

## Assignment -2

## Data visualization and Preprocessing

Assignment Date	21 September 2022
Student Name	Kumaravel
Student Roll Number	610519104056
Maximum Marks	2 Marks

## 1.DOWNLOAD THE DATASET

## 2.LOAD THE

# DATASET

```
numpyas      np      import
```

matplotlib.pyplot as plt

```
import seaborn as sns
```

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

df

In [1]:

In [2]:

In [6]:

Out[6]:

[illegible]

3	4	15701354	Boni	699	France	maFe	39	1	0.00	2	0
		0	93826.63	0							
					le						

			Mit		Fe		125				
4	5	15737888	chell	850	Spai_n	male	43	2	510.82	1	1
		1	79084.100								

...	...	...	...	...	...	...	..	...	...	...	...	...	...
-----	-----	-----	-----	-----	-----	-----	----	-----	-----	-----	-----	-----	-----

99		1560	Obi		Fran	Ma	3	5	0.00	2	1	0	96270.	0
	9996		jiak	771										
95		6229	u		ce	le	9						64	

	Row Num	Cust number	Sur name	Cred itSco re	Geo graphy	Ge nd er	A g e	Te nu re	Bal anc e	NumOfProducts	Has CrCard	IsActiveMember	EstimatedSalary
99996	9997	1559892	Joh nstone	516	France	Male	35	10	57369.61	1	1	1	101699.77
99997	9998	1554532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58
99998	9999	1562355	Sab batini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52
99999	1000	1560831	Wal ker	792	France	Female	28	4	130142.79	1	1	0	38190.78

10000 rows × 14 columns

```
df.head()
```

	Row Num	Cust number	Sur name	Cred itSco re	Geo graphy	Ge nd er	A g e	Te nu re	Bal anc e	NumOfProducts	Has CrCard	IsActiveMember	EstimatedSalary
0			1	460215631	1	Harve	619	France	male	24	2	0.00	1
						101348.88			1				
1			Fe	838									
			2	156473110	1	Hill	608	Spain	male	41	1	07.86	1
						112542.58			0				

```

2          15619304  Onio  502  France  maleFe  24      8      660.15980      3
3          1          0  113931.57      1

3          15701354  Boni      France  lemaFe39  1 0.00  2      0      0 93826.63      0
4          699

      Row  Cust  Sur  Cred  Geo  GA  Te  Bal  NumO  Has  IsActivEstima  Ex  g  nu
NumomernaitScograpndber Id me re hy er  ancfProduCrCeMembtdSalaite e re e ctsard er ry d
4          5 78881573chelMitl      850 Spain leFe3      510.12582      79084.10      0

      ma  4  2      1      1      1

```

In [4]: df.shape

(10000, 14)

Out[4]:

## 3.Univariate,Bivariate&MultiVariate Analysis

### Univariate Analysis

```

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

```

In [9]:

In [17]:

```

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()

```

### Bivariate Analysis

In [18]:

```

sns.FacetGrid(df,hue="Geography",size=5).map(plt.scatter,"Age","Balance")
.a dd_legend(); plt.show()

/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:337: UserWarning
: The `size` parameter has been renamed to `height`; please update your code.
warnings.warn(msg, UserWarning)

```

# Multivariate Analysis

```
In [24]: sns.pairplot(df, hue="Gender", size=3) /usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:2076: UserWarning: The `size` parameter has been renamed to `height`; please update your code. warnings.warn(msg, UserWarning)
```

Out[24]:

```
<seaborn.axisgrid.PairGrid at 0x7f9a9f3029d0>
```

## 4.Descriptive Statistics

In [29]:

```
df.head()
```

Out[29]:

	Row	Cust	Sur	Cred	Geo	Ge	A	Te	Ba	NumOfProduct	Has	IsActiveMemb	Estima	Ex
	Numomernait	Scograpnd	g	nu	ber	Id	me	re	hy	er	e	re	anc	e
0	1	15634602			Hargrave	619	France	male	Fe	42	2	0.00	1	
		1	1		101348.88	1								
1	2	1564			Spai	Fe	4		838				112542	
		7311	Hill	608	n	male	1	1	07.86	1	0	1		
		.58	0											
2	3	93041561			Onio	502	France	male	Fe	42	8	660.15980	3	
		1	0		113931.57	1								
3	4	15701354			Boni	699	France	male	Fe	39	1	0.00	2	0
		0			93826.63	0								

```

4      5      15737888      chelMit 850      Spain      maFele 43      2      510.12582      1
      1      1      79084.10      0

```

In [30]: `df.mean()` *# Get the mean of each column*

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarni
ng: Dropping of nuisance columns in DataFrame reductions (with 'numeric_onl
y=None') is deprecated; in a future version this will raise TypeError.
Select only valid columns before calling the reduction.

```

```

"""Entry point for launching an IPython kernel.

```

Out[30]:

```

RowNumber      5.000500e+03
CustomerId      1.569094e+07
CreditScore     6.505288e+02
Age             3.892180e+01
Tenure          5.012800e+00
Balance         7.648589e+04
NumOfProducts  1.530200e+00
HasCrCard       7.055000e-01
IsActiveMember  5.151000e-01
EstimatedSalary1.000902e+05
Exited          2.037000e-01

```

```

dtype:          In
float64          [31]:
df.mean(axis=1) # Get the
                  mean of
                  each row

```

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarni
ng: Dropping of nuisance columns in DataFrame reductions (with 'numeric_onl
y=None') is deprecated; in a future version this will raise TypeError.
Select only valid columns before calling the reduction.

