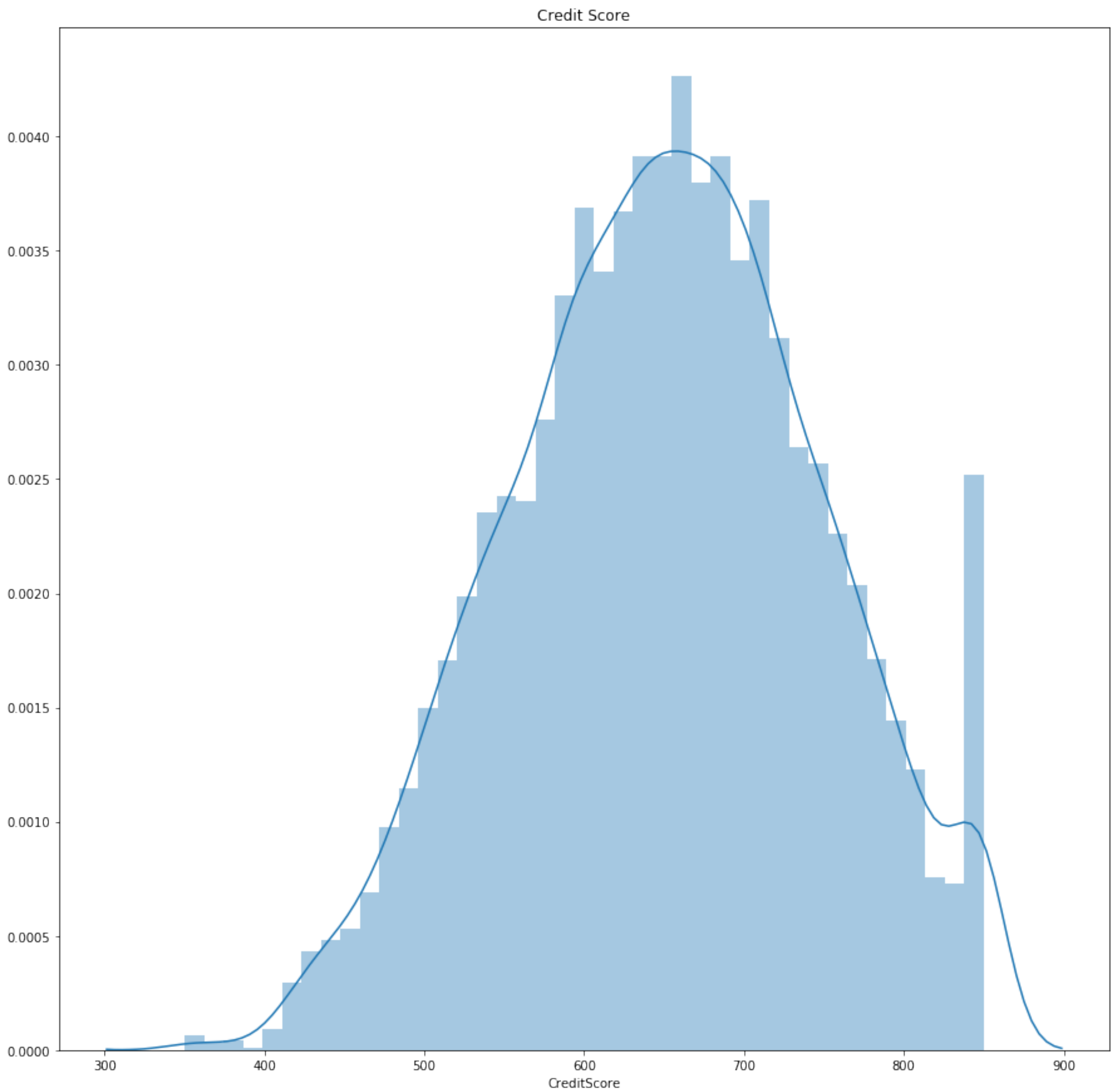
For checking skwness in the data

[226]:
```
plt.figure(figsize = (15,15))
sns.distplot(data['Age'])
plt.title("Age")
plt.show()
```



