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In [1]:

```
import matplotlib.pyplot as plt import pandas as
pd import numpy as np import tensorflow as tf
import seaborn as sns from sklearn.compose import
ColumnTransformer from sklearn.pipeline import
Pipeline from sklearn.preprocessing import
OneHotEncoder from sklearn.preprocessing import
StandardScaler from sklearn.model_selection import
train_test_split
```

2. Load the data set

In [4]:

```
df = pd.read_csv(r"./Churn_Modelling.csv")
```

In [5]:

```
df.head()
```

Out[5]:N

	RowNumber	CustomerId	Surname	CreditScore	Geograp hy	Gend er	Ag e	Tenur e	Bal ce
0	1	15634602	Hargrave	619	France	Female	42	2	0.00
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86
2	3	15619304	Onio	502	France	Female	42	8	159660.80
3	4	15701354	Boni	699	France	Female	39	1	0.00
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82

3. Data Visualizations

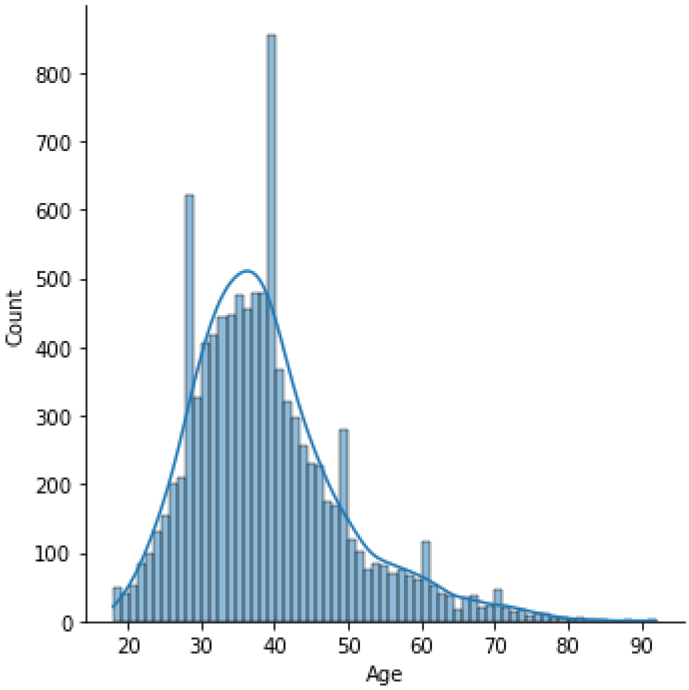
3.1. Univariate Analysis

In [6]:

```
sns.displot(df['Age'], kde=True)
```

<seaborn.axisgrid.FacetGrid at 0x1f63a02fa30>

Out[6]:



3.2. Bi - Variate Analysis

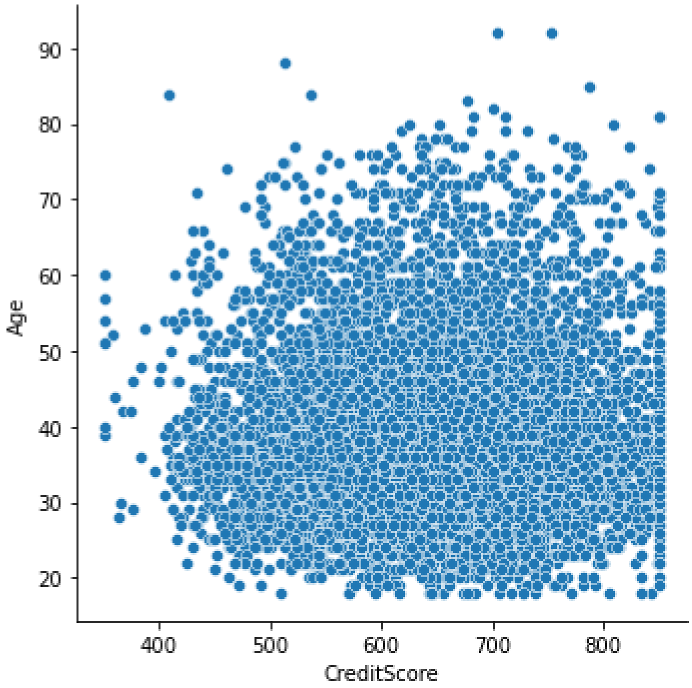
In [7]:

```
sns.relplot(x='CreditScore', y='Age', data=df)
```

