

Descriptive Statistics



Python Programming Lab

05506231 Statistics and Probability





- Churn_Modelling Dataset
- Descriptive Statistics for Numeric Data
- Descriptive Statistics Categorical Data
- Data Visualization



Churn_Modelling Dataset

Row			Credit						NumOf	HasCr	IsActive	Estimated	
Number	CustomerId	Surname	Score	Geography	Gender	Age	Tenure	Balance	Product	Card	Member	Salary	Exited
1	15634602	Hargrave	619	France	Female	42	2	0	1	1	1	101348.9	1
2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.6	0
3	15619304	Onio	502	France	Female	42	8	159660.8	3	1	0	113931.6	1
4	15701354	Boni	699	France	Female	39	1	0	2	0	0	93826.63	0
5	15737888	Mitchell	850	Spain	Female	43	2	125510.8	1	1	1	79084.1	0
6	15574012	Chu	645	Spain	Male	44	8	113755.8	2	1	0	149756.7	1
7	15592531	Bartlett	822	France	Male	50	7	0	2	1	1	10062.8	0
8	15656148	Obinna	376	Germany	Female	29	4	115046.7	4	1	0	119346.9	1
9	15792365	He	501	France	Male	44	4	142051.1	2	0	1	74940.5	0
10	15592389	H?	684	France	Male	27	2	134603.9	1	1	1	71725.73	0
11	15767821	Bearce	528	France	Male	31	6	102016.7	2	0	0	80181.12	0
12	15737173	Andrews	497	Spain	Male	24	3	0	2	1	0	76390.01	0
13	15632264	Kay	476	France	Female	34	10	0	2	1	0	26260.98	0





```
from google.colab import files
uploaded = files.upload()
```

```
import pandas as pd
df = pd.read_csv( 'Churn_Modelling.csv' )
```

df.dtypes

0	df.dtypes	
	RowNumber CustomerId Surname CreditScore Geography Gender Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: object	int64 int64 object int64 object int64 int64 float64 int64 int64 int64 int64 int64
	Gender Age Tenure Balance NumOfProducts HasCrCard IsActiveMember	object int64 int64 float64 int64 int64
		int64

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Descriptive Statistics for Numeric Data

df.describe()

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000



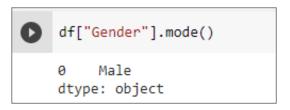
Mode

df.mode()

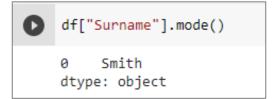
	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15565701	Smith	850.0	France	Male	37.0	2.0	0.0	1.0	1.0	1.0	24924.92	0.0
1	2	15565706	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	3	15565714	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

df.mode(numeric_only=True)

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15565701	850.0	37.0	2.0	0.0	1.0	1.0	1.0	24924.92	0.0
1	2	15565706	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	3	15565714	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN











```
df.var()
```

```
df.var()
RowNumber
                   8.334167e+06
CustomerId
                   5.174815e+09
CreditScore
                   9.341860e+03
                   1.099941e+02
Age
Tenure
                   8.364673e+00
                  3.893436e+09
Balance
NumOfProducts
                  3.383218e-01
                  2.077905e-01
HasCrCard
IsActiveMember
                   2.497970e-01
EstimatedSalary
                  3.307457e+09
Exited
                  1.622225e-01
dtype: float64
```

```
df.var()['Age']
```

```
df.var()['Age']

□ 109.99408416841645
```

```
from scipy.stats import variation
variation(df['Age'])
```

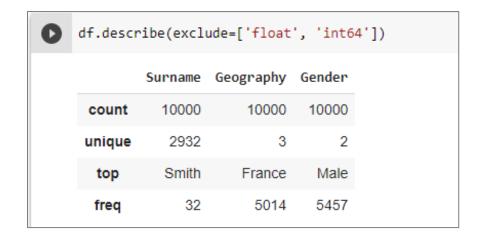
```
from scipy.stats import variation variation(df['Age'])

0.26944493955242593
```



Descriptive Statistics for Categorical Data

df.describe(exclude=['float', 'int64'])



df.describe(include = 'object')

O d	df.describe(include = 'object') Surname Geography Gender count 10000 10000 10000 unique 2932 3 2 top Smith France Male				
		Surname	Gender		
	count	10000	10000	10000	
ι	unique	2932	3	2	
	top	Smith	France	Male	
	freq	32	5014	5457	



```
S
```

```
df.RowNumber=df.RowNumber.astype('category')
df.CustomerId=df.CustomerId.astype('category')
df.HasCrCard=df.HasCrCard.astype('category')
df.IsActiveMember=df.IsActiveMember.astype('category')
df.Exited=df.Exited.astype('category')
df.NumOfProducts=df.NumOfProducts.astype('category')

df.Geography = df.Geography.astype('category')
df.Surname = df.Surname.astype('category')
df.Gender = df.Gender.astype('category')
```