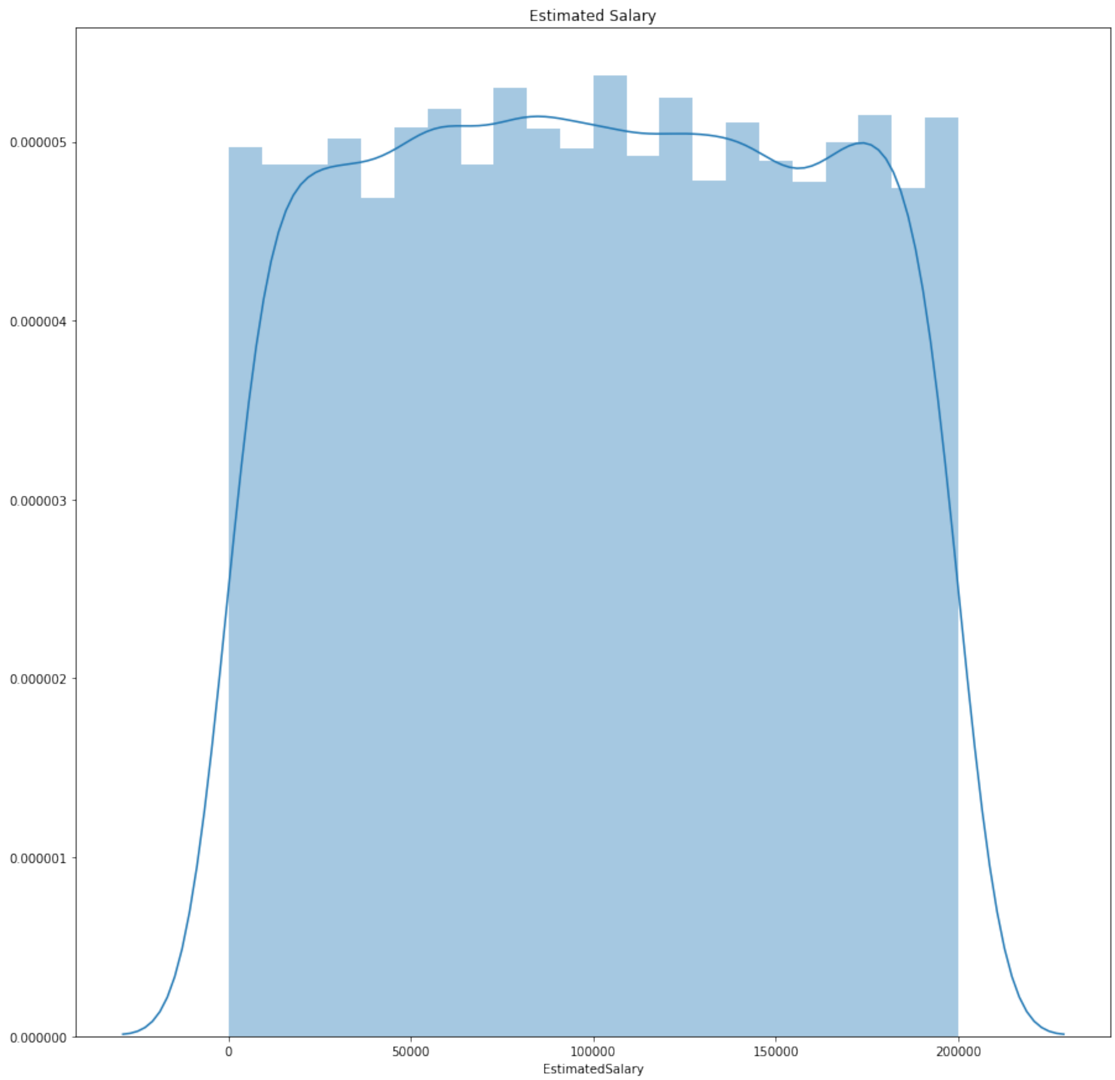
[227]:

```
plt.figure(figsize = (15,15))
sns.distplot(data["CreditScore"])
plt.title("Credit Score")
plt.show()
```



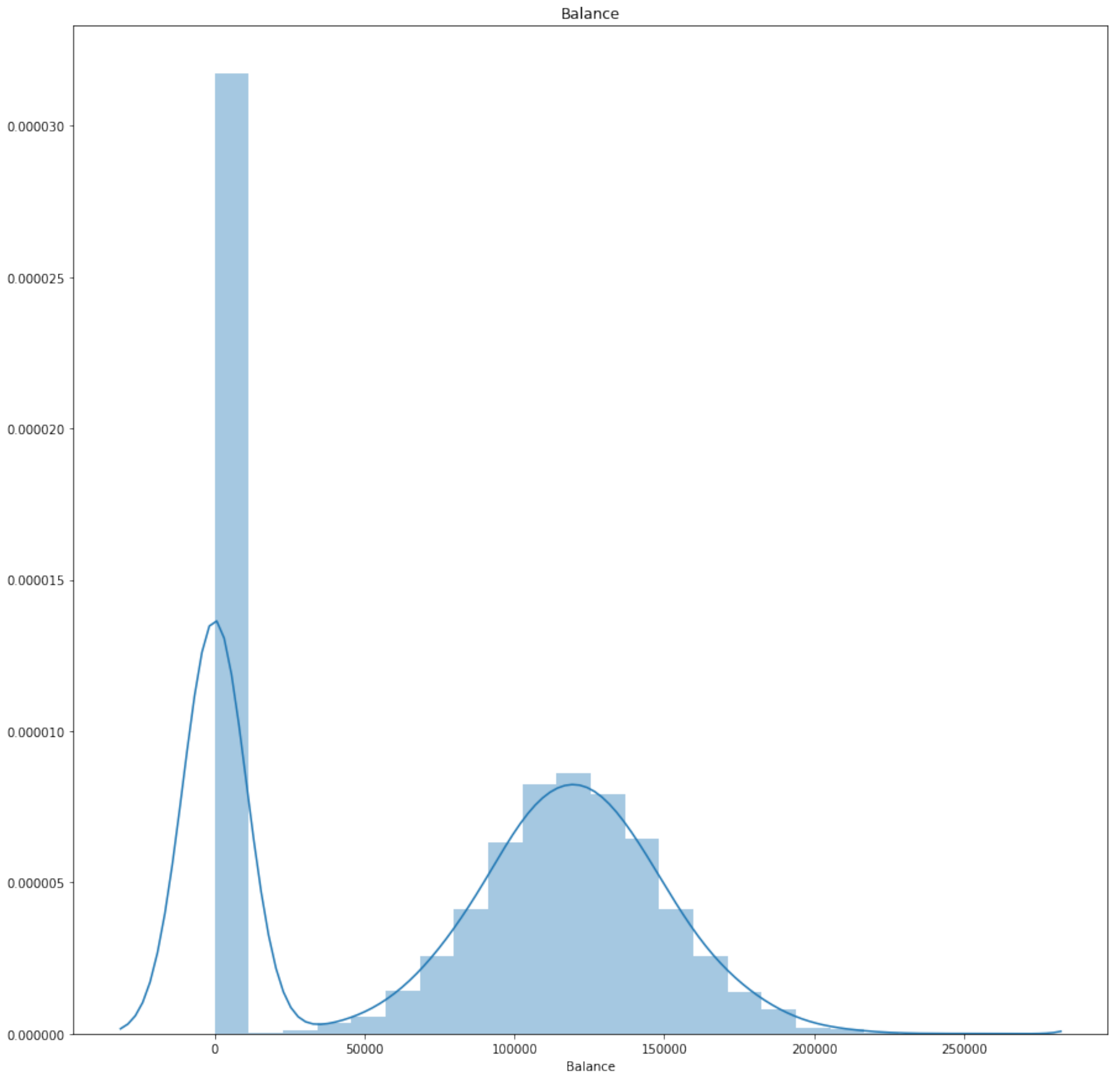
[228]:

```
plt.figure(figsize = (15,15))
sns.distplot(data["EstimatedSalary"])
plt.title("Estimated Salary")
plt.show()
```