```

```

"""Entry point for launching an IPython kernel.

```

Out[31]:

```

0      1.430602e+06
1      1.440392e+06
2      1.444860e+06

3      1.435993e+06
4      1.449399e+06
...
9995   1.428483e+06
9996   1.430866e+06
9997   1.421579e+06
9998   1.441922e+06
9999   1.437044e+06
Length: 10000, dtype: float64

```

`df.median()` *# Get the median of each column* In [32]:

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction. """Entry point for launching an IPython kernel.
```

```

                    5.000500e+03 1.569074e+07
RowNumber          6.520000e+02 3.700000e+01
CustomerId         5.000000e+00
CreditScore        9.719854e+04
Age                1.000000e+00
Tenure             1.000000e+00 1.000000e+00
Balance            1.001939e+05
NumOfProducts      0.000000e+00
HasCrCard
IsActiveMember
EstimatedSalary
Exited dtype:
float64
```

Out[32]:

In [39]:

```

norm_data= pd.DataFrame(np.random.normal(size=100000))
norm_data.plot(kind="density",
                figsize=(10,10)); plt.vlines(norm_data.mean(), # Plot black line at
mean
                ymin=0, ymax=0.4,
                linewidth=5.0);
plt.vlines(norm_data.median(), # Plot red line at median
            ymin=0,          ymax=0.4,          linewidth=2.0,
            color="red");
```

In [36]:

```

skewed_data= pd.DataFrame(np.random.exponential(size=100000))

skewed_data.plot(kind="density",
                  figsize=(10,10), xlim=(-1,5));

plt.vlines(skewed_data.mean(), # Plot black line at mean
            ymin=0, ymax=0.8,
            linewidth=5.0);

plt.vlines(skewed_data.median(), # Plot red line at median
            ymax=0.8,          linewidth=2.0,
            color="red");
ymin=0,
```

```

In [40]: norm_data= np.random.normal(size=50) outliers = np.random.normal(15,
size=3)

combined_data= pd.DataFrame(np.concatenate((norm_data, outliers), axis=0))
combined_data.plot(kind="density",
                  figsize=(10,10), xlim=(-5,20));
```





[illegible]

10000 rows × 14 columns

## Measures of Spread

In [43]:

```
max(df["Age"]) - min(df["Age"])
```

Out[43]:

74

In [45]:

```
five_num= [df["Age"].quantile(0), df["Age"].quantile(0.25),  
           df["Age"].quantile(0.50),  
           df["Age"].quantile(0.75),  
           df["Age"].quantile(1)]
```

five\_num

```
[18.0, 32.0, 37.0, 44.0, 92.0]
```

Out[45]:

```
df["Age"].describe()
```

In [46]:

```
count 10000.000000 mean
```

```
    38.921800 std
```

```
    10.487806 min
```

```
    18.000000 25%
```

```
    32.000000
```

```
50%  37.000000 75%
```

```
    44.000000 max
```

```
    92.000000
```

```
Name: Age, dtype: float64
```

Out[46]:

```
df["Age"].quantile(0.75) - df["Age"].quantile(0.25)
```

12.0

Out[47]:

```
df.boxplot(column="Age",  
            return_type='axes',  
            figsize=(8,8))
```

In [49]:

```
plt.text(x=0.74, y=22.25, s="3rd Quartile")  
plt.text(x=0.8, y=18.75, s="Median")  
plt.text(x=0.75, y=15.5, s="1st Quartile")  
plt.text(x=0.9, y=10, s="Min")  
plt.text(x=0.9, y=33.5, s="Max")  
plt.text(x=0.7, y=19.5, s="IQR", rotation=90, size=25);
```

In [50]:

```
df["Age"].var()
```

Out[50]:

109.99408416841683

In [51]:

```
df["Age"].std()
```

```
10.487806451704609
```

Out[51]:

```
abs_median_devs= abs(df["Age"] - df["Age"].median())
abs_median_devs.median() * 1.4826
```

In [52]:

Out[52]:

```
8.8956
```

## Skewness and Kurtosis

In [53]:

```
df["Age"].skew() # Check skewness
```

Out[53]:

```
1.0113202630234552
```

In [54]:

```
df["Age"].kurt() # Check kurtosis
```

Out[54]:

```
1.3953470615086956
```

In [55]:

```
norm_data= np.random.normal(size=100000)
skewed_data= np.concatenate((np.random.normal(size=35000)+2,
                               np.random.exponential(size=65000)),
                              axis=0)
uniform_data= np.random.uniform(0,2, size=100000)
peaked_data= np.concatenate((np.random.exponential(size=50000),
                               np.random.exponential(size=50000)*(-
1)), axis=0)
```

