

# Data Visualization and Pre-processing

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

## 2. Load the dataset

*#1. Loading DataSet*

```
df=pd.read_csv('C:/Users/Pavi/Downloads/Churn_Modelling.csv')
df
```

	Row Number	Customer Id	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
9999	9997	15569892	Johnston	516	France	Male	35	10	57369.6	1	1	1	101699.77	0

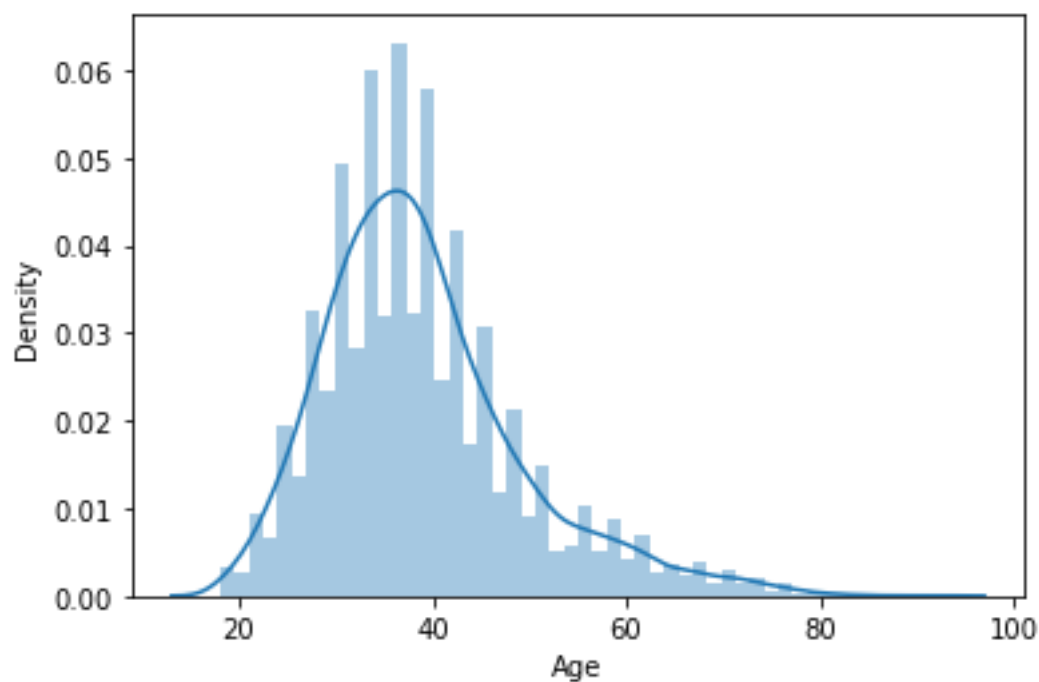
	Row Number	Customer Id	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
6			ne						1					
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1
9998	9999	15682355	Sabattini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 14 columns