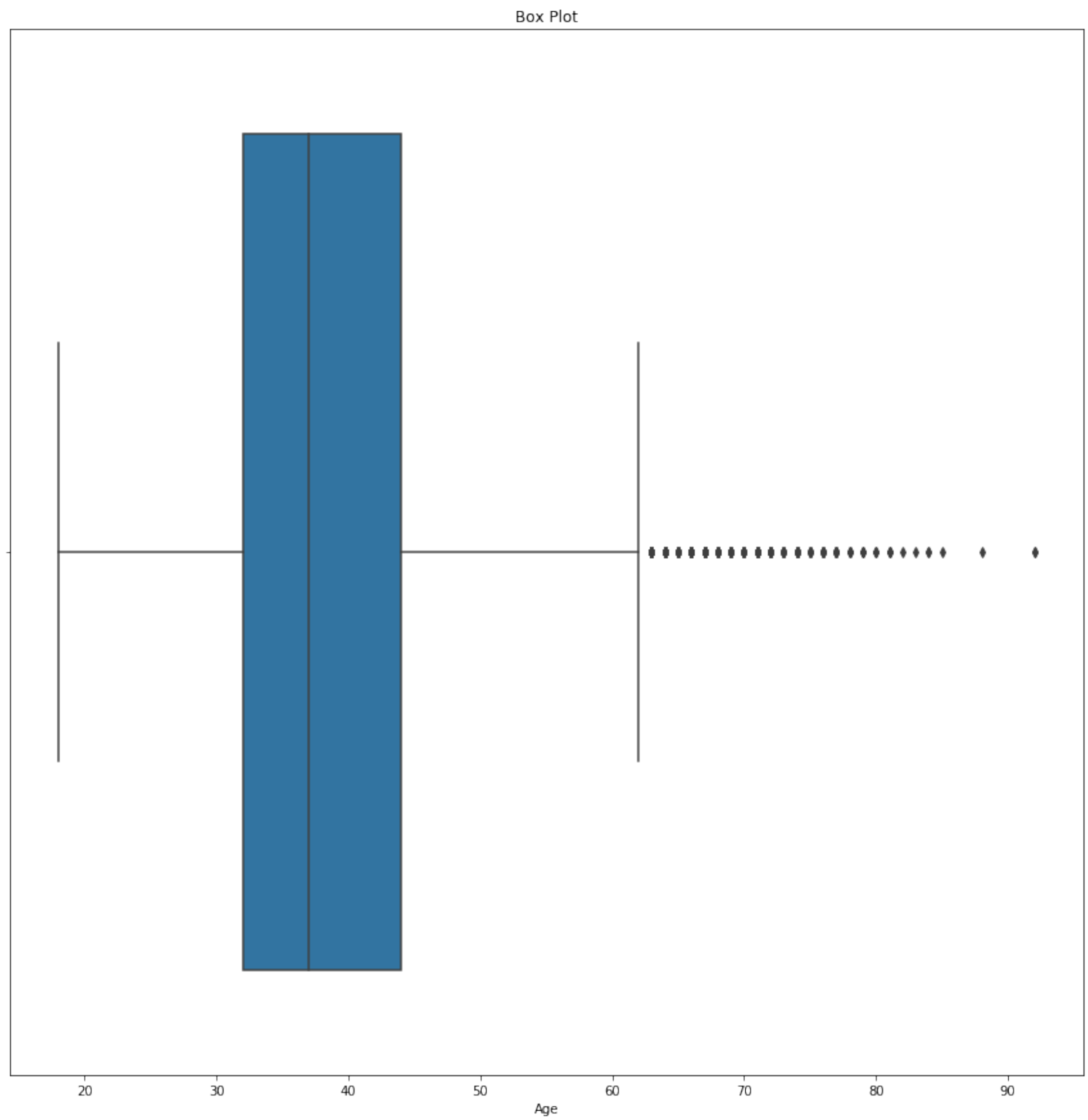
[229]:

