

```
import numpy as np
import pandas as pd
```

```
#1.loading the file
```

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

```
(10000, 14)
```

```
df.head()
```

	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

	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	

	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0
2	113931.57	1
3	93826.63	0
4	79084.10	0

```
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	2886.89568	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

```

3.000000
50%      5000.50000  1.569074e+07   652.000000   37.000000
5.000000
75%      7500.25000  1.575323e+07   718.000000   44.000000
7.000000
max     10000.00000  1.581569e+07   850.000000   92.000000
10.000000

```

	Balance	NumOfProducts	HasCrCard	IsActiveMember \
count	10000.000000	10000.000000	10000.00000	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

```
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

```

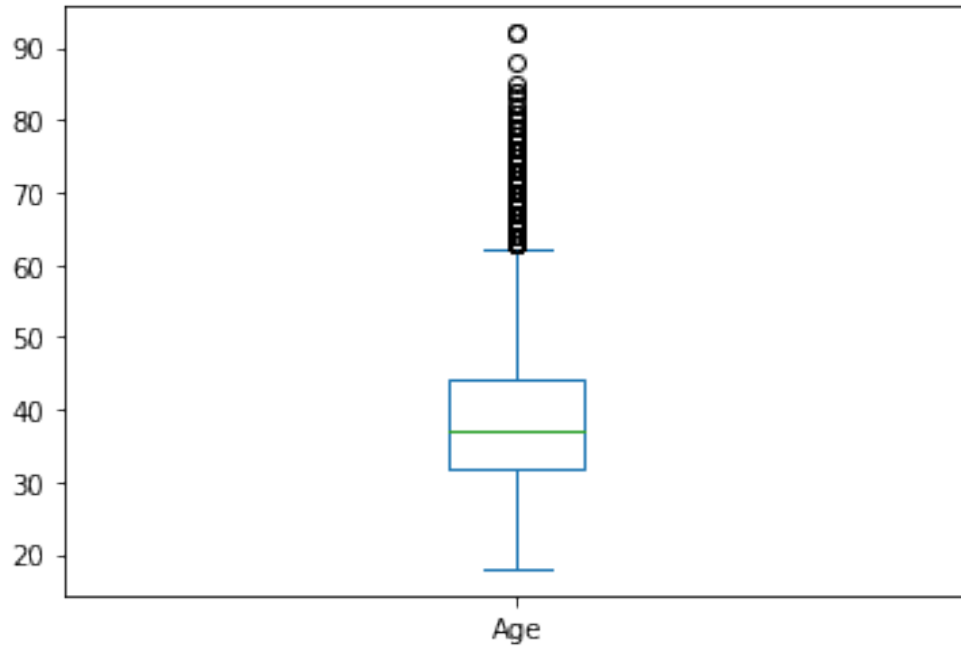
#2.1univarient

