

Pushpamala R  
19ITR066

Data Visualization and Pre-processing:  
Perform Below Tasks to complete the assignment:  
Tasks:

### 1. Download the dataset: Dataset

The screenshot shows a Google Drive interface with two tabs: 'Firewall Authentication Keepalive' and 'EL-IBM - Google Drive'. The main view displays the 'My Drive' folder containing two files: 'ASSIGNMENT-1\_19ITR066.docx' and 'Churn\_Modelling.csv'. The 'Churn\_Modelling.csv' file is selected, and a preview window is open showing the first 19 rows of the dataset. The preview window includes a table with columns A through J, representing various customer attributes and their corresponding churn status.

	A	B	C	D	E	F	G	H	I	J
	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts
1	1	15634602	Hargrave	619	France	Female	42	2	0	
2	2	15647311	Hill	608	Spain	Female	41	1	83807.86	
3	3	15619304	Onio	502	France	Female	42	8	159660.8	
4	4	15701354	Boni	699	France	Female	39	1	0	
5	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	
6	6	15574012	Chu	645	Spain	Male	44	8	113755.78	
7	7	15592531	Bartlett	822	France	Male	50	7	0	
8	8	15656148	Obinna	376	Germany	Female	29	4	115046.74	
9	9	15792365	He	501	France	Male	44	4	142051.07	
10	10	15592389	H?	684	France	Male	27	2	134603.88	
11	11	15767821	Bearce	528	France	Male	31	6	102016.72	
12	12	15737173	Andrews	497	Spain	Male	24	3	0	
13	13	15632264	Kay	476	France	Female	34	10	0	
14	14	15691483	Chin	549	France	Female	25	5	0	
15	15	15600882	Scott	635	Spain	Female	35	7	0	
16	16	15643966	Goforth	616	Germany	Male	45	3	143129.41	
17	17	15737452	Romeo	653	Germany	Male	58	1	132602.88	
18										
19							24	9	0	

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

## 2. Load the dataset.

```
data = pd.read_csv("/content/drive/MyDrive/EL-IBM/Churn_Modelling.csv")
```

data

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
<b>0</b>	1	15634602	Hargrave	619	France	Female	42	2
<b>1</b>	2	15647311	Hill	608	Spain	Female	41	1
<b>2</b>	3	15619304	Onio	502	France	Female	42	8
<b>3</b>	4	15701354	Boni	699	France	Female	39	1
<b>4</b>	5	15737888	Mitchell	850	Spain	Female	43	2
...	...	...	...	...	...	...	...	...
<b>9995</b>	9996	15606229	Obijiaku	771	France	Male	39	5
<b>9996</b>	9997	15569892	Johnstone	516	France	Male	35	10
<b>9997</b>	9998	15584532	Liu	709	France	Female	36	7
<b>9998</b>	9999	15682355	Sabbatini	772	Germany	Male	42	3
<b>9999</b>	10000	15628319	Walker	792	France	Female	28	4

10000 rows × 14 columns



data.tail()

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
<b>9995</b>	9996	15606229	Obijiaku	771	France	Male	39	5
<b>9996</b>	9997	15569892	Johnstone	516	France	Male	35	10
<b>9997</b>	9998	15584532	Liu	709	France	Female	36	7
<b>9998</b>	9999	15682355	Sabbatini	772	Germany	Male	42	3
<b>9999</b>	10000	15628319	Walker	792	France	Female	28	4



