Assignment -2

Assignment Date	25 September 2022
Student Name	J.Mohamed Jasim
Student Roll Number	820319205021
Maximum Marks	2 Marks

1. **Download the dataset: Dataset**
2. **Load the dataset**

```
from google.colab import drive
drive.mount("/content/gdrive")
Mounted at /content/gdrive
```

```
import pandas as pd
import numpy as np
from numpy.lib.shape_base import dsplit
```

```
ds=pd.read_csv("gdrive/My Drive/Churn_Modelling.csv")
df=pd.DataFrame(ds)
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

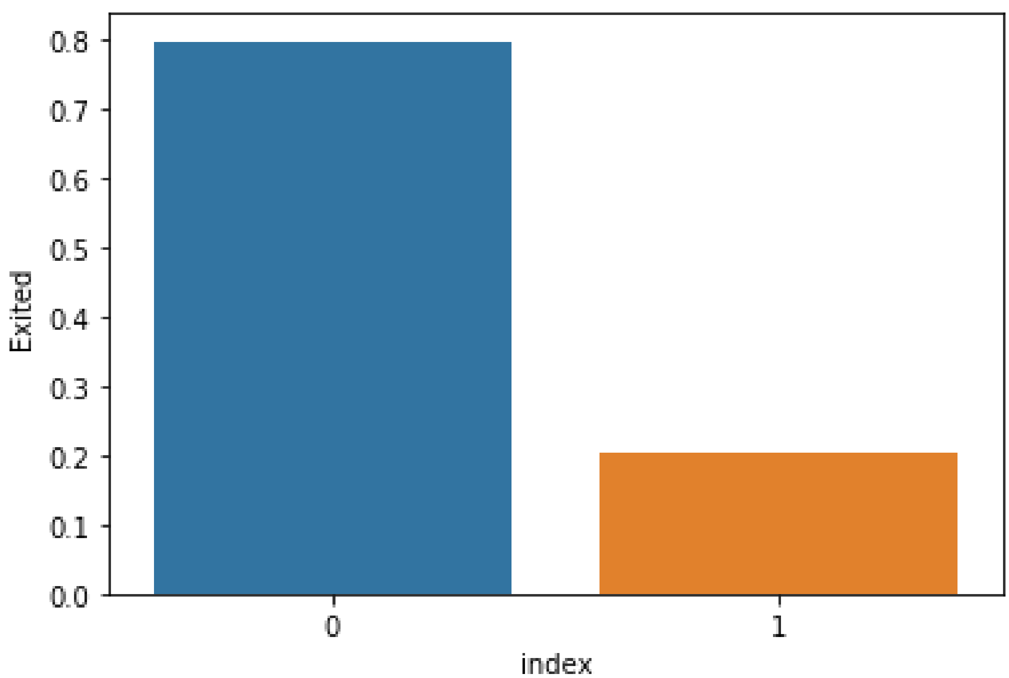
```
df['HasCrCard'] = df['HasCrCard'].astype('category')
df['IsActiveMember'] = df['IsActiveMember'].astype('category')
df['Exited'] = df['Exited'].astype('category')
df = df.drop(columns=['RowNumber', 'CustomerId', 'Surname'])
df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

3. Perform Below Visualizations.

● Univariate Analysis ● Bi - Variate Analysis ● Multi - Variate Analysis

[21]
import seaborn **as** sn
density = df['Exited'].value_counts(normalize=True).reset_index()
sn.barplot(data=density, x='index', y='Exited',);
density



