

1.Download the dataset 2.Load the dataset

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

```
data=pd.read_csv("Churn_Modelling.csv",encoding='ISO-8859-1')
data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Bal
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	838
2	3	15619304	Onio	502	France	Female	42	8	1596
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	1255

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	RowNumber	CustomerId	CreditScore	Age	Tenure	Bal
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889000
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405000
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

```
data.dtypes
```

```
RowNumber      int64
CustomerId      int64
Surname         object
CreditScore     int64
```

```

Geography      object
Gender          object
Age            int64
Tenure         int64
Balance        float64
NumOfProducts int64
HasCrCard      int64
IsActiveMember int64
EstimatedSalary float64
Exited         int64
dtype: object

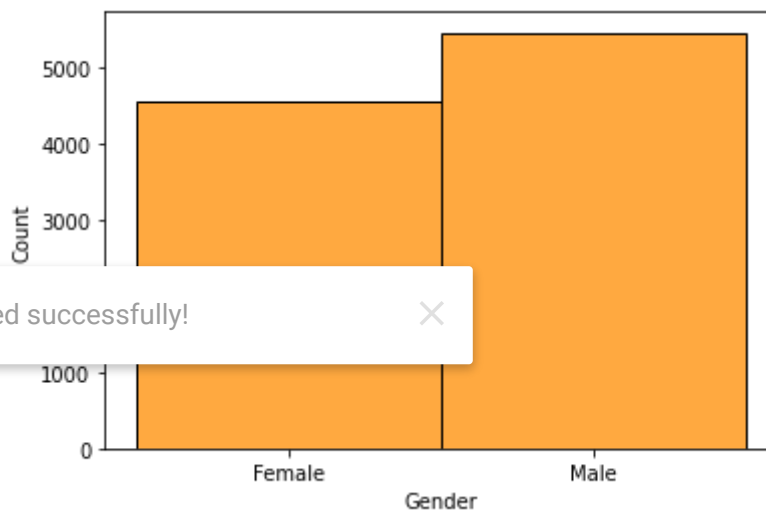
```

3.Perform Below Visualizations Univariate Analysis ,Bi - Variate Analysis,Multi - Variate Analysis

**

```
sns.histplot(data["Gender"],color='darkorange')
```

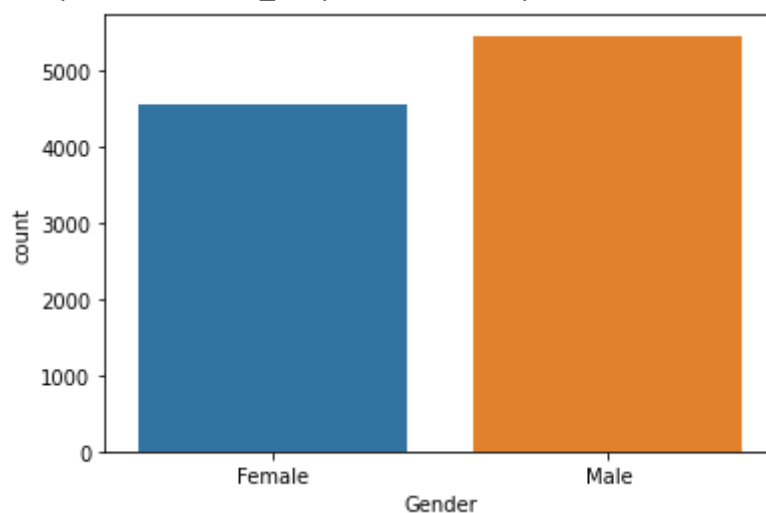
<matplotlib.axes._subplots.AxesSubplot at 0x7f3f675c9c50>