```
data_df= pd.DataFrame({"norm":norm_data,
                        "skewed":skewed_data,
                        "uniform":uniform_data,
                        "peaked":peaked_data})
```

In [56]:

```
data_df.plot(kind="density",
              figsize=(10,10), xlim=(-5,5));
```

```
data_df.skew()
```

In [57]:

```
norm      -0.007037
skewed     1.002549
uniform -0.004434 peaked
      0.018058 dtype:
float64 data_df.kurt()
```

Out[57]:

```
norm      -0.009914      skewed
1.314497
```

In [58]:

Out[58]:

```
uniform -1.201740
peaked    2.971592
```

```
dtype: float64
```

## 5.Handle the Missing

### values

In [83]:

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

In [84]:

Out[84]:

	Row	Cust	Sur	Cred	Geo	Ge	A	Te	Bal	NumO	Has	IsActiv	Estima	Ex
	Num	omer	na	itSco	grap	nd	g	nu	anc	fProdu	CrC	eMemb	tedSala	ite
	ber	Id	me	re	hy	er	e	re	e	cts	ard	er	ry	d
Har														
0	1	15634602			grave	619		France	maleFe	42		2		
	0.00	1	1	1	101348.88			1						
		1564			Spai	Fe	4		838				112542	
1	2	7311	Hill	608	n	male	1		1	07.86	1		0	
	1	.58	0											
		1561	Onio	502	Fran	maFe	4	8	660.159	3	1		0	113931
2	3	9304	ce	le	2	80		.57						1
				699	France	Fe	3	1	0.00	2	0		0	93826.
3	4	15701354		Boni	male	9		63						0

```

4      5      1573  chelMit  850  Spai  maFe  4      2  510.125      1      1      1      79084.      0
      7888      1      n      le      3      82      10

```

In [86]:

```
df.isnull()
```

Out[86]:

	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geo grap hy	Ge nd er	A ge	Te nu re	Bal anc e	NumO ffProdu cts	Has CrC ard	IsActiv eMem ber	Estima tedSala ry	Ex ite d
0	False	False False	e False	False False	False lse	se	al	se	se	False				Fa
1	False	False False	Fals e lse	False	False	se	sealF	False	False	False	False	False	False	False
2	False	False	Fals e	False se	False se	Fal se	alF	Fal se	Fal se	False lse	False	False	False	Fa
3	False	False False	Fals e lse	False	False	se	seal	se	se	False	False	False	False	Fa

4	False	False	False	False	False	False	False	False	False	False	False	False	False	False
---	-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	-------

...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----

9	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9														
5														

9	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9														
6														

9	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9														
7														

9	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9														
8														

9	False	False	False	False	False	False	False	False	False	False	False	False	False	False
9														
9														

10000 rows × 14 columns

In [89]: sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')

```

<matplotlib.axes._subplots.AxesSubplot at 0x7f9a987d8290>
Out[89]:
In [93]:
sns.set_style('whitegrid')
sns.countplot(x='Geography',data=df)
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a92a88850>
Out[93]:
sns.set_style('whitegrid')
sns.countplot(x='Geography',hue='Gender',data=df,palette='RdBu_r')
In [94]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a92ec10d0>
Out[94]:
sns.set_style('whitegrid')
sns.countplot(x='Geography',hue='Gender',data=df,palette='rainbow')
In [96]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a92afac50>
sns.distplot(df['Age'].dropna(),kde=False,color='darkred',bins=40)
Out[96]:

```

```

In [97]:
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-
level function with similar flexibility) or `histplot` (an axes-level
function for histograms).
  warnings.warn(msg, FutureWarning)
Out[97]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a98787590>
In [98]:
df['Age'].hist(bins=30,color='darkred',alpha=0.3)
Out[98]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a92d64c10>
sns.countplot(x='NumOfProducts',data=df)
In [100]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f9a9306f790>
df['Age'].hist(color='green',bins=40,figsize=(8,4))
Out[100]:
<matplotlib.axes._subplots.AxesSubplot at
0x7f9a90f52d90>

```

## Cufflinks for plots

```

In [101]:

Out[101]:

```

```
import cufflinks as cfcf.go_offline()
```

In [102]:

```
df['Age'].plot(kind='hist',bins=30,color='green')
```

In [ ]:

## Data Cleaning

```
plt.figure(figsize=(12, 7))
sns.boxplot(x='Gender',y='Age',data=df,palette='winter')
```

In [107]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f9a90f59450>

Out[107]:

In [307]:

```
def impute_age(cols):
    Age = cols[0]
    Pclass= cols[1]
```

```
    if pd.isnull(Age):
```

```
        if Pclass== 1:
```

```
            return 37
```

```
        elif Pclass== 2: return
```

```
            29
```

```
        else:
```

```
            return 24
```

```
    else:
```

```
        return Age sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

In [122]:

Out[122]:

In [112]:

