

Assignment – 2

Data Visualization and Pre-processing

Assignment Date	26 September 2022
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Student Roll Number	2019PITIT103
Maximum Marks	2 Marks

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

1. Load the dataset.

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

df

	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	15669892	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

df.head()

	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

df.shape

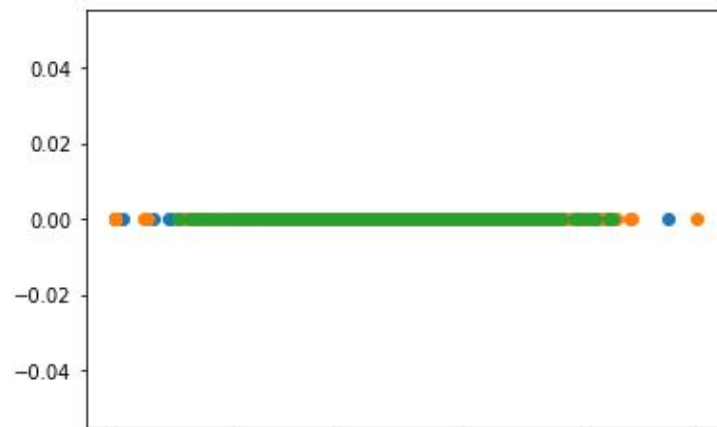
(10000, 14)

2. Perform Below Visualizations

a. Univariate Analysis

```
df_france=df.loc[df['Geography']=='France']  
df_spain=df.loc[df['Geography']=='Spain']  
df_germany=df.loc[df['Geography']=='Germany']
```

```
plt.plot(df_france['Balance'],np.zeros_like(df_france['Balance']),'o')  
plt.plot(df_spain['Balance'],np.zeros_like(df_spain['Balance']),'o')  
plt.plot(df_germany['Balance'],np.zeros_like(df_germany['Balance']),'o')  
plt.xlabel('Age')  
plt.show()
```

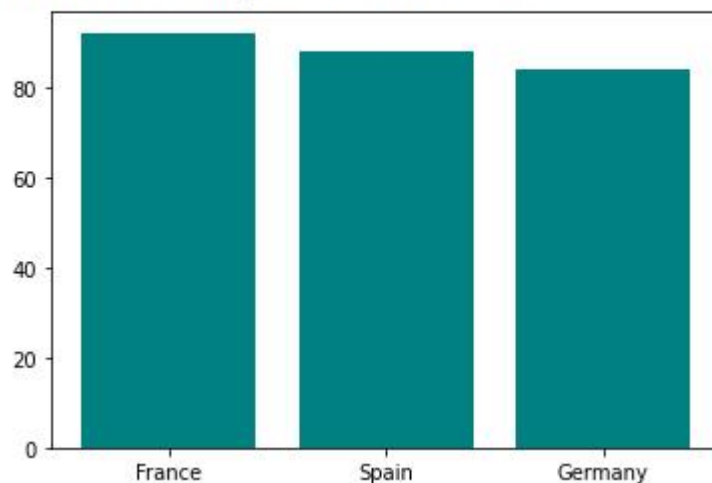


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b. Bivariate Analysis

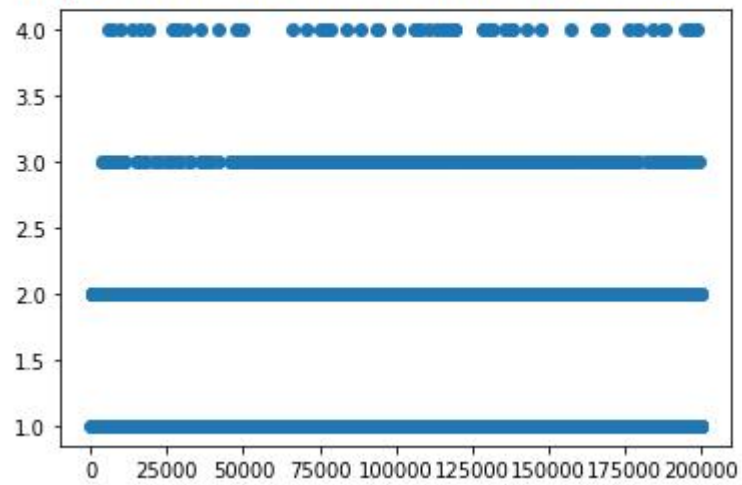
```
plt.bar('Geography','Age',data=df,color='teal')
```