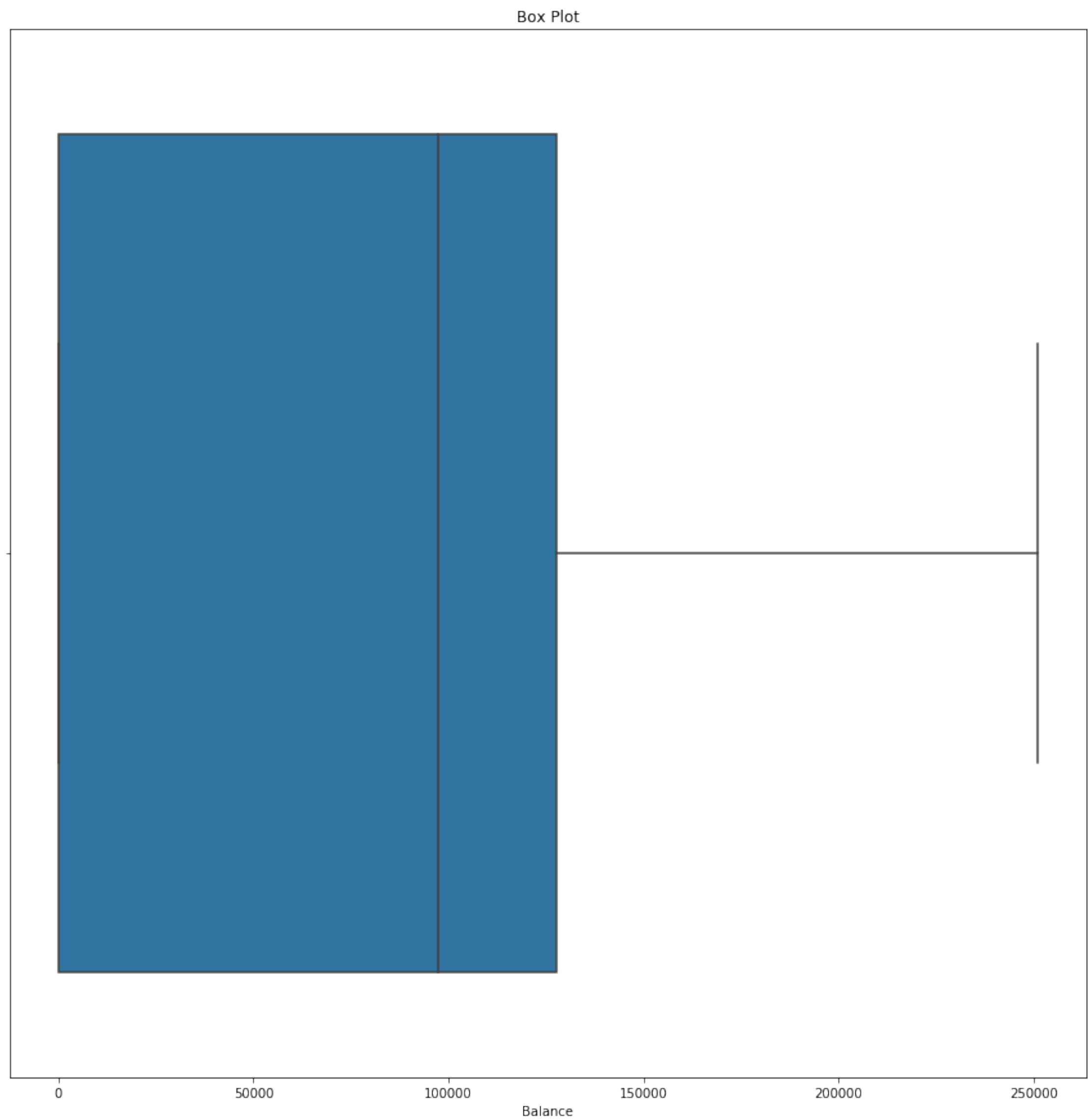
```
plt.figure(figsize = (15,15))
sns.distplot(data["Balance"])
plt.title("Balance")
plt.show()
```