## 3. Perform Below Visualizations.

## Univariate Analysis

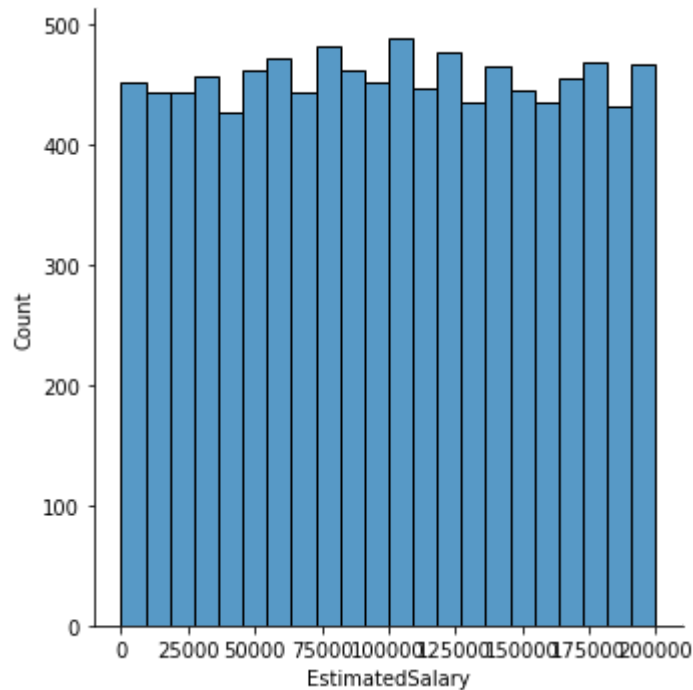
### Bi - Variate Analysis

### Multi - Variate Analysis

## Univariate Analysis

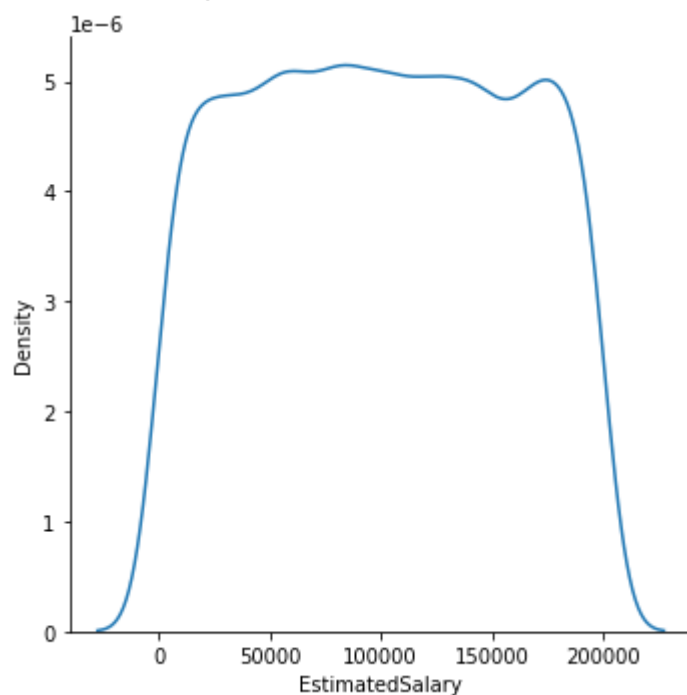
```
sns.displot(data.EstimatedSalary)
```

<seaborn.axisgrid.FacetGrid at 0x7f8303fbbb90>



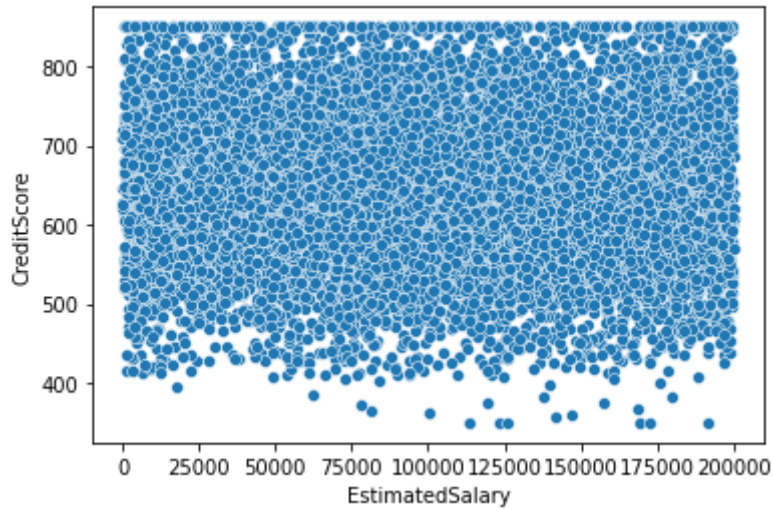
```
sns.displot(data.EstimatedSalary,kind="kde")
```