<BarContainer object of 10000 artists>



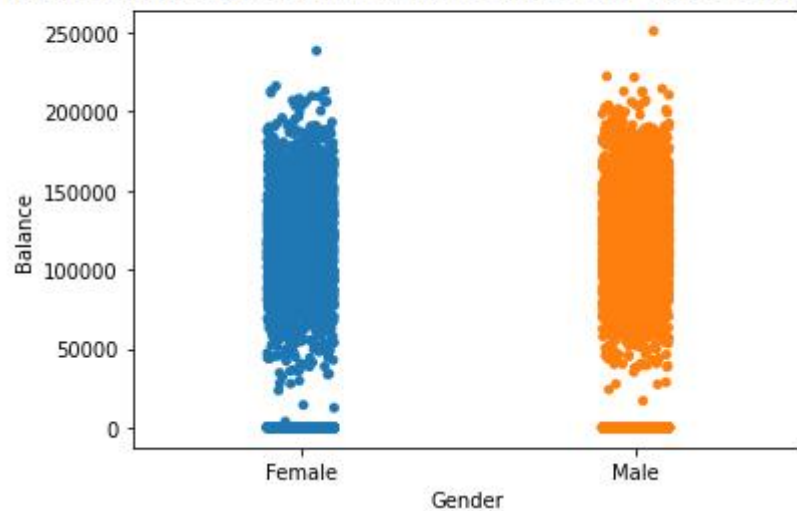
```
plt.scatter('EstimatedSalary', 'NumOfProducts', data=df)
```