```
sns.countplot(data['Gender'])
```

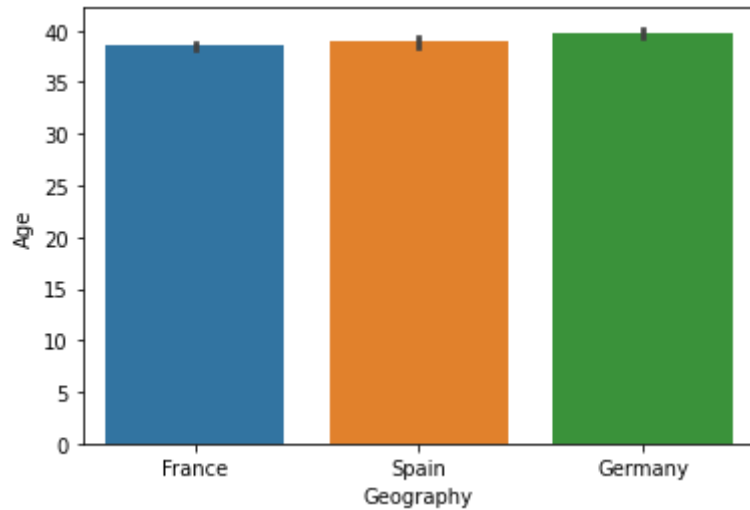
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass FutureWarning

<matplotlib.axes._subplots.AxesSubplot at 0x7f3f6752bf50>



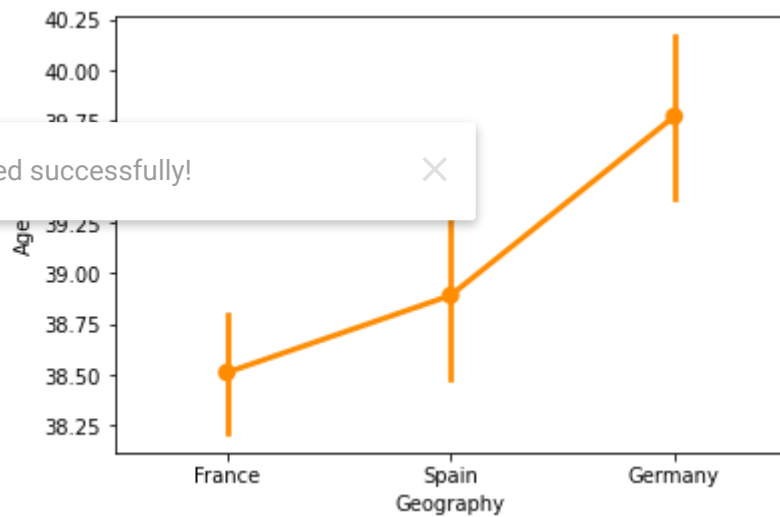
```
sns.barplot(x='Geography',y='Age',data=data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3f66ff5310>



