

1. Importing Required Package

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

```
%matplotlib inline
```

1. Loading the Dataset

```
df=pd.read_csv('/content/Churn_Modelling.csv')
df
```

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

| | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | \ |
|------|--------|-----------|---------------|-----------|----------------|-----|
| 0 | 2 | 0.00 | 1 | 1 | | 1 |
| 1 | 1 | 83807.86 | 1 | 0 | | 1 |
| 2 | 8 | 159660.80 | 3 | 1 | | 0 |
| 3 | 1 | 0.00 | 2 | 0 | | 0 |
| 4 | 2 | 125510.82 | 1 | 1 | | 1 |
| ... | ... | ... | ... | ... | | ... |
| 9995 | 5 | 0.00 | 2 | 1 | | 0 |
| 9996 | 10 | 57369.61 | 1 | 1 | | 1 |
| 9997 | 7 | 0.00 | 1 | 0 | | 1 |
| 9998 | 3 | 75075.31 | 2 | 1 | | 0 |
| 9999 | 4 | 130142.79 | 1 | 1 | | 0 |

| | EstimatedSalary | Exited |
|------|-----------------|--------|
| 0 | 101348.88 | 1 |
| 1 | 112542.58 | 0 |
| 2 | 113931.57 | 1 |
| 3 | 93826.63 | 0 |
| 4 | 79084.10 | 0 |
| ... | ... | ... |
| 9995 | 96270.64 | 0 |
| 9996 | 101699.77 | 0 |
| 9997 | 42085.58 | 1 |
| 9998 | 92888.52 | 1 |
| 9999 | 38190.78 | 0 |

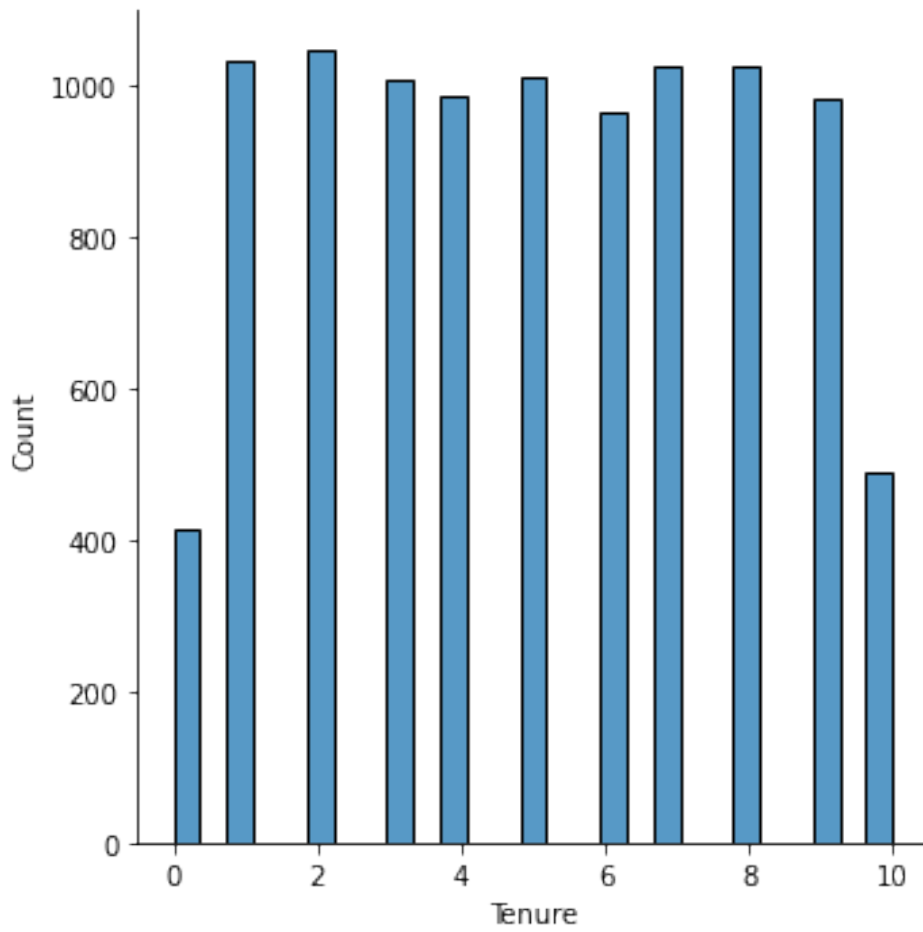
[10000 rows x 14 columns]