In [114]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f9a8aa699d0>

Out[114]:

```
df.drop('Gender',axis=1,inplace=True)
```

```
df.head()
```

RowN	Custo	Sur	Credi	Geog	Age	Tenure	Balance	ProductNumOfs	Estimat	Ex
HasCrCard	e	IsActiveMember	umbe	y	merI	nam	tScor	raph r d	edSalarite	y



0	1	15634602	grave	619	France	42	2	0.00	1	1	1
		101348.88	1								

	Row	NCusto	Sur	Credi	Geog	Age	Tenure	Balance				
	Product	NumOfs	HasCrCard	IsActive	Member	EstimatedSalary	Exited	umbemerInamtScorr	aph r d e y			
1	2	15647311		Hill	608	Spain	41	1	83807.86	1	0	
		1		112542.58	0							
	156192	Oni8	Franc60.80	43	15961	113931.20	357	3041	o	502	e	
3	4	1570135493826.63		Boni0	699	France	39	1	0.00	2	0	0
4	5	15737888		Mitchell	850	Spain	43	2	125510.82	1	1	
		1		79084.10	0							

## Converting Categorical Features

In [116]:

```
df.info()

<class
'pandas.core.frame.DataFrame'>RangeIndex:
10000 entries, 0 to 9999 Data columns
(total 13 columns):
# Column          Non-Null Count  Dtype
-----  -
RowNumber      10000 non-null int64
CustomerId     10000 non-null int64
Surname        10000 non-null object
CreditScore    10000 non-null int64
Geography      10000 non-null object
Age            10000 non-null int64
Tenure         10000 non-null int64
Balance        10000 non-null float64
NumOfProducts 10000 non-null int64
HasCrCard      10000 non-null int64
```

```

10 IsActiveMember 10000 non-null int64
11 EstimatedSalary 10000 non-null float64
12 Exited 10000 non-null int64 dtypes: float64(2), int64(9), object(2)
memory usage: 1015.8+ KB

```

```
In [118]: pd.get_dummies(df['Geography'],drop_first=True).head()
```

Out[118]:

```

      Germany  Spain
0           0  0
      Germany  Spain
1           0  1
2           0  0
3           0  0
4           0  1

```

```
In [124]: df.info
```

Out[124]:

```

<bound method DataFrame.info of RowNumberCustomerId Surname CreditScoreGeography Age Tenure \
0           1 15634602 Hargrave 619 France 42      2
1           2 15647311      Hill 608   Spain 41      1 2    3 15619304 Onio
           502 France 42      8
3 4 15701354 Boni 699 France 39 1 4 5 15737888 Mitchell 850 Spain 43 2
... ..
9995           9996 15606229 Obijiaku 771 France 39      5
9996           9997 15569892 Johnstone      516 France 35      10
9997           9998 15584532      Liu 709 France 36      7
9998           9999 15682355 Sabbatini 772 Germany 42      3
9999           10000 15628319      Walker      792 France 28      4

      Balance NumOfProductsHasCrCardIsActiveMemberEstimatedSalary
\
0           0.00 1      1      1      101348.88
1           83807.86      1      0      1      112542.58
2           159660.80 3 1 0 113931.57 3 0.00 2 0 0 93826.63 4 125510.82 1 1
           1 79084.10 ... .. 9995 0.00 2 1 0 96270.64
9996           57369.61      1      1      1      101699.77
9997           0.00 1      0      1      42085.58
9998           75075.31      2      1      0      92888.52
9999           130142.79      1      1      0      38190.78

      Exited
0           1

```

```

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

```

```
[10000 rows x 13 columns]>
```

```

sex = pd.get_dummies(df['Age'],drop_first=True)
embark =
pd.get_dummies(df['Balance'],drop_first=True)

```

In [125]:

In [127]:

```
df.drop(['Age','HasCrCard','Surname','CustomerId'],axis=1,inplace=True)
```

In [129]:

```
df.head()
```

Out[129]:

	RowNum	CreditSc	Geogra	Tenu	Balanc	NumOfProd	IsActiveMe	EstimatedSa	Exit
	ber	ore	phy	re	e	ucts	mber	lary	ed
0	1	619	France	2	0.00	1	1	101348.88	1
1	2	608	Spain	1	83807.86	1	1	112542.58	0
					159660.				
2	3	502	France	8	80	3	0	113931.57	1
3	4	699	France	1	0.00	2	0	93826.63	0
4	5	850	Spain	2	125510.82	1	1	79084.10	0

In [130]:

```
train = pd.concat([df,sex,embark],axis=1)
```

```
train.head()
```

In [131]:

[illegible]

[illegible]

8

2

5 rows  $\times$  6459 columns

## 6. Find the outliers and replace the outliers

In [147]:

```
dataset= [11,10,12,14,12,15,14,13,15,102,12,14,17,19,107,  
10,13,12,14,12,108,12,11,14,13,15,10,15,12,10,14,13,15,10]
```

