# **Assignment 2**

# **Data Visualization and Pre-processing**

### 1. Perform Below Visualizations.

#### **Univariate Analysis**

#### 1. Summary Statistics

In [1]: import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns import statsmodels.api as sm In [2]: file\_data = pd.read\_csv('C:\Harinitha\Churn Modelling.csv') file data Out[2]: Ex Row Cust Cred Geo  $\mathbf{A}$ Te NumOf Has **IsActiv Estima** Bala Produc CrCtedSala ite Num omer na itSco grap nd g nu eMemb nce hy ard ber Id er re ts me re e er ry Har Fe 101348. 1563 Fran 4 0 grav 619 2 0.00 1 1 ma 4602 2 ce e Fe 838 1564 Spai 4 112542. 0 Hill 608 07.8 1 0 1 ma 7311 58 n 1 le 6 Fe 159 1561 Oni Fran 4 113931. 502 2 3 3 1 1 660. ma 2 9304 57 ce le 80 Fe Fran 1570 Bon 3 93826.6 3 699 0.00 2 0 0 ma 1354 9 ce le Mit Fe 125 1573 Spai 4 79084.1 850 1 0 4 chel 510. 1 7888 3 1 82

	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
9 9 9 5	9996	1560 6229	Obij iaku	771	Fran ce	Ma le	3 9	5	0.00	2	1	0	96270.6 4	0
9 9 9 6	9997	1556 9892	Joh nsto ne	516	Fran ce	Ma le	3 5	10	573 69.6 1	1	1	1	101699. 77	0
9 9 9 7	9998	1558 4532	Liu	709	Fran ce	Fe ma le	3 6	7	0.00	1	0	1	42085.5 8	1
9 9 9 8	9999	1568 2355	Sab bati ni	772	Ger man y	Ma le	4 2	3	750 75.3 1	2	1	0	92888.5	1
														0
100	00 rows	× 14 cc	olumns											
fil	_e_data	a[ <b>'</b> Bal	ance'	].mean	n ()								ln	[3]:
764	185.889	928799	961											t[3]:
fil	_e_data	a['Bal	ance'	].med	ian()									[4]:
971	98.540	00000	0001											t[4]:
fil	_e_data	a['Bal	ance'	].std	()									[5]:
623	397.405	520238	8623										Ou	t[5]:
2. 1	Freque	ncy Ta	ble											
fil	_e_data	a[ <b>'</b> Sur	name'	].val	ue_cou	ınts(	()						In	[6]:
Smi Sco		32 29											Ou	t[6]:

```
Martin
Walker
            28
Brown
            26
Izmailov
             1
Bold
Bonham
Poninski
Burbidge
             1
Name: Surname, Length: 2932, dtype: int64
3. Create Charts
                                                                            In [7]:
file_data.boxplot(column=['Balance'], grid=False)
                                                                           Out[7]:
<AxesSubplot:>
                                                                            In [8]:
file data.hist(column='Balance', grid=False, edgecolor='black')
                                                                           Out[8]:
array([[<AxesSubplot:title={'center':'Balance'}>]], dtype=object)
                                                                            In [9]:
sns.kdeplot(file data['Balance'])
                                                                           Out[9]:
<AxesSubplot:xlabel='Balance', ylabel='Density'>
Bi - Variate Analysis
1. Scatterplots
                                                                           In [10]:
plt.scatter(file data.CreditScore.head(100), file data.Age.head(100))
plt.title('Scatter')
plt.xlabel('CreditScore')
plt.ylabel('Age')
                                                                          Out[10]:
Text(0, 0.5, 'Age')
2. Correlation Coefficients
                                                                           In [11]:
file data.corr()
                                                                          Out[11]:
```