<matplotlib.collections.PathCollection at 0x7fcc81cb4c50>



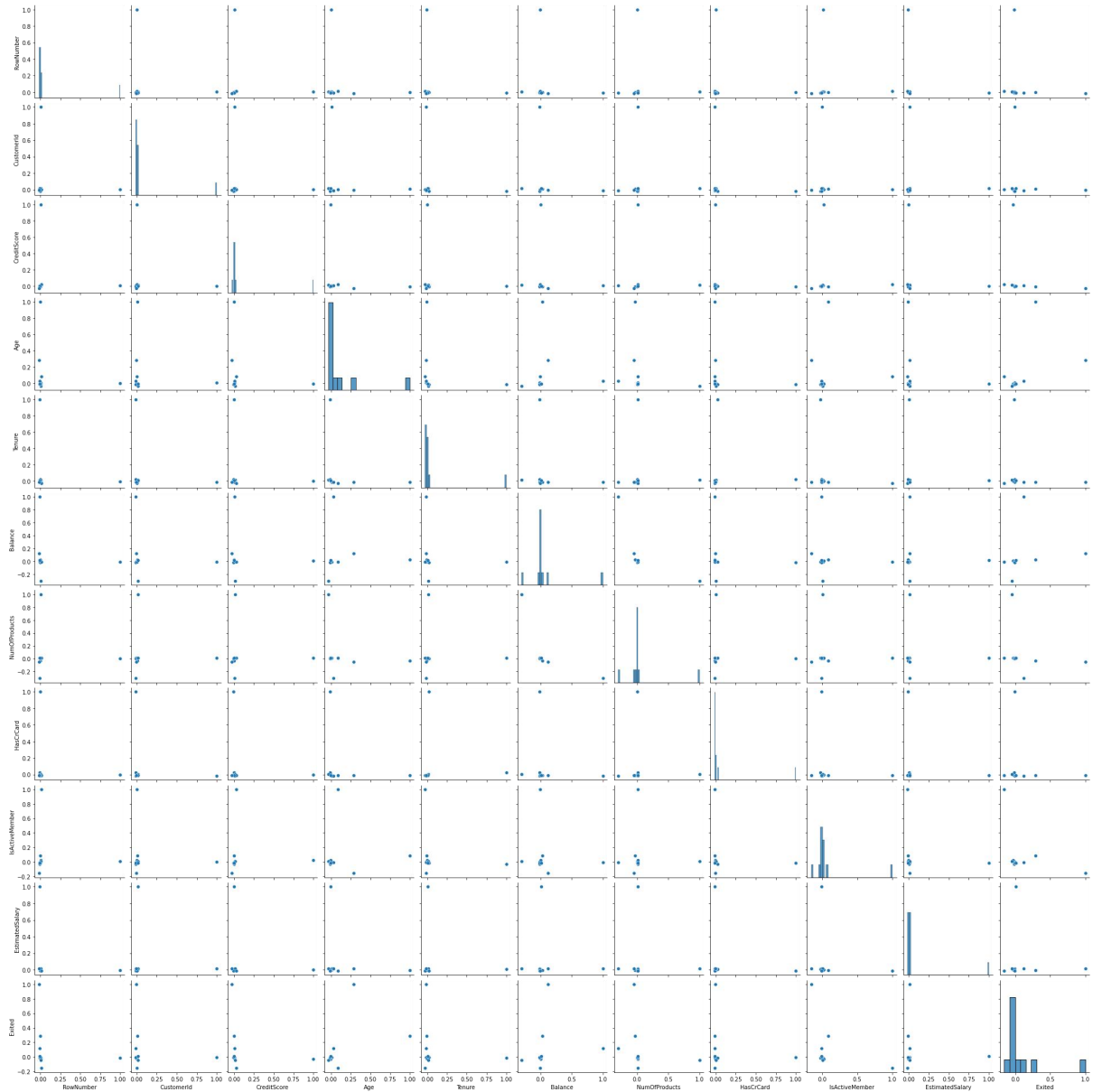
```
sns.stripplot(x='Gender', y='Balance', data=df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