### Detecting outlier using Z score

#### Using Z score

In [148]:

```
outliers=[] def detect_outliers(data):  
threshold=3 mean =  
np.mean(data)
```

```
std =np.std(data)
```

```
for iin data:
```

```
    z_score=(i- mean)/std
```

```
    if np.abs(z_score) >threshold:
```

```
        outliers.append(y)
```

```
return outliers
```

In [151]:

```
outlier_pt=detect_outliers(dataset)
```

In [152]:

```
outlier_pt
```

Out[152]:

```
[0      101348.88

1      112542.58
2      113931.57 3  93826.63
4      79084.10
...
9995  96270.64 9996
101699.77      9997
42085.58

9998      92888.52

9999      38190.78
Name: EstimatedSalary, Length: 10000, dtype: float64, 0      101348.88
1      112542.58
2      113931.57 3  93826.63 4  79084.10
...
9995  96270.64 9996
101699.77      9997
42085.58

9998      92888.52

9999      38190.78
Name: EstimatedSalary, Length: 10000, dtype: float64, 0      101348.88
1      112542.58 2
113931.57      3
93826.63
4      79084.10
...
9995  96270.64 9996
101699.77      9997
42085.58

9998      92888.52

9999      38190.78
Name: EstimatedSalary, Length: 10000, dtype: float64]
```

In [153]:

```
## Perform all the steps of IQR
```



```
dataset)
```

```
sorted(d
```

Out[153]:

```
[10,  
 10,  
 10,  
 10,  
 10,  
 11,  
 11,  
 12,  
 12,  
 12,  
 12,  
 12,  
 12,  
 12,  
 13,  
 13,  
 13,  
 13,  
 14,  
 14,  
 14,  
 14,  
 14,  
 14,  
 15,  
 15,  
 15,  
 15,  
 15,  
 17,  
 19,  
 102,  
 107,  
 108]
```

In  
[155]:

In  
[156]:

```
quantile1, quantile3= np.percentile(dataset, [25,75])  
print(quantile1,quantile3)
```

```
12.0 15.0
```

In  
[157]:

```
## Find the IQR
```

```
iqr_value=quantile3-quantile1  
print(iqr_value)
```

```
3.0
```

```
## Find the lower bound value and the higher bound value
```

```
lower_bound_val= quantile1 -(1.5 * iqr_value)  
upper_bound_val= quantile3 +(1.5 * iqr_value)  
print(lower_bound_val,upper_bound_val)
```

In  
[159]:

In  
[160]:

```
7.5 19.5
```

## 7.Check for Categorical columns and perform encoding

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

In [161]:

```
df.head()
```

In [162]:

Out[162]:

Row	Cust	Sur	Cred	Geo	Ge	A	Te	Bal	NumOfProduct	Has	IsActiveMemb	Estima	Ex
NumomernaitScograpnd g nu ancher Id me re hy er e re e	s	CrCard	er	tedSalaitery	d								
0	1	15634602		Hargra	619	France	male	101348.88	42	2	0.00	1	1
		ve			le				1				
1	2	15647311	Hill	Spain	608	France	male	838	1	07.86	1	0	1
								.58	0				
2	3	15619304	Onio	France	502	France	male	159	2	660.80	3	1	0
								.57	1				
3	4	13541570		Boni	699	France	male	93826.63	93	1	0.00	2	0
					0				0	ma			
4	5	78881573	Mitl	Spain	1573	France	male	12582			79084.10	0	
		chel	850						2	510.	1	1	

In [163]:

```
df_numeric= df[['RowNumber', 'CustomerId', 'CreditScore', 'Age', 'Tenure', 'Balance',
```

```
'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited']]
df_categorical= df[['Surname', 'Geography', 'Gender']]
```

```
In [164]: df_numeric.head()
```

```
Out[164]:
```

```
RowNuCusto Credit A Ten Balan NumOfPrHasCrIsActiveM Estimated EximbermerId Score geureceoducts Card
ember Salary ted
```

```
0 1 156346 02 619 42 2 0.00 1 1 1 101348.88 1
```

```
RowNuCusto Credit A Ten Balan NumOfPrHasCrIsActiveM Estimated EximbermerId Score geureceoducts Card
ember Salary ted
```

```
1 2 156473 11 608 41 1 .86 1 0 1 112542.58 0
```

```
2 3 156193 04 502 42 8 15966 0.80 3 1 0
113931.57 1
```

```
3 4 157013 54 699 39 1 0.00 2 0 0 93826.63 0
```

```
4 5 157378 88 850 43 2 12551 0.82 1 1 1
79084.10 0
```

```
In [165]:
df_categorical.head()
```

```
Out[165]:
```

```
Surname Geography Gender
```

```
0 Hargrave France Female
```

```
1 Hill Spain Female
```

```
2 OnioFrance Female
```

```
3 Boni France Female
```

```
4 Mitchell Spain Female
```

```
In [166]:
```

```
In [167]:
```

```
print(df['Surname'].unique())
print(df['Geography'].unique())
print(df['Gender'].unique())
```

```
['Hargrave' 'Hill' 'Onio' ... 'Kashiwagi' 'Aldridge' 'Burbidge']
['France' 'Spain' 'Germany']
['Female' 'Male']
```