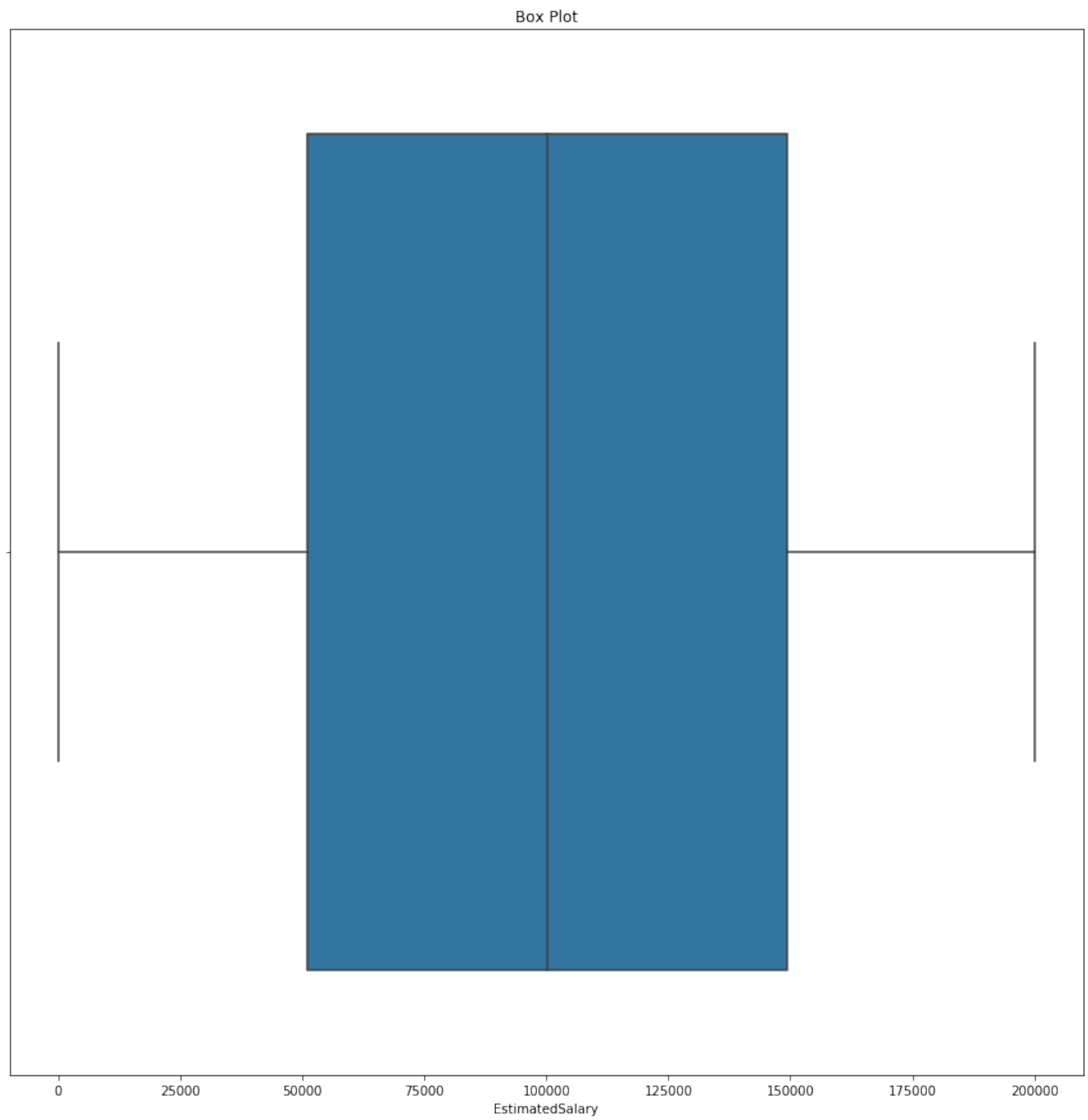


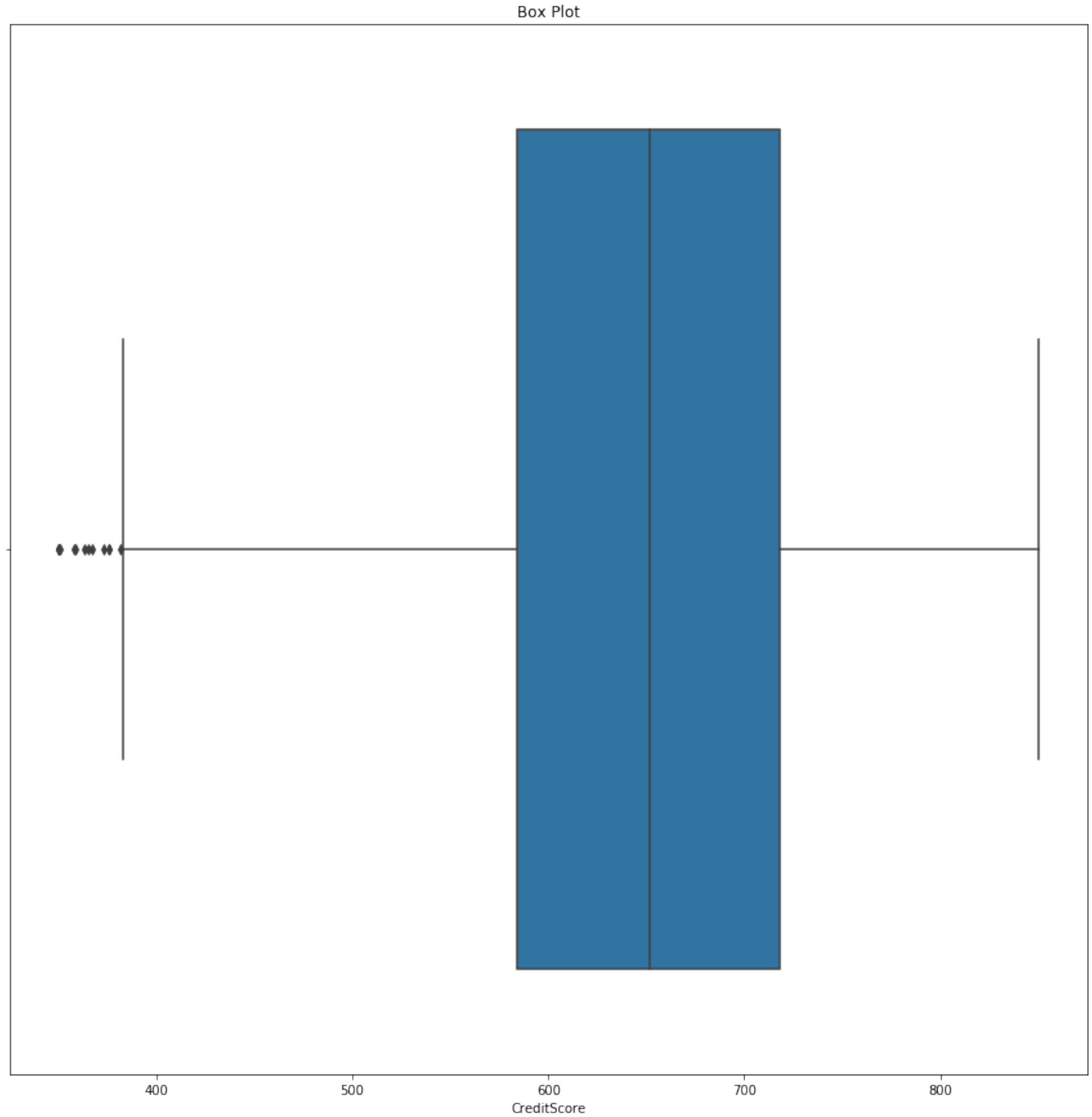
For detecting outliers in data

[230]:
```
column = ["Age", "Balance", "EstimatedSalary", "CreditScore"]
for i in column:
    plt.figure(figsize = (15,15))
    sns.boxplot(data[i])
    plt.title('Box Plot')
    plt.show()
```


