

# Assignment 2: Data Visualization and Pre-processing

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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]:
```

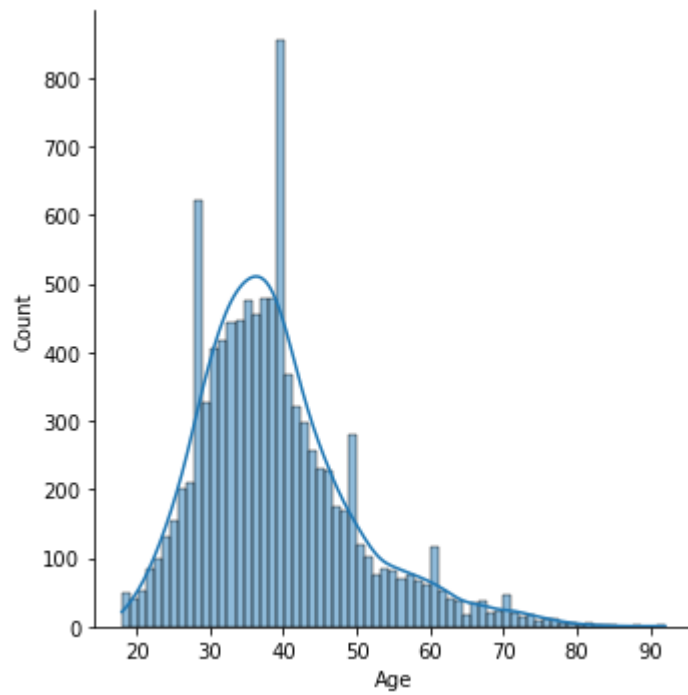
	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
0	1	15634602	Hargrave	619	France	Female	42	2	0.00
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86
2	3	15619304	Onio	502	France	Female	42	8	159660.80
3	4	15701354	Boni	699	France	Female	39	1	0.00
4	5	15737888	Mitchell	850	Spain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

## 3. Data Visualizations

### 3.1. Univariate Analysis

```
In [6]: sns.displot(df['Age'], kde=True)
```

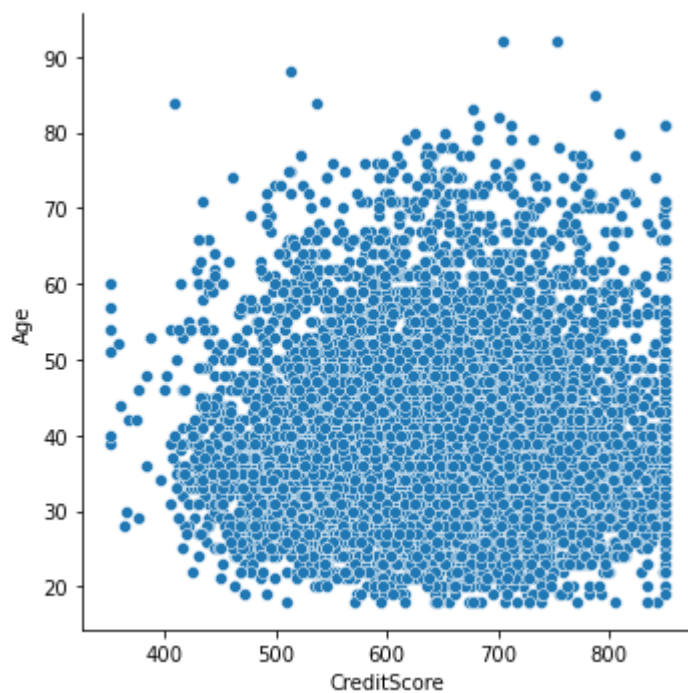
```
Out[6]: <seaborn.axisgrid.FacetGrid at 0x1f63a02fa30>
```



### 3.2. Bi - Variate Analysis

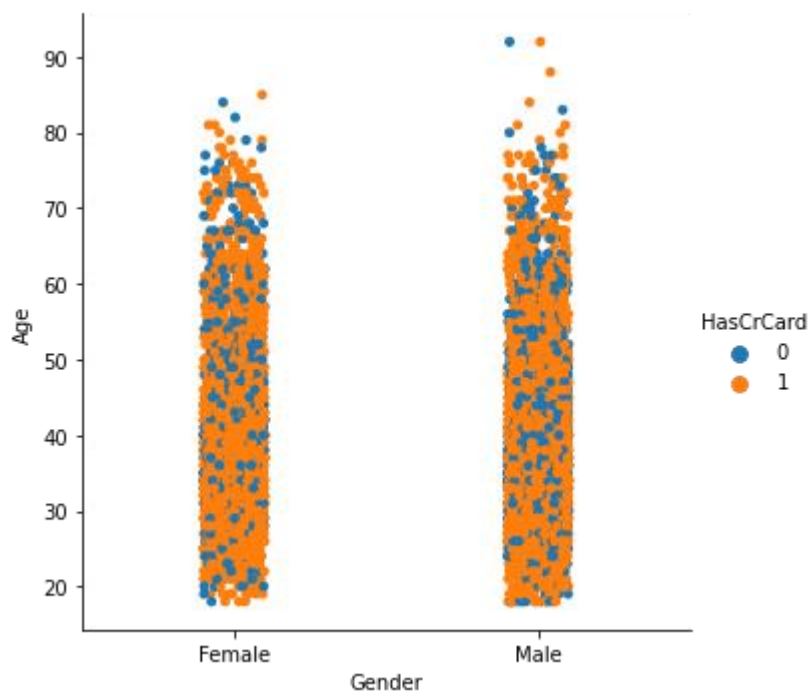
```
In [7]: sns.relplot(x='CreditScore', y='Age', data=df)
```