fcc81b965d0>

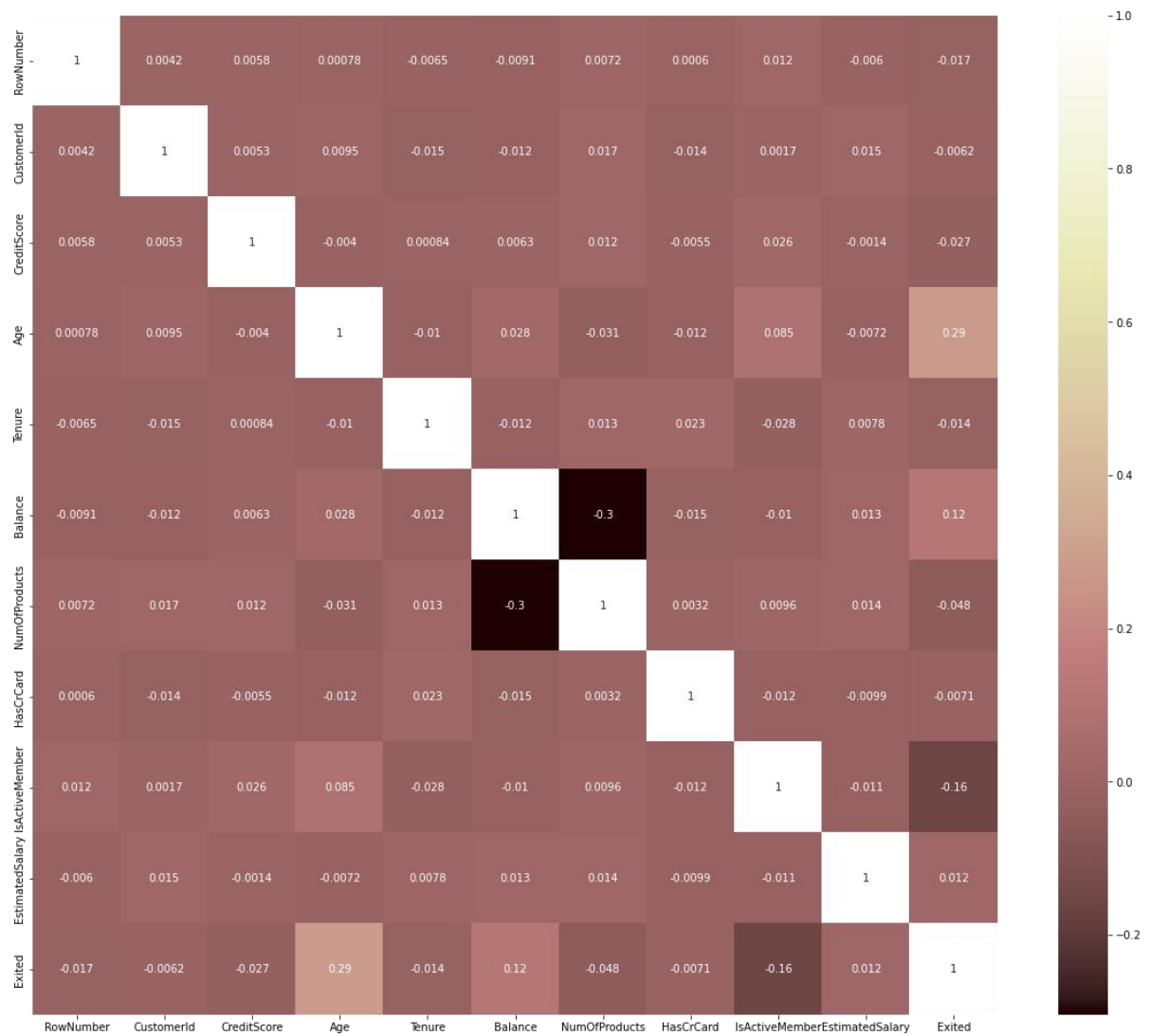


3. Multivariate Analysis

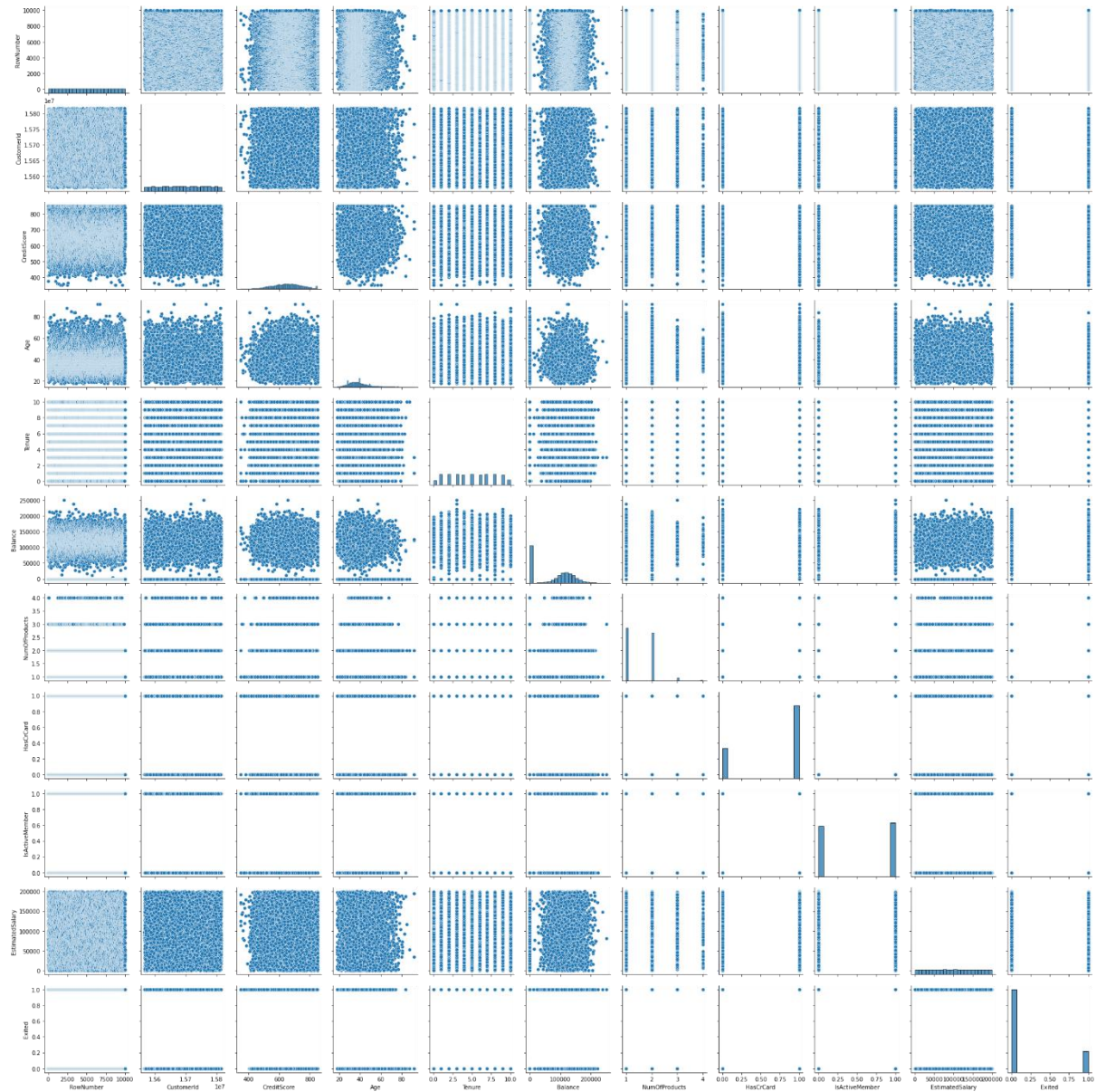
```
sns.pairplot(df.corr())
```