<seaborn.axisgrid.FacetGrid at 0x1f63a024160>

Out[7]:

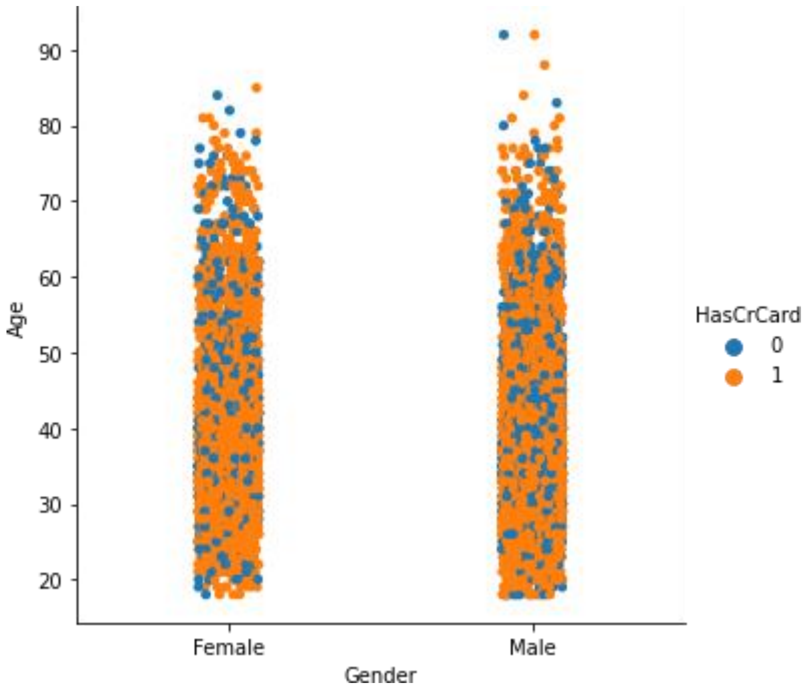
In [8]:




```
sns.catplot(x='Gender', y='Age', hue='HasCrCard', data=df)
```

<seaborn.axisgrid.FacetGrid at 0x1f647affeb0>

Out[8]:



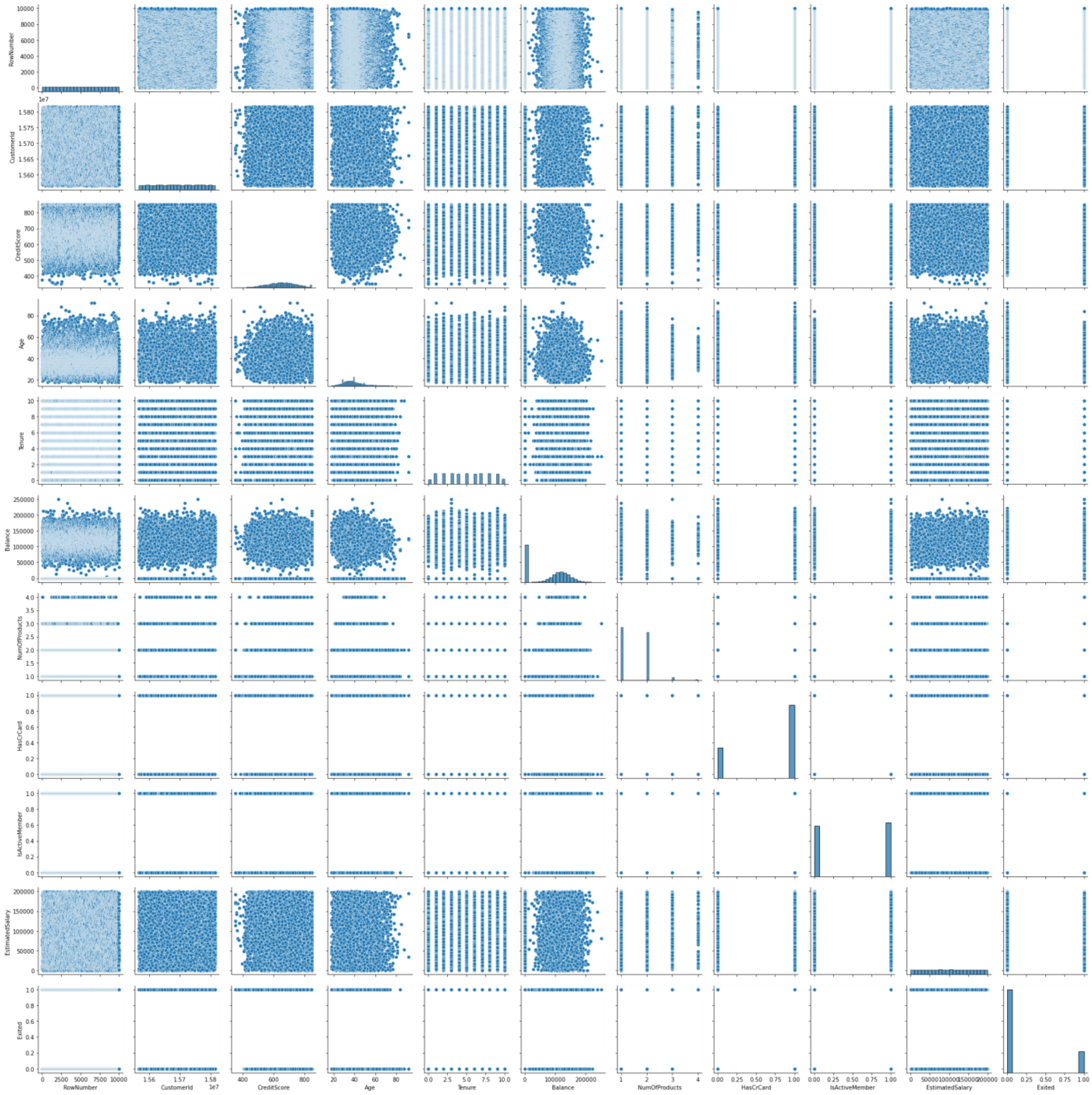
3.3. Multi - Variate Analysis

In [9]:

```
sns.pairplot(df)
```

<seaborn.axisgrid.PairGrid at 0x1f6483b69a0>

Out[9]:

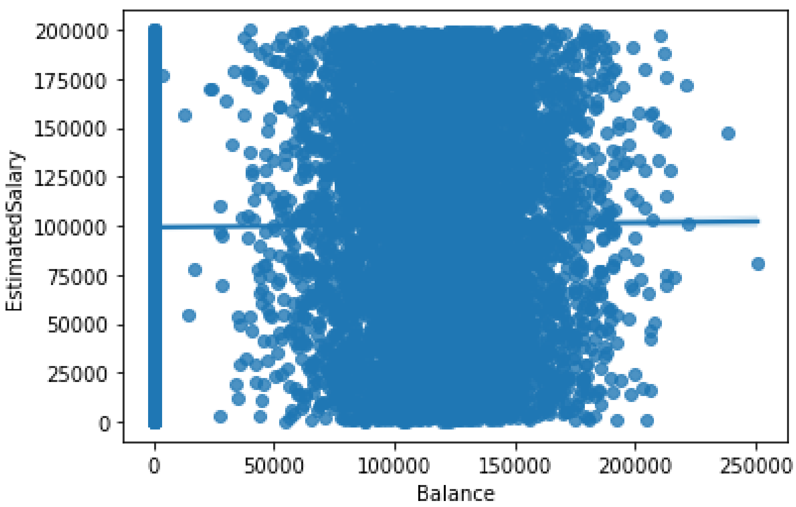


In [10]:

```python
sns.regplot(x='Balance', y='EstimatedSalary', data=df)
```

Out[10]:

<AxesSubplot:xlabel='Balance', ylabel='EstimatedSalary'>



4. Descriptive Statistics

In [11]:

```
df.describe()
```

Out[11]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOf
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	100
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	