Descriptive Statistics for Categorical Data

df.describe(include = 'category')

>	<pre>df.describe(include = 'category')</pre>													
		RowNumber	CustomerId	Surname	Geography	Gender	NumOfProducts	HasCrCard	IsActiveMember	Exited				
	count	10000	10000	10000	10000	10000	10000	10000	10000	10000				
	unique	10000	10000	2932	3	2	4	2	2	2				
	top	10000	15815690	Smith	France	Male	1	1	1	0				
	freq	1	1	32	5014	5457	5084	7055	5151	7963				

df.Geography.value counts()

```
df.Geography.value_counts()

France 5014
Germany 2509
Spain 2477
Name: Geography, dtype: int64
```



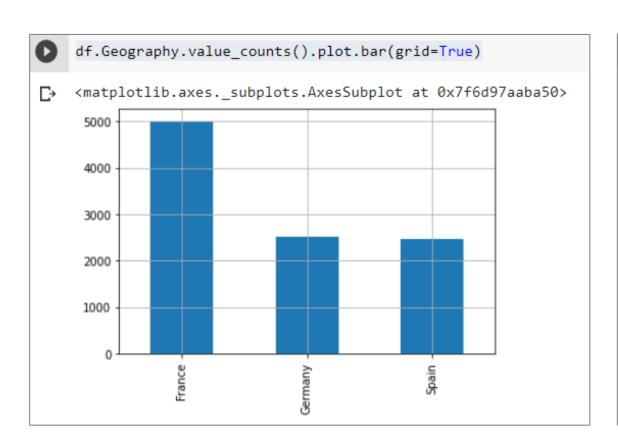


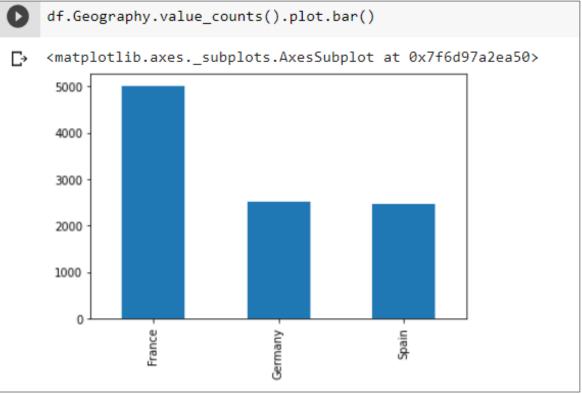
- Bar charts
- Box plot
- Histogram





df.Geography.value counts().plot.bar(grid=True)



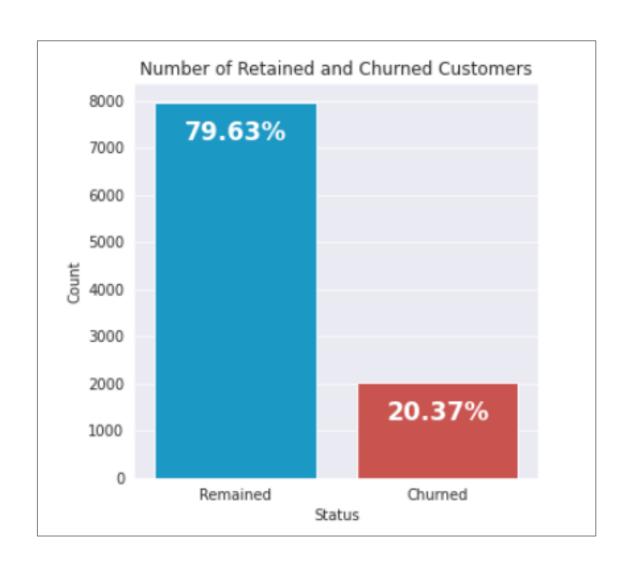




```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set style('darkgrid')
colors = ['#00A5E0', '#DD403A']
fig = plt.figure(figsize = (5, 5))
sns.countplot(x = 'Exited', data = df, palette = colors)
for index, value in enumerate(df['Exited'].value counts()):
    label = '{}%'.format(round( (value/df['Exited'].shape[0])*100, 2))
    plt.annotate(label, xy = (index -0.25, value -800), color = 'w', fontweight='bold', size=17)
plt.title('Number of Retained and Churned Customers')
plt.xticks([0, 1], ['Remained', 'Churned'])
plt.xlabel('Status')
plt.ylabel('Count');
```









