

ASSIGNMENT-2  
PythonProgramming

AssignmentDate	29-09-2022
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MaximumMarks	2 Mark

Question-1:

### 1 . Importing Required

#### PackageSolution:

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

Question-2:

### 2. Loading the

#### DatasetSolution:

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

#### Output:

	RowNumber	CustomerId	Surname	Creditscore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	15606229	Obijaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	0
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 14 columns

### 3. Visualizations

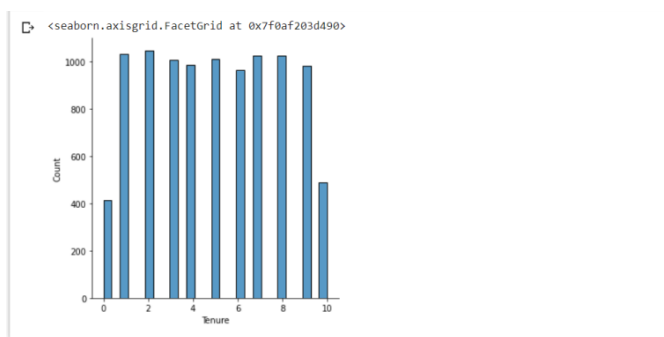
## Question-3:

### 3.1 UnivariateAnalysis

#### Solution:

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

#### Output:



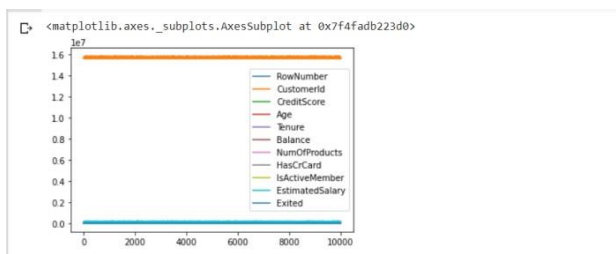
### 3.2 Bi-

### VariateAnalysisSolution:

#### on:

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

#### Output:

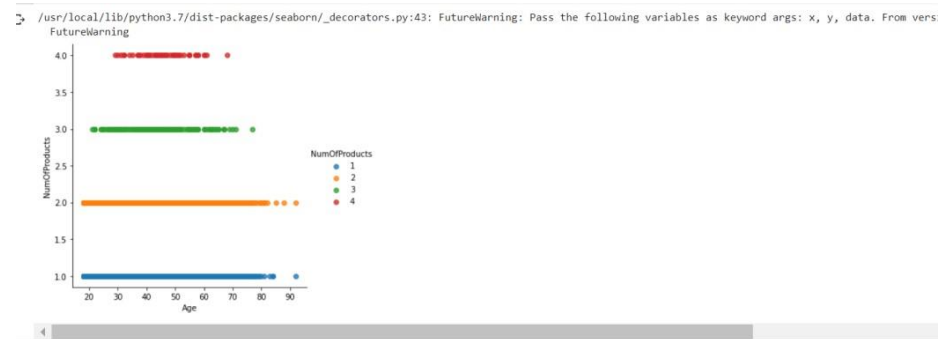


### 3.3 Multi-

### VariateAnalysisSolution:

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

## Output:



## 4. Performdescriptivestatisticsonthedataset.

### Question-4:

## Solution:

```
df.describe()
```

## Output:

	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	10000.000000	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	0.000000	0.000000	11.580000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.000000	0.000000	51002.110000	0.000000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.000000	1.000000	100193.915000	0.000000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.000000	1.000000	149388.247500	0.000000
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.000000	1.000000	199992.480000	1.000000

## 5. HandletheMissingvalues.

### Question-5:

## Solution:

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

## Output:

```
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
```

## Question-6:

### 6. Find the outliers and replace the outliers. Solution:

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

## Output:

```
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
```

## Question-7:

### 7. Check for categorical columns and perform encoding. Solution:

```
pd.get_dummies(df, columns=["Gender", "Age"], prefix=["Age", "Gender"])
).head()
```

## Output:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	...	Gender_78
0	1	15634602	Hargrave	619	France	2	0.00	1	1	1	...	0
1	2	15647311	Hill	608	Spain	1	83807.86	1	0	1	...	0
2	3	15619304	Onio	502	France	8	159660.80	3	1	0	...	0
3	4	15701354	Boni	699	France	1	0.00	2	0	0	...	0
4	5	15737888	Mitchell	850	Spain	2	125510.82	1	1	1	...	0

5 rows × 84 columns

## Output:

	HasCrCard	IsActiveMember	...	Gender_78	Gender_79	Gender_80	Gender_81	Gender_82	Gender_83	Gender_84	Gender_85	Gender_88	Gender_92
	1	1	...	0	0	0	0	0	0	0	0	0	0
	0	1	...	0	0	0	0	0	0	0	0	0	0
	1	0	...	0	0	0	0	0	0	0	0	0	0
	0	0	...	0	0	0	0	0	0	0	0	0	0
	1	1	...	0	0	0	0	0	0	0	0	0	0

5 rows × 84 columns

## Question-8:

### 8. Split the data into dependent and independent variables

#### 8.1 Split the data into independent variables. So

#### lution:

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

## Output:

```

[1 15634602 'Hangrave' ... 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. So

**lution:**

```

Y = df.iloc[:, -
1].values
print(Y)

```

**Output:**

```

[1 0 1 ... 1 1 0]

```

Question-9:

## 9. Scale the independent

**variables**

```

import pandas as pd
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df[["RowNumber"]] = scaler.fit_transform(df[["RowNumber"]])
print(df)

```

**Output:**

	Rollnumber	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	Objiaiku	771	France	Male	39		
9996	0.9997	15659892	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	28		
	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\			
0	2	0.00	0	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	125518.82	1	1	1				
...	...	...	...	...	...				
9995	5	0.00	2	1	1				
9996	10	57369.61	1	1	0				
9997	7	0.00	1	0	1				
9998	3	75075.31	2	1	0				
9999	4	130142.79	1	1	0				
	EstimatedSalary	Exited							
0	101348.08	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							