In [168]:

```
from sklearn.preprocessing import LabelEncoder
marry_encoder =
```

```
LabelEncoder()
```

```
marry_encoder.fit(df_categorical['Gender'])
```

```
LabelEncoder()
```

Out[168]:

In [169]:

```
marry_values = marry_encoder.transform(df_categorical['Gender'])
```

In [170]:

```
print("Before Encoding:", list(df_categorical['Gender'][-10:]))
print("After Encoding:", marry_values[-10:])
print("The inverse from the encoding result:", marry_encoder.inverse_transform(marry_values[-10:]))
```

```
Before Encoding: ['Male', 'Female', 'Male', 'Male', 'Female', 'Male', 'Male', 'Male', 'Female', 'Male', 'Female']
```

```
After Encoding: [1 0 1 1 0 1 1 0 1 0]
```

```
The inverse from the encoding result: ['Male' 'Female' 'Male' 'Male' 'Female' 'Male' 'Male' 'Female' 'Male' 'Female']
```

In [171]:

```
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])
print("The inverse from the encoding result:", residence_encoder.inverse_transform(residence_values[:5]))
```

```
Before Encoding: ['France', 'Spain', 'France', 'France', 'Spain']
```

```
After Encoding: [0 2 0 0 2]
```

```
The inverse from the encoding result: ['France' 'Spain' 'France' 'France' 'Spain']
```

In [172]: **from** sklearn.preprocessing **import** OneHotEncoder

```
gender_encoder = OneHotEncoder()
```

In [174]:

**from** sklearn.preprocessing **import** OneHotEncoder

**import** numpy as np

```
gender_encoder = OneHotEncoder()
gender_resaped = np.array(df_categorical['Gender']).reshape(-1, 1)
gender_values = gender_encoder.fit_transform(gender_resaped)
print(df_categorical['Gender'][:5])
print()
print(gender_values.toarray()[:5])
print()
print(gender_encoder.inverse_transform(gender_values[:5])[:5])
```

```

0    Female
1    Female
2    Female
3    Female
4    Female
Name: Gender, dtype: object

```

```

[[1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]

```

```

['Female']
['Female']
['Female']
['Female']
['Female']

```

In [175]:

```

smoke_encoder= OneHotEncoder()
[1. 0.]
smoke_resaped= np.array(df_categorical['Surname']).reshape(-1, 1)
smoke_values= smoke_encoder.fit_transform(smoke_resaped)
print(df_categorical['Surname'][:5])
print(
)
print(smoke_values.toarray()[:5]) print()
print(smoke_encoder.inverse_transform(smoke_values)[:5])

```

```

0    Hargrave
1    Hill
2    Onio
3    Boni
4    Mitchell
Name: Surname, dtype: object

```

```

[[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.]]

```

```

['Hargrave']

```

```

['Hill']
['Onio']
['Boni']

```

```

['Mitchell']]

```

In [176]:

```

work_encoder= OneHotEncoder()
work_resaped= np.array(df_categorical['Geography']).reshape(-1, 1)
work_values= work_encoder.fit_transform(work_resaped)
print(df_categorical['Geography'][:5]) print()
print(work_values.toarray()[:5]) print()
print(work_encoder.inverse_transform(work_values)[:5])

```

```
[1. 0. 0.]
[0. 0. 1.]
[1. 0. 0.]
[1. 0. 0.]
[0. 0. 1.]]
[['France'] ['Spain']]
[['France']]
[['France']]
[['Spain']]
```

```
df_categorical_encoded= pd.get_dummies(df_categorical, drop_first=True)
df_categorical_encoded.head()
```

S S S S S Su  
u

n	n	na	na	r	a	na
		a	a	me	n	n
		Z	Z	e	n	n
		ra	gr	n a	u	ub

**e**

e

-

e

-

-

A

m

a a m m n m m m me owa br\_Aitz ... e\_mZ  
mae barev areva Zue ma\_e e\_mZa Gephy\_r y\_pha d\_re

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\_ A b b e be br br a ot \_ Z u m S M

A b d d \_ rn a a m Z

b b ul ul A at m m ov vao ox uy yev  
any aip lea

bi ot la ov b hy ov ov ic

e t h el a h v v<sup>e</sup> a n

0 0 0 0 0 0 0 0 0 0 0 . 0 0 0 0 0 0 0 0 0 0 0

000000001010000000000.