```
plt.subplots(figsize=(20,17))
sns.heatmap(df.corr(),annot=True,cmap='pink')
```



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



4. Perform descriptive statistics on the dataset

```
df.describe(include='all')
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
count	10000.00000	1.000000e+04	10000	10000.000000	10000	10000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000
unique	NaN	NaN	2932	NaN	3	2	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	NaN	NaN	Smith	NaN	France	Male	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	NaN	NaN	32	NaN	5014	5457	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	5000.50000	1.569094e+07	NaN	650.528800	NaN	NaN	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881
std	2886.89568	7.193619e+04	NaN	96.653299	NaN	NaN	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818
min	1.00000	1.556570e+07	NaN	350.000000	NaN	NaN	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000
25%	2500.75000	1.562853e+07	NaN	584.000000	NaN	NaN	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000
50%	5000.50000	1.569074e+07	NaN	652.000000	NaN	NaN	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000
75%	7500.25000	1.575323e+07	NaN	718.000000	NaN	NaN	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149386.247500
max	10000.00000	1.581569e+07	NaN	850.000000	NaN	NaN	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000

5. Handle the Missing values

```
df.isnull()
```

[illegible]

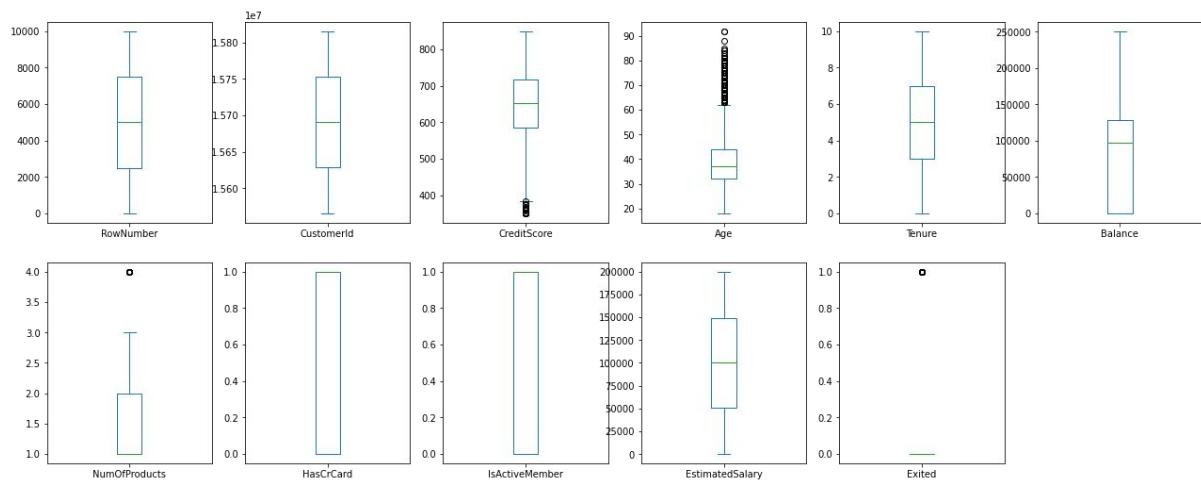
6. Find the outliers and replace the outliers

```
df.plot(subplots=True,layout=(4,6),kind='box',figsize=(22,18))
```

```

RowNumber      AxesSubplot(0.125,0.71587;0.110714x0.16413)
CustomerId     AxesSubplot(0.257857,0.71587;0.110714x0.16413)
CreditScore    AxesSubplot(0.390714,0.71587;0.110714x0.16413)
Age            AxesSubplot(0.523571,0.71587;0.110714x0.16413)
Tenure         AxesSubplot(0.656429,0.71587;0.110714x0.16413)
Balance        AxesSubplot(0.789286,0.71587;0.110714x0.16413)
NumOfProducts AxesSubplot(0.125,0.518913;0.110714x0.16413)
HasCrCard      AxesSubplot(0.257857,0.518913;0.110714x0.16413)
IsActiveMember AxesSubplot(0.390714,0.518913;0.110714x0.16413)
EstimatedSalary AxesSubplot(0.523571,0.518913;0.110714x0.16413)
Exited         AxesSubplot(0.656429,0.518913;0.110714x0.16413)
dtype: object

```



```

Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1
n = 1.5
df = df[(df['Age'] < Q1 - n*IQR) | (df['Age'] > Q3 + n*IQR)]
df.head()