↗ <seaborn.axisgrid.FacetGrid at 0x7f82e8ae4d10>



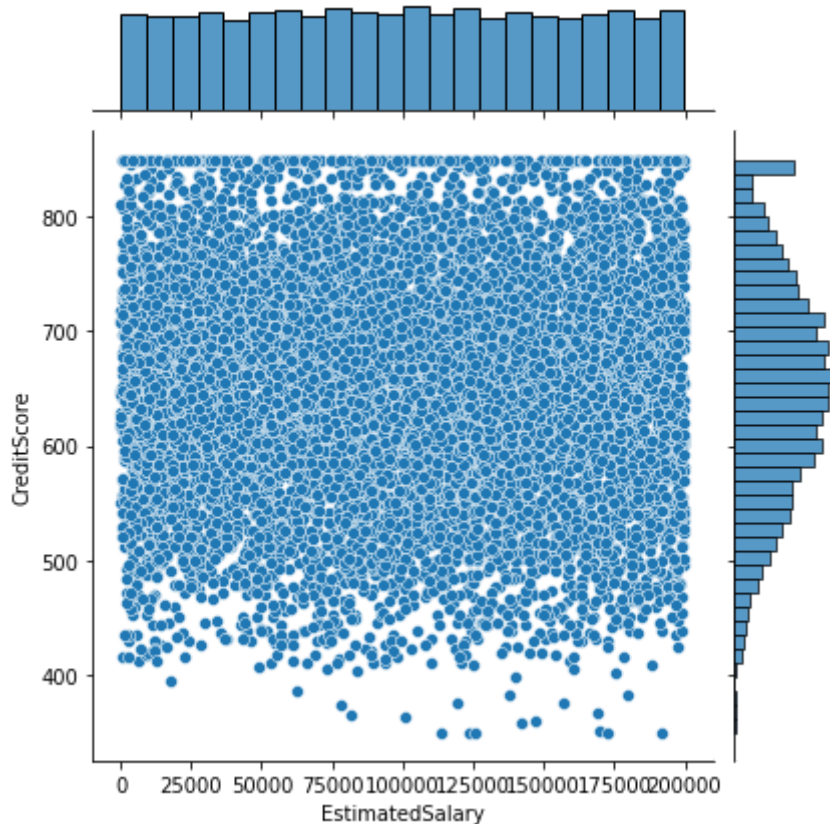
```
sns.scatterplot(data.EstimatedSalary,data.CreditScore)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass  
FutureWarning  
<matplotlib.axes._subplots.AxesSubplot at 0x7f82e864a250>
```



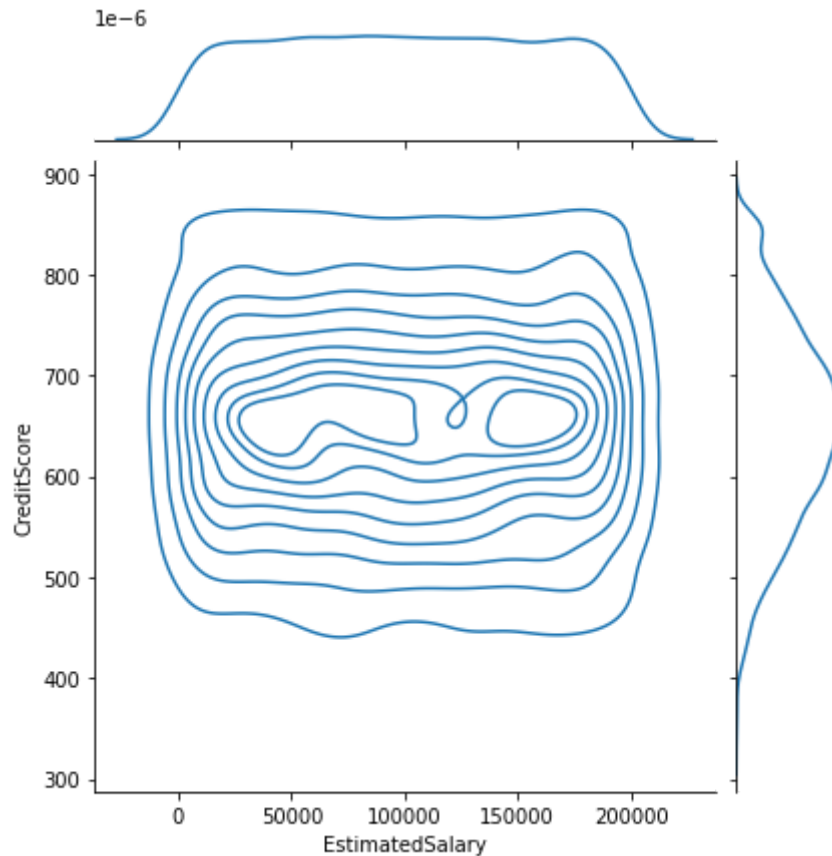
```
sns.jointplot(data.EstimatedSalary,data.CreditScore)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass  
FutureWarning  
<seaborn.axisgrid.JointGrid at 0x7f82e8584410>
```