Ten Bala NumOfP

nce

ure

HasC

roducts rCard

**IsActive** 

Member

**Estimate** 

dSalary

Exit

29

RowN

umber

Custo

merId

Credit

Score

	RowN umber	Custo merId	Credit Score	Age	Ten ure	Bala nce	NumOfP roducts	HasC rCard	IsActive Member	Estimate dSalary	Exit ed
RowNu mber	1.0000	0.0042 02	0.0058 40	0.00 0783	0.00 6495	0.00 9067	0.007246	0.0005 99	0.012044	0.005988	0.01 6571
Custome rId	0.0042 02	1.0000	0.0053 08	0.00 9497	0.01 4883	0.01 2419	0.016972	0.0140 25	0.001665	0.015271	0.00 6248
CreditSc ore	0.0058 40	0.0053 08	1.0000	0.00 3965	0.00 0842	0.00 6268	0.012238	0.0054 58	0.025651	0.001384	0.02 7094
Age	0.0007 83	0.0094 97	0.0039	1.00 0000	0.00 9997	0.02 8308	0.030680	0.0117 21	0.085472	0.007201	0.28 5323
Tenure	0.0064 95	0.0148	0.0008 42	0.00 9997	1.00 0000	0.01 2254	0.013444	0.0225 83	0.028362	0.007784	0.01 4001
Balance	0.0090 67	0.0124 19	0.0062 68	0.02 8308	0.01 2254	1.00 0000	0.304180	0.0148 58	0.010084	0.012797	0.11 8533
NumOfP roducts	0.0072 46	0.0169 72	0.0122 38	0.03 0680	0.01 3444	0.30 4180	1.000000	0.0031 83	0.009612	0.014204	0.04 7820
HasCrC ard	0.0005 99	0.0140 25	0.0054 58	0.01 1721	0.02 2583	0.01 4858	0.003183	1.0000	0.011866	0.009933	0.00 7138
IsActive Member	0.0120 44	0.0016 65	0.0256 51	0.08 5472	0.02 8362	0.01 0084	0.009612	0.0118 66	1.000000	0.011421	0.15 6128
Estimate dSalary	0.0059 88	0.0152 71	0.0013 84	0.00 7201	0.00 7784	0.01 2797	0.014204	0.0099	0.011421	1.000000	0.01 2097
Exited	0.0165 71	0.0062 48	0.0270 94	0.28 5323	0.01 4001	0.11 8533	0.047820	0.0071	0.156128	0.012097	1.00 0000

### 3. Simple Linear Regression

```
In [12]:
```

```
y = file_data['CustomerId']
x = file_data['HasCrCard']
x = sm.add_constant(x)
model = sm.OLS(y,x).fit()
model.summary()
```

Out[12]:

#### **OLS** Regression Results

Dep. Variable:	CustomerId	R-squared:	0.000
----------------	------------	------------	-------

Model: OLS Adj. R-squared: 0.000

Method: Least Squares F-statistic: 1.967

**Date:** Sun, 25 Sep 2022 **Prob (F-statistic):** 0.161

**Time:** 15:55:30 **Log-Likelihood:** -1.2602e+05

**No. Observations:** 10000 **AIC:** 2.521e+05

**Df Residuals:** 9998 **BIC:** 2.521e+05

Df Model:

Covariance Type: nonrobust

 $coef \qquad std \ err \qquad \qquad t \qquad P{>}|t| \qquad \quad \left[0.025 \qquad \ \, 0.975\right]$ 

**const** 1.569e+07 1325.512 1.18e+04 0.000 1.57e+07 1.57e+07

 $\textbf{HasCrCard} \quad \text{-}2213.3059 \quad 1578.103 \qquad \text{-}1.403 \quad 0.161 \quad \text{-}5306.705 \quad 880.093$ 