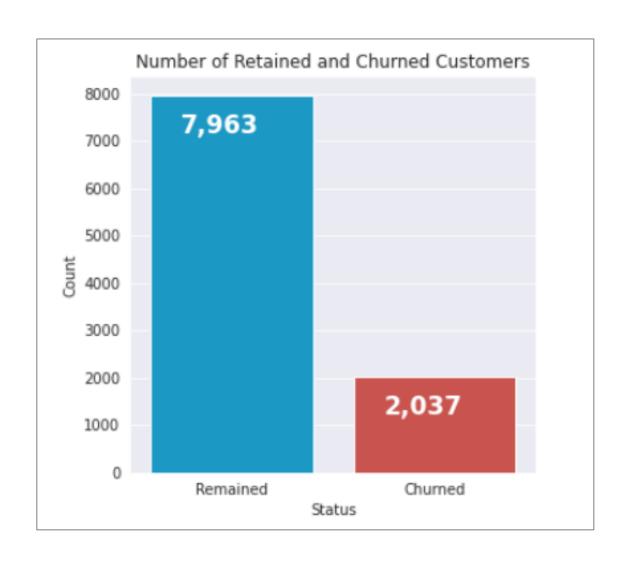
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```

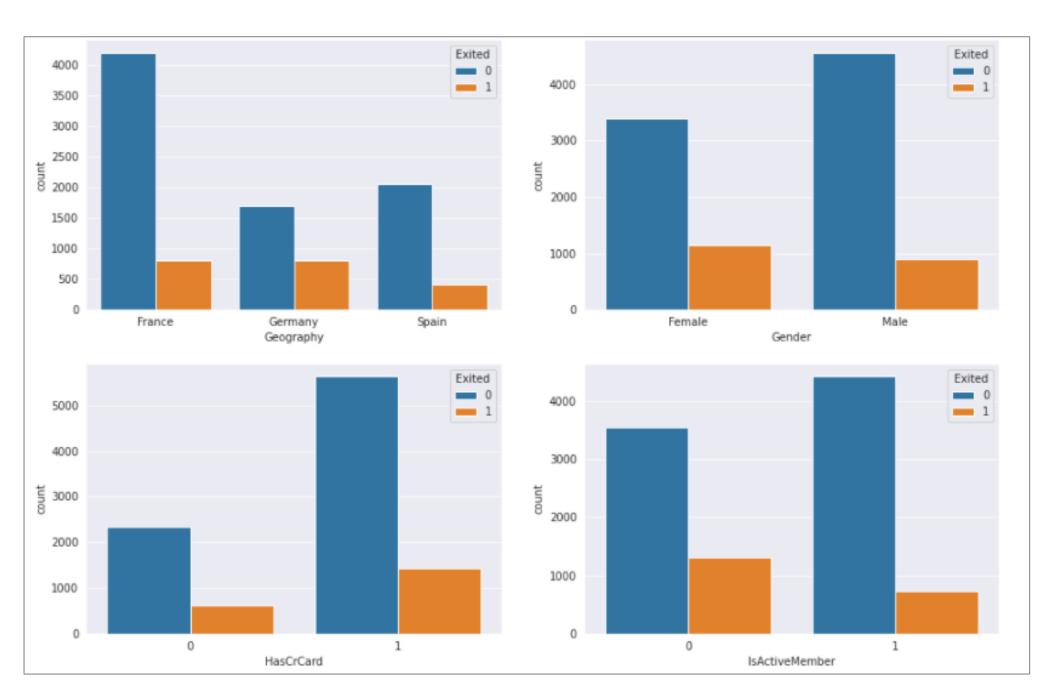






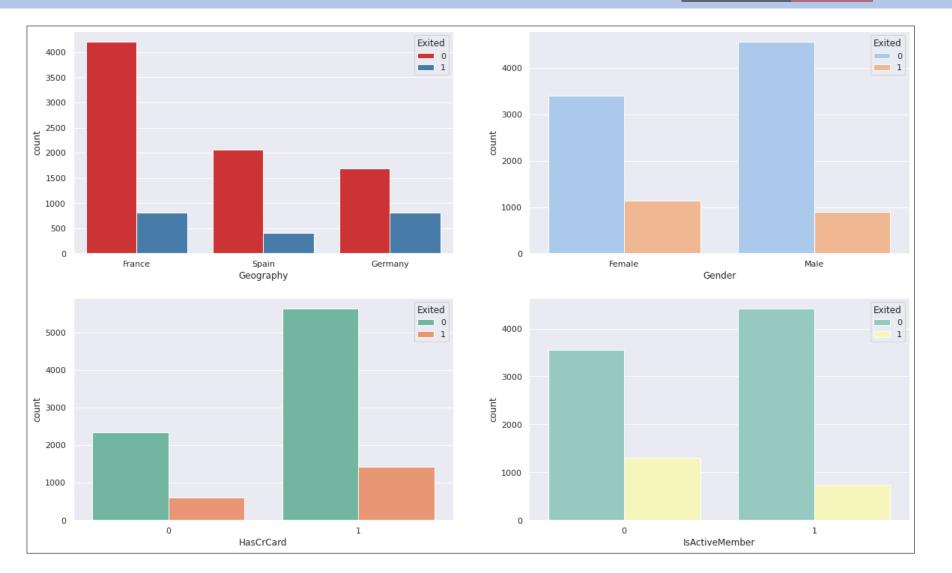


```
fig, axarr = plt.subplots(2, 2, figsize=(20, 12))
sns.countplot(x='Geography', hue = 'Exited', data = df, ax=axarr[0][0])
sns.countplot(x='Gender', hue = 'Exited', data = df, ax=axarr[0][1])
sns.countplot(x='HasCrCard', hue = 'Exited', data = df, ax=axarr[1][0])
sns.countplot(x='IsActiveMember', hue = 'Exited', data = df, ax=axarr[1][1])
```