1. Visualizations

3.1 Univariate Analysis

```
sns.displot(df.Tenure)
```

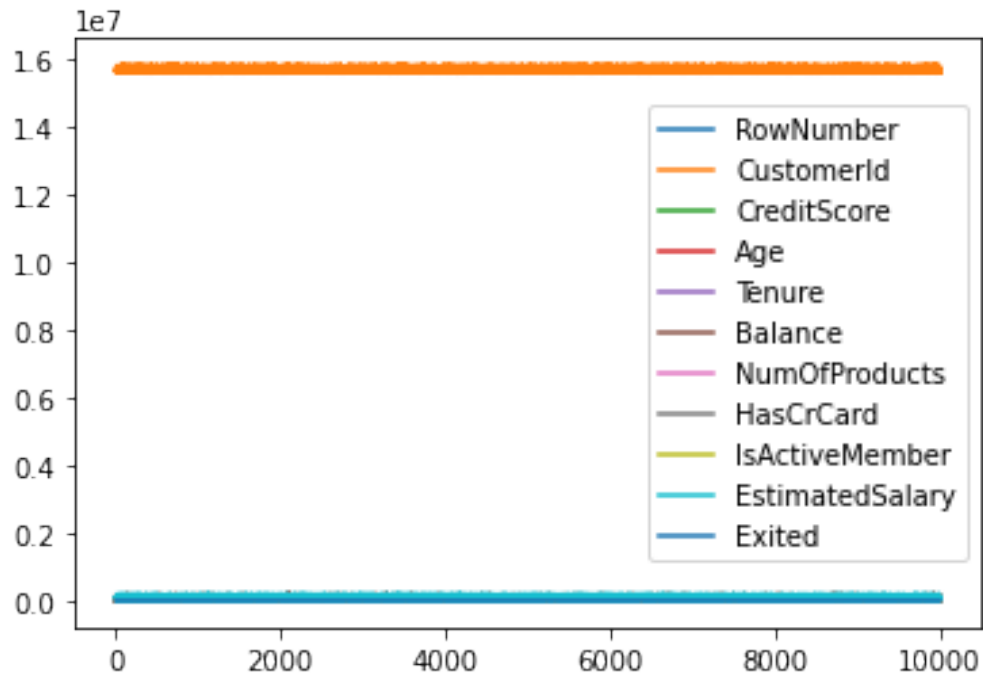
```
<seaborn.axisgrid.FacetGrid at 0x7fc35cdb3e10>
```