```

import matplotlib.pyplot as plt
%matplotlib inline
df['Age'].plot.box()

```

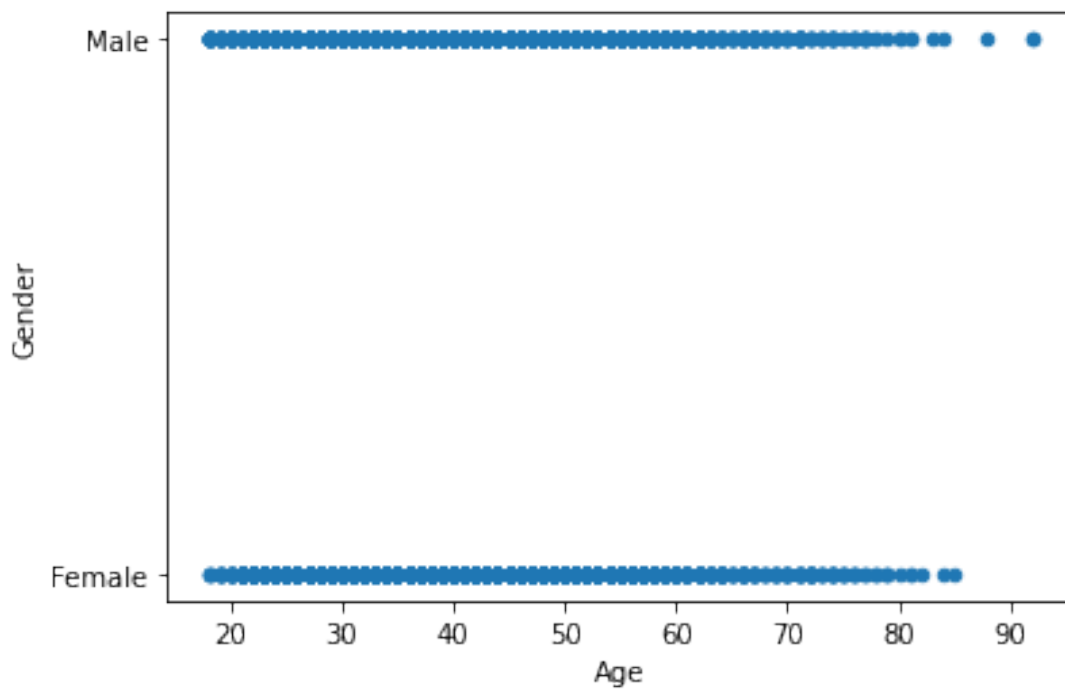
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6467a34e10>
```



```
#2.2bivariant
```

```
df.plot.scatter('Age', 'Gender')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f64678caa50>
```



```
df.corr()
```

	RowNumber	CustomerId	CreditScore	Age
Tenure \				
RowNumber	1.000000	0.004202	0.005840	0.000783 -
0.006495				
CustomerId	0.004202	1.000000	0.005308	0.009497 -
0.014883				
CreditScore	0.005840	0.005308	1.000000	-0.003965
0.000842				
Age	0.000783	0.009497	-0.003965	1.000000 -
0.009997				
Tenure	-0.006495	-0.014883	0.000842	-0.009997
1.000000				
Balance	-0.009067	-0.012419	0.006268	0.028308 -
0.012254				
NumOfProducts	0.007246	0.016972	0.012238	-0.030680
0.013444				
HasCrCard	0.000599	-0.014025	-0.005458	-0.011721
0.022583				
IsActiveMember	0.012044	0.001665	0.025651	0.085472 -
0.028362				
EstimatedSalary	-0.005988	0.015271	-0.001384	-0.007201
0.007784				
Exited	-0.016571	-0.006248	-0.027094	0.285323 -
0.014001				

	Balance	NumOfProducts	HasCrCard	IsActiveMember \
RowNumber	-0.009067	0.007246	0.000599	0.012044
CustomerId	-0.012419	0.016972	-0.014025	0.001665
CreditScore	0.006268	0.012238	-0.005458	0.025651
Age	0.028308	-0.030680	-0.011721	0.085472
Tenure	-0.012254	0.013444	0.022583	-0.028362
Balance	1.000000	-0.304180	-0.014858	-0.010084
NumOfProducts	-0.304180	1.000000	0.003183	0.009612
HasCrCard	-0.014858	0.003183	1.000000	-0.011866
IsActiveMember	-0.010084	0.009612	-0.011866	1.000000
EstimatedSalary	0.012797	0.014204	-0.009933	-0.011421
Exited	0.118533	-0.047820	-0.007138	-0.156128

	EstimatedSalary	Exited
RowNumber	-0.005988	-0.016571
CustomerId	0.015271	-0.006248
CreditScore	-0.001384	-0.027094
Age	-0.007201	0.285323
Tenure	0.007784	-0.014001
Balance	0.012797	0.118533
NumOfProducts	0.014204	-0.047820
HasCrCard	-0.009933	-0.007138
IsActiveMember	-0.011421	-0.156128
EstimatedSalary	1.000000	0.012097
Exited	0.012097	1.000000

```
x=df.drop(['Exited'],axis=1).values
y=df['Exited'].values
```