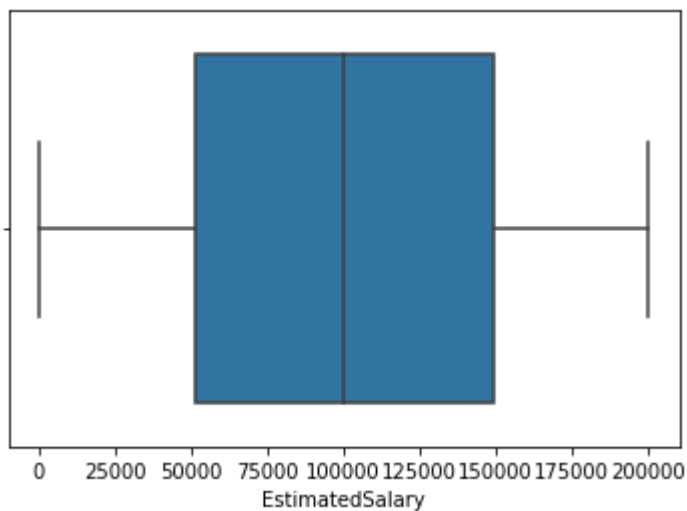
```
sns.jointplot(data.EstimatedSalary,data.CreditScore,kind="kde")
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass  
FutureWarning  
<seaborn.axisgrid.JointGrid at 0x7f82e6ba0ad0>
```



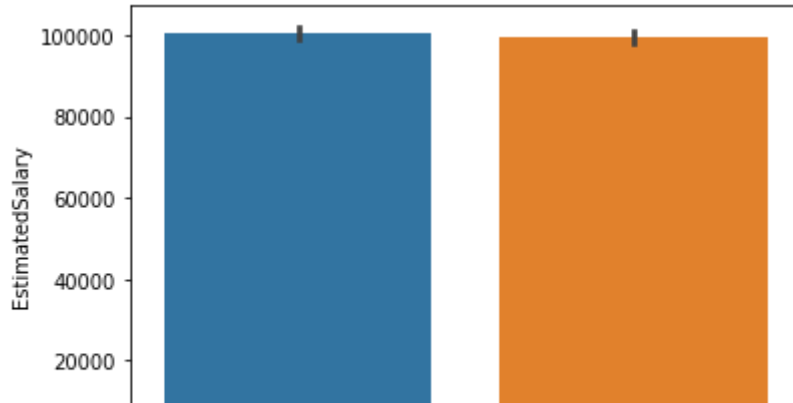
```
sns.boxplot(data.EstimatedSalary)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass  
FutureWarning  
<matplotlib.axes._subplots.AxesSubplot at 0x7f82e681f290>
```



```
sns.barplot(y = data.EstimatedSalary,x = data.Gender)
```

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f82e67d1cd0>



data.corr()

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts
RowNumber	1.000000	0.004202	0.005840	0.000783	-0.006495	-0.009067	
CustomerId	0.004202	1.000000	0.005308	0.009497	-0.014883	-0.012419	
CreditScore	0.005840	0.005308	1.000000	-0.003965	0.000842	0.006268	
Age	0.000783	0.009497	-0.003965	1.000000	-0.009997	0.028308	
Tenure	-0.006495	-0.014883	0.000842	-0.009997	1.000000	-0.012254	
Balance	-0.009067	-0.012419	0.006268	0.028308	-0.012254	1.000000	
NumOfProducts	0.007246	0.016972	0.012238	-0.030680	0.013444	-0.304180	
HasCrCard	0.000599	-0.014025	-0.005458	-0.011721	0.022583	-0.014858	
IsActiveMember	0.012044	0.001665	0.025651	0.085472	-0.028362	-0.010084	
EstimatedSalary	-0.005988	0.015271	-0.001384	-0.007201	0.007784	0.012797	
Exited	-0.016571	-0.006248	-0.027094	0.285323	-0.014001	0.118533	