3.2 Bi-Variate Analysis

```
df.plot.line()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc359e7c410>
```

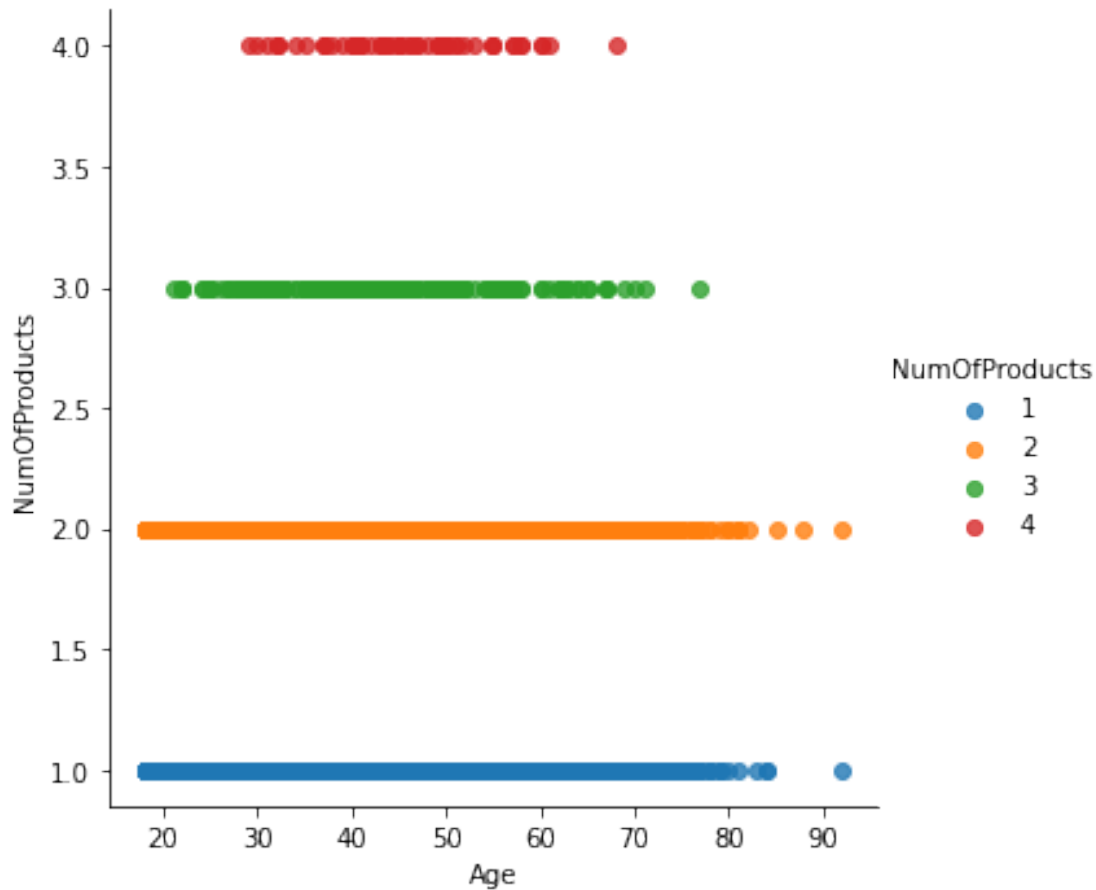


3.3 Multi - Variate Analysis

```
sns.lmplot("Age", "NumOfProducts", df, hue="NumOfProducts",
fit_reg=False);
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variables as keyword args: x, y,
data. From version 0.12, the only valid positional argument will be
`data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
```

```
FutureWarning
```



1. Perform descriptive statistics on the dataset
`df.describe()`

| | RowNumber | CustomerId | CreditScore | Age |
|----------|--------------|---------------|--------------|------------------|
| Tenure \ | | | | |
| count | 10000.000000 | 1.000000e+04 | 10000.000000 | 10000.000000 |
| mean | 5000.500000 | 1.569094e+07 | 650.528800 | 38.921800 |
| std | 2886.895682 | 7.193619e+04 | 96.653299 | 10.487806 |
| min | 1.000000 | 1.556570e+07 | 350.000000 | 18.000000 |
| 25% | 2500.750000 | 1.562853e+07 | 584.000000 | 32.000000 |
| 50% | 5000.500000 | 1.569074e+07 | 652.000000 | 37.000000 |
| 75% | 7500.250000 | 1.575323e+07 | 718.000000 | 44.000000 |
| max | 10000.000000 | 1.581569e+07 | 850.000000 | 92.000000 |
| | | | | |
| | Balance | NumOfProducts | HasCrCard | IsActiveMember \ |