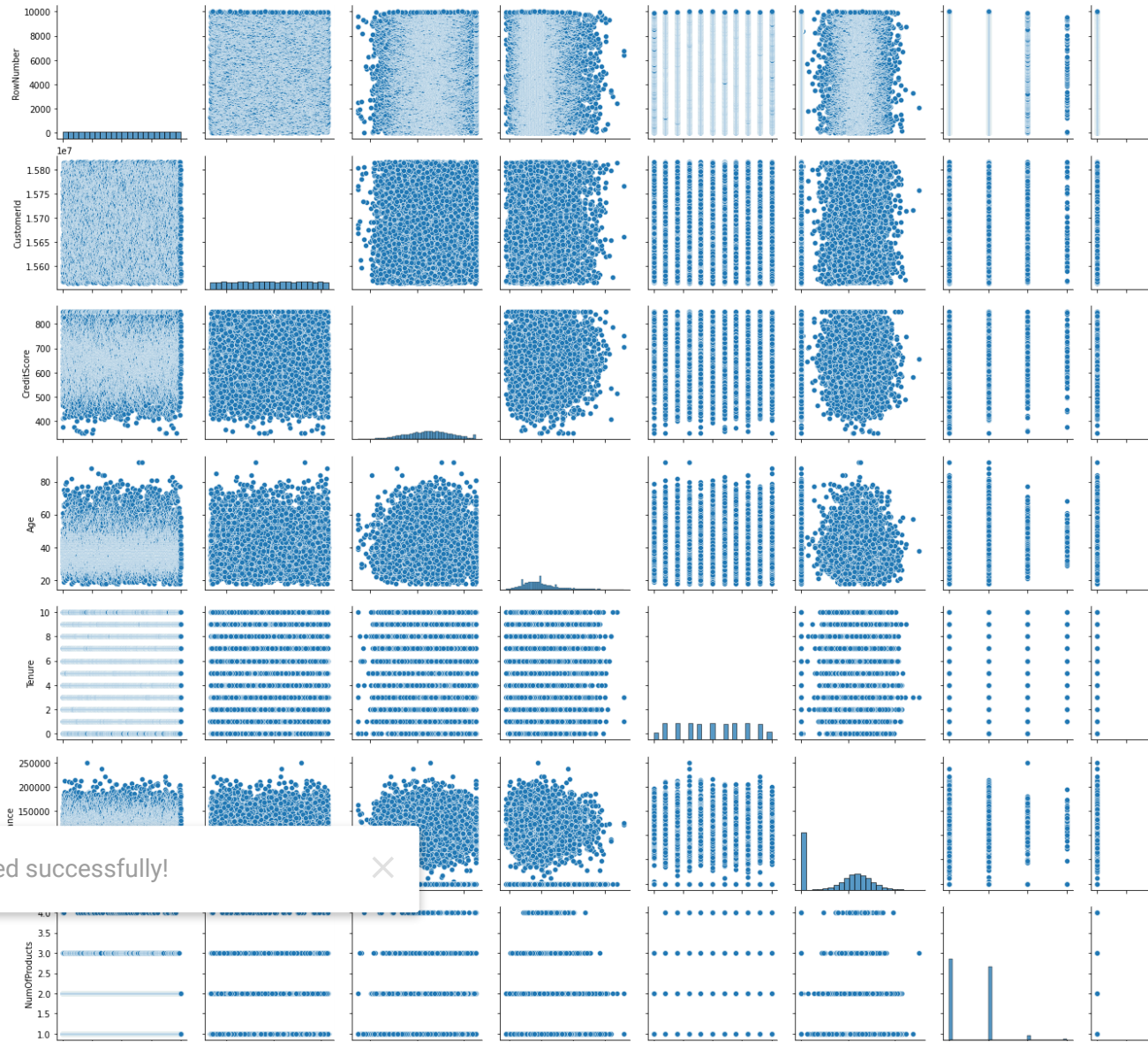
```
sns.pointplot(x='Geography',y='Age',data=data,color='darkorange')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f3f66f68810>



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

<seaborn.axisgrid.PairGrid at 0x7f3f66ee65d0>



4. Perform descriptive statistics on the dataset

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```
data.describe().T
```

	count	mean	std	min	25%	75%	max
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.000500e+03	10000.00
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.569074e+07	15690940.00
CreditScore	10000.0	6.505288e+02	96.653299	350.00	584.00	6.520000e+02	900.00

5. Handle the Missing values.

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

0

```
CustomerId      10000.0    1.569094e+07    71936.186123    15565701.00    15628528.25    1.569074e+07    15690940.00
```

There is no missing values in this dataset

```
EstimatedSalary  10000.0    1.000902e+05    57510.492818    11.58    51002.11    1.001939e+05    1000000.00
```

```
missing_values=data.isnull().sum()
```

```
missing_values[missing_values>0]/len(data)*100
```

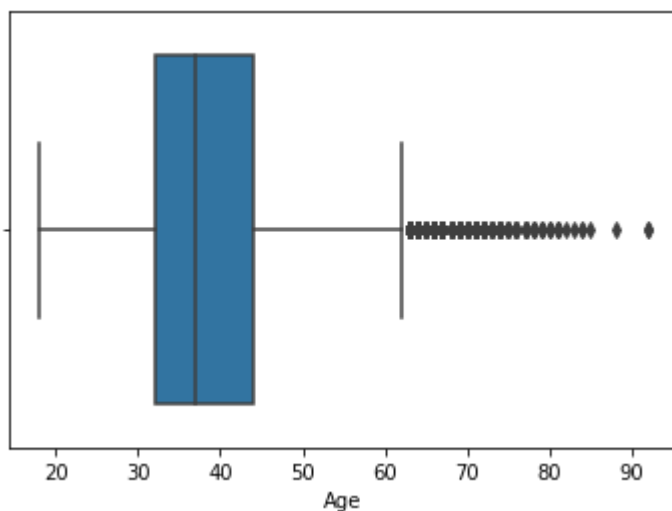
Series([], dtype: float64)