## 2. Perform Univariate, Bi - Variate and Multi - Variate Analysis Visualizations

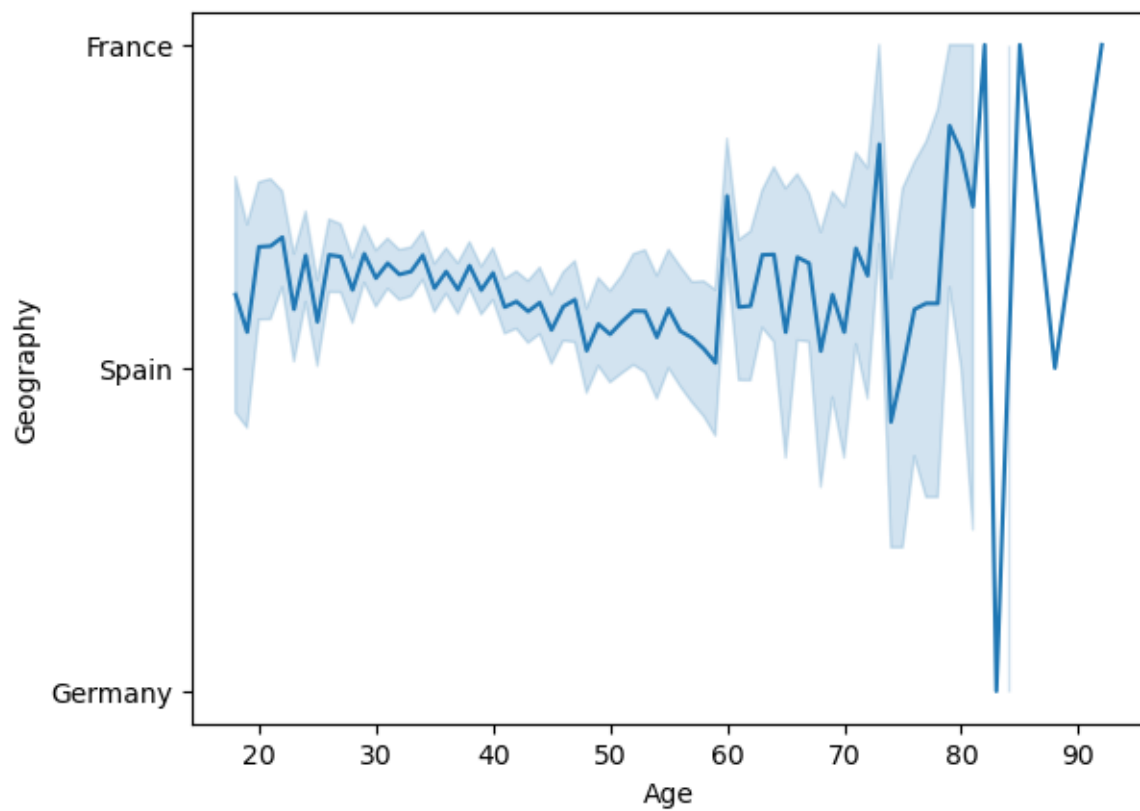
```
sns.distplot(df.Age) #Univariate Analysis
```

```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```



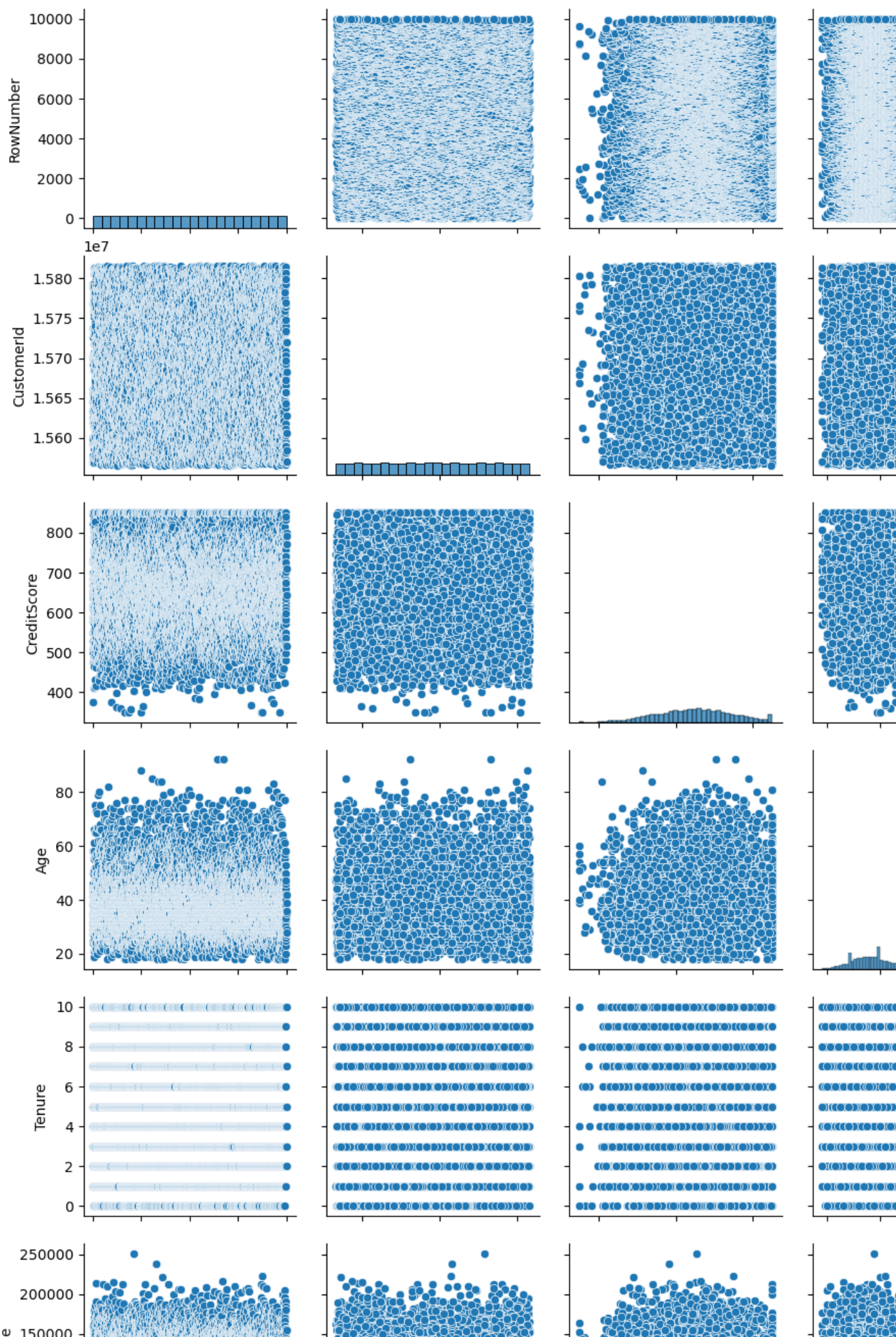
```
sns.lineplot(df.Age,df.Geography) # Bi - Variate Analysis
```

```
<AxesSubplot:xlabel='Age', ylabel='Geography'>
```



```
sns.pairplot(df) #Multi - Variate Analysis
```

```
<seaborn.axisgrid.PairGrid at 0x2055b3070a0>
```



## 4. Perform descriptive statistics on the dataset.

df.describe()

	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. Handle the Missing values.

df.isnull().any()

RowNumber	False
CustomerId	False
Surname	False
CreditScore	False
Geography	False
Gender	False
Age	False

```

Tenure      False
Balance     False
NumOfProducts  False
HasCrCard   False
IsActiveMember  False
EstimatedSalary  False
Exited      False
dtype: bool
df['CreditScore'].fillna(df['CreditScore'].mean(),inplace=True)
df

```

Row Number	Customer Id	Sur name	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	1931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	26.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...	...	.
9995	9996	15606229	Obijaku	771	France	Male	39	5	0.00	2	1	96270.64	0
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	101699.77	0
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	42085.58	1

Row Number	Customer Id	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	
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

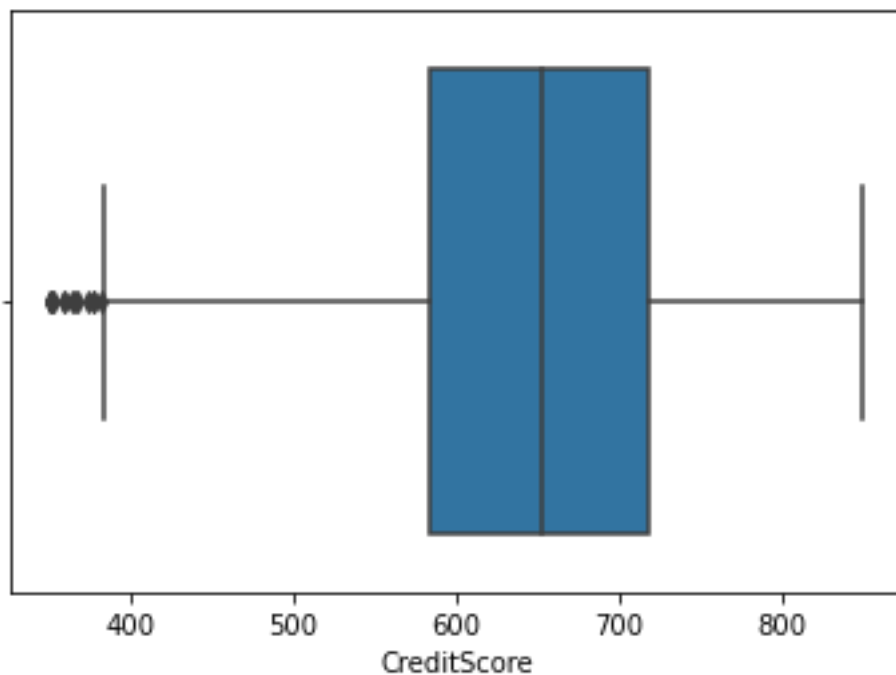
10000 rows × 14 columns