*#Descriptive statistics4.1.1 Measures of central tendency4.1.2
Measures of dispersion4.1.3 Summary statistics*

```
df['Age'].mode()
round(df["Age"].mean(), 2)
df["Age"].median()
print(f'The median of age is {df["Age"].median()}')
```

The median of age is 37.0

```
df['Age'].quantile([.25, .5, .75])
```

```
0.25    32.0
0.50    37.0
0.75    44.0
```

Name: Age, dtype: float64

```
round(df.describe(),2)
```

	RowNumber	CustomerId	CreditScore	Age	Tenure
Balance \					
count	10000.00	10000.00	10000.00	10000.00	10000.00
10000.00					
mean	5000.50	15690940.57	650.53	38.92	5.01
76485.89					
std	2886.90	71936.19	96.65	10.49	2.89
62397.41					
min	1.00	15565701.00	350.00	18.00	0.00
0.00					
25%	2500.75	15628528.25	584.00	32.00	3.00
0.00					
50%	5000.50	15690738.00	652.00	37.00	5.00
97198.54					
75%	7500.25	15753233.75	718.00	44.00	7.00
127644.24					
max	10000.00	15815690.00	850.00	92.00	10.00
250898.09					

	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
Exited				
count	10000.00	10000.00	10000.00	10000.00
10000.0				
mean	1.53	0.71	0.52	100090.24
0.2				
std	0.58	0.46	0.50	57510.49
0.4				
min	1.00	0.00	0.00	11.58
0.0				
25%	1.00	0.00	0.00	51002.11

```

0.0
50%          1.00          1.00          1.00          100193.92
0.0
75%          2.00          1.00          1.00          149388.25
0.0
max           4.00          1.00          1.00          199992.48
1.0

```

```
df['Age'].groupby(df['CustomerId']).describe()
```

```

      count  mean  std  min  25%  50%  75%  max
CustomerId
15565701    1.0  39.0  NaN  39.0  39.0  39.0  39.0
15565706    1.0  35.0  NaN  35.0  35.0  35.0  35.0
15565714    1.0  47.0  NaN  47.0  47.0  47.0  47.0
15565779    1.0  30.0  NaN  30.0  30.0  30.0  30.0
15565796    1.0  48.0  NaN  48.0  48.0  48.0  48.0
...
15815628    1.0  37.0  NaN  37.0  37.0  37.0  37.0
15815645    1.0  37.0  NaN  37.0  37.0  37.0  37.0
15815656    1.0  39.0  NaN  39.0  39.0  39.0  39.0
15815660    1.0  34.0  NaN  34.0  34.0  34.0  34.0
15815690    1.0  40.0  NaN  40.0  40.0  40.0  40.0

```

```
[10000 rows x 8 columns]
```

```
#handling missing values
```

```
df.isnull().sum()
```

```

RowNumber      0
CustomerId      0
Surname         0
CreditScore     0
Geography       0
Gender          0
Age             0
Tenure          0
Balance         0
NumOfProducts  0
HasCrCard       0
IsActiveMember  0
EstimatedSalary 0
Exited          0
dtype: int64

```

```
data_without_missing_values = df.dropna(axis=1)
```

```
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]