Box Plot
20
30
40
50
60
70
80
90
Age


Box Plot
0
50000
100000
150000
200000
250000
Balance


Box Plot
0
25000
50000
75000
100000
125000
150000
175000
200000
EstimatedSalary



[231]:
```
data = data[(data["Age"] <60)]
data = data[(data["CreditScore"] >400)]
```

[232]:
```
data.describe()
```

[232]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	\
count	9456.000000	9456.000000	9456.000000	9456.000000	9456.000000	
mean	650.898266	37.373308	5.018084	76521.194565	1.531514	
std	95.810805	8.316748	2.887855	62444.638692	0.579448	
min	401.000000	18.000000	0.000000	0.000000	1.000000	
25%	584.000000	31.000000	3.000000	0.000000	1.000000	
50%	652.000000	37.000000	5.000000	97302.205000	1.000000	

```
75%     717.000000    42.000000     8.000000  127644.240000        2.000000
max     850.000000    59.000000    10.000000  250898.090000        4.000000

         HasCrCard  IsActiveMember  EstimatedSalary      Exited
count  9456.000000     9456.000000      9456.000000  9456.00000
mean      0.704949        0.500212    100176.595754     0.19797
std       0.456090        0.500026     57503.154035     0.39849
min       0.000000        0.000000        11.580000     0.00000
25%       0.000000        0.000000     51228.457500     0.00000
50%       1.000000        1.000000    100350.530000     0.00000
75%       1.000000        1.000000    149406.545000     0.00000
max       1.000000        1.000000    199992.480000     1.00000
```

Normalizing the data

[233]:
```
data["Balance"] = QuantileTransformer().fit_transform(data["Balance"].values.
↪reshape(-1,1))
data["CreditScore"] = QuantileTransformer().fit_transform(data["CreditScore"].
↪values.reshape(-1,1))
data["EstimatedSalary"] = QuantileTransformer().
↪fit_transform(data["EstimatedSalary"].values.reshape(-1,1))
data["Age"] = QuantileTransformer().fit_transform(data["Age"].values.
↪reshape(-1,1))
```

[234]:
```
data["Balance"] = StandardScaler().fit_transform(data["Balance"].values.
↪reshape(-1,1))
data["CreditScore"] = StandardScaler().fit_transform(data["CreditScore"].values.
↪reshape(-1,1))
data["EstimatedSalary"] = StandardScaler().fit_transform(data["CreditScore"].
↪values.reshape(-1,1))
```

[235]:
```
data.describe()
```

[235]:
```
        CreditScore          Age       Tenure       Balance  NumOfProducts  \
count  9.456000e+03  9456.000000  9456.000000  9.456000e+03    9456.000000
mean   3.497156e-16     0.500092     5.018084 -1.539002e-16       1.531514
std    1.000053e+00     0.288540     2.887855  1.000053e+00       0.579448
min   -1.730136e+00     0.000000     0.000000 -1.211056e+00       1.000000
25%   -8.629531e-01     0.229229     3.000000 -1.211056e+00       1.000000
50%    7.675240e-04     0.512012     5.000000  1.829459e-01       1.000000
75%    8.610264e-01     0.733734     8.000000  8.787345e-01       2.000000
max    1.728209e+00     1.000000    10.000000  1.576003e+00       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary      Exited
count  9456.000000     9456.000000     9.456000e+03  9456.00000
mean      0.704949        0.500212     9.052263e-17     0.19797
std       0.456090        0.500026     1.000053e+00     0.39849
```

```
min        0.000000        0.000000    -1.730136e+00      0.00000
25%        0.000000        0.000000    -8.629531e-01      0.00000
50%        1.000000        1.000000     7.675240e-04      0.00000
75%        1.000000        1.000000     8.610264e-01      0.00000
max        1.000000        1.000000     1.728209e+00      1.00000
```

Label Encoding for categorical columns

[236]:
```
data["Geography"] = LabelEncoder().fit_transform(data["Geography"])
data["Gender"] = LabelEncoder().fit_transform(data["Gender"])
```

[237]:
```
data.head()
```

[237]:
```
   CreditScore  Geography  Gender       Age  Tenure   Balance  NumOfProducts  \
0    -0.447536          0       0  0.733734       2 -1.211056              1
1    -0.575623          2       0  0.697698       1  0.001502              1
2    -1.505118          0       0  0.733734       8  1.411246              3
3     0.632547          0       0  0.610110       1 -1.211056              2
4     1.728209          2       0  0.766266       2  0.827109              1

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0          1               1        -0.447536       1
1          0               1        -0.575623       0
2          1               0        -1.505118       1
3          0               0         0.632547       0
4          1               1         1.728209       0
```