| | | | | |
|-------|---------------|--------------|--------------|--------------|
| count | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 |
| mean | 76485.889288 | 1.530200 | 0.70550 | 0.515100 |
| std | 62397.405202 | 0.581654 | 0.45584 | 0.499797 |
| min | 0.000000 | 1.000000 | 0.00000 | 0.000000 |
| 25% | 0.000000 | 1.000000 | 0.00000 | 0.000000 |
| 50% | 97198.540000 | 1.000000 | 1.00000 | 1.000000 |
| 75% | 127644.240000 | 2.000000 | 1.00000 | 1.000000 |
| max | 250898.090000 | 4.000000 | 1.00000 | 1.000000 |

| | | |
|-------|-----------------|--------------|
| | EstimatedSalary | Exited |
| count | 10000.000000 | 10000.000000 |
| mean | 100090.239881 | 0.203700 |
| std | 57510.492818 | 0.402769 |
| min | 11.580000 | 0.000000 |
| 25% | 51002.110000 | 0.000000 |
| 50% | 100193.915000 | 0.000000 |
| 75% | 149388.247500 | 0.000000 |
| max | 199992.480000 | 1.000000 |

1. Handle the Missing values

```
data = pd.read_csv('/content/Churn_Modelling.csv')
pd.isnull(data["Gender"])
```

```
0      False
1      False
2      False
3      False
4      False
...
9995   False
9996   False
9997   False
9998   False
9999   False
```

Name: Gender, Length: 10000, dtype: bool

1. Find the outliers and replace the outliers

```
df["Tenure"] = np.where(df["Tenure"] > 10, np.median(df["Tenure"])
df["Tenure"]
```

```
0      2
1      1
2      8
3      1
4      2
...
9995   5
9996  10
9997   7
9998   3
```

```
9999      4
Name: Tenure, Length: 10000, dtype: object
```

```
1. Check for Categorical columns and perform encoding
pd.get_dummies(df, columns=["Gender", "Age"], prefix=["Age",
"Gender"]).head()
```

| RowNumber | CustomerId | Surname | CreditScore | Geography | Tenure |
|-----------|------------|----------|-------------|-----------|--------|
| 0 | 1 | Hargrave | 619 | France | 2 |
| 1 | 2 | Hill | 608 | Spain | 1 |
| 2 | 3 | Onio | 502 | France | 8 |
| 3 | 4 | Boni | 699 | France | 1 |
| 4 | 5 | Mitchell | 850 | Spain | 2 |

| | NumOfProducts | HasCrCard | IsActiveMember | ... | Gender_78 | Gender_79 |
|---|---------------|-----------|----------------|-----|-----------|-----------|
| 0 | 1 | 1 | 1 | ... | 0 | 0 |
| 1 | 1 | 0 | 1 | ... | 0 | 0 |
| 2 | 3 | 1 | 0 | ... | 0 | 0 |
| 3 | 2 | 0 | 0 | ... | 0 | 0 |
| 4 | 1 | 1 | 1 | ... | 0 | 0 |

| | Gender_80 | Gender_81 | Gender_82 | Gender_83 | Gender_84 | Gender_85 | \ |
|---|-----------|-----------|-----------|-----------|-----------|-----------|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | |

| | Gender_88 | Gender_92 |
|---|-----------|-----------|
| 0 | 0 | 0 |
| 1 | 0 | 0 |
| 2 | 0 | 0 |
| 3 | 0 | 0 |
| 4 | 0 | 0 |

```
[5 rows x 84 columns]
```

```
1. Split the data into dependent and independent variables
```

8.1 Split the data into Independent variables

```
X = df.iloc[:, :-2].values
print(X)

[[1 15634602 'Hargrave' ... 1 1 1]
 [2 15647311 'Hill' ... 1 0 1]
 [3 15619304 'Onio' ... 3 1 0]
 ...
 [9998 15584532 'Liu' ... 1 0 1]
 [9999 15682355 'Sabbatini' ... 2 1 0]
 [10000 15628319 'Walker' ... 1 1 0]]
```