```

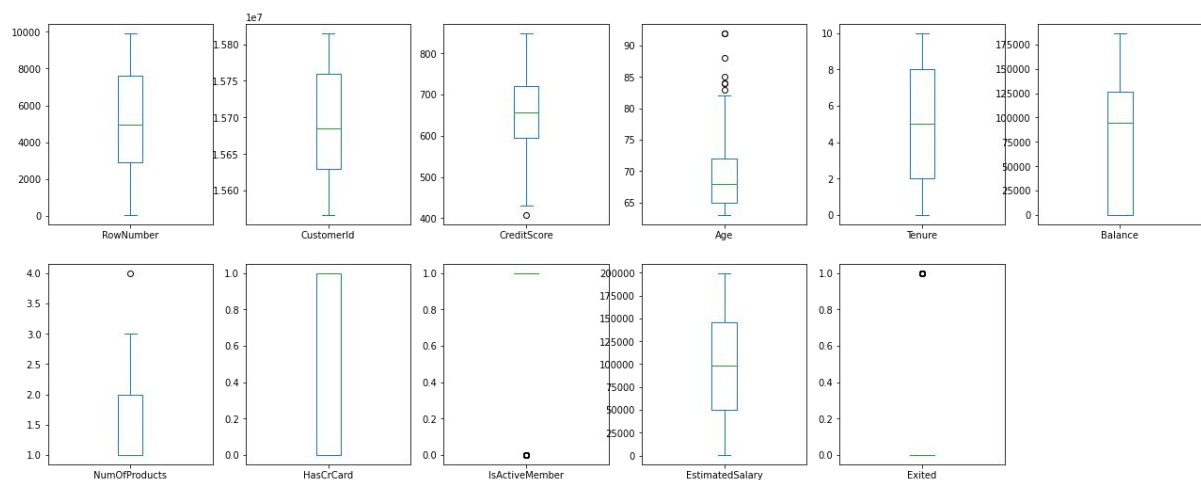
	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
58	59	15623944	T'ien	511	Spain	Female	66	4	0.00	1	1	0	1643.11	1
85	86	15805254	Ndukaku	652	Spain	Female	75	10	0.00	2	1	1	114675.75	0
104	105	15804919	Dunbabin	670	Spain	Female	65	1	0.00	1	1	1	177655.68	1
158	159	15589975	Maclean	646	France	Female	73	6	97259.25	1	0	1	104719.66	0
181	182	15789669	Hsia	510	France	Male	65	2	0.00	2	1	1	48071.61	0


```
df.plot(subplots=True,layout=(4,6),kind='box',figsize=(22,18))
```

```

RowNumber      AxesSubplot(0.125,0.71587;0.110714x0.16413)
CustomerId     AxesSubplot(0.257857,0.71587;0.110714x0.16413)
CreditScore    AxesSubplot(0.390714,0.71587;0.110714x0.16413)
Age            AxesSubplot(0.523571,0.71587;0.110714x0.16413)
Tenure         AxesSubplot(0.656429,0.71587;0.110714x0.16413)
Balance        AxesSubplot(0.789286,0.71587;0.110714x0.16413)
NumOfProducts  AxesSubplot(0.125,0.518913;0.110714x0.16413)
HasCrCard      AxesSubplot(0.257857,0.518913;0.110714x0.16413)
IsActiveMember AxesSubplot(0.390714,0.518913;0.110714x0.16413)
EstimatedSalary AxesSubplot(0.523571,0.518913;0.110714x0.16413)
Exited         AxesSubplot(0.656429,0.518913;0.110714x0.16413)
dtype: object

```



7. Check for Categorical columns and perform encoding

```
df.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

```

```
df['Geography'].unique()
```

```
array(['Spain', 'France', 'Germany'], dtype=object)
```

```
Geography=pd.get_dummies(df["Geography"])
df=pd.concat([df,Geography],axis=1)
df.drop(["Geography"],axis=1,inplace=True)
```

```
df['Gender'].unique()
```

```
array(['Female', 'Male'], dtype=object)
```

```
Gender=pd.get_dummies(df["Gender"])
df=pd.concat([df,Gender],axis=1)
df.drop(["Gender"],axis=1,inplace=True)
```

```
df.columns
```

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Age', 'Tenure',
       'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember',
       'EstimatedSalary', 'Exited', 'France', 'Germany', 'Spain', 'Female',
       'Male'],
      dtype='object')
```