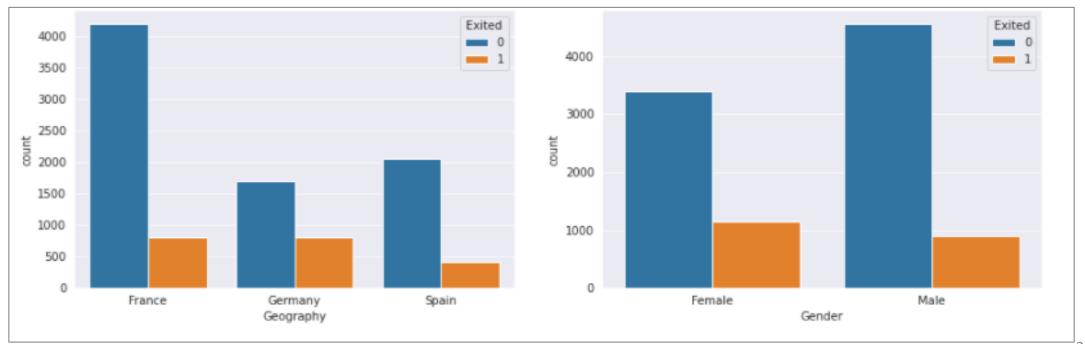


```
sns.countplot(x='Geography', hue='Exited',data = df, palette="Set1", ax=axarr[0][0])
sns.countplot(x='Gender', hue ='Exited',data = df, palette="pastel", ax=axarr[0][1])
sns.countplot(x='HasCrCard', hue='Exited',data = df, palette="Set2", ax=axarr[1][0])
sns.countplot(x='IsActiveMember', hue='Exited',data = df, palette="Set3", ax=axarr[1][1])
```



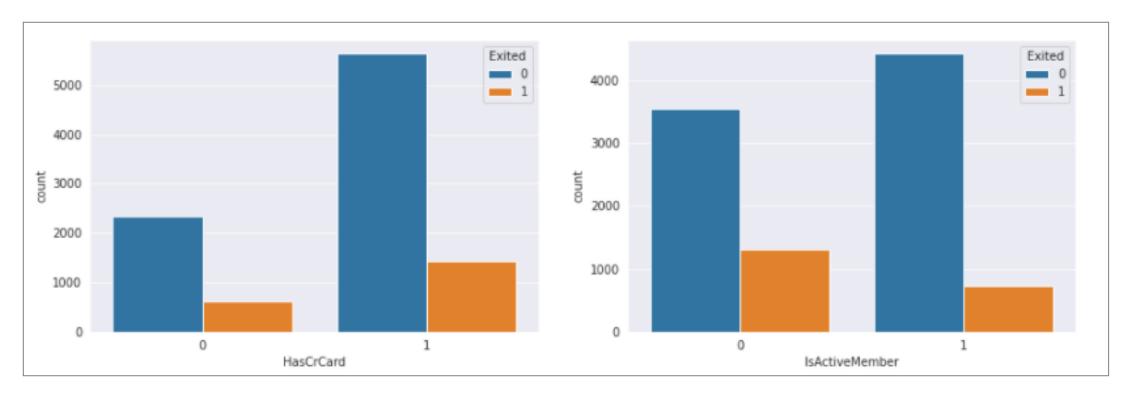


- Majority of the data is from persons from France. Germany has the highest proportion of churned customers.
- The proportion of female customers churning is also greater than that of male customers





- No different proportion of customer churning between HasCrCard and not have.
- The inactive members have a greater churn.







- Data is represented with a box
- The ends of the box are at the first and third quartiles, i.e., the height of the box is IQR

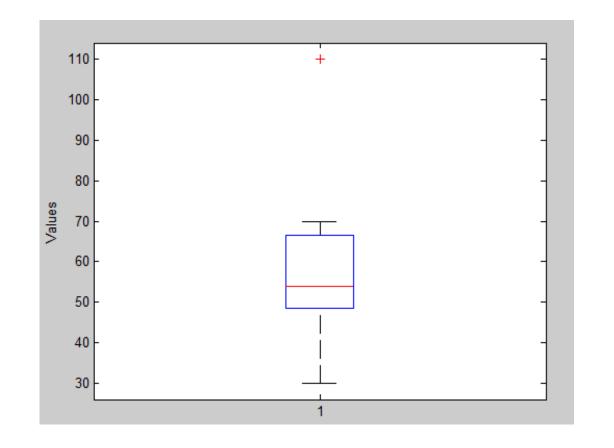
$$IQR = Q_3 - Q_1$$

- The median is marked by a line within the box
- Whiskers: two lines outside the box extended to Minimum and Maximum
- Outliers: points beyond a specified outlier threshold, plotted individually