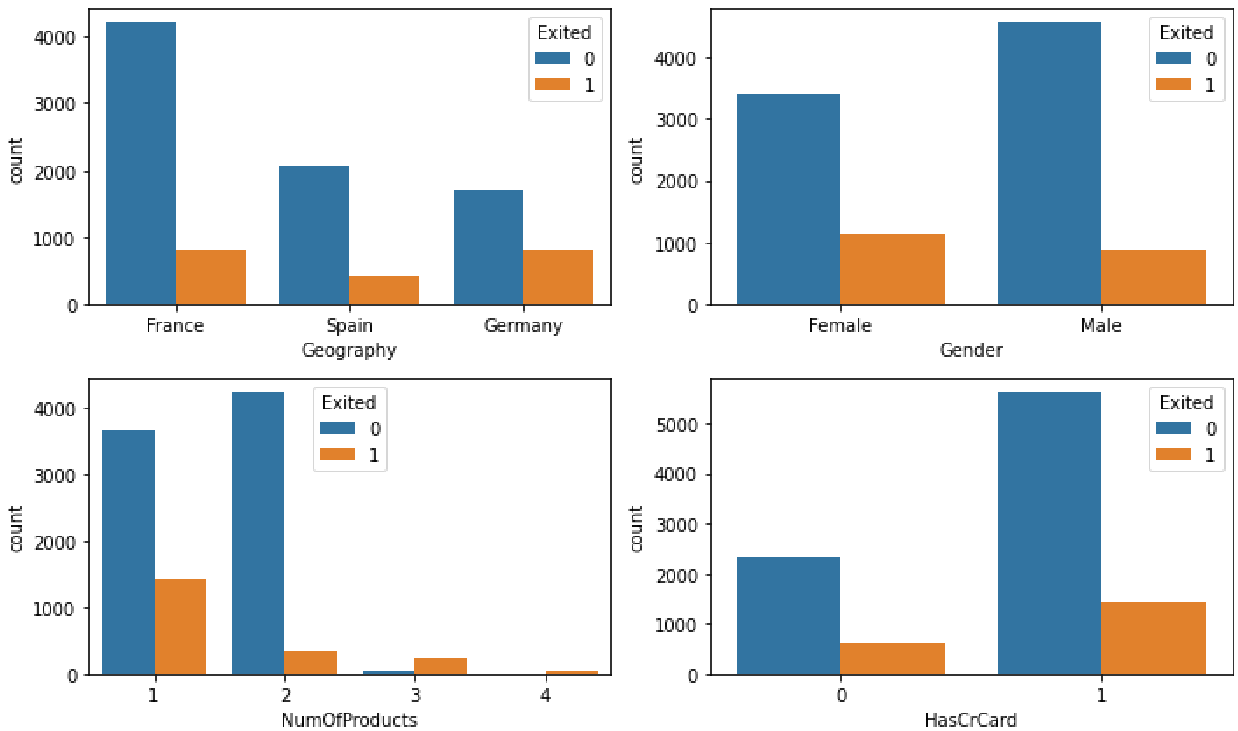
[22]
import matplotlib.pyplot **as** plt
[23]
categorical = df.drop(columns=['CreditScore', 'Age', 'Tenure', 'Balance', 'Estimated Salary'])
rows = int(np.ceil(categorical.shape[1] / 2)) - 1

```
# create sub-plots anf title them
fig, axes = plt.subplots(nrows=rows, ncols=2, figsize=(10,6))
axes = axes.flatten()

for row in range(rows):
    cols = min(2, categorical.shape[1] - row*2)
    for col in range(cols):
        col_name = categorical.columns[2 * row + col]
        ax = axes[row*2 + col]

        sn.countplot(data=categorical, x=col_name, hue="Exited", ax=ax);

plt.tight_layout()
```



4. **Perform descriptive statistics on the dataset**

[24]

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
```

```
 1   Geography        10000 non-null  object  
 2   Gender           10000 non-null  object  
 3   Age              10000 non-null  int64   
 4   Tenure           10000 non-null  int64   
 5   Balance          10000 non-null  float64 
 6   NumOfProducts    10000 non-null  int64   
 7   HasCrCard        10000 non-null  category
 8   IsActiveMember   10000 non-null  category
 9   EstimatedSalary  10000 non-null  float64 
 10  Exited           10000 non-null  category
dtypes: category(3), float64(2), int64(4), object(2)
memory usage: 654.8+ KB
```

[25]

```
df.describe()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	100090.239881
std	96.653299	10.487806	2.892174	62397.405202	0.581654	57510.492818
min	350.000000	18.000000	0.000000	0.000000	1.000000	11.580000
25%	584.000000	32.000000	3.000000	0.000000	1.000000	51002.110000
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	100193.915000
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	149388.247500
max	850.000000	92.000000	10.000000	250898.090000	4.000000	199992.480000

5. Handle the Missing values

[26]

```
df.isna().sum()
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
```

Exited   0
dtype: int64

In this dataset, there is no missing value.