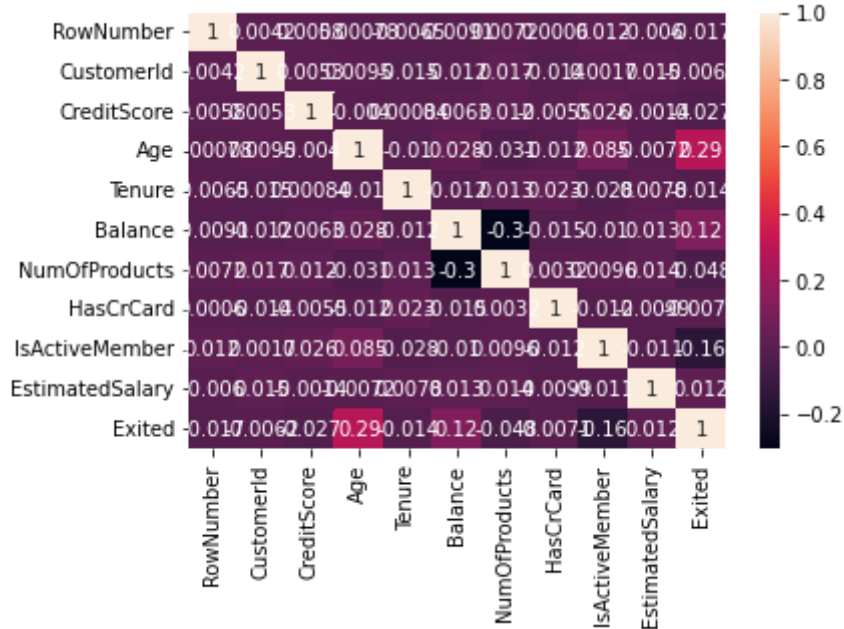
sns.heatmap(data.corr())

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f82e6b81150>
```



```
sns.heatmap(data.corr(),annot=True)
```

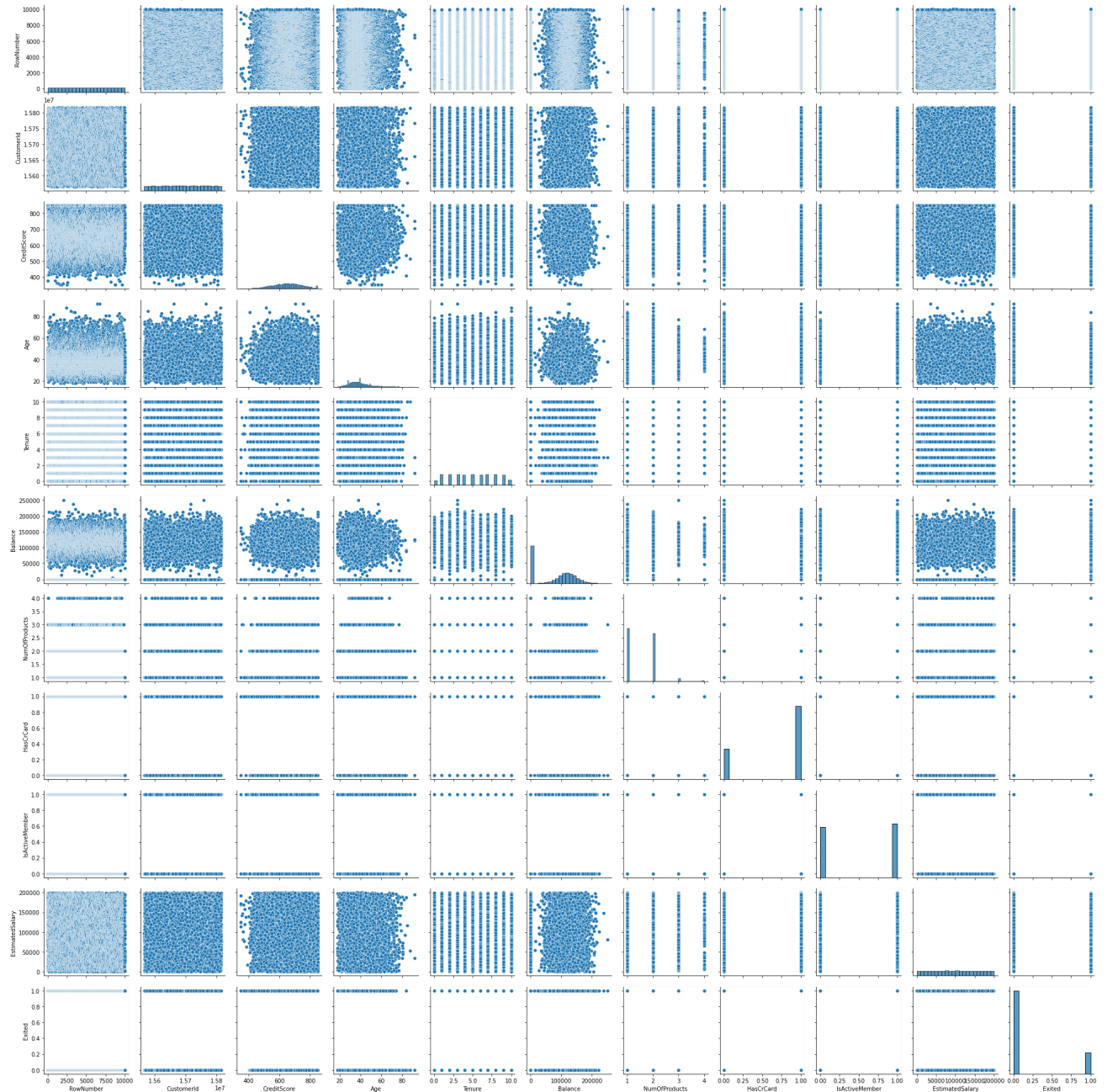
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f82e6654f50>
```



```
sns.pairplot(data)
```



```
<seaborn.axisgrid.PairGrid at 0x7f82e649b110>
```