Example: 30, 36, 47, 50, 52, 52, 56, 60, 63, 70, 70, 110



$$Q_1 = 48.5$$

 $Q_2 = 54$
 $Q_3 = 66.5$

$$IQR = 18$$

Box Plot





(Quartile 3 - Quartile 2) = (Quartile 2 - Quartile 1)



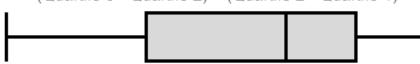
Positive Skew

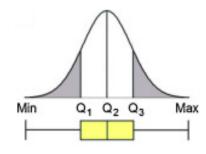
(Quartile 3 - Quartile 2) > (Quartile 2 - Quartile 1)



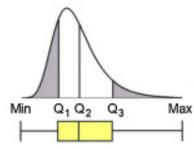
Negative Skew

(Quartile 3 - Quartile 2) < (Quartile 2 - Quartile 1)

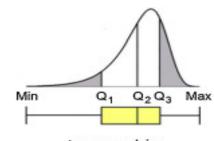




Symmetric



Asymmetric (positive or right skewed)

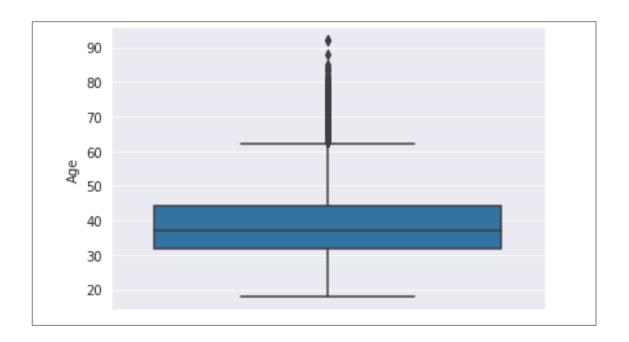


Asymmetric (negative or left skewed)





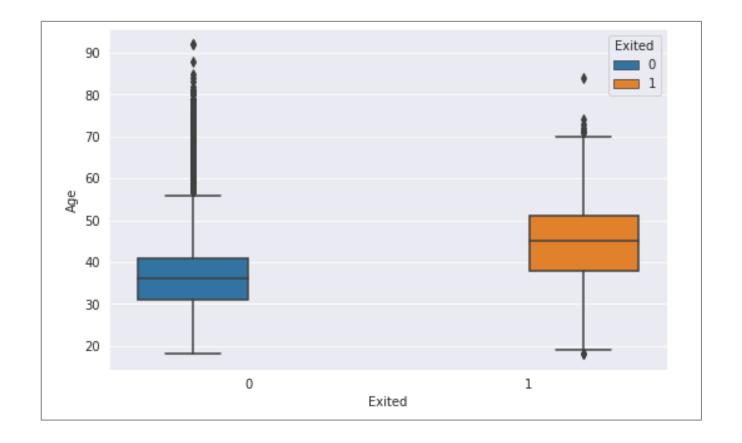
sns.boxplot(y='Age', data = df)







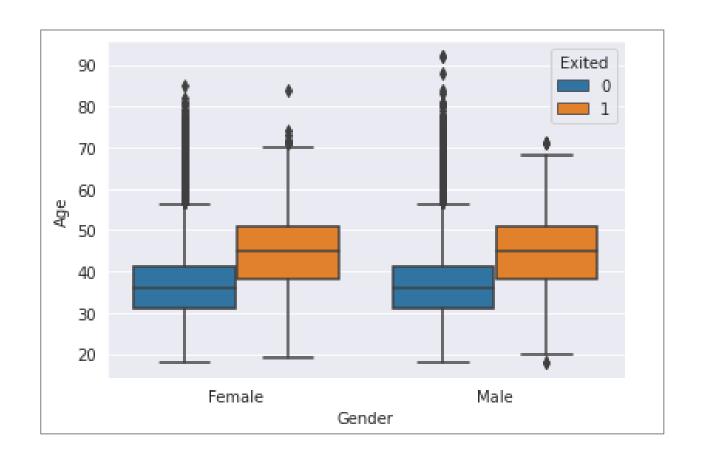
```
fig = plt.figure(figsize = (8, 5))
sns.boxplot(y='Age', x = 'Exited', hue = 'Exited', data = df)
```