```
df['Surname'].unique()
```

```
array(['T'ien', 'Ndukaku', 'Dunbabin', 'Maclean', 'Hsia', 'Ringrose',
       'Smith', 'McIntosh', 'Matveyeva', 'Pokrovskii', 'Madukaego',
       'Cole', 'Black', 'Outhwaite', 'Ritchie', 'Teng', 'Stout',
       'Crawford', 'Fleming', 'Pugliesi', 'Romani', 'Williamson',
       'McKenzie', 'Cox', 'Alexander', 'Lloyd', 'Landry', 'Herrera',
       'Artemieva', 'Blackburn', 'Wood', 'Ts'ui', 'Nepean', 'Sinclair',
       'Sanders', 'Ch'iu', 'McKay', 'Lampungmeiua', 'Mitchell',
       'Lucchesi', 'Pan', 'Kung', 'Lo', 'Hsiao', 'Nnamutaezinwa',
       'Avdeeva', 'Byrne', 'Hardy', 'P'eng', 'Simmons', 'Shelton',
       'Macarthur', 'Gordon', 'Hsueh', 'Sopuluchi', 'Forbes',
       'Zikoranachidimma', 'Moore', 'Mason', 'Miller', 'O'Toole', 'Bogle',
       'Rosas', 'Blair', 'Shen', 'Melton', 'Oluchi', 'Kapustina', 'Hay',
       'Milne', 'Anderson', 'Becker', 'Marchesi', 'Kao', 'Rearick',
       'Genovesi', 'Hung', 'Walker', 'Pagnotto', 'Poole', 'Yuriev',
       'Iredale', 'Palerma', 'Brim', 'Powell', 'Calabrese', 'Kibble',
       'Lavrov', 'Chiekwugo', 'Yao', 'Leibius', 'Chung', 'Azikiwe',
       'Chimaoko', 'Chao', 'Fulks', 'McMorran', 'Hotchin', 'Hughes',
       'Donaldson', 'Tuan', 'Liu', 'Estep', 'Alexeyeva', 'Kilgour',
       'Lori', 'Knowles', 'Valentin', 'Maughan', 'Tochukwu', 'Tomlinson',
       'Hickey', 'Ch'ang', 'Chinomso', 'Wan', 'Mazzanti', 'Thompson',
       'Onyeoruru', 'Townsend', 'Hope', 'Ives', 'Bergamaschi', 'Bateman',
       'Jarvis', 'Long', 'Paniciucci', 'Monnier', 'Andreev', 'Steele',
       'Sung', 'Baker', 'Richards', 'Herbert', 'Ch'ien', 'Siciliano',
```

```
'Allan', 'Hobbs', 'Coates', 'Ignatyev', 'McConnell', 'Tang',
'Bell', 'Nwora', 'McDonald', 'Davidson', 'Hs?', 'Onyemauchekwu',
'Connolly', 'King', 'Greco', 'Fanucci', 'Su', 'Woolnough',
'Harrison', 'Isayeva', 'Martin', 'Ch'en', 'Nnonso', 'Trentino',
'Kelly', 'Sullivan', 'Thomson', 'Rogers', 'Ponomarev', 'De Luca',
'Sheppard', 'Birk', 'Obioma', 'Iheatu', 'Dellucci', 'Hs?eh',
'Davies', 'Fields', 'Page', 'Wu', 'Chen', 'Young', 'Sabbatini',
'Harvey', 'Sal', 'Tan', 'Otitodilinna', 'Chinonyelum', 'Munro',
'Sargent', 'Bianchi', 'Chiu', 'Buccho', 'Dolgorukova', 'Green',
'Ibezimako', 'Dennis', 'Eve', 'Stradford', 'Liao', 'Abramovich',
'Cross', 'Ko', 'Fiorentini', 'Gray', 'Lu', 'Yevseyev', 'Horton',
'Wall', 'Cummins', 'Kodilinyechukwu', 'Scott', 'Harris', 'Ofodile',
'Highland', 'Botts', 'Baresi', 'Afarefuna', 'Rogova', 'Bufkin',
'Boniwell', 'Lombardi', 'Kuykendall', 'Browne', 'Niu', 'Mackie',
'Ifeatu', 'Fan', 'Davey', 'Kennedy', 'Gibson', 'Ferguson',
'Onyenachiya', 'Combes', 'Kent', 'Ngozichukwu', 'Okonkwo',
'Lappin', 'Zhdanova', 'Ibekwe', 'Pettry', 'Wright', 'Felix',
'Nnaife', 'Schofield', 'Onwubiko', 'Rubin', 'Perry', 'Ma',
'Akudinobi', 'Flemming', 'Spencer', 'Okwuadigbo', 'Tu',
'Chidiebere', 'Yuan', 'Jamieson', 'Davis', 'Conway',
'Okwudiliolisa', 'Lavrentyev', 'Muir', 'Soares', 'Lucas', 'Hudson',
'Winter-Irving', 'North', 'Rahman', 'Samaniego', 'Mayrhofer',
'Esomchi', 'Findlay', 'Seleznyov', 'Mickey', 'Spaul', 'Brown',
'Evseyev', 'Vorobyova', 'McClaran', 'Mueller', 'Hao', 'Peng',
'Sykes', 'Woronoff', 'Duncan', 'Whitson', 'Loggia', 'Parkin',
'Tsai', 'Pugh', 'Chin', 'Chiemezie', 'Curtis', 'Russell', 'Rose',
'Fiorentino', 'Shaw', 'Zakharov', 'Tsui', 'Bolton', 'Golubev',
'Vanzetti', 'Tretiakova', 'Owens', 'Chifley', 'Murphy',
```