[27]

```
for i in df:
    if df[i].dtype=='object' or df[i].dtype=='category':
        print("unique of "+i+" is "+str(len(set(df[i])))+" they are "+str(set(df[i])))
```

unique of Geography is 3 they are {'France', 'Germany', 'Spain'}
unique of Gender is 2 they are {'Female', 'Male'}
unique of HasCrCard is 2 they are {0, 1}
unique of IsActiveMember is 2 they are {0, 1}
unique of Exited is 2 they are {0, 1}

6. Find the outliers and replace the outliers

Finding whether the outlier is present

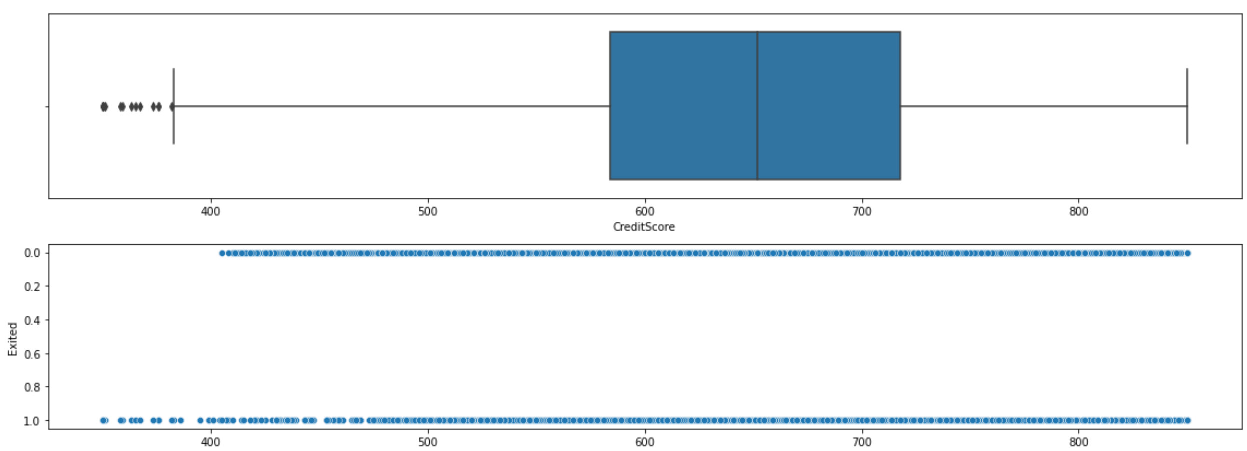
[28]

```
def box_scatter(data, x, y):
    fig, (ax1, ax2) = plt.subplots(nrows=2, ncols=1, figsize=(16,6))
    sn.boxplot(data=data, x=x, ax=ax1)
    sn.scatterplot(data=data, x=x,y=y,ax=ax2)
```

[29]

```
box_scatter(df,'CreditScore','Exited');
plt.tight_layout()
print(f"# of Bivariate Outliers: {len(df.loc[df['CreditScore'] < 400])}")
```

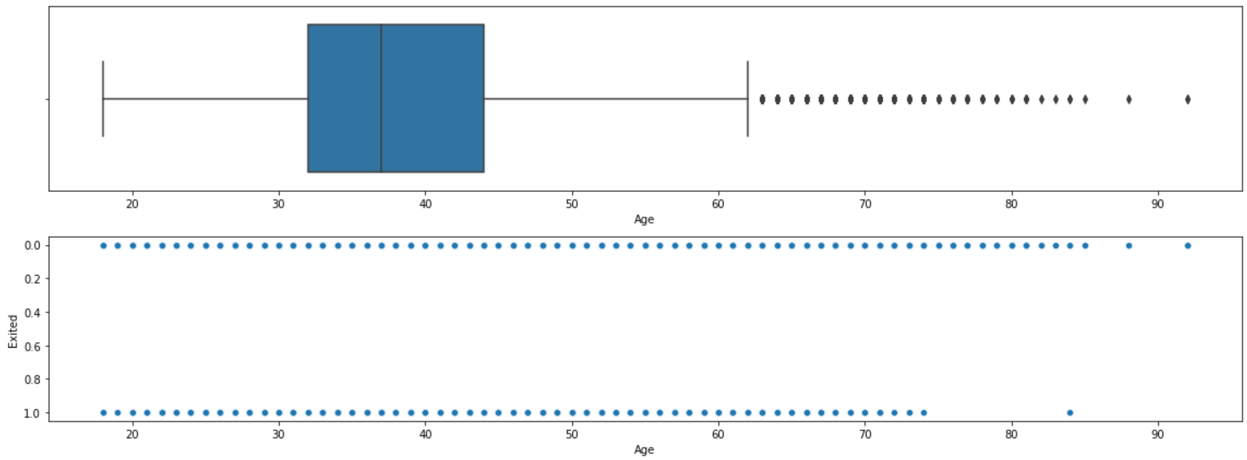
# of Bivariate Outliers: 19



[30]

```
box_scatter(df,'Age','Exited');
plt.tight_layout()
print(f"# of Bivariate Outliers: {len(df.loc[df['Age'] > 87])}")
```