[238]:
```
data.corr()
```

[238]:
```
                 CreditScore  Geography    Gender       Age    Tenure  \
CreditScore         1.000000   0.008769 -0.004181 -0.010590  0.000090
Geography           0.008769   1.000000  0.001382  0.035955  0.004042
Gender             -0.004181   0.001382  1.000000 -0.032190  0.015198
Age                -0.010590   0.035955 -0.032190  1.000000 -0.009384
Tenure              0.000090   0.004042  0.015198 -0.009384  1.000000
Balance             0.009128   0.064577  0.013669  0.041863 -0.013175
NumOfProducts       0.009310   0.008042 -0.022634 -0.029477  0.014734
HasCrCard          -0.003054  -0.012153  0.006354 -0.018187  0.020272
IsActiveMember      0.022464   0.008056  0.020352 -0.011665 -0.026627
EstimatedSalary     1.000000   0.008769 -0.004181 -0.010590  0.000090
Exited             -0.017423   0.036878 -0.105182  0.345086 -0.012670

                 Balance  NumOfProducts  HasCrCard  IsActiveMember  \
CreditScore     0.009128       0.009310  -0.003054        0.022464
Geography       0.064577       0.008042  -0.012153        0.008056
Gender          0.013669      -0.022634   0.006354        0.020352
Age             0.041863      -0.029477  -0.018187       -0.011665
```

```
Tenure           -0.013175       0.014734   0.020272       -0.026627
Balance           1.000000      -0.302849  -0.008085       -0.005267
NumOfProducts    -0.302849       1.000000   0.002371        0.008738
HasCrCard        -0.008085       0.002371   1.000000       -0.011784
IsActiveMember   -0.005267       0.008738  -0.011784        1.000000
EstimatedSalary   0.009128       0.009310  -0.003054        0.022464
Exited            0.113251      -0.048550  -0.009116       -0.137686

                 EstimatedSalary    Exited
CreditScore             1.000000 -0.017423
Geography               0.008769  0.036878
Gender                 -0.004181 -0.105182
Age                    -0.010590  0.345086
Tenure                  0.000090 -0.012670
Balance                 0.009128  0.113251
NumOfProducts           0.009310 -0.048550
HasCrCard              -0.003054 -0.009116
IsActiveMember          0.022464 -0.137686
EstimatedSalary         1.000000 -0.017423
Exited                 -0.017423  1.000000
```

4 Splitting Train and Test Data

[239]:
```
y = data["Exited"]
```

[240]:
```
y.head()
```

[240]:
```
0    1
1    0
2    1
3    0
4    0
Name: Exited, dtype: int64
```

[241]:
```
data.drop(["Exited"], axis = 1, inplace = True)
```

[242]:
```
data.head()
```

[242]:
```
   CreditScore  Geography  Gender       Age  Tenure   Balance  NumOfProducts  \
0    -0.447536          0       0  0.733734       2 -1.211056              1
1    -0.575623          2       0  0.697698       1  0.001502              1
2    -1.505118          0       0  0.733734       8  1.411246              3
3     0.632547          0       0  0.610110       1 -1.211056              2
4     1.728209          2       0  0.766266       2  0.827109              1
```

```
   HasCrCard  IsActiveMember  EstimatedSalary
0          1               1        -0.447536
1          0               1        -0.575623
2          1               0        -1.505118
3          0               0         0.632547
4          1               1         1.728209
```

[243]:
```
train_x,test_x,train_y,test_y = train_test_split(data,y, test_size = 0.3,␣
↪random_state = 50)
```

5 Model Fitting

6 Logistic Regression

[244]:
```
logistic = LogisticRegression()
logistic.fit(train_x,train_y)
log_y = logistic.predict(test_x)
print(accuracy_score(log_y,test_y))
```

```
0.8290447655974621
```

Tuning the model

[245]:
```
random_parameters = {'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000] ,'penalty':
↪['l1','l2']}
print(random_parameters)
```

```
{'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000], 'penalty': ['l1', 'l2']}
```

[246]:
```
random_para = RandomizedSearchCV(estimator = logistic, param_distributions =␣
↪random_parameters, n_iter = 50, cv = 10, verbose=2, random_state= 50, n_jobs␣
↪= -1)
random_para.fit(train_x,train_y)
```

```
Fitting 10 folds for each of 14 candidates, totalling 140 fits
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/model_selection/_search.py:281:
UserWarning: The total space of parameters 14 is smaller than n_iter=50. Running
14 iterations. For exhaustive searches, use GridSearchCV.
  % (grid_size, self.n_iter, grid_size), UserWarning)
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  38 tasks      | elapsed:    2.1s
[Parallel(n_jobs=-1)]: Done 140 out of 140 | elapsed:    3.2s finished
```

[246]:
```
RandomizedSearchCV(cv=10, error_score=nan,
                   estimator=LogisticRegression(C=1.0, class_weight=None,
```

```
                                              dual=False, fit_intercept=True,
                                              intercept_scaling=1,
                                              l1_ratio=None, max_iter=100,
                                              multi_class='auto', n_jobs=None,
                                              penalty='l2', random_state=None,
                                              solver='lbfgs', tol=0.0001,
                                              verbose=0, warm_start=False),
                   iid='deprecated', n_iter=50, n_jobs=-1,
                   param_distributions={'C': [0.001, 0.01, 0.1, 1, 10, 100,
                                              1000],
                                        'penalty': ['l1', 'l2']},
                   pre_dispatch='2*n_jobs', random_state=50, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

[247]:
```
random_para.best_params_
```

[247]:
```
{'penalty': 'l2', 'C': 1}
```

[256]:
```
logistic2 = LogisticRegression(penalty ='l2', C =1)
logistic2.fit(train_x,train_y)
log_y = logistic2.predict(test_x)
print(accuracy_score(log_y,test_y))
```

```
0.8290447655974621
```

Feature Selection

[257]:
```
feature = SelectFromModel(LogisticRegression())
feature.fit(train_x,train_y)
feature_support = feature.get_support()
feature_selected = train_x.loc[:,feature_support].columns.tolist()
print(str(len(feature_selected)), 'selected features')
```