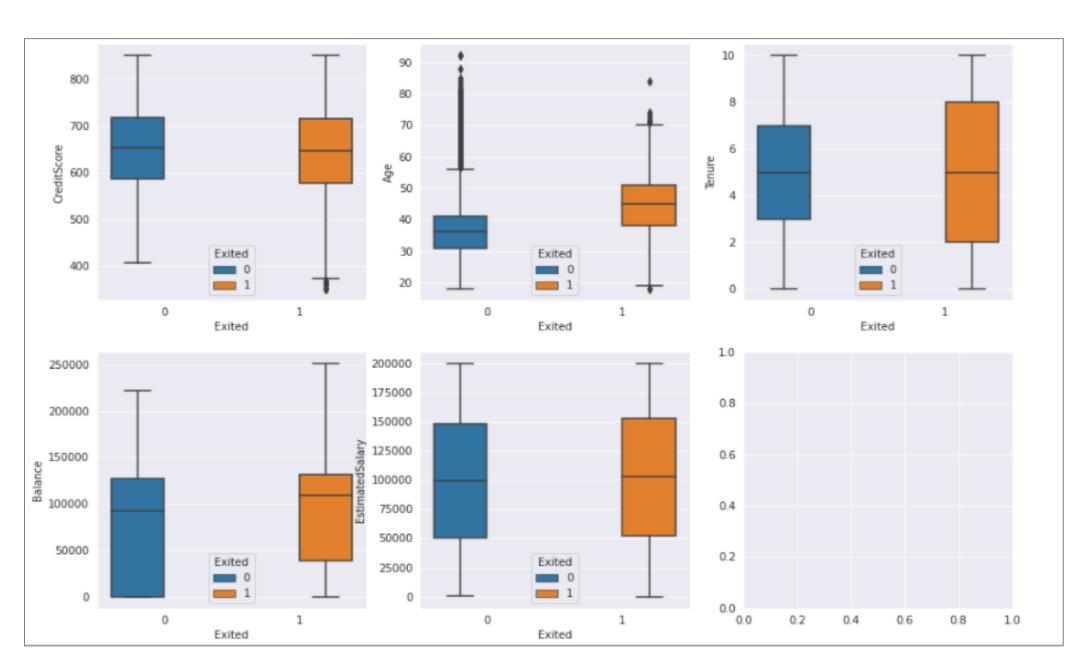
sns.boxplot(y='Age',x = 'Gender', hue = 'Exited', data = df)





Box Plot

```
fig, axarr = plt.subplots( 2, 3, figsize=(15, 10))
sns.boxplot(y='CreditScore',x = 'Exited', hue = 'Exited',data = df, ax=axarr[0][0])
sns.boxplot(y='Age',x = 'Exited', hue = 'Exited',data = df, ax=axarr[0][1])
sns.boxplot(y='Tenure',x = 'Exited', hue = 'Exited',data = df, ax=axarr[0][2])
sns.boxplot(y='Balance',x = 'Exited', hue = 'Exited',data = df, ax=axarr[1][0])
sns.boxplot(y='EstimatedSalary',x = 'Exited', hue = 'Exited',data = df, ax=axarr[1][1])
```

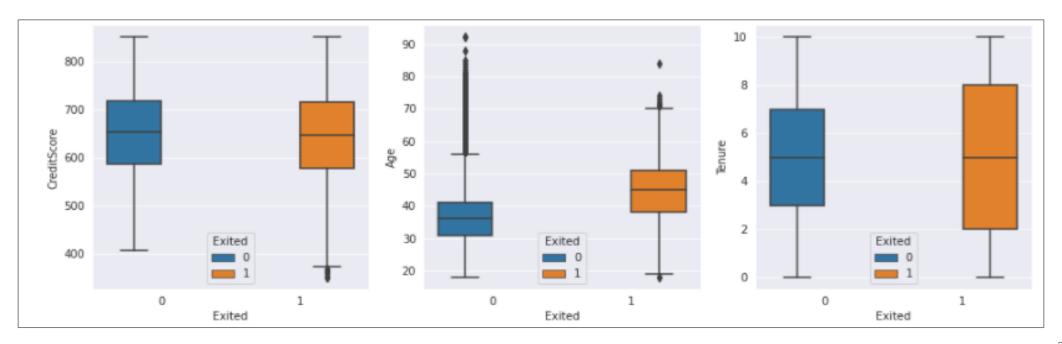






Box Plot

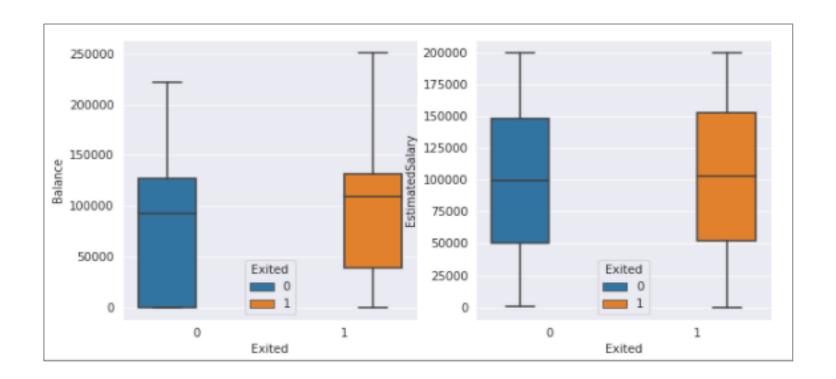
- There is no significant difference in the credit score distribution between retained and churned customers.
- The older customers are churning at more than the younger ones.
- The customers on either extreme end (spent little time with the bank or a lot of time with the bank) are more likely to churn compared to those that are of average tenure.