```

print('skewness value of : ',df['Age'].skew())
print('skewness value of : ',df['RowNumber'].skew())
print('skewness value of : ',df['CustomerId'].skew())
print('skewness value of : ',df['CreditScore'].skew())
print('skewness value of : ',df['Tenure'].skew())
print('skewness value of : ',df['Balance'].skew())
print('skewness value of : ',df['NumOfProducts'].skew())
print('skewness value of : ',df['HasCrCard'].skew())
print('skewness value of : ',df['IsActiveMember'].skew())
print('skewness value of : ',df['EstimatedSalary'].skew())
print('skewness value of: ',df['Exited'].skew())

```

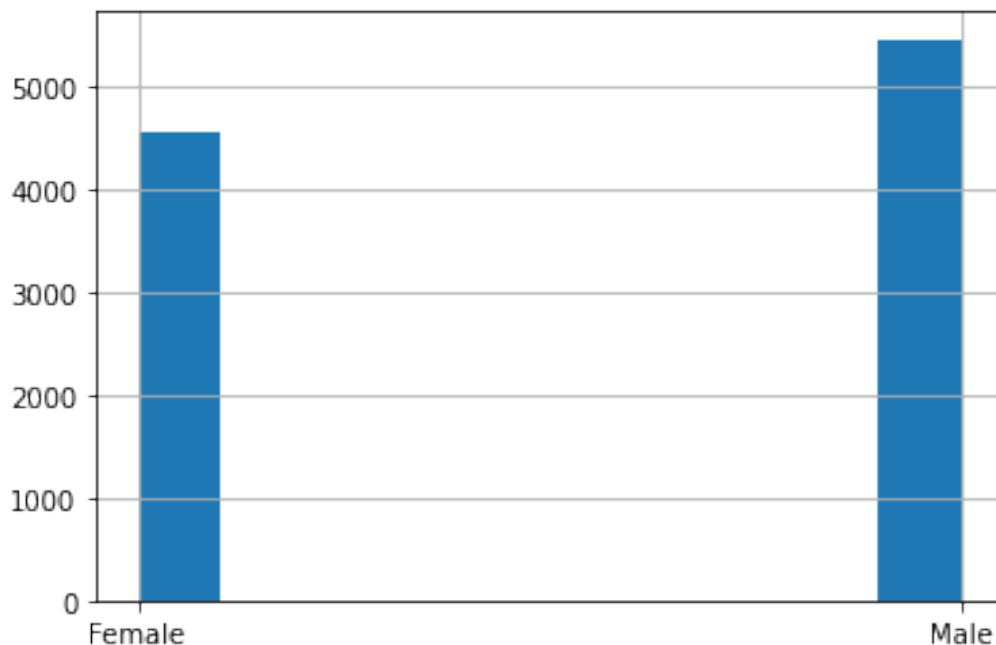
```