8.2 Split the data into Dependent variables

```
import pandas as pd
df = pd.read_csv('/content/Churn_Modelling.csv')
Y = df.iloc[:, -1].values
print(Y)
```

```
[1 0 1 ... 1 1 0]
```

1. Scale the independent variables

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
```

```
df[["RowNumber"]]=scaler.fit_transform(df[["RowNumber"]])
print(df)
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender |
|-------|-----------|------------|-----------|-------------|-----------|--------|
| Age \ | | | | | | |
| 0 | 0.0000 | 15634602 | Hargrave | 619 | France | Female |
| 42 | | | | | | |
| 1 | 0.0001 | 15647311 | Hill | 608 | Spain | Female |
| 41 | | | | | | |
| 2 | 0.0002 | 15619304 | Onio | 502 | France | Female |
| 42 | | | | | | |
| 3 | 0.0003 | 15701354 | Boni | 699 | France | Female |
| 39 | | | | | | |
| 4 | 0.0004 | 15737888 | Mitchell | 850 | Spain | Female |
| 43 | | | | | | |
| ... | ... | ... | ... | ... | ... | ... |
| ... | | | | | | |
| 9995 | 0.9996 | 15606229 | Obijiaku | 771 | France | Male |
| 39 | | | | | | |
| 9996 | 0.9997 | 15569892 | Johnstone | 516 | France | Male |
| 35 | | | | | | |
| 9997 | 0.9998 | 15584532 | Liu | 709 | France | Female |
| 36 | | | | | | |
| 9998 | 0.9999 | 15682355 | Sabbatini | 772 | Germany | Male |
| 42 | | | | | | |
| 9999 | 1.0000 | 15628319 | Walker | 792 | France | Female |

| | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | \ |
|------|--------|-----------|---------------|-----------|----------------|-----|
| 0 | 2 | 0.00 | 1 | 1 | 1 | 1 |
| 1 | 1 | 83807.86 | 1 | 0 | 1 | 1 |
| 2 | 8 | 159660.80 | 3 | 1 | 0 | 0 |
| 3 | 1 | 0.00 | 2 | 0 | 0 | 0 |
| 4 | 2 | 125510.82 | 1 | 1 | 1 | 1 |
| ... | ... | ... | ... | ... | ... | ... |
| 9995 | 5 | 0.00 | 2 | 1 | 0 | 0 |
| 9996 | 10 | 57369.61 | 1 | 1 | 1 | 1 |
| 9997 | 7 | 0.00 | 1 | 0 | 1 | 1 |
| 9998 | 3 | 75075.31 | 2 | 1 | 0 | 0 |
| 9999 | 4 | 130142.79 | 1 | 1 | 0 | 0 |

| | EstimatedSalary | Exited |
|------|-----------------|--------|
| 0 | 101348.88 | 1 |
| 1 | 112542.58 | 0 |
| 2 | 113931.57 | 1 |
| 3 | 93826.63 | 0 |
| 4 | 79084.10 | 0 |
| ... | ... | ... |
| 9995 | 96270.64 | 0 |
| 9996 | 101699.77 | 0 |
| 9997 | 42085.58 | 1 |
| 9998 | 92888.52 | 1 |
| 9999 | 38190.78 | 0 |

[10000 rows x 14 columns]

1. Split the data into training and testing

```

from sklearn.model_selection import train_test_split
train_size=0.8
X = df.drop(columns = ['Tenure']).copy()
y = df['Tenure']
X_train, X_rem, y_train, y_rem = train_test_split(X,y, train_size=0.8)
test_size = 0.5
X_valid, X_test, y_valid, y_test = train_test_split(X_rem,y_rem,
test_size=0.5)
print(X_train.shape), print(y_train.shape)
print(X_valid.shape), print(y_valid.shape)
print(X_test.shape), print(y_test.shape)

(8000, 13)
(8000,)
(1000, 13)
(1000,)
(1000, 13)
(1000,)

```

(None, None)