6. Find the outliers and replace the outliers

Saved successfully!



```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass
FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f3f617ca550>
```



7. Check for Categorical columns and perform encoding.

```
print(data['Gender'].unique())
```

```
print(data['Age'].unique())
```

['Female' 'Male']

```
[42 41 39 43 44 50 29 27 31 24 34 25 35 45 58 32 38 46 36 33 40 51 61 49
 37 19 66 56 26 21 55 75 22 30 28 65 48 52 57 73 47 54 72 20 67 79 62 53
 80 59 68 23 60 70 63 64 18 82 69 74 71 76 77 88 85 84 78 81 92 83]
```

```
data['Gender'].value_counts()
data['Age'].value_counts()
```

```
37    478
38    477
35    474
36    456
34    447
...
92     2
82     1
88     1
85     1
83     1
Name: Age, Length: 70, dtype: int64
```

```
one_hot_encoded_data = pd.get_dummies(data, columns = ['Age', 'Gender'])
print(one_hot_encoded_data)
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Tenure	\
0	1	15634602	Hargrave	619	France	2	
1	2	15647311	Hill	608	Spain	1	
			Onio	502	France	8	
			Boni	699	France	1	
			Mitchell	850	Spain	2	
...	
9995	9996	15606229	Obijiaku	771	France	5	
9996	9997	15569892	Johnstone	516	France	10	
9997	9998	15584532	Liu	709	France	7	
9998	9999	15682355	Sabbatini	772	Germany	3	
9999	10000	15628319	Walker	792	France	4	

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	Balance	NumOfProducts	HasCrCard	IsActiveMember	...	Age_80	\
0	0.00	1	1	1	...	0	
1	83807.86	1	0	1	...	0	
2	159660.80	3	1	0	...	0	
3	0.00	2	0	0	...	0	
4	125510.82	1	1	1	...	0	
...	
9995	0.00	2	1	0	...	0	
9996	57369.61	1	1	1	...	0	
9997	0.00	1	0	1	...	0	
9998	75075.31	2	1	0	...	0	
9999	130142.79	1	1	0	...	0	

	Age_81	Age_82	Age_83	Age_84	Age_85	Age_88	Age_92	Gender_Female	\
0	0	0	0	0	0	0	0		1
1	0	0	0	0	0	0	0		1
2	0	0	0	0	0	0	0		1
3	0	0	0	0	0	0	0		1
4	0	0	0	0	0	0	0		1
...
9995	0	0	0	0	0	0	0		0
9996	0	0	0	0	0	0	0		0

9997	0	0	0	0	0	0	0	1
9998	0	0	0	0	0	0	0	0
9999	0	0	0	0	0	0	0	1

```

Gender_Male
0      0
1      0
2      0
3      0
4      0
...
9995    1
9996    1
9997    0
9998    1
9999    0

```

[10000 rows x 84 columns]

8.Split the data into dependent and independent variables.

```
from sklearn.datasets import load_iris
```

```
from sklearn import preprocessing
data = load_iris()
```

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```

print("Dependent variable")
print(X_data)
print("Independent variable")
print(target)

```

```

Dependent variable
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]
 [5.7 4.4 1.5 0.4]
 [5.4 3.9 1.3 0.4]
 [5.1 3.5 1.4 0.3]
 [5.7 3.8 1.7 0.3]
 [5.1 3.8 1.5 0.3]
 [5.4 3.4 1.7 0.2]
 [5.1 3.7 1.5 0.4]