```
df['Gender'].fillna(df['Gender'].mode(),inplace=True)
```

## 5. outlier detection

```
sns.boxplot(df.CreditScore)
```

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



## outlier removal- IQR method

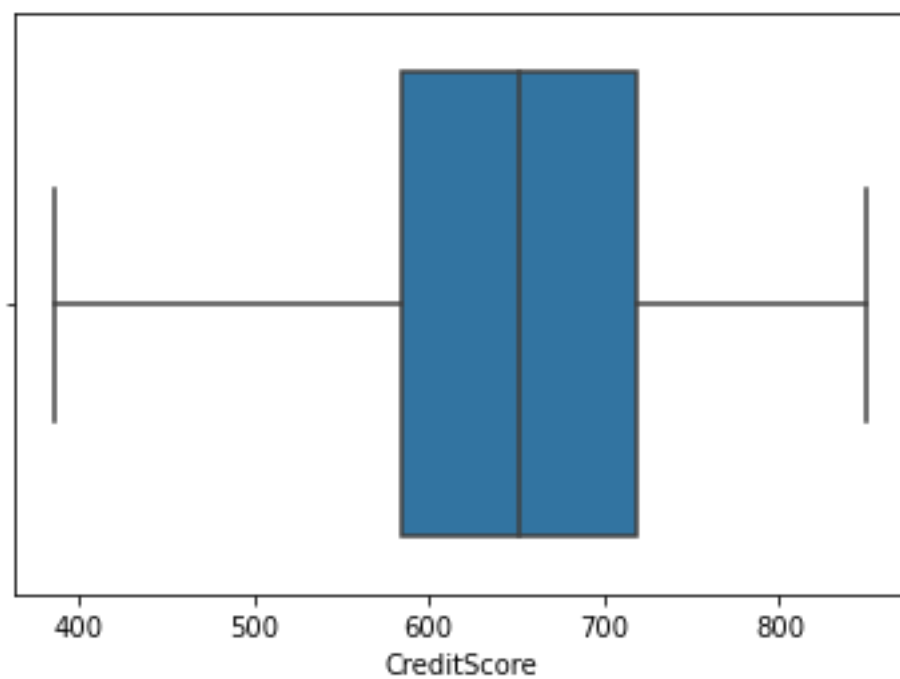
```
Q1= df.CreditScore.quantile(0.25)
```

```
Q3=df.CreditScore.quantile(0.75)
```

```
IQR=Q3-Q1
```

```
IQR
134.0
upper_limit = Q3 + 1.5*IQR
lower_limit = Q1 - 1.5*IQR
upper_limit
919.0
lower_limit
383.0
df=df[df.CreditScore>lower_limit]
sns.boxplot(df.CreditScore)

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



```
df.shape
(9984, 14)
```

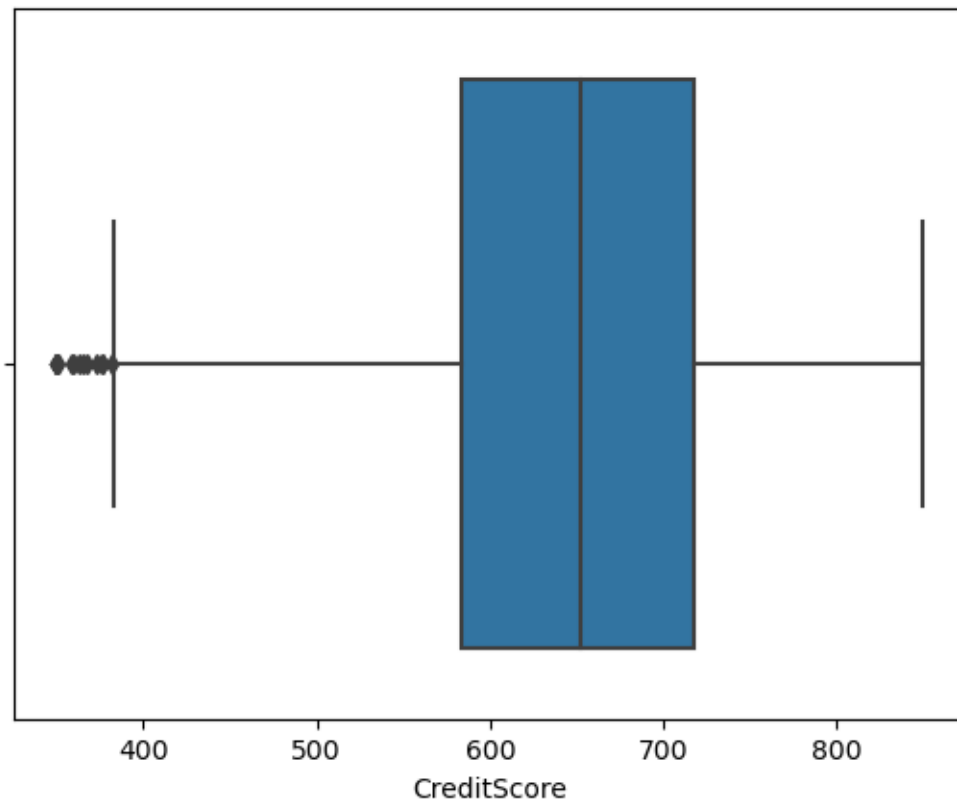
Out[11]:

## Outlier replacement using median

In [23]:

```
sns.boxplot(df.CreditScore)
```





```
df.shape
```

Out[11]:

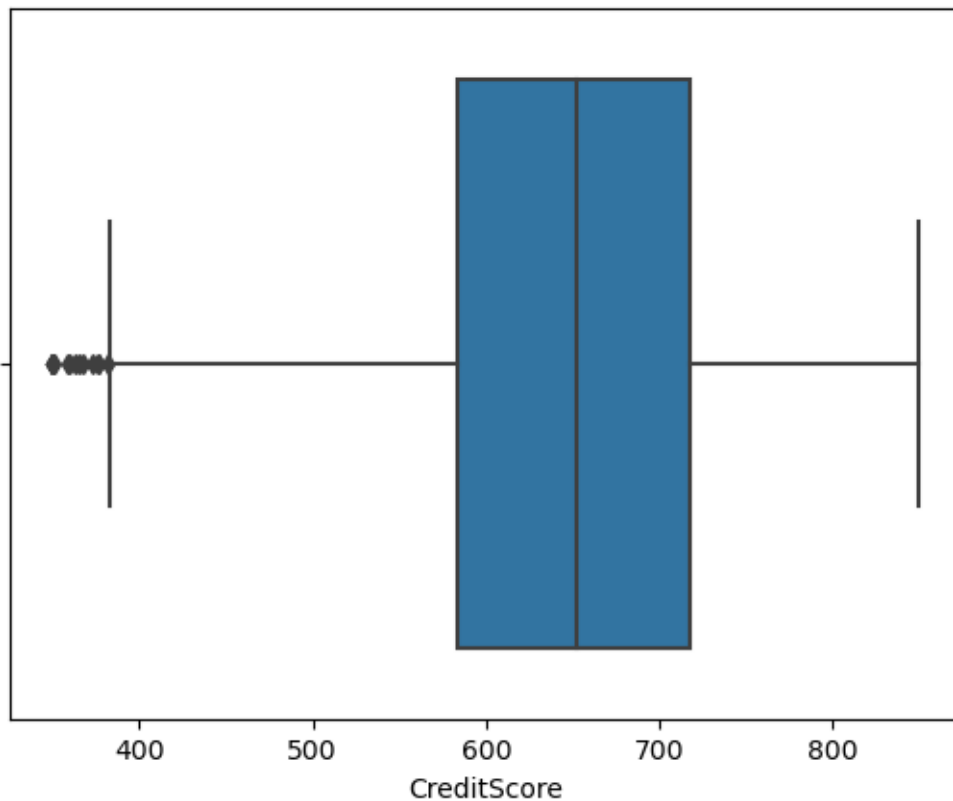
```
(9984, 14)
```

## Outlier replacement using median

In [23]:

```
sns.boxplot(df.CreditScore)
```

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



```
df.median()
```

```

RowNumber      5.001500e+03
CustomerId     1.569073e+07
CreditScore    6.520000e+02
Age            3.700000e+01
Tenure         5.000000e+00
Balance        9.717329e+04
NumOfProducts  1.000000e+00
HasCrCard      1.000000e+00
IsActiveMember 1.000000e+00
EstimatedSalary 1.001144e+05
Exited         0.000000e+00

```

```
dtype: float64
```

```
Q1= df.CreditScore.quantile(0.25)
```

```
Q3=df.CreditScore.quantile(0.75)
```

```
IQR=Q3-Q1
```

```
IQR
```

```
134.0
```

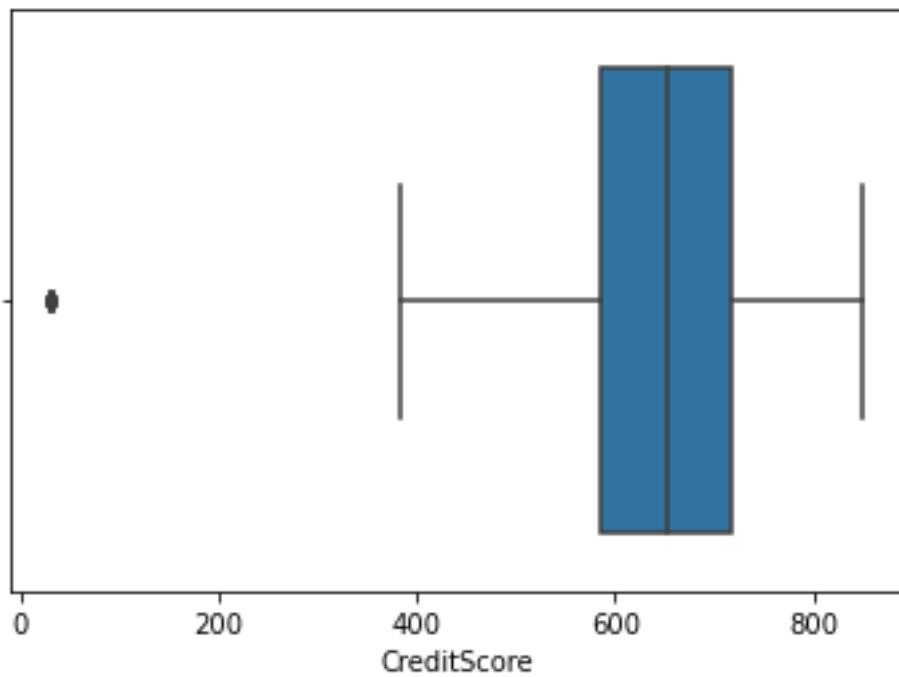
```
upper_limit =Q3 + 1.5*IQR
```

```
lower_limit =Q1 - 1.5*IQR
```

```
df['CreditScore'] = np.where(df['CreditScore']<lower_limit,30,df['CreditScore'])
```

```
sns.boxplot(df.CreditScore)
```