skewness value of : 1.0113202630234552
skewness value of : 0.0
skewness value of : 0.001149145900554239
skewness value of : -0.07160660820092675
skewness value of : 0.01099145797717904
skewness value of : -0.14110871094154384
skewness value of : 0.7455678882823168
skewness value of : -0.9018115952400578
skewness value of : -0.06043662833499078
skewness value of : 0.0020853576615585162
skewness value of: 1.4716106649378211

```

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe059d0cd90>
```



```

import seaborn as sns
sns.scatterplot(df['Surname'], df['Surname'])

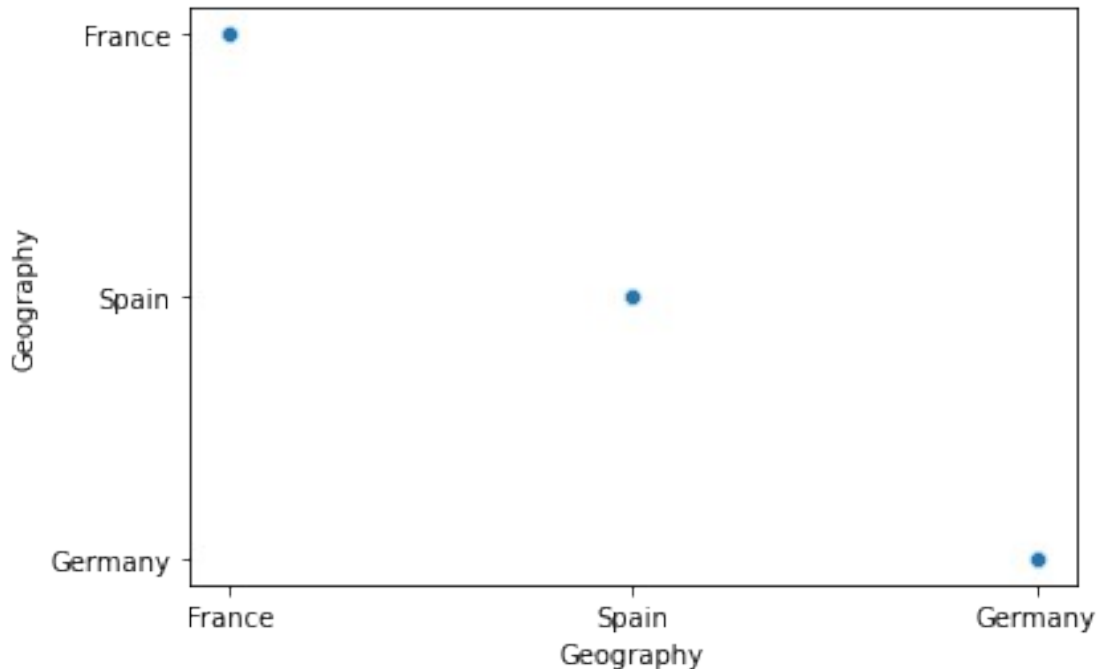
```



```
sns.scatterplot(df['Geography'], df['Geography'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:  
FutureWarning: Pass the following variables as keyword args: x, y.  
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
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe04fd64a10>
```



```
df.drop('Surname', axis =1)
```

```
df = df.drop('Surname', axis = 1).reset_index(drop=True)
```

```
df_categorical = df[['Gender', 'Geography']]  
df_categorical.head()
```

```
   Gender Geography  
0  Female    France  
1  Female    Spain  
2  Female    France  
3  Female    France  
4  Female    Spain
```

```
#encoding of catagorical data
```

```
from sklearn.preprocessing import LabelEncoder  
encoder = LabelEncoder()  
encoder.fit(df_categorical['Gender'])
```

```

LabelEncoder()
values =encoder.transform(df_categorical['Gender'])
print("Before Encoding:", list(df_categorical['Gender'][-10:]))
print("After Encoding:", values[-10:])

Before Encoding: ['Male', 'Female', 'Male', 'Male', 'Female', 'Male',
'Male', 'Female', 'Male', 'Female']
After Encoding: [1 0 1 1 0 1 1 0 1 0]

residence_encoder = LabelEncoder()
residence_values =
residence_encoder.fit_transform(df_categorical['Geography'])

print("Before Encoding:", list(df_categorical['Geography'][:5]))
print("After Encoding:", residence_values[:5])

Before Encoding: ['France', 'Spain', 'France', 'France', 'Spain']
After Encoding: [0 2 0 0 2]

#splitting dep and indep data
x = df.iloc[:, 0:9].values
print(x)

[[1 15634602 619 ... 2 0.0 1]
 [2 15647311 608 ... 1 83807.86 1]
 [3 15619304 502 ... 8 159660.8 3]
 ...
 [9998 15584532 709 ... 7 0.0 1]
 [9999 15682355 772 ... 3 75075.31 2]
 [10000 15628319 792 ... 4 130142.79 1]]

y = df.iloc[:, 9:].values
print(y)

[[1.00000000e+00 1.00000000e+00 1.0134888e+05 1.00000000e+00]
 [0.00000000e+00 1.00000000e+00 1.1254258e+05 0.00000000e+00]
 [1.00000000e+00 0.00000000e+00 1.1393157e+05 1.00000000e+00]
 ...
 [0.00000000e+00 1.00000000e+00 4.2085580e+04 1.00000000e+00]
 [1.00000000e+00 0.00000000e+00 9.2888520e+04 1.00000000e+00]
 [1.00000000e+00 0.00000000e+00 3.8190780e+04 0.00000000e+00]]

#splitting the data
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=0)
xtrain.shape,xtest.shape

((7000, 9), (3000, 9))

```