0000000000020000000000.

```
.
000000000000300000000000.
.

.
00000000010400000000000.
.
```

5rows × 2934 columns

```
In [179]: df_new= pd.concat([df_numeric, df_categorical_encoded], axis=1)
df_new.head()
```

Out[179]:



[illegible]

5 rows  $\times$  2945 columns

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

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

In [180]:

```
print(df["Balance"].min()) print(df["Balance"].max())
print(df["Balance"].mean())
```

In [182]:

```
0.0
250898.09 76485.889288
print(df.count(0))
```

In [183]:

```
RowNumber      10000
CustomerId      10000
Surname         10000
CreditScore     10000
Geography       10000
Gender Age      10000
Tenure          10000
Balance         10000
NumOfProducts  10000
HasCrCard       10000
IsActiveMember  10000
EstimatedSalary 10000
Exited dtype:    10000
int64            10000
```

In [184]:

```
print(df.shape)
(10000, 14)
```

In [185]:

```
print(df.size)
140000
```

In [187]:

```
X = df.iloc[:, :-1].values print(X)
[[1 15634602 'Hargrave' ... 1 1 101348.88]
 [2 15647311 'Hill' ... 0 1 112542.58]
 [3 15619304 'Onio' ... 1 0 113931.57] ...
 [9998 15584532 'Liu' ... 0 1 42085.58]
 [9999 15682355 'Sabbatini' ... 1 0 92888.52]
 [10000 15628319 'Walker' ... 1 0 38190.78]]
Y = df.iloc[:, -1].values print(Y)
[1 0 1 ... 1 1 0]
```

In [271]:

## 9.Scale the independent variables

In [215]:

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

x    =    df[['Age',    'Tenure']].values    y    =
df['Gender'].values                fig,                ax=
plt.subplots(ncols=2, figsize=(12, 4))

ax[0].scatter(x[:,0], y) ax[1].scatter(x[:,1],
y)
plt.show()
```

In [216]:

```
fig, ax= plt.subplots(figsize=(12, 4))

ax.scatter(x[:,0], y)
ax.scatter(x[:,1], y)

<matplotlib.collections.PathCollection at 0x7f9a8a854ad0>
```

Out[216]:

In [217]:

```
fig, ax= plt.subplots(figsize=(12, 4))

ax.hist(x[:,0]) ax.hist(x[:,1])
```

Out[217]:

```
(array([ 413., 1035., 1048., 1009., 989., 1012., 967., 1028., 1025.,
        1474.]), array([ 0., 1., 2., 3., 4., 5., 6., 7., 8.,
        9., 10.])),
<a list of 10 Patch objects>)
```

In [220]:

```
from sklearn.preprocessingimport StandardScalerfrom
sklearn.preprocessingimport MinMaxScaler fig, ax= plt.subplots(figsize=(12,
4))

scaler = StandardScaler() x_std=
scaler.fit_transform(x)
ax.hist(x_std[:,0])
ax.hist(x_std[:,1])
```

Out[220]:

```
(array([ 413., 1035., 1048., 1009., 2001.,      0., 1995.,      0., 1025.,
        1474.]), array([-1.73331549, -1.38753759, -1.04175968, -
        0.69598177, -0.35020386,
        -0.00442596, 0.34135195, 0.68712986, 1.03290776, 1.37868567,
        1.72446358])),
<a list of 10 Patch objects>)
```

In [219]:

```
fig, ax= plt.subplots(figsize=(12, 4))
```

```
scaler = StandardScaler()  
x_std= scaler.fit_transform(x)  
ax.scatter(x_std[:,0], y)  
ax.scatter(x_std[:,1], y)
```

Out[219]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a2fde50>
```

In [221]:

```
fig, ax= plt.subplots(figsize=(12, 4))  
  
scaler = MinMaxScaler()  
x_minmax= scaler.fit_transform(x)  
ax.hist(x_minmax[:,0])  
ax.hist(x_minmax  
[:,1])
```

Out[221]:

```
(array([ 413., 1035., 1048., 1009., 989., 1012., 967., 1028., 1025.,  
        1474.]), array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7,  
        0.8, 0.9, 1. ]),  
<a list of 10 Patch objects>)
```

In [222]:

```
fig, ax= plt.subplots(figsize=(12, 4))
```

```
scaler = MinMaxScaler()  
x_minmax= scaler.fit_transform(x)  
ax.scatter(x_minmax[:,0], y)  
ax.scatter(x_minmax[:,1], y)
```

Out[222]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a0cae10>
```

In [223]:

```
fig, ax= plt.subplots(figsize=(12, 4))  
  
scaler = MinMaxScaler() x_minmax=  
scaler.fit_transform(x)  
ax.scatter(x_minmax[:,0], y)
```

Out[223]:

```
<matplotlib.collections.PathCollection at 0x7f9a8a0caf10>
```

In [224]:

```
fig, ax= plt.subplots(figsize=(12, 4))  
  
scaler = MinMaxScaler() x_minmax=  
scaler.fit_transform(x)  
ax.hist(x_minmax[:,0])
```

Out[224]:

```
(array([ 611., 2179., 3629., 1871., 910., 441., 208., 127., 20.,  
        4.]),
```

```
array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),  
<a list of 10 Patch objects>)
```

In [227]:

```
from sklearn.model_selectionimport train_test_splitfrom  
sklearn.pipelineimport Pipeline  
  
from sklearn.linear_modelimport SGDRegressorfrom  
sklearn.preprocessingimport StandardScalerfrom  
sklearn.preprocessingimport MinMaxScalerfrom sklearn.metricsimport  
mean_absolute_errorimport sklearn.metricsas metrics  
  
import pandas as pd import  
numpyas np import  
matplotlib.pyplotas plt  
  
# Import Data  
df= pd.read_csv('/content/Churn_Modelling.csv')  
x = df[['Age', 'Tenure']].values y =  
df['Balance'].values  
  