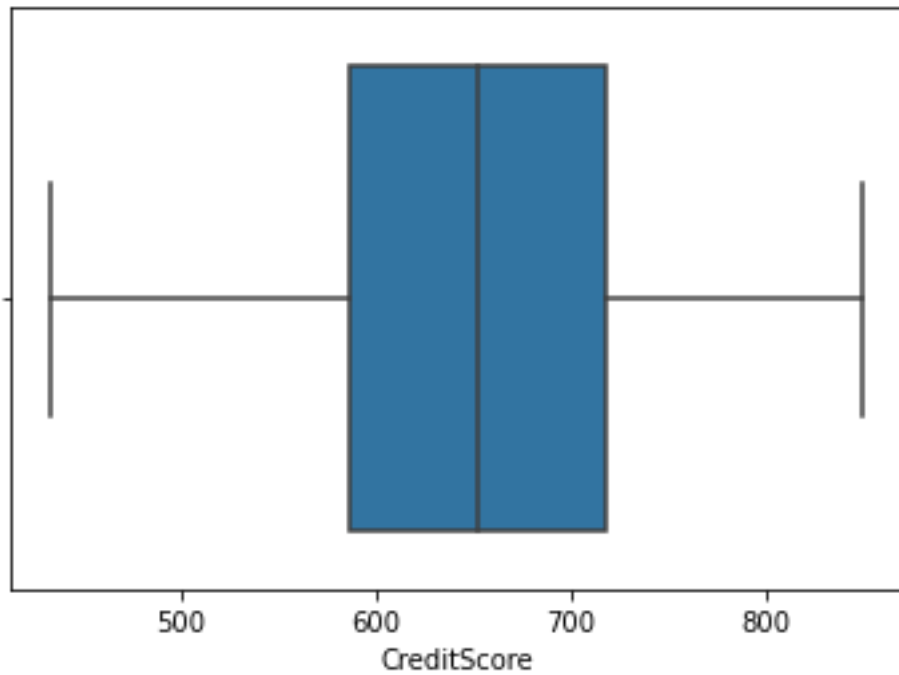
```
<AxesSubplot:xlabel='CreditScore'>
```



## outlier removal- Percentile method

```
p99= df.CreditScore.quantile(0.01)
p99
432.0
df = df[df.CreditScore>p99]
df.CreditScore
0    619
1    608
2    502
3    699
4    850
...
9995   771
9996   516
9997   709
9998   772
9999   792
Name: CreditScore, Length: 9896, dtype: int64
sns.boxplot(df.CreditScore)
```

<AxesSubplot:xlabel='CreditScore'>



## outlier removal- z-score

```
from scipy import stats
```

```
CreditScore_zscore = stats.zscore(df.CreditScore)
```

```
CreditScore_zscore
```

```
0    -0.362351  
1    -0.479437  
2    -1.607724  
3     0.489187  
4     2.096463
```

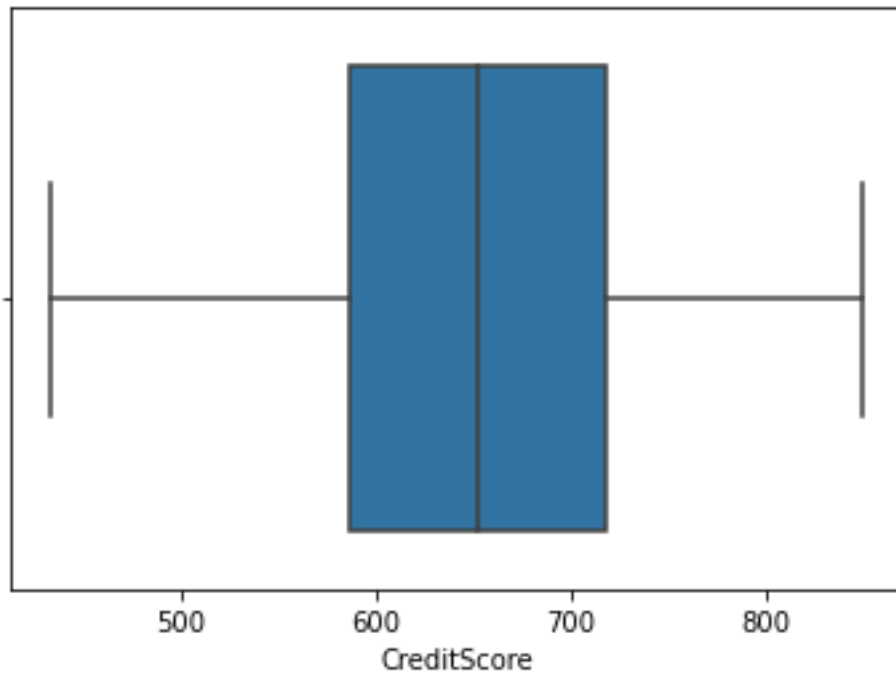
```
...  
9995    1.255570  
9996   -1.458705  
9997    0.595629  
9998    1.266214  
9999    1.479099
```

```
Name: CreditScore, Length: 9896, dtype: float64
```

```
df_z = df[np.abs(CreditScore_zscore)<=3]
```

```
sns.boxplot(df_z.CreditScore)
```

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



df.head()

	Row Number	Customer Id	Sur name	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOf Products	HasCreditCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	1115	619	France	0	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	1177	608	Spain	0	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	2040	502	France	0	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	289	699	France	0	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	1822	850	Spain	0	43	2	125510.82	1	1	1	79084.10	0