```

```
[4.6 3.6 1. 0.2]
[5.1 3.3 1.7 0.5]
[4.8 3.4 1.9 0.2]
[5. 3. 1.6 0.2]
[5. 3.4 1.6 0.4]
[5.2 3.5 1.5 0.2]
[5.2 3.4 1.4 0.2]
[4.7 3.2 1.6 0.2]
[4.8 3.1 1.6 0.2]
[5.4 3.4 1.5 0.4]
[5.2 4.1 1.5 0.1]
[5.5 4.2 1.4 0.2]
[4.9 3.1 1.5 0.2]
[5. 3.2 1.2 0.2]
[5.5 3.5 1.3 0.2]
[4.9 3.6 1.4 0.1]
[4.4 3. 1.3 0.2]
[5.1 3.4 1.5 0.2]
[5. 3.5 1.3 0.3]
[4.5 2.3 1.3 0.3]
[4.4 3.2 1.3 0.2]
[5. 3.5 1.6 0.6]
[5.1 3.8 1.9 0.4]
[4.8 3. 1.4 0.3]
[5.1 3.8 1.6 0.2]
[4.6 3.2 1.4 0.2]
[5.3 3.7 1.5 0.2]
[5. 3.3 1.4 0.2]
```

Saved successfully!



```
[5.5 2.3 4. 1.3]
[6.5 2.8 4.6 1.5]
[5.7 2.8 4.5 1.3]
[6.3 3.3 4.7 1.6]
```

9. Scale the independent variable

```
standard = preprocessing.scale(target)
print(standard)
```

```
[-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487 -1.22474487
-1.22474487 -1.22474487 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 1.22474487 1.22474487]
```



```

1.22474487 1.22474487 1.22474487 1.22474487 1.22474487 1.22474487
1.22474487 1.22474487 1.22474487 1.22474487 1.22474487 1.22474487
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1.22474487 1.22474487 1.22474487 1.22474487 1.22474487 1.22474487
1.22474487 1.22474487 1.22474487 1.22474487 1.22474487 1.22474487]

```

10.Split the data into training and testing

```

import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

```

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

```

X = df.iloc[:, :-1]
y = df.iloc[:, -1]

```

```

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.05, random_state=0)

```

Saved successfully!

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	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	\
799	800	15567367	Tao	601	Germany	Female	
1069	1070	15628674	Iadanza	844	France	Male	
8410	8411	15609913	Clark	743	France	Female	
9436	9437	15771000	Powell	684	France	Male	
5099	5100	15731555	Ross-Watt	595	Germany	Female	
...	
9225	9226	15584928	Ugochukwutubelum	594	Germany	Female	
4859	4860	15647111	White	794	Spain	Female	
3264	3265	15574372	Hoolan	738	France	Male	
9845	9846	15664035	Parsons	590	Spain	Female	
2732	2733	15592816	Udokamma	623	Germany	Female	

	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
799	42	9	133636.16	1	0	1	
1069	40	7	113348.14	1	1	0	
8410	46	9	0.00	1	1	0	
9436	38	4	0.00	3	1	0	
5099	45	9	106000.12	1	0	0	
...	
9225	32	4	120074.97	2	1	1	
4859	22	4	114440.24	1	1	1	
3264	35	5	161274.05	2	1	0	
9845	38	9	0.00	2	1	1	
2732	48	1	108076.33	1	1	0	

	EstimatedSalary
799	103315.74

```
1069      31904.31
8410      113436.08
9436      75609.84
5099      191448.96
...
9225      162961.79
4859      107753.07
3264      181429.87
9845      148750.16
2732      118855.26
```

```
[9500 rows x 13 columns]      RowNumber  CustomerId  Surname  CreditScore  Geog
9394      9395      15615753  Upchurch      597      Germany  Female      35
898      899      15654700  Fallaci      523      France  Female      40
2398      2399      15633877  Morrison      706      Spain  Female      42
5906      5907      15745623  Worsnop      788      France  Male      32
2343      2344      15765902  Gibson      706      Germany  Male      38
...
8938      8939      15722409  Ritchie      693      Spain  Male      47
9291      9292      15679804  Esquivel      636      France  Male      36
491      492      15699005  Martin      710      France  Female      41
2021      2022      15795519  Vasiliev      716      Germany  Female      18
4299      4300      15711991  Chiawuotu      615      France  Male      30
```

```
      Tenure      Balance  NumOfProducts  HasCrCard  IsActiveMember  \
9394      8      131101.04      1      1      1
898      2      102967.41      1      1      0
2398      8      95386.82      1      1      1
```

Saved successfully!

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