```
Out[7]: <seaborn.axisgrid.FacetGrid at 0x1f63a024160>
```



```
In [8]: sns.catplot(x='Gender', y='Age', hue='HasCrCard', data=df)
```

```
Out[8]: <seaborn.axisgrid.FacetGrid at 0x1f647affeb0>
```



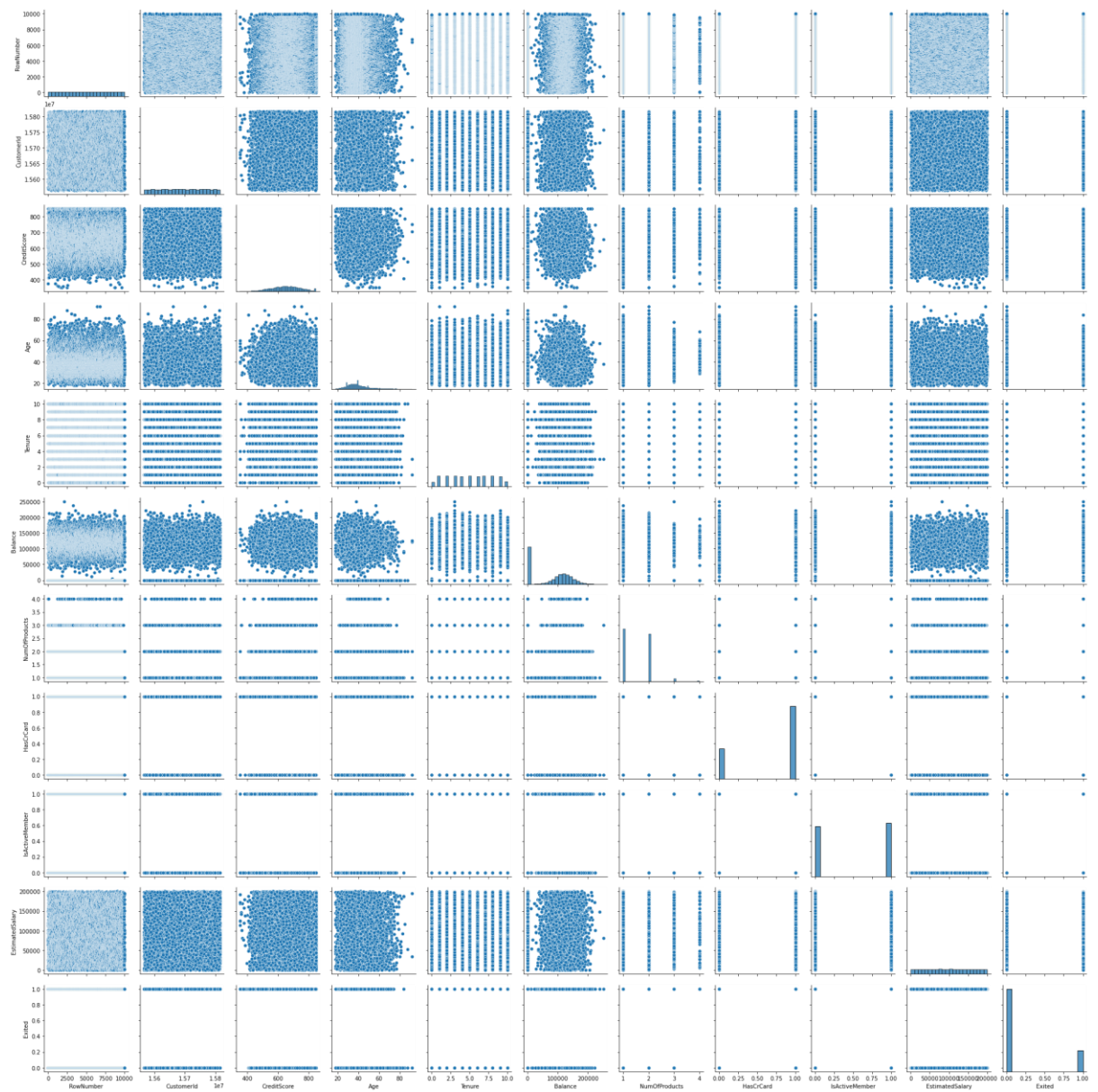
### 3.3. Multi - Variate Analysis

In [9]:

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

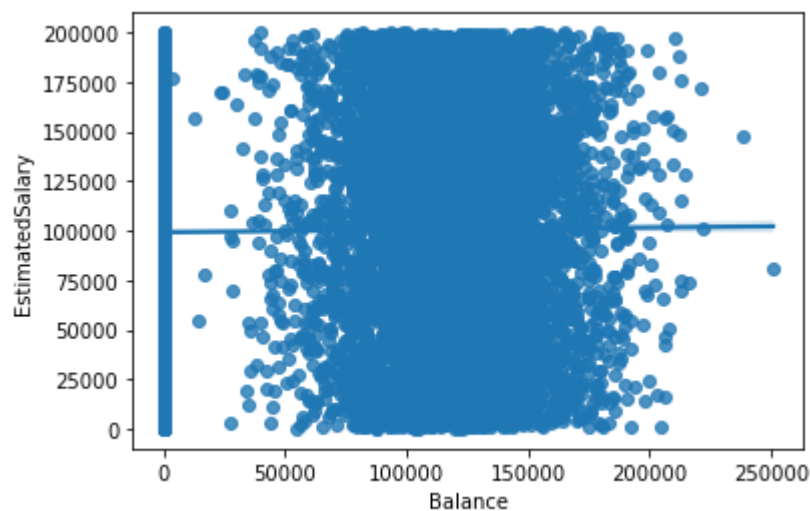
Out[9]:

```
<seaborn.axisgrid.PairGrid at 0x1f6483b69a0>
```



```
In [10]: 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	NumO
<b>count</b>	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	100
<b>mean</b>	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	
<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

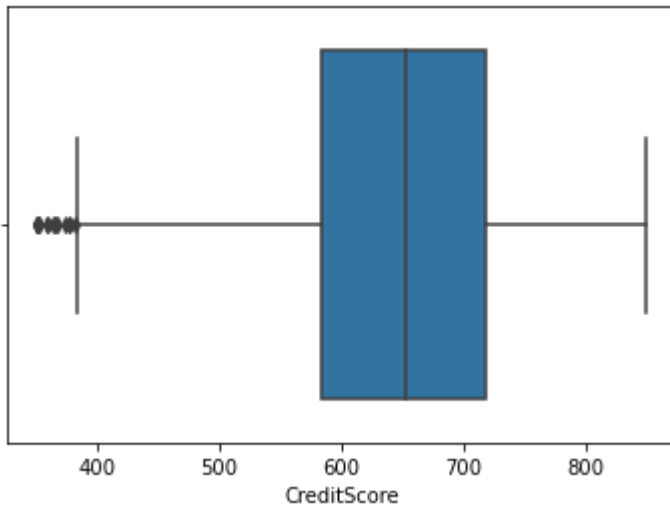
```
In [12]: df.isnull().sum()
```

```
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)
```

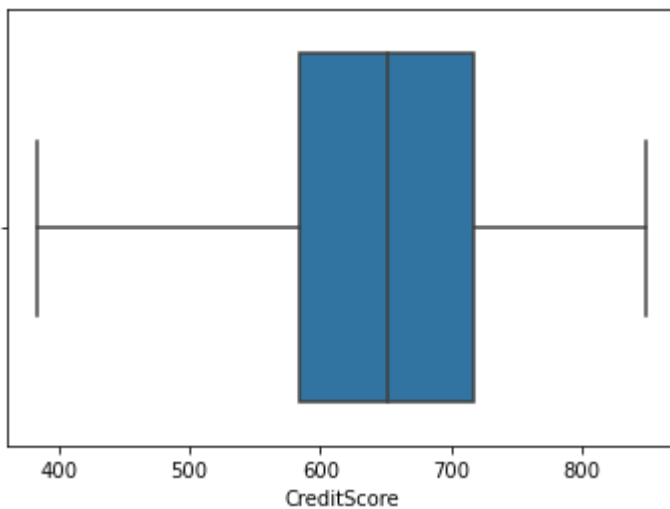
```
Out[13]: <AxesSubplot:xlabel='CreditScore'>
```



```
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)
```

```
Out[15]: <AxesSubplot:xlabel='CreditScore'>
```



## 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].values
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]: In [21]:

```



```

array([[ 742289674765, -1.041759679225302, -1.2258476714090163,
 1.0, -0.911583494040172, 1, 1],
 [0.0, 0.0, 1.0, 2, 15647311, 'Hill', 608.0, 'Female',
 0.19816383219544578, -1.387537586562431, 0.11735002143511637,
 0.0, 1, -0.911583494040172, 0, 1],
 'Hargrave', [1.0, 0.0, 0.0, 3, 15619304, 'Onio', 502.0, 'Female',
 0.29351742289674765, 1.0329077647974714, 1.333053345722891,
 619.0, 2.5270566192762067, 1, 0],
 'Female', [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, 0.0, 1.0, 5, 15737888, 'Mitchell', 850.0, 'Female',
 . 0.3888710135980495, -1.041759679225302, 0.7857278997960621,
 2, -0.911583494040172, 1, 1]], dtype=object)
9
3
5
1

```

## 10. Split the data into training and testing

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

In [22]: x\_train

```
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]])
```