7. Check for Categorical columns and perform encoding.

## Encoding Techniques

# Label Encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
le=LabelEncoder()
```

```
df.Gender = le.fit_transform(df.Gender)
```

```
df.Surname = le.fit_transform(df.Surname)
```

```
df
```

	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geo grap hy	Ge nd er	A g e	Te nu re	Bala nce	NumOf Produc ts	Has CrC ard	IsActiv eMemb er	Estima tedSala ry	Ex ite d
0	1	1563 4602	111 5	619	France	0	4 2	2	0.00	1	1	1	101348. 88	1
1	2	1564 7311	117 7	608	Spain	0	4 1	1	838 07.8 6	1	0	1	112542. 58	0
2	3	1561 9304	204 0	502	France	0	4 2	8	159 660. 80	3	1	0	113931. 57	1
3	4	1570 1354	289	699	France	0	3 9	1	0.00	2	0	0	93826.6 3	0
4	5	1573 7888	182 2	850	Spain	0	4 3	2	125 510. 82	1	1	1	79084.1 0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9 9 9 5	9996	1560 6229	199 9	771	France	1	3 9	5	0.00	2	1	0	96270.6 4	0
9 9 9 6	9997	1556 9892	133 6	516	France	1	3 5	10	573 69.6 1	1	1	1	101699. 77	0
9 9 9 7	9998	1558 4532	157 0	709	France	0	3 6	7	0.00	1	0	1	42085.5 8	1
9 9 9 9	9999	1568 2355	234 5	772	Germany	1	4 2	3	750 75.3 1	2	1	0	92888.5 2	1

	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geo grap hy	Ge nd er	A g e	Te nu re	Bala nce	NumOf Produc ts	Has CrC ard	IsActiv eMemb er	Estima tedSala ry	Ex ite d
8														
9														
9	10000	1562	275	792	Fran	0	2		130				38190.7	
9		8319	1		ce		8	4	142.79	1	1	0	8	0
9														

10000 rows × 14 columns

## One hot Encoding

```
df_main=pd.get_dummies(df,columns=['Geography'])
df_main.head()
```

	Ro wN um ber	Cus tom erI d	Su rn a me	Cre dit Sco re	G en de r	A g e	T en ure	Ba lan ce	Num OfPr oduc ts	Has Cr Car d	IsAct iveM embe r	Esti mate dSal ary	E xi te d	Geogr aphy_ Franc e	Geogr aphy_ Germa ny	Geogr aphy_ Spai n
0	1	156 346 02	11 15	619	0	4 2	2	0.0 0	1	1	1	1013 48.88	1	1	0	0
1	2	156 473 11	11 77	608	0	4 1	1	83 80 7.8 6	1	0	1	1125 42.58	0	0	0	1
2	3	156 193 04	20 40	502	0	4 2	8	15 96 60. 80	3	1	0	1139 31.57	1	1	0	0
3	4	157 013 54	28 9	699	0	3 9	1	0.0 0	2	0	0	9382 6.63	0	1	0	0
4	5	157 378 88	18 22	850	0	4 3	2	12 55 10. 82	1	1	1	7908 4.10	0	0	0	1

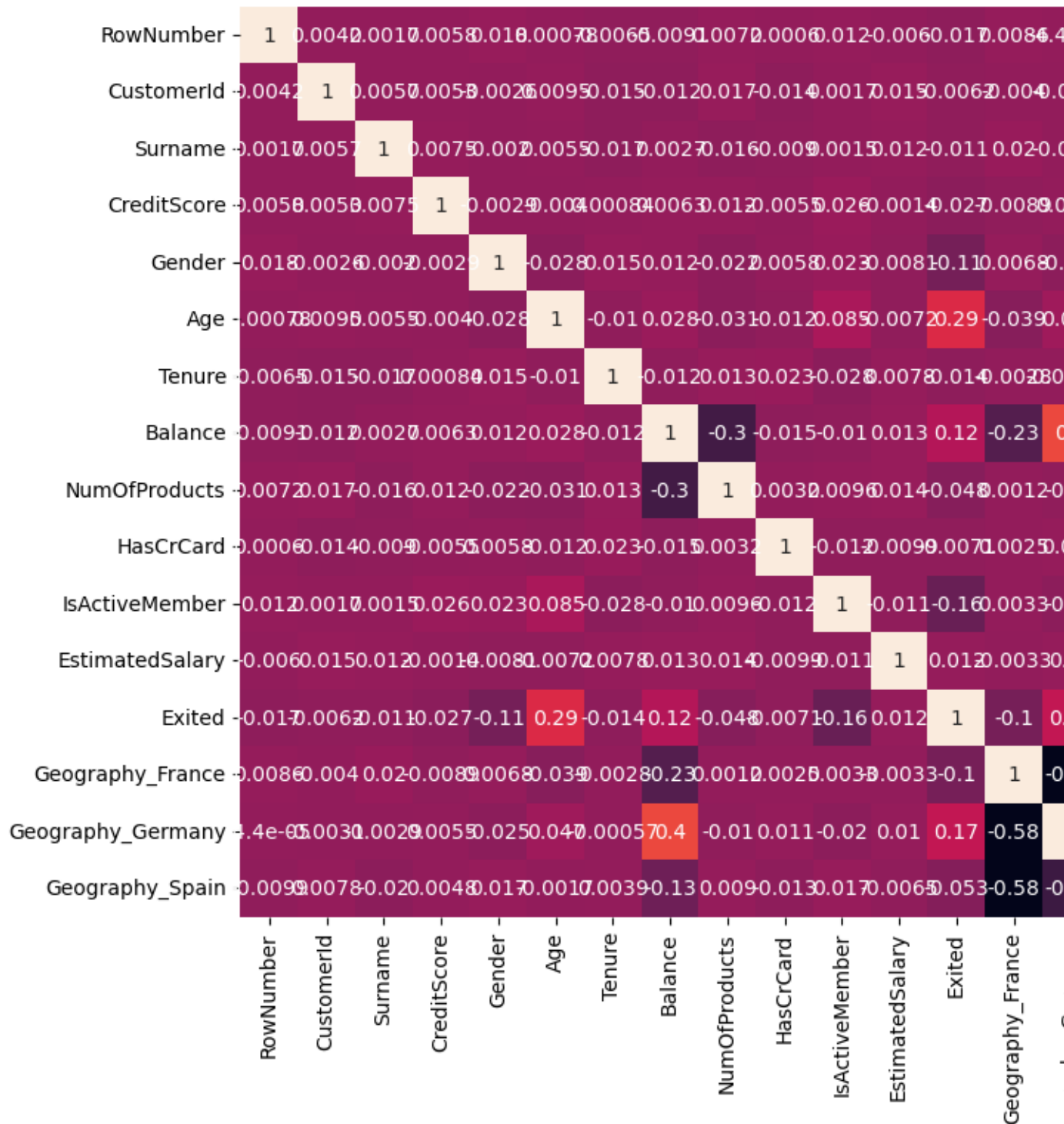
```
df_main.describe()
```

	Row Number	Customer ID	Surname	Credit Score	Gender	Age	Tenure	Balance	Num of Products	Housing	IsActive	Estimated Salary	Exited	Geography_France	Geography_Germany	Geography_Spain
Customer	1000.000	1.000e+04	100.000	100.00.000	100.00.000	100.00.000	100.00.000	100.00.000	100.00.000	10.00.000	100.00.000	100.00.000	100.00.000	1000.0000	10000.0000	1000.0000
	500.500	1.569e+07	150.7.742	650.52.880	0.5457	38.921	5.0128	764.85.889	1.53020	0.705	0.51510	100.090.239	0.2037	0.501400	0.250900	0.247700
	288.8956	7.1936e+04	846.20.431	96.653	0.4979	10.487	2.8921	623.97.405	0.58165	0.455	0.49979	575.10.4928	0.4027	0.500023	0.433553	0.431698
	1.000	1.5565e+07	0.000	350.00.000	0.000	18.000	0.000	0.000	1.000	0.000	0.000	11.5800	0.000	0.000000	0.000000	0.000000
25%	250.750	1.5628e+07	773.75.000	584.00.000	0.000	32.000	3.000	0.000	1.000	0.000	0.000	510.02.1100	0.000	0.000000	0.000000	0.000000
	500.500	1.5690e+07	154.2.000	652.00.000	1.000	37.000	5.000	971.98.540	1.000	1.000	1.000	100.193.915	0.000	1.000000	0.000000	0.000000
75%	750.250	1.5753e+07	223.8.250	718.00.000	1.000	44.000	7.000	127.644.240	2.000	1.000	1.000	149.388.247	0.000	1.000000	1.000000	0.000000
	1000.000	1.5815e+07	293.1.000	850.00.000	1.000	92.000	10.000	250.898.090	4.000	1.000	1.000	199.992.480	1.000	1.000000	1.000000	1.000000



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