```
'Yermakova', 'Chikelu', 'Otitodilichukwu', 'Nonniss', 'Mott',
'Henry', 'Pope', 'Romano', 'Watson', 'Ward', 'Fitzgerald',
'Arnold', 'Wells', 'Iweobiegbunam', 'Chiedozie', 'Thomas',
'Chukwuje kwu', 'Vagin', 'Parks'], dtype=object)
```

```
df.dtypes
```

```
RowNumber      int64
CustomerId      int64
Surname         object
CreditScore     int64
Age             int64
Tenure          int64
Balance         float64
NumOfProducts  int64
HasCrCard       int64
IsActiveMember  int64
EstimatedSalary float64
Exited          int64
France          uint8
Germany         uint8
Spain           uint8
Female          uint8
Male            uint8
dtype: object
```

```
df.drop(["Surname"],axis=1,inplace=True)
```

8. Split the data into dependent and independent variables

```
dependent_data=df['Exited']
```

```
independent_data=df.drop('Exited',axis=1)
```

9. Scale the independent variables

```
#minmax_scalar
df_norm = (independent_data-independent_data.min())/(independent_data.max()-independent_data.min())
```

```
df_norm.head()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	Female	Male
58	0.000000	0.229998	0.233032	0.103448	0.4	0.000000	0.000000	1.0	0.0	0.005731	0.0	0.0	1.0	1.0	0.0
85	0.002733	0.958335	0.552036	0.413793	1.0	0.000000	0.333333	1.0	1.0	0.573761	0.0	0.0	1.0	1.0	0.0
104	0.004657	0.956989	0.592760	0.068966	0.1	0.000000	0.000000	1.0	1.0	0.890258	0.0	0.0	1.0	1.0	0.0
158	0.010124	0.093542	0.538462	0.344828	0.6	0.520066	0.000000	0.0	1.0	0.523728	1.0	0.0	0.0	1.0	0.0
181	0.012452	0.895729	0.230769	0.068966	0.2	0.000000	0.333333	1.0	1.0	0.239051	1.0	0.0	0.0	0.0	1.0

10. Split the data into training and testing

```
X_train, X_test, y_train, y_test = train_test_split( independent_data, dependent_data, test_size=0.30, random_state=42)
```

```
sc=StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
print(X_train)
```

```
[[ -0.11823064  0.61271238  1.23747734 ... -0.61572793  1.07879243
  -1.07879243]
 [ 0.8471792  0.31996526  0.46317624 ... -0.61572793 -0.92696238
  0.92696238]
 [-0.22875737 -0.7671311  -0.57601735 ...  1.62409395  1.07879243
  -1.07879243]
 ...
 [ 0.88831374 -1.36057018  0.70769237 ... -0.61572793  1.07879243
  -1.07879243]
 [ 1.62408552  0.21836558  1.42086444 ... -0.61572793 -0.92696238
  0.92696238]
 [-0.65405277 -1.57586185  1.27823003 ... -0.61572793 -0.92696238
  0.92696238]]
```

```
print(X_test)
```

```
[[ 0.43654915 -0.19958681  0.30016548 ... -0.61572793 -0.92696238
  0.92696238]
 [-1.39268608 -0.45567995  0.4020472  ... -0.61572793 -0.92696238
  0.92696238]
 [ 0.9845328  -0.86183628 -0.1888668  ... -0.61572793  1.07879243
  -1.07879243]
 ...
 [ 0.43905299 -0.72549476 -0.57601735 ... -0.61572793 -0.92696238
  0.92696238]
 [ 1.64805086  0.17543652  0.02508482 ... -0.61572793 -0.92696238
  0.92696238]
 [ 0.71411789 -0.50209666 -0.42319476 ...  1.62409395  1.07879243
  -1.07879243]]
```