5. Handle the Missing values

In [12]:

```
df.isnull().sum()
```

Out[12]:

```
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
```

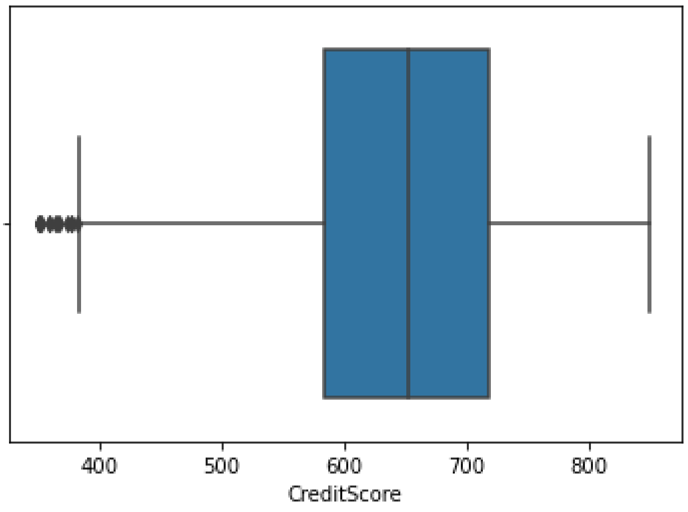
6. Find the outliers and replace the outliers

In [13]:

```
sns.boxplot(x='CreditScore',data=df)
```

Out[13]:

```
<AxesSubplot:xlabel='CreditScore'>
```



In [14]:

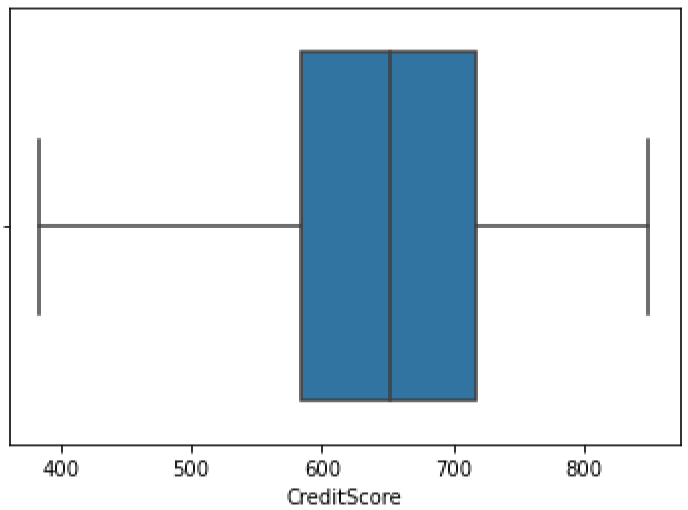
```
Q1 = df['CreditScore'].quantile(0.25)
Q3 = df['CreditScore'].quantile(0.75)
IQR = Q3 - Q1 whisker_width = 1.5
lower_whisker = Q1 - (whisker_width*IQR) upper_whisker = Q3 + (whisker_width*IQR)
df['CreditScore']=np.where(df['CreditScore']>upper_whisker,upper_whisker,np.where(df
```

In [15]:

```
sns.boxplot(x='CreditScore',data=df)
```

```
<AxesSubplot:xlabel='CreditScore'>
```

Out[15]:



7. Check for Categorical columns and perform encoding

```
In [16]: df['Geography'].unique()
    ct= ColumnTransformer([('oh', OneHotEncoder(), [4])],
                          remainder="passthrough")
```

8. Split the data into dependent and independent variables.

```
In [17]: x=df.iloc[:,0:12].values
     y=df.iloc[:,12:14].value
     s x[0:5,:]
```

Out[17]:
```
array([[1, 15634602, 'Hargrave', 619.0, 'France', 'Female', 42, 2, 0.0,
        1, 1, 1],
       [2, 15647311, 'Hill', 608.0, 'Spain', 'Female', 41, 1, 83807.86,
        1, 0, 1],
       [3, 15619304, 'Onio', 502.0, 'France', 'Female', 42, 8, 159660.8,
3, 1, 0],
       [4, 15701354, 'Boni', 699.0, 'France', 'Female', 39, 1, 0.0, 2, 0,
        0],
       [5, 15737888, 'Mitchell', 850.0, 'Spain', 'Female', 43, 2,
        125510.82, 1, 1, 1]], dtype=object)
```

In [18]:
```
x=ct.fit_transform(
x)
#INDEPENDENT VARIABLES
x[0:5,:]
```

Out[18]:
```
array([[1.0, 0.0, 0.0, 1, 15634602, 'Hargrave', 619.0, 'Female', 42, 2,
        0.0, 1, 1, 1],
       [0.0, 0.0, 1.0, 2, 15647311, 'Hill', 608.0, 'Female', 41, 1,
83807.86, 1, 0, 1],
       [1.0, 0.0, 0.0, 3, 15619304, 'Onio', 502.0, 'Female', 42, 8,
        159660.8, 3, 1, 0],
       [1.0, 0.0, 0.0, 4, 15701354, 'Boni', 699.0, 'Female', 39, 1, 0.0,
2, 0, 0],
       [0.0, 0.0, 1.0, 5, 15737888, 'Mitchell', 850.0, 'Female', 43, 2,
        125510.82, 1, 1, 1]], dtype=object)
```