```
plt.figure(figsize=(10,8))
sns.heatmap(df_main.corr(),annot=True)
<AxesSubplot:>
```



# X and y split

*# y target-dependent variable*

```
y=df_main.Balance
```

y

```
0      0.00
1    83807.86
2   159660.80
3      0.00
4   125510.82
```

...

```
9995    0.00
9996   57369.61
9997    0.00
9998   75075.31
9999  130142.79
```

Name: Balance, Length: 10000, dtype: float64

*# independent variables-X*

```
X=df_main.drop(columns=['Balance'],axis=1)
```

```
X.head()
```

	Row Number	CustomerId	Surname	CreditScore	Gender	Age	Tenure	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Exited	Geography_France	Geography_Germany	Geography_Spain
0	1	15634602	1115	619	0	42	2	1	1	1	101348.88	1	1	0	0
1	2	15647311	1177	608	0	41	1	1	0	1	112542.58	0	0	0	1
2	3	15619304	2040	502	0	42	8	3	1	0	113931.57	1	1	0	0
3	4	15701354	289	699	0	39	1	2	0	0	93826.63	0	1	0	0
4	5	15737888	1822	850	0	43	2	1	1	1	79084.10	0	0	0	1

## 9. Scale the independent variables

```
from sklearn.preprocessing import scale
```

```
X_scaled=pd.DataFrame(scale(X),columns=X.columns)
```

```
X_scaled.head()
```

	Row Number	CustomerID	Surname	CreditScore	Gender	Age	Tenure	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Geography_France	Geography_Germany	Geography_Spain
0	-	-	-	-	-	0.2	-	-	0.64	0.970	0.021	1.9	-	-	-
	1.73	0.78	0.4	0.32	1.0	93	1.0	-	609	243	886	77	0.9972	-	-
	1878	3213	64183	6221	95988	517	41760	0.911583	2			165	04	0.578736	0.573809
1	-	-	-	-	-	0.1	-	-	-	0.970	0.216	-	-	-	1.742
	1.73	0.60	0.3	0.44	1.0	98	1.3	-	1.54	243	534	0.5	1.0028	0.5787	740
	1531	6534	90911	0036	95988	164	87538	0.911583	7768			05775	04	36	
2	-	-	0.6	-	-	0.2	1.0	-	0.64	-	0.240	1.9	-	-	-
	1.73	0.99	28	1.53	1.0	93	32	2.527	609	1.030	687	77	0.9972	0.5787	0.573
	1185	5885	988	6794	95988	517	908	057	2	670		165	04	36	809
3	-	0.14	-	0.50	-	0.0	-	0.807	-	-	-	-	0.9972	-	-
	1.73	476	1.4	152	1.0	07	1.3	0.807	1.54	1.030	0.108	0.5	0.9972	0.5787	0.573
	0838	7	40356	1	95988	457	87538	737	7768	670	918	05775	04	36	809
4	-	0.65	0.3	2.06	-	0.3	-	-	0.64	0.970	-	0.5	-	-	1.742
	1.73	265	71	388	1.0	88	1.0	-	609	243	0.365	0.5	1.0028	0.5787	740
	0492	9	354	4	95988	871	41760	0.911583	2		276	05775	04	36	

## 10. Split the data into training and testing

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test =train_test_split(X_scaled,y, test_size=0.3,random_state=0)
```

```
X_train
```

	Row Number	CustomerID	Surname	CreditScore	Gender	Age	Tenure	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Geography_France	Geography_Germany	Geography_Spain
7681	0.92	-	1.4	-	0.9	-	-	-	0.6	0.970	-	1.9	-	-	-
	889	0.79	75	0.09	12	64	41	0.807	460	243	0.770	77	0.9972	-	-
	9	7032	810	8592	419	665	760	737	92		218	165	04	0.578736	0.573809
903	1.39	0.71	-	-	0.9	0.0	0.6	0.807	0.6	-	-	-	0.9972	-	-
	655	431	1.5	1.13	12	07	87	0.807	460	1.030	1.395	0.5	0.9972	0.5787	0.573
			88	327	41	45	13					05			