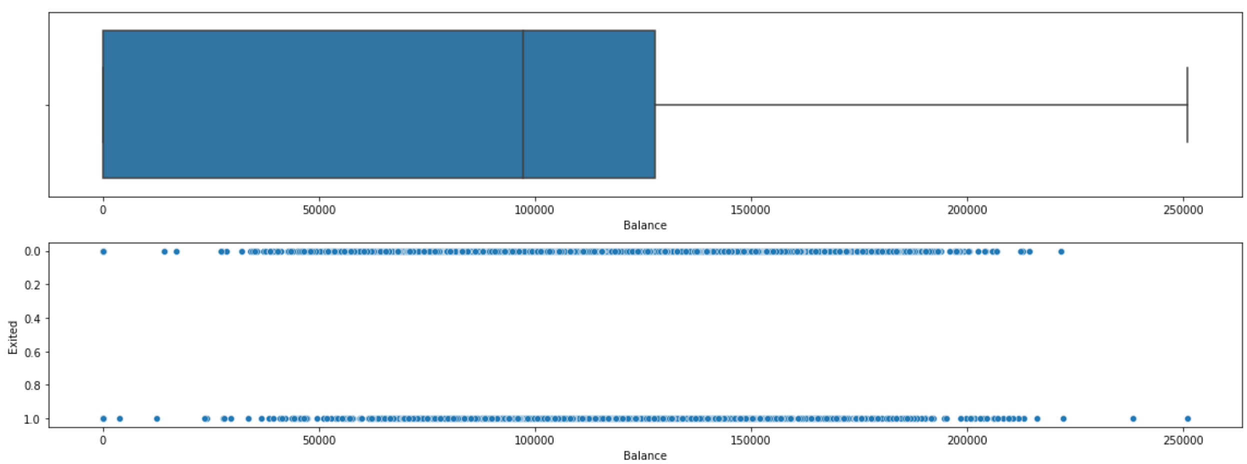
# of Bivariate Outliers: 3



[31]

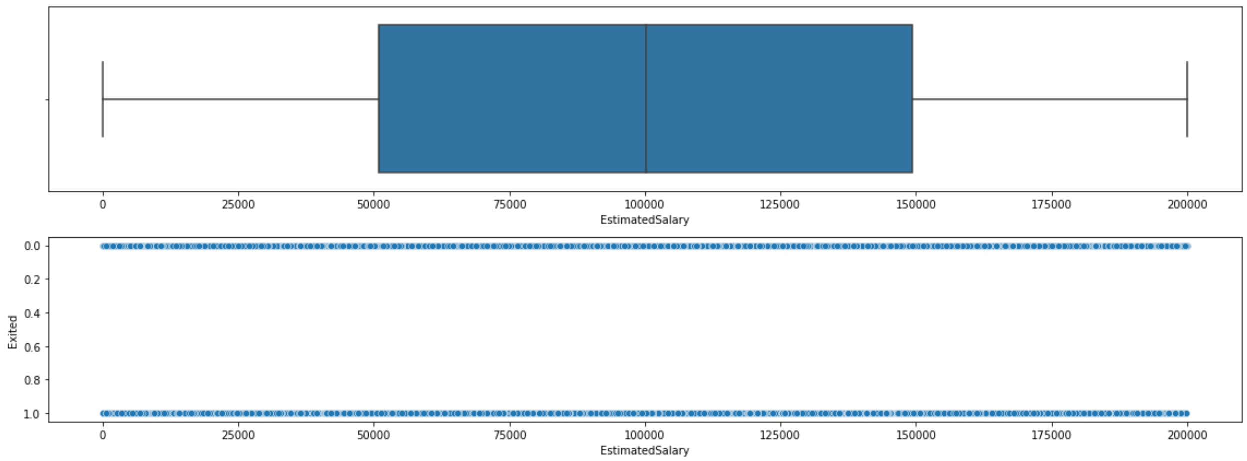
```
box_scatter(df,'Balance','Exited');
plt.tight_layout()
print(f"# of Bivariate Outliers: {len(df.loc[df['Balance'] > 220000])}")
```

# of Bivariate Outliers: 4



[32]

```
box_scatter(df,'EstimatedSalary','Exited');
plt.tight_layout()
```



Removing of Outliers

[33]