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

```
data.sum(1)
```



```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: Droppi
    """Entry point for launching an IPython kernel.
0      15736618.88
1      15844315.44
2      15893456.37
3      15795925.63
4      15943385.92
...
9995   15713313.64
9996   15739522.38
9997   15637370.58
9998   15861138.83
9999   15807478.57
Length: 10000, dtype: float64

```

data.std()

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: Droppi
    """Entry point for launching an IPython kernel.
RowNumber      2886.895680
CustomerId     71936.186123
CreditScore     96.653299
Age            10.487806
Tenure         2.892174
Balance       62397.405202
NumOfProducts  0.581654
HasCrCard      0.455840
IsActiveMember 0.499797
EstimatedSalary 57510.492818
Exited         0.402769
dtype: float64

```

data.describe()

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance
<b>count</b>	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000
<b>mean</b>	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889000
<b>std</b>	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202
<b>min</b>	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000
<b>25%</b>	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000
<b>50%</b>	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000
<b>75%</b>	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000
<b>max</b>	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000

5. Handle the Missing values.

```
data.isnull()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
0	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...
9995	False	False	False	False	False	False	False	False
9996	False	False	False	False	False	False	False	False
9997	False	False	False	False	False	False	False	False
9998	False	False	False	False	False	False	False	False
9999	False	False	False	False	False	False	False	False

10000 rows × 14 columns



```
data[pd.isnull(data)]
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	E
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	...	
9995	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
9996	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
9997	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
9998	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
9999	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

10000 rows × 14 columns