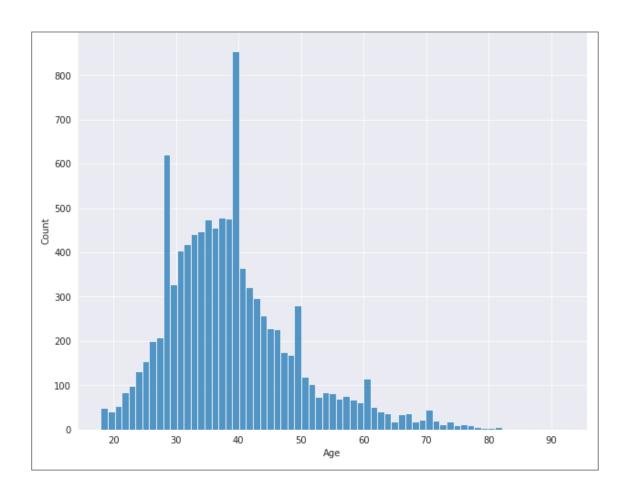
- The bank is losing customers with significant bank balances.
- The salary has no significant effect on the likelihood to churn.







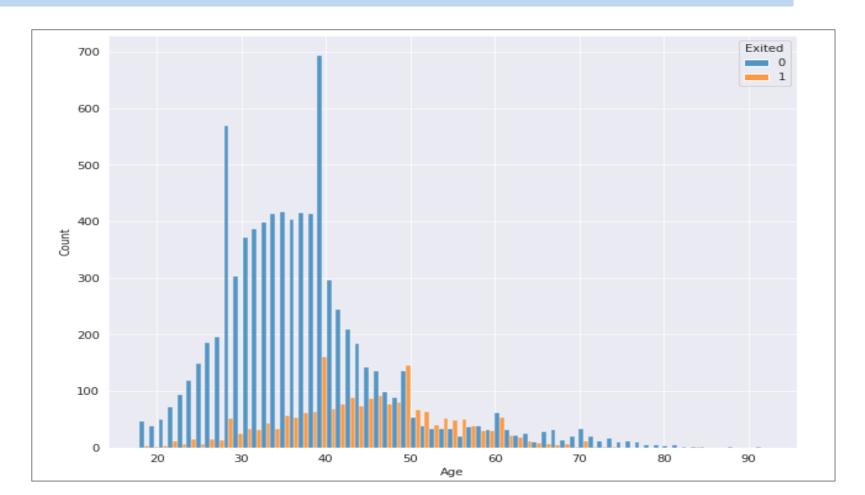
```
fig = plt.figure(figsize = (10,8))
sns.histplot(df, x="Age")
```







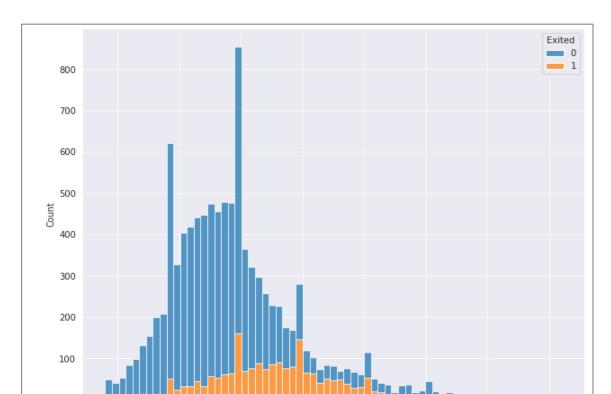
```
fig = plt.figure(figsize = (10, 8))
sns.histplot(df, x="Age", hue = 'Exited', multiple="dodge")
```





30

multiple="stack"