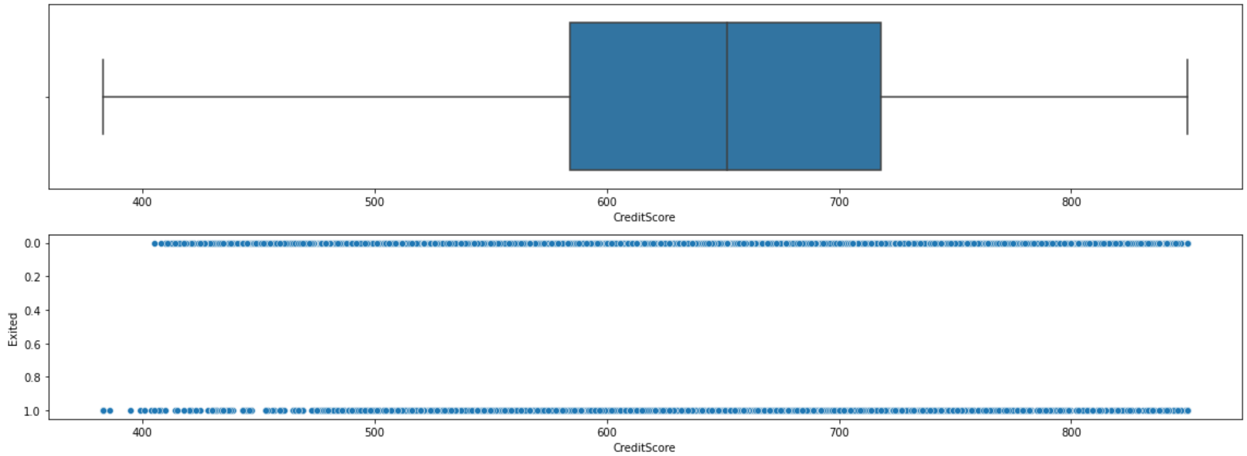
```
for i in df:
    if df[i].dtype=='int64' or df[i].dtypes=='float64':
        q1=df[i].quantile(0.25)
        q3=df[i].quantile(0.75)
        iqr=q3-q1
        upper=q3+1.5*iqr
        lower=q1-1.5*iqr
        df[i]=np.where(df[i] >upper, upper, df[i])
        df[i]=np.where(df[i] <lower, lower, df[i])
```

After removing the outliers, the boxplot will be looks like

[34]

```
box_scatter(df,'CreditScore','Exited');
plt.tight_layout()
print(f"# of Bivariate Outliers: {len(df.loc[df['CreditScore'] < 400])}")
```

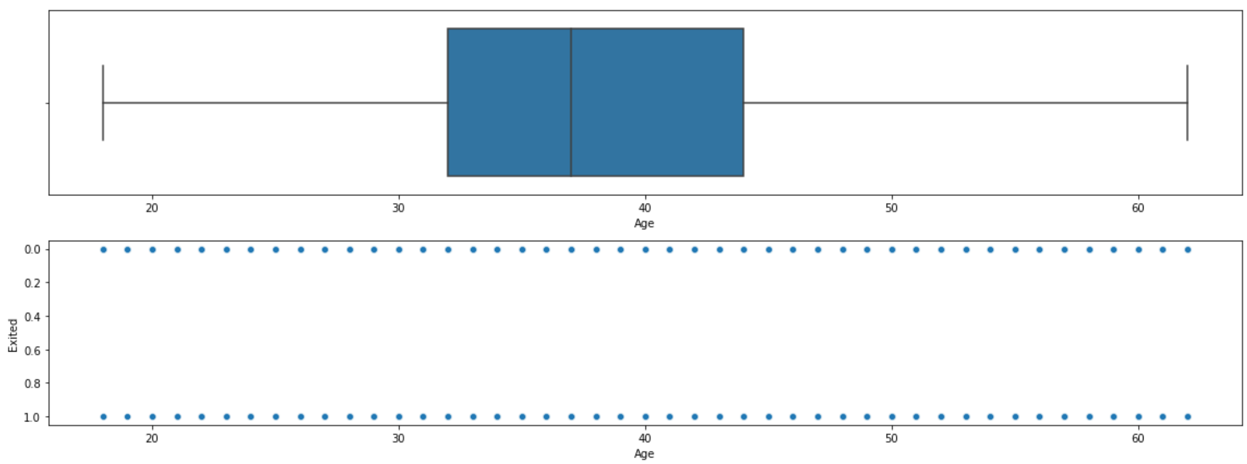
# of Bivariate Outliers: 19



[35]

```
box_scatter(df,'Age','Exited');
plt.tight_layout()
print(f"# of Bivariate Outliers: {len(df.loc[df['Age'] > 87])}")
```