In [19]:
```
#DEPENDENT VARIABLES
y[0:5,:]
```

Out[19]:
```
array([[1.0134888e+05, 1.0000000e+00],
       [1.1254258e+05, 0.0000000e+00],
[1.1393157e+05, 1.0000000e+00],
       [9.3826630e+04, 0.0000000e+00],
[7.9084100e+04, 0.0000000e+00]])
```

9. Scale the independent variables

In [20]:
```
sc= StandardScaler()
x[:,8:12]=sc.fit_transform(x[:,8:12])
x[0:5,:]
```

Out[20]:
```
array([[1.0, 0.0, 0.0, 1, 15634602, 'Hargrave', 619.0, 'Female',
        0.29351742289674765, -1.041759679225302, -1.2258476714090163,
        -0.911583494040172, 1, 1],
       [0.0, 0.0, 1.0, 2, 15647311, 'Hill', 608.0, 'Female',
0.19816383219544578, -1.387537586562431, 0.11735002143511637,
        -0.911583494040172, 0, 1],
```

```
        [1.0, 0.0, 0.0, 3, 15619304, 'Onio', 502.0, 'Female',
0.29351742289674765, 1.0329077647974714, 1.333053345722891,
        2.5270566192762067, 1, 0],
       [1.0, 0.0, 0.0, 4, 15701354, 'Boni', 699.0, 'Female',
        0.007456650792842043, -1.387537586562431, -1.2258476714090163,
        0.8077365626180174, 0, 0],        [0.0, 0.0, 1.0, 5,
15737888, 'Mitchell', 850.0, 'Female',
        0.3888710135980495, -1.041759679225302, 0.7857278997960621,
        -0.911583494040172, 1, 1]], dtype=object)
```

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3,
random_state=
```

10. Split the data into training and testing

In [21]:

```
x_train
```

In [22]:

Out[22]:

```
array([[1.0, 0.0, 0.0, ..., 0.8077365626180174, 1, 1],
       [1.0, 0.0, 0.0, ..., 0.8077365626180174, 1, 0],
[1.0, 0.0, 0.0, ..., -0.911583494040172, 0, 1],
...,
       [1.0, 0.0, 0.0, ..., 0.8077365626180174, 1, 0],
       [0.0, 0.0, 1.0, ..., 0.8077365626180174, 1, 1],
       [0.0, 1.0, 0.0, ..., -0.911583494040172, 1, 0]], dtype=object)
```

In [23]:

```
x_test
```

Out[23]:

```
array([[0.0, 1.0, 0.0, ..., -0.911583494040172, 1, 1],
       [1.0, 0.0, 0.0, ..., -0.911583494040172, 1, 0],
[0.0, 0.0, 1.0, ..., -0.911583494040172, 1, 1],
...,
       [1.0, 0.0, 0.0, ..., 0.8077365626180174, 1, 1],
       [1.0, 0.0, 0.0, ..., -0.911583494040172, 1, 1],
       [0.0, 1.0, 0.0, ..., -0.911583494040172, 1, 1]], dtype=object)
```

In [24]:

```
y_train
```

Out[24]:

```
array([[5.5796830e+04, 1.0000000e+00],
       [1.9823020e+04, 0.0000000e+00],
[1.3848580e+04, 0.0000000e+00],
...,
       [1.8142987e+05, 0.0000000e+00],
[1.4875016e+05, 0.0000000e+00],
       [1.1885526e+05, 1.0000000e+00]])
```

In [25]:

```
y_test
```

Out[25]:

```
array([[1.9285267e+05, 0.0000000e+00],
       [1.2870210e+05, 1.0000000e+00],
       [7.5732250e+04, 0.0000000e+00],
       ...,
       [1.6740029e+05, 0.0000000e+00],
       [7.0849470e+04, 0.0000000e+00],
       [3.3759410e+04, 1.0000000e+00]])
```