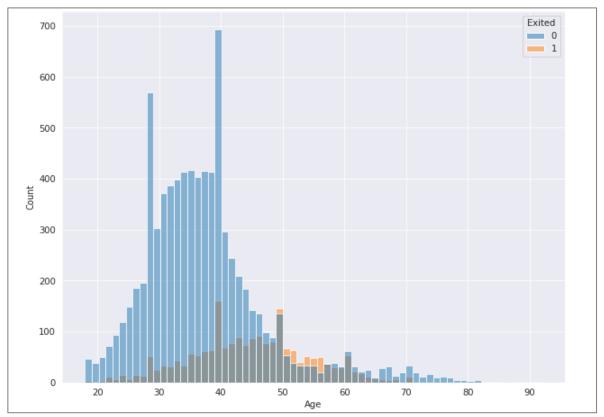
50

Age

80

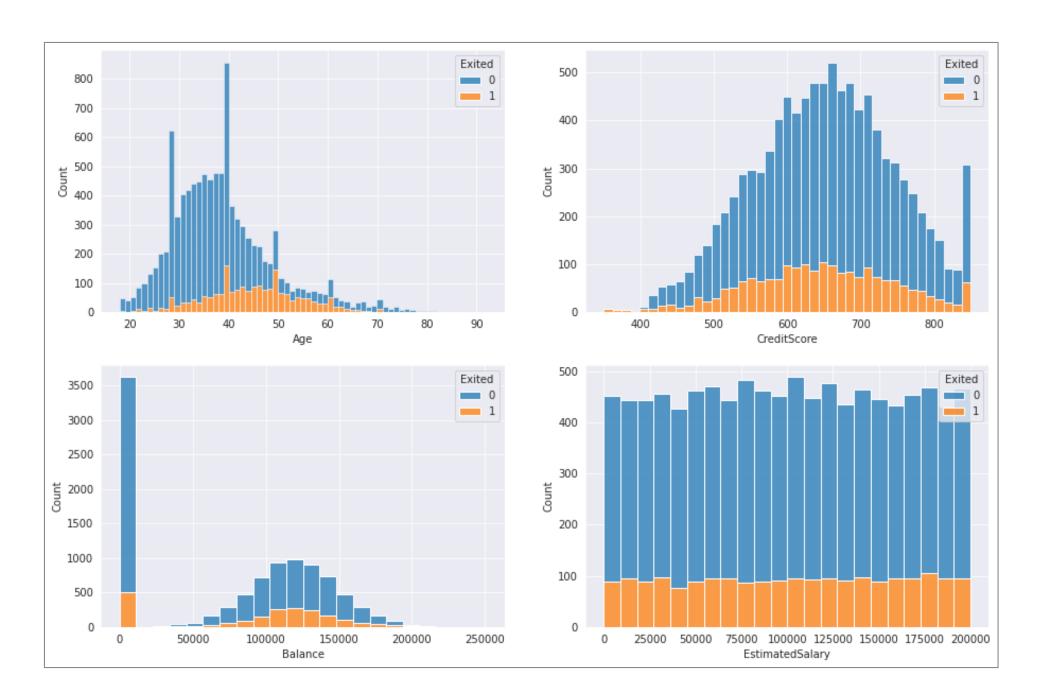
90

multiple="layer"





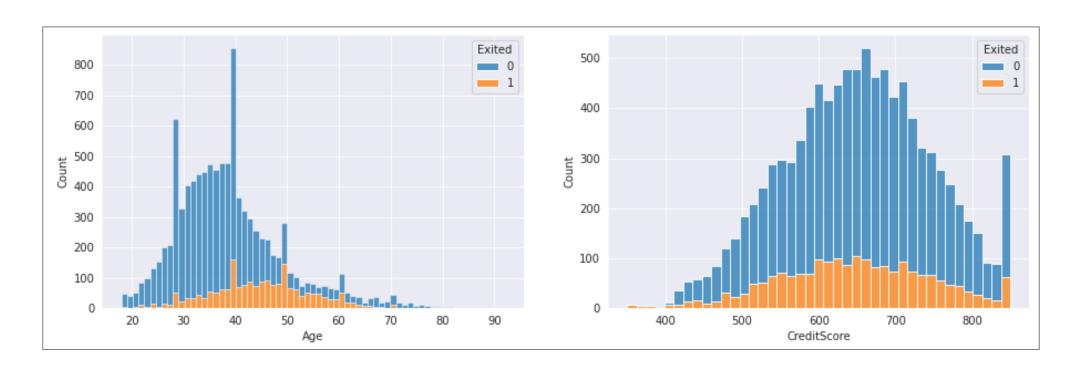
```
fig, axarr = plt.subplots( 2, 2, figsize=(15, 10))
sns.histplot(df, x="Age", hue = 'Exited', multiple="stack", ax=axarr[0][0])
sns.histplot(df, x="CreditScore", hue = 'Exited', multiple="stack", ax=axarr[0][1])
sns.histplot(df, x="Balance", hue = 'Exited', multiple="stack", ax=axarr[1][0])
sns.histplot(df, x="EstimatedSalary", hue = 'Exited', multiple="stack", ax=axarr[1][1])
```







- Most of our customers are between the age of 28 to 40.
- Credit Score seems like left skewed.





- Balances of the customers are seemed to be symmetrically distributed.
- There is not much variation in Estimated salary.