# Split into a training and testing set  
X_train, X_test, Y_train, Y_test= train_test_split(x, y)  
# Define the pipeline for scaling and model fitting  
pipeline = Pipeline([  
    ("MinMax Scaling", MinMaxScaler()),  
    ("SGD Regression", SGDRegressor())  
])  
  
# Scale the data and fit the model  
pipeline.fit(X_train, Y_train)  
  
# Evaluate the model  
  
Y_pred= pipeline.predict(X_test)  
  
Mean Absolute Error: ', mean_absolute_error(Y_pred, Y_test))  
print('Score', pipeline.score(X_test, Y_test))  
Mean Absolute Error: 57120.533393590835  
Score 0.0004207814312172653
```

## 10.Split the data into training and testing

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

In [267]:

```
 \      RowNumberCustomerId      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 NumOfProductsHasCrCardIsActiveMember \
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]

In [287]:

```
dataset.drop(["HasCrCard"],axis=1,inplace=True)
```

print(dataset.shape)#no. of rows and columne

In [288]:

```

print(dataset.head(10))
(10000, 7)
      CustomerIdCreditScore Age Tenure      Balance IsActiveMember \
0      15634602      619 42      2 0.00      1
1      15647311      608 41      1 83807.86 1
2      15619304      502 42      8 159660.80      0 3 15701354      699 39
      1      0.00 0 4 15737888      850 43      2 125510.82      1
5 15574012      645 44      8 113755.78      0 6 15592531      822
50 7      0.00 1
7 15656148      376 29      4 115046.74      0 8 15792365      501
44 4 142051.07      1
9 15592389      684 27      2 134603.88      1

```

EstimatedSalary



```

0    101348.88 1
    112542.58 2
    113931.57
3      93826.63
4      79084.10
5     149756.71
6      10062.80
7     119346.88
8      74940.50
9      71725.73

```

In [289]:

```

X=dataset.iloc[:, :-1].values
X

```

```

Out[289]: array([[1.5634602e+07, 6.1900000e+02, 4.2000000e+01, 2.0000000e+00,
        0.0000000e+00, 1.0000000e+00],
        [1.5647311e+07, 6.0800000e+02, 4.1000000e+01, 1.0000000e+00,
        8.3807860e+04, 1.0000000e+00],
        [1.5619304e+07, 5.0200000e+02, 4.2000000e+01, 8.0000000e+00,
        1.5966080e+05, 0.0000000e+00],
        ...,
        [1.5584532e+07, 7.0900000e+02, 3.6000000e+01, 7.0000000e+00,
        0.0000000e+00, 1.0000000e+00],
        [1.5682355e+07, 7.7200000e+02, 4.2000000e+01, 3.0000000e+00,
        7.5075310e+04, 0.0000000e+00],
        [1.5628319e+07, 7.9200000e+02, 2.8000000e+01, 4.0000000e+00,
        1.3014279e+05, 0.0000000e+00]])

```

```

Y=dataset.iloc[:, -1].values
Y

```

In [290]:

```

array([101348.88, 112542.58, 113931.57, ..., 42085.58, 92888.52,
Out[290]: 38190.78])

```

```

from sklearn.model_selection import train_test_split

```

In [291]:

```

X_train,X_test,Y_train,Y_test= train_test_split( X, Y, test_size= 0.25,
random_state= 0 )

```

In [306]:

```

from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train= sc.fit_transform(X_train) X_test=
sc.transform(X_test) print(X_train)

[[-1.34333028 -0.73550706 0.01526571 0.00886037 0.67316003 -1.03446007]
 [ 1.55832963 1.02442719 -0.65260917 0.00886037 -1.20772417 -1.03446007]
 [-0.65515619 0.80829492 -0.46178778 1.39329338 -0.35693706 0.96668786]
 ...
 [-1.63542994 0.90092304 -0.36637708 0.00886037 1.36657199 -1.03446007]

```

```
[-0.38540456 -0.62229491 -0.08014499 1.39329338 -1.20772417 0.96668786] [-  
1.37829524 -0.28265848 0.87396199 -1.37557264 0.51741687 -1.03446007]]
```

In [305]:

```
print(X_test)
```

```
[[-1.05852196 -0.55025082 -0.36637708 1.04718513 0.88494297 0.96668786]  
 [-0.51554728 -1.31185979 0.11067641 -1.02946438 0.43586703 -1.03446007]  
 [-0.8058485 0.57157862 0.3014978 1.04718513 0.31486378 0.96668786]  
 ...]
```

```
[ 0.25326371 1.95070838 0.01526571 -1.37557264 0.30819395 -1.03446007]
[-0.17836122 0.29369426 -0.08014499 0.70107688 0.55698791 -1.03446007]
[ 0.40190663 0.870047 -0.74801987 -0.68335613 0.7006957 -1.03446007]]
```