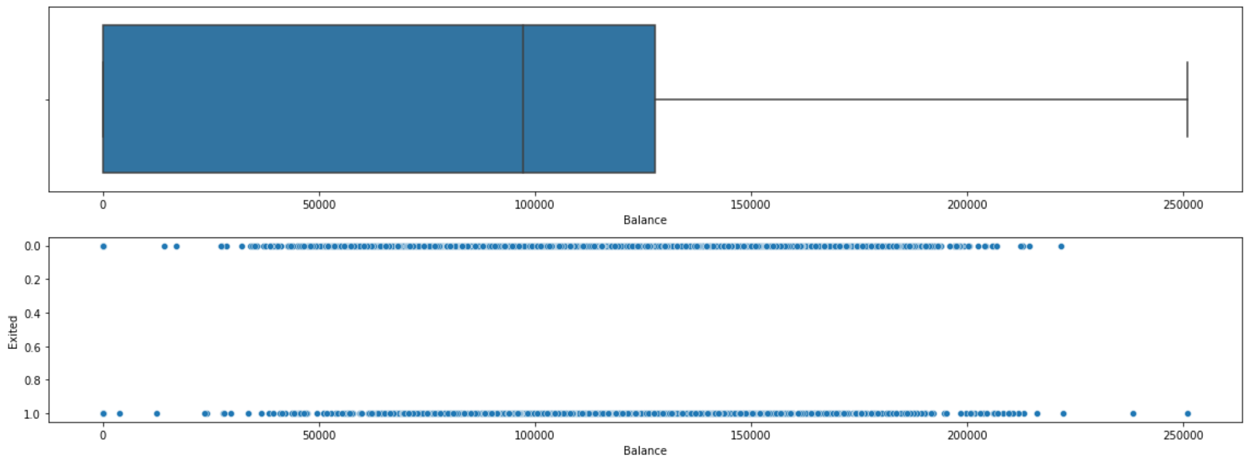
# of Bivariate Outliers: 0



[36]

```
box_scatter(df,'Balance','Exited');
plt.tight_layout()
print(f"# of Bivariate Outliers: {len(df.loc[df['Balance'] > 220000])}")
```

# of Bivariate Outliers: 4



7. Check for Categorical columns and perform encoding

[37]

```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
for i in df:
    if df[i].dtype=='object' or df[i].dtype=='category':
        df[i]=encoder.fit_transform(df[i])
```

8. Splitting the data into dependent and independent variables

[ ]

[38]

```
x=df.iloc[:,:-1]
x.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619.0	0	0	42.0	2.0	0.00	1.0	1	1	101348.88
1	608.0	2	0	41.0	1.0	83807.86	1.0	0	1	112542.58
2	502.0	0	0	42.0	8.0	159660.80	3.0	1	0	113931.57
3	699.0	0	0	39.0	1.0	0.00	2.0	0	0	93826.63
4	850.0	2	0	43.0	2.0	125510.82	1.0	1	1	79084.10

[39]

```
y=df.iloc[:,-1]
y.head()
```

```
0    1
1    0
2    1
3    0
```

4   0
Name: Exited, dtype: int64

9. Scale the independent variables

[40]

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
x=scaler.fit_transform(x)
```

[41]

```
x
```

```
array([[-0.32687761, -0.90188624, -1.09598752, ...,  0.64609167,
         0.97024255,  0.02188649],
       [-0.44080365,  1.51506738, -1.09598752, ..., -1.54776799,
         0.97024255,  0.21653375],
       [-1.53863634, -0.90188624, -1.09598752, ...,  0.64609167,
        -1.03067011,  0.2406869 ],
       ...,
       [ 0.60524449, -0.90188624, -1.09598752, ..., -1.54776799,
         0.97024255, -1.00864308],
       [ 1.25772996,  0.30659057,  0.91241915, ...,  0.64609167,
        -1.03067011, -0.12523071],
       [ 1.4648682 , -0.90188624, -1.09598752, ...,  0.64609167,
        -1.03067011, -1.07636976]])
```

10. Split the data into Training and Testing

[42]

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33)
```

[43]

```
x_train.shape
```

(6700, 10)

[44]

```
x_test.shape
```

(3300, 10)

[45]

```
y_train.shape
```

(6700,)

[46]

```
y_test.shape
```

[redacted]