```
data.isnull().sum()
```

```

RowNumber      0
CustomerId     0
Surname        0
CreditScore    0
Geography      0
Gender         0
Age           0
Tenure        0
Balance       0
NumOfProducts 0
HasCrCard     0
IsActiveMember 0
EstimatedSalary 0
Exited        0
dtype: int64

```

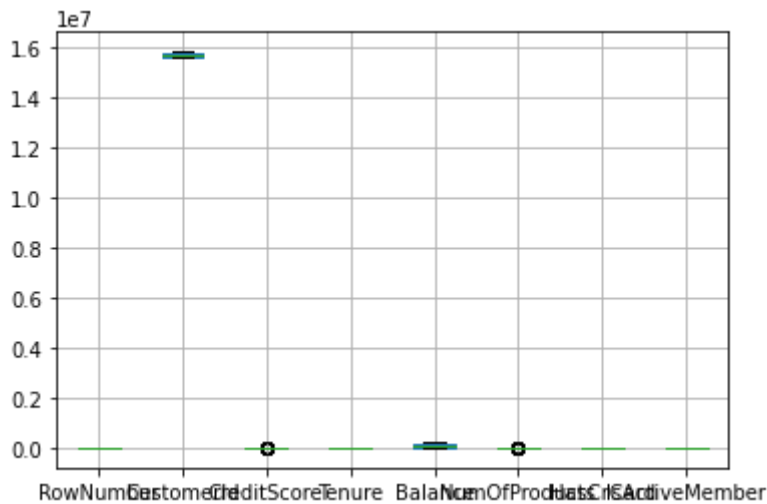
```
data["Gender"].fillna("No Gender", inplace = True)
```

6. Find the outliers and replace the outliers.

```
numeric_col = ['RowNumber', 'CustomerId', 'CreditScore', 'Tenure', 'Balance', 'NumOfProd
```

```
data.boxplot(numeric_col)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f82e3434e50>
```



```

for x in ['CreditScore']:
    q75,q25 = np.percentile(data.loc[:,x],[75,25])
    intr_qr = q75-q25

    max = q75+(1.5*intr_qr)
    min = q25-(1.5*intr_qr)

    data.loc[data[x] < min,x] = np.nan
    data.loc[data[x] > max,x] = np.nan

```

```
data.isnull().sum()
```

```
RowNumber      0
CustomerId     0
Surname        0
CreditScore    15
Geography      0
Gender         0
Age           0
Tenure        0
Balance        0
NumOfProducts 0
HasCrCard     0
IsActiveMember 0
EstimatedSalary 0
Exited        0
dtype: int64
```

```
data = data.dropna(axis=0)
data
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
0	1	15634602	Hargrave	619.0	France	Female	42	2
1	2	15647311	Hill	608.0	Spain	Female	41	1
2	3	15619304	Onio	502.0	France	Female	42	8
3	4	15701354	Boni	699.0	France	Female	39	1
4	5	15737888	Mitchell	850.0	Spain	Female	43	2
...	...	...	...	...	...	...	...	...
9995	9996	15606229	Obijiaku	771.0	France	Male	39	5
9996	9997	15569892	Johnstone	516.0	France	Male	35	10
9997	9998	15584532	Liu	709.0	France	Female	36	7
9998	9999	15682355	Sabbatini	772.0	Germany	Male	42	3
9999	10000	15628319	Walker	792.0	France	Female	28	4

9985 rows × 14 columns



```
data.isnull().sum()
```

```
RowNumber      0
CustomerId     0
Surname        0
CreditScore    0
Geography      0
Gender         0
Age           0
Tenure        0
Balance        0
NumOfProducts 0
```

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

## 7. Check for Categorical columns and perform encoding.

data.dtypes

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

```
obj = data.select_dtypes(include=['object']).copy()
obj.head()
```

	Surname	Geography	Gender
0	Hargrave	France	Female
1	Hill	Spain	Female
2	Onio	France	Female
3	Boni	France	Female
4	Mitchell	Spain	Female

```
obj[obj.isnull().any(axis=1)].sum()
```

```
Surname      0.0
Geography     0.0
Gender       0.0
dtype: float64
```

```
pd.get_dummies(obj, columns=["Geography"]).head()
```

	Surname	Gender	Geography_France	Geography_Germany	Geography_Spain	
0	Hargrave	Female	1	0	0	
1	Hill	Female	0	0	1	
2	Onio	Female	1	0	0	

```
pd.get_dummies(obj, columns=["Geography", "Gender"], prefix=["Geo", "Gen"]).head()
```

	Surname	Geo_France	Geo_Germany	Geo_Spain	Gen_Female	Gen_Male	
0	Hargrave	1	0	0	1	0	
1	Hill	0	0	1	1	0	
2	Onio	1	0	0	1	0	
3	Boni	1	0	0	1	0	
4	Mitchell	0	0	1	1	0	

```
data["CreditScore"].min()
```

```
383.0
```

```
data["CreditScore"].max()
```

```
850.0
```

```
data["CreditScore"].mean()
```

```
650.963244867301
```

```
data.count(0)
```

```

RowNumber      9985
CustomerId      9985
Surname         9985
CreditScore     9985
Geography       9985
Gender          9985
Age            9985
Tenure         9985
Balance        9985
NumOfProducts  9985
HasCrCard      9985
IsActiveMember 9985
EstimatedSalary 9985
Exited         9985
dtype: int64