	Row number	Customer Id	Surname	CreditScore	Gender	Age	Tenure	Num OfProducts	Has Credit Card	IsActiveMember	EstimatedSalary	Exited	Geography_ France	Geography_ Germany	Geography_ Spain
1	3	4	081	0	9	7	0	737	92	670	767	775	04	36	809
3691	- 0.453278	- 0.963450	- 0.240822	- 0.626278	- 1.095988	3.535540	- 0.004426	- 0.911583	- 1.547768	0.970243	- 1.499656	- 0.505775	0.997204	- 0.578736	- 0.573809
202	- 1.661903	- 1.250707	- 0.427547	- 1.391939	0.912419	1.056346	- 0.004426	- 0.911583	- 1.547768	0.970243	0.800862	1.977165	- 1.002804	- 0.578736	1.742740
5625	0.216680	- 0.385174	- 1.478173	- 1.474714	- 1.095988	2.009882	0.687130	- 0.911583	0.646092	0.970243	0.512497	- 0.505775	0.997204	- 0.578736	- 0.573809
..	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9225	1.463756	- 1.473777	1.385344	- 0.584891	- 1.095988	- 0.660018	- 0.350204	0.807737	0.646092	0.970243	1.093273	- 0.505775	- 1.002804	1.727904	- 0.573809
4859	- 0.048671	- 0.609314	1.530707	1.484464	- 1.095988	- 1.613554	0.350204	- 0.911583	0.646092	0.970243	0.133249	- 0.505775	- 1.002804	- 0.578736	1.742740
3264	- 0.601195	- 1.620525	- 0.361366	0.905045	0.912419	- 0.373958	- 0.004426	0.807737	0.646092	- 1.030670	1.414415	- 0.505775	0.997204	- 0.578736	- 0.573809
9845	1.678530	- 0.374039	0.725896	- 0.626278	- 1.095988	- 0.087897	1.378686	0.807737	0.646092	0.970243	0.846147	- 0.505775	- 1.002804	- 0.578736	1.742740

	Row Number	CustomerID	SupplierName	CreditScore	Gender	Age	Tenure	NumberOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Exited	Geography_France	Geography_Germany	Geography_Spain
2	-	-	1.3	-	-	0.8	-	-	-	-	-	1.9	-	-	-
7	0.78	1.36	82	0.28	1.0	65	1.3	-	0.6	-	0.326	77	-	1.7279	-
3	548	411	98	483	95	63	87	0.911	460	1.030	305	16	1.0028	04	0.573
2	5	8	1	4	98	9	53	583	92	670		5			809

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	Row Number	CustomerID	SupplierName	CreditScore	Gender	Age	Tenure	NumberOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Exited	Geography_France	Geography_Germany	Geography_Spain
9	1.52	-	1.3	-	-	-	1.0	-	0.6	-	-	-	-	-	-
3	229	1.04	98	0.55	1.0	0.3	32	0.911	460	0.970	1.613	0.5	1.0028	1.7279	0.573
9	9	525	34	385	98	95	90	583	92	243	046	77	04	04	809
4		0	4	0	8	8	8					5			
8	-	-	-	-	-	0.1	-	-	-	-	-	1.9	-	-	-
9	1.42	0.50	0.7	1.31	1.0	0.2	1.0	-	0.6	-	0.497	77	0.9972	-	-
8	080	381	82	951	95	81	41	0.911	460	1.030	532	16	04	0.5787	0.573
	1	3	9	2	8	0	76	583	92	670		5		36	809
2	-	-	0.4	-	-	0.2	1.0	-	0.6	-	-	-	-	-	-
3	0.90	0.79	12	0.57	1.0	0.93	32	-	-	-	-	0.5	-	-	-
9	118	329	71	394	95	51	90	0.911	460	0.970	0.423	05	1.0028	0.5787	1.742
8	6	2	7	8	98	7	8	583	92	243	561	77	04	36	740
					8							5			
5	0.31	0.76	1.5	1.42	0.9	-	-	-	-	-	-	-	-	-	-
9	402	019	90	238	12	0.6	0.3	0.911	1.5	-	-	0.5	0.9972	-	-
0	1	0	97	4	41	60	50	583	477	1.030	0.186	05	04	0.5787	0.573
6			9		9	01	20		68	670	439	77		36	809
						8	4					5			
2	-	-	-	-	0.9	-	-	-	-	-	-	-	-	-	-
3	0.92	1.04	0.6	0.57	12	0.0	0.0	0.807	0.6	0.970	0.618	0.5	1.0028	1.7279	0.573
4	023	210	03	394	41	87	04	737	460	243	560	05	04	04	809
3	9	7	63	8	9	89	42		92			77			
			6			7	6					5			

	Row Number	CustomId	Surname	CreditScore	Gender	Age	Tenure	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Exited	Geography_France	Geography_Germany	Geography_Spain
..	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
.	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4004	-0.344851	0.661806	-0.626091	-1.247084	-1.095988	0.198164	-0.350204	0.807737	-1.547768	0.970243	0.826264	-0.505775	-1.002804	-0.578736	1.742740
7375	0.822897	-0.723866	-1.266630	-0.119286	0.912419	3.630893	0.341352	0.807737	0.646092	0.970243	-0.769654	-0.505775	0.997204	-0.578736	-0.573809
9307	1.492162	-0.14644	0.686897	0.356666	0.912419	0.102810	-1.041760	0.807737	0.646092	0.970243	1.170455	-0.505775	0.997204	-0.578736	-0.573809
8394	1.175889	-1.292287	-1.384811	0.429093	0.912419	2.868064	1.724464	-0.911583	0.646092	0.970243	-0.508468	-0.505775	0.997204	-0.578736	-0.573809
5233	0.080887	-1.385388	1.117074	0.832617	-1.095988	0.960993	-0.350204	-0.911583	0.646092	0.970243	-1.153427	1.977165	-1.002804	1.727904	-0.573809

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