```
2 selected features
```

[258]:
```
print(feature_selected)
```

```
['Age', 'IsActiveMember']
```

[259]:
```
train_x_feature = train_x[["Age", "IsActiveMember"]]
train_x_feature.head()
```

[259]:

	Age	IsActiveMember
2371	0.019520	1
6521	0.413914	0
9487	0.272773	1
2253	0.697698	1
2120	0.957958	1

[260]:
```
test_x_feature = test_x[["Age", "IsActiveMember"]]
test_x_feature.head()
```

[260]:

	Age	IsActiveMember
1624	0.056557	0
2169	0.766266	1
4285	0.655155	0
71	0.155155	0
4049	0.318318	1

[261]:
```
logistic.fit(train_x_feature, train_y)
log_y_feature = logistic.predict(test_x_feature)
print(accuracy_score(log_y_feature, test_y))
```

```
0.8304547056750088
```

7 Random Forest Classifier

[262]:
```
random = RandomForestClassifier()
random.fit(train_x,train_y)
random_y = random.predict(test_x)
print(accuracy_score(random_y,test_y))
```

```
0.8579485371871696
```

Tuning Parameters

[263]:
```
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
max_features = ['auto','sqrt']
max_depth = [int(x) for x in np.linspace(10,110,num=11)]
max_depth.append(None)
min_samples_split = [2,5,10]
min_samples_leaf = [1,2,4]
bootstrap = [True, False]
random_grid = {'n_estimators': n_estimators,
'max_features': max_features,
'max_depth': max_depth,
'min_samples_split': min_samples_split,
'min_samples_leaf': min_samples_leaf,
'bootstrap': bootstrap
}
print(random_grid)
```

```
{'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000],
'max_features': ['auto', 'sqrt'], 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80,
90, 100, 110, None], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2,
4], 'bootstrap': [True, False]}
```

[264]:
```
random_para = RandomizedSearchCV(estimator = random, param_distributions =␣
↪random_grid, n_iter = 100, cv = 3, verbose=2, random_state=42, n_jobs = -1)
random_para.fit(train_x,train_y)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
/opt/conda/lib/python3.6/site-
packages/joblib/externals/loky/process_executor.py:706: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  9.0min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 17.1min finished
```

[264]:
```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
min_weight_fraction_leaf=0.0,
                                                    n_estimators=100,
                                                    n_jobs…
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      None],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

[265]:
```
random_para.best_params_
```

[265]: {'n_estimators': 400,
 'min_samples_split': 10,
 'min_samples_leaf': 4,
 'max_features': 'auto',
 'max_depth': 70,
 'bootstrap': True}

[278]:
```
random_2 = RandomForestClassifier(n_estimators=1400,min_samples_split␣
 ↪=10,min_samples_leaf= 2,max_features = 'sqrt',max_depth=80,bootstrap= True)
random_2.fit(train_x,train_y)
random_2_y = random_2.predict(test_x)
print(accuracy_score(random_2_y,test_y))
```

0.8621783574198096

Feature Selection

[267]:
```
feature =␣
 ↪SelectFromModel(RandomForestClassifier(n_estimators=1400,min_samples_split␣
 ↪=10,min_samples_leaf= 2,max_features = 'sqrt',max_depth=80,bootstrap= True))
feature.fit(train_x,train_y)
feature_support = feature.get_support()
feature_selected = train_x.loc[:,feature_support].columns.tolist()
print(str(len(feature_selected)), 'selected features')
```

3 selected features

[268]:
```
feature_selected
```

[268]: ['Age', 'Balance', 'NumOfProducts']

[269]:
```
train_x_feature = train_x[['Age', 'Balance', 'NumOfProducts']]
train_x_feature.head()
```

[269]:

	Age	Balance	NumOfProducts
2371	0.019520	-0.136437	1
6521	0.413914	0.155280	2
9487	0.272773	-1.211056	1
2253	0.697698	-1.211056	1
2120	0.957958	0.655888	1

[270]:
```
test_x_feature = test_x[['Age', 'Balance', 'NumOfProducts']]
test_x_feature.head()
```

[270]:

	Age	Balance	NumOfProducts
1624	0.056557	-1.211056	2
2169	0.766266	-0.022564	2
4285	0.655155	0.663712	1

```
71     0.155155 -1.211056              1
4049   0.318318 -1.211056              2
```

[271]:
```
random_2.fit(train_x_feature,train_y)
random_2_feature_y = random_2.predict(test_x_feature)
print(accuracy_score(random_2_feature_y,test_y))
```

```
0.8375044060627423
```

8 Naive Bayes

[272]:
```
bayes = GaussianNB()
bayes.fit(train_x,train_y)
bayes_y = bayes.predict(test_x)
print(accuracy_score(bayes_y,test_y))
```

```
0.8463165315474093
```

Feature Selection

[273]:
```
train_x_feature = train_x[["Age", "Balance"]] #based on correlation values
train_x_feature.head()
```

[273]:
```
           Age   Balance
2371  0.019520 -0.136437
6521  0.413914  0.155280
9487  0.272773 -1.211056
2253  0.697698 -1.211056
2120  0.957958  0.655888
```

[274]:
```
test_x_feature = test_x[["Age", "Balance"]] #based on correlation values
test_x_feature.head()
```

[274]:
```
           Age   Balance
1624  0.056557 -1.211056
2169  0.766266 -0.022564
4285  0.655155  0.663712
71    0.155155 -1.211056
4049  0.318318 -1.211056
```

[275]:
```
bayes.fit(train_x_feature,train_y)
bayes_feature_y =bayes.predict(test_x_feature)
print(accuracy_score(bayes_feature_y, test_y))
```

```
0.8121254846669017
```

9 Conclusion

The highest accuracy we achieved is by hypertuning RandomForestClassifier and using all the features.

[276]:
```
print(str((accuracy_score(random_2_y,test_y)) * 100) + "%")
```

```
86.25308424391963%
```

When we get time this notebook will be updated

If you like my work, please upvote.