```

```
data.shape
```

```
(9985, 14)
```

```
data.size
```

```
139790
```

```
data.iloc[:, :-1].values
```

```
array([[1, 15634602, 'Hargrave', ..., 1, 1, 101348.88],
       [2, 15647311, 'Hill', ..., 0, 1, 112542.58],
       [3, 15619304, 'Onio', ..., 1, 0, 113931.57],
       ...,
       [9998, 15584532, 'Liu', ..., 0, 1, 42085.58],
       [9999, 15682355, 'Sabbatini', ..., 1, 0, 92888.52],
       [10000, 15628319, 'Walker', ..., 1, 0, 38190.78]], dtype=object)
```

```
data.iloc[:, -1].values
```

```
array([1, 0, 1, ..., 1, 1, 0])
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit_transform(data[numeric_col])
```

```
array([[ -1.73298629, -0.78261344, -0.3327168 , ..., -0.91274609,
         0.64646813,  0.96951794],
       [ -1.7326397 , -0.6059255 , -0.44721972, ..., -0.91274609,
        -1.54686666,  0.96951794],
       [ -1.73229312, -0.99529517, -1.55061149, ...,  2.53031008,
         0.64646813, -1.03144043],
       ...,
       [ 1.73179791, -1.47871581,  0.60412526, ..., -0.91274609,
        -1.54686666,  0.96951794],
       [ 1.73214449, -0.11872336,  1.25991471, ...,  0.808782 ,
         0.64646813, -1.03144043],
       [ 1.73249107, -0.86996338,  1.46810183, ..., -0.91274609,
         0.64646813, -1.03144043]])
```

```
from sklearn.model_selection import train_test_split
X = data.loc[:, numeric_col]
categorical_col=['Surname','Geography','Gender']
y = data.loc[:, categorical_col]
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0, train_size = .75
X_train
```



	RowNumber	CustomerId	CreditScore	Tenure	Balance	NumOfProducts	HasCrCard
8158	8159	15744127	641.0	2	0.00	2	1
2469	2470	15630617	727.0	6	140418.81	1	1
6455	6456	15701522	711.0	9	0.00	2	1
2763	2764	15654495	706.0	6	120621.89	1	1
8243	8244	15572174	825.0	3	148874.01	2	1
...	...	...	...	...	...	...	...
9238	9239	15639133	773.0	4	0.00	2	1
4868	4869	15661330	754.0	6	0.00	1	1


X\_test

	RowNumber	CustomerId	CreditScore	Tenure	Balance	NumOfProducts	HasCrCard
335	336	15697441	485.0	7	182123.79	1	1
6245	6246	15722083	591.0	8	0.00	2	1
5807	5808	15607395	679.0	9	112528.65	2	1
6041	6042	15749472	775.0	8	0.00	1	1
8506	8507	15605215	767.0	9	0.00	2	1
...	...	...	...	...	...	...	...
5108	5109	15777772	650.0	9	119618.42	1	1
3052	3053	15605327	607.0	2	0.00	2	1
2337	2338	15660688	701.0	9	0.00	2	1
6866	6867	15664506	675.0	8	197436.82	1	1
641	642	15580684	706.0	5	112564.62	1	1

2497 rows × 8 columns



y\_train

	Surname	Geography	Gender	
8158	Kosovich	France	Female	
2469	Lo Duca	Germany	Male	
6455	Yermolayeva	France	Female	
2763	Potter	Germany	Female	
8243	Mazzi	France	Male	

y\_test

	Surname	Geography	Gender	
335	Hsueh	France	Male	
6245	Ch'ang	Spain	Male	
5807	Holt	France	Female	
6041	Lucciano	France	Male	
8506	Stevenson	France	Male	
...	...	...	...	
5108	Whittaker	Spain	Male	
3052	Namatjira	France	Male	
2337	King	Spain	Female	
6866	Goodwin	Spain	Male	
641	Feng	France	Female	

2497 rows × 3 columns