**Omnibus:** 8394.858 **Durbin-Watson:** 2.019

**Prob(Omnibus):** 0.000 **Jarque-Bera (JB):** 596.113

**Skew:** 0.001 **Prob(JB):** 3.60e-130

**Kurtosis:** 1.804 **Cond. No.** 3.45

```
Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
                                                                                     In [13]:
plt.plot(file data['RowNumber'].head() , file data['CreditScore'].head(), )
plt.title('Line plot')
plt.xlabel('RowNumber')
plt.ylabel('CreditScore')
                                                                                    Out[13]:
Text(0, 0.5, 'CreditScore')
Multi - Variate Analysis
                                                                                     In [14]:
f = plt.subplots(figsize=(12,10))
sns.heatmap(file data.head().corr(), cmap="YlGnBu")
                                                                                    Out[14]:
<AxesSubplot:>
                                                                                     In [15]:
corrmat = file_data.corr(method='spearman')
cg = sns.clustermap(corrmat, cmap="YlGnBu", linewidths=0.1);
plt.setp(cg.ax_heatmap.yaxis.get_majorticklabels(), rotation=0)
                                                                                    Out[15]:
<seaborn.matrix.ClusterGrid at 0x1e3cd562e20>
4. Perform descriptive statistics on the dataset.
                                                                                     In [16]:
file data.shape
                                                                                    Out[16]:
(10000, 14)
                                                                                     In [17]:
file data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 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
Gender 10000 non-null object
Age 10000 non-null int64
 0
 1
 5
                       10000 non-null int64
10000 non-null int64
10000 non-null floate
 6
    Age
 7
     Tenure
                          10000 non-null float64
     Balance
```

```
9 NumOfProducts 10000 non-null int64
10 HasCrCard 10000 non-null int64
11 IsActiveMember 10000 non-null int64
12 EstimatedSalary 10000 non-null float64
13 Exited 10000 non-null int64
dtypes: float64(2), int64(9), object(3)
```

memory usage: 1.1+ MB

file\_data.describe()

In [18]:

Out[18]:

										C	)ut[18]:
	RowN umbe r	Custo merId	Credit Score	Age	Tenur e	Balanc e	NumOf Product s	HasC rCard	IsActive Membe r	Estimat edSalar y	Exited
co un t	10000. 00000	1.0000 00e+0 4	10000. 00000 0	10000. 00000 0	10000. 00000 0	10000. 000000	10000.0 00000	10000 .0000 0	10000.0 00000	10000.0 00000	10000. 00000 0
m ea n	5000.5 0000	1.5690 94e+0 7	650.52 8800	38.921 800	5.0128 00	76485. 889288	1.53020	0.705 50	0.51510	100090. 239881	0.2037
st d	2886.8 9568	7.1936 19e+0 4	96.653 299	10.487 806	2.8921 74	62397. 405202	0.58165 4	0.455 84	0.49979 7	57510.4 92818	0.4027 69
mi n	1.0000	1.5565 70e+0 7	350.00 0000	18.000 000	0.0000	0.0000	1.00000	0.000	0.00000	11.5800 00	0.0000
25 %	2500.7 5000	1.5628 53e+0 7	584.00 0000	32.000 000	3.0000	0.0000	1.00000	0.000	0.00000	51002.1 10000	0.0000
50 %	5000.5 0000	1.5690 74e+0 7	652.00 0000	37.000 000	5.0000	97198. 540000	1.00000	1.000	1.00000	100193. 915000	0.0000
75 %	7500.2 5000	1.5753 23e+0 7	718.00 0000	44.000 000	7.0000	127644 .24000 0	2.00000	1.000	1.00000	149388. 247500	0.0000
m ax	10000. 00000	1.5815 69e+0 7	850.00 0000	92.000 000	10.000 000	250898 .09000 0	4.00000	1.000	1.00000	199992. 480000	1.0000

In [19]:

file\_data.head()

Out[19]:

	Row Num ber	Cust omer Id	Sur na me	Credi tScor e	Geog raph y	Ge nd er	A g e	Te nu re	Bala nce	NumOf Produc ts	HasC rCar d	IsActiv eMemb er	Estimat edSalar y	Ex ite d
0	1	1563 4602	Har grav e	619	Fran ce	Fe mal e	4 2	2	0.00	1	1	1	101348. 88	1
1	2	1564 7311	Hill	608	Spai n	Fe mal e	4	1	8380 7.86	1	0	1	112542. 58	0
2	3	1561 9304	Oni o	502	Fran ce	Fe mal e	4 2	8	1596 60.8 0	3	1	0	113931. 57	1
3	4	1570 1354	Bon i	699	Fran ce	Fe mal e	3 9	1	0.00	2	0	0	93826.6	0
4	5	1573 7888	Mit chel l	850	Spai n	Fe mal e	4 3	2	1255 10.8 2	1	1	1	79084.1 0	0
fi	le_dat	a.tail	l()										ln [	20]:
													Out[	20]:
	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geo grap	Ge nd	A g	Te	Dala	NumOf	Has	IsActiv	Estima	Ex
9 9 9				10	hy	er	e	nu re	Bala nce	Produc ts	CrC ard	eMemb er	tedSala ry	ite d
5	9996	1560 6229	Obij iaku	771	Fran ce	er Ma le								ite
5 9 9 9 6	9996 9997	1560 6229 1556 9892	Obij iaku Joh nsto ne		Fran	Ma	e 3	re	nce	ts	ard	er	<b>ry</b> 96270.6	ite d
5 9 9 9		6229 1556	Joh nsto	771	Fran ce Fran	Ma le Ma	<b>e</b> 3 9	<b>re</b> 5	0.00 573 69.6	<b>ts</b> 2	ard	<b>er</b> 0	96270.6 4	ite d

	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
9 9 9	10000	1562 8319	Wal ker	792	Fran ce	Fe ma le	2 8	4	130 142. 79	1	1	0	38190.7 8	0
fil	_e_data	a.mean	(num	eric_o	nly <b>=Tr</b>	rue)							ln	[21]:
Cus Cre Age Ter Bal Num Has IsA	nure ance nOfProd sCrCard Activel	Id ore ducts d Member		5.000 1.569 6.505 3.892 5.012 7.648 1.530 7.055 5.151 1.000 2.037	094e+0 288e+0 180e+0 800e+0 589e+0 200e+0 000e-0 902e+0	07 02 01 00 04 00 01							Out	21]:
Exited 2.037000e-01 dtype: float64													ln	[22]:
fil	_e_data	a.medi	.an (n	umeric	_only=	True	<u>.</u> )							
Cus Cre Age Ter Bal Num Has Is Est	nure Lance MOfProc SCrCarc Activel Limated	Id ore ducts d Member dSalar	У	5.000 1.569 6.520 3.700 5.000 9.719 1.000 1.000 1.000	074e+0 000e+0 000e+0 000e+0 854e+0 000e+0 000e+0 939e+0	07 02 01 00 04 00 00 00							Out	_22j:
Exited 0.000000 dtype: float64 file data.mode()													ln	[23]:
	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geog raph y	Ge nd er	A g e	Te nu re	Bal anc e	NumOf Produc ts	Has CrC ard	IsActiv eMemb er	Out  Estima tedSala ry	[23]: Ex ite d
0	1	1556 5701	Smi th	850.0	Fran ce	Ma le	3 7. 0	2.0	0.0	1.0	1.0	1.0	24924.9 2	0.0
1	2	1556	Na	NaN	NaN	Na	N a	Na	Na	NaN	NaN	NaN	NaN	Na

	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geog raph y	Ge nd er	A g e	Te nu re	Bal anc e	NumOf Produc ts	Has CrC ard	IsActiv eMemb er	Estima tedSala ry	Ex ite d
		5706	N			N	N	N	N					N
2	3	1556 5714	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
3	4	1556 5779	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
4	5	1556 5796	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
•••							•••							
9 9 9 5	9996	1581 5628	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
9 9 9 6	9997	1581 5645	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
9 9 9 7	9998	1581 5656	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
9 9 9 8	9999	1581 5660	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N
9 9 9	10000	1581 5690	Na N	NaN	NaN	Na N	N a N	Na N	Na N	NaN	NaN	NaN	NaN	Na N

 $10000 \text{ rows} \times 14 \text{ columns}$ 

In [24]:

file\_data.var(numeric\_only=True)

Out[24]:

RowNumber 8.334167e+06

CustomerId	5.174815e+09	
CreditScore	9.341860e+03	
Age	1.099941e+02	
Tenure	8.364673e+00	
Balance	3.893436e+09	
NumOfProducts	3.383218e-01	
HasCrCard	2.077905e-01	
IsActiveMember		
EstimatedSalary		
Exited	1.622225e-01	
dtype: float64	1.022223e-01	
acype. 110aco4		1
file data atd/ny	oonia only—mana)	I
file_data.std(num	meric_onry <b>-rrue</b> )	
		Oı
RowNumber	2886.895680	
CustomerId	71936.186123	
CreditScore	96.653299	
Age	10.487806	
Tenure	2.892174	
Balance	62397.405202	
NumOfProducts	0.581654	
HasCrCard	0.455840	
IsActiveMember	0.499797	
EstimatedSalary		
Exited	0.402769	
dtype: float64		
		I
file_data.skew(n	umeric_only <b>=True</b> )	
		O
RowNumber	0.00000	9
CustomerId		
CreditScore		
CreditScore Age	1.011320	
CreditScore Age Tenure	1.011320 0.010991	
CreditScore Age Tenure Balance	1.011320 0.010991 -0.141109	
CreditScore Age Tenure Balance NumOfProducts	1.011320 0.010991 -0.141109 0.745568	
CreditScore Age Tenure Balance NumOfProducts HasCrCard	1.011320 0.010991 -0.141109 0.745568 -0.901812	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611	lı
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(na	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611	I
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(no	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(notes)	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(notes) RowNumber CustomerId	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True) -1.200000 -1.196113	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(no	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True) -1.200000 -1.196113 -0.425726	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(number) RowNumber CustomerId CreditScore Age	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 americ_only=True) -1.200000 -1.196113 -0.425726 1.395347	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(notes) RowNumber CustomerId CreditScore Age Tenure	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 americ_only=True) -1.200000 -1.196113 -0.425726 1.395347 -1.165225	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(note) RowNumber CustomerId CreditScore Age Tenure Balance	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True) -1.200000 -1.196113 -0.425726 1.395347 -1.165225 -1.489412	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(note) RowNumber CustomerId CreditScore Age Tenure Balance	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 americ_only=True) -1.200000 -1.196113 -0.425726 1.395347 -1.165225	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(note) RowNumber CustomerId CreditScore Age Tenure Balance NumOfProducts	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True) -1.200000 -1.196113 -0.425726 1.395347 -1.165225 -1.489412	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64 file_data.kurt(number) CustomerId CreditScore Age Tenure Balance NumOfProducts HasCrCard	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True) -1.200000 -1.196113 -0.425726 1.395347 -1.165225 -1.489412 0.582981	
CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited dtype: float64	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True)  -1.200000 -1.196113 -0.425726 1.395347 -1.165225 -1.489412 0.582981 -1.186973 -1.996747	lı Ot
reditScore age Penure Balance JumOfProducts JasCrCard EsActiveMember EstimatedSalary Exited Atype: float64 File_data.kurt(note) CustomerId EreditScore Age Jenure Balance JumOfProducts JasCrCard Ja	1.011320 0.010991 -0.141109 0.745568 -0.901812 -0.060437 0.002085 1.471611 meric_only=True)  -1.200000 -1.196113 -0.425726 1.395347 -1.165225 -1.489412 0.582981 -1.186973 -1.996747	

# 5. Handle the Missing values.

print	(file dat	ta.isnull	l())					In [30]:
-	RowNumbe		omerId	Surname	CreditScore	e Geography	Gender	Age
\								
0	Fal	se	False	False	False	e False	False	False
1	Fal	se	False	False	False	e False	False	False
2	Fal	se	False	False	False	e False	False	False
3	Fal	se	False	False	False	e False	False	False
4	Fal	se	False	False	False	e False	False	False
	•	• •	• • •	• • •	• •		• • •	
9995	Fal	se	False	False	False	e False	False	False
9996	Fal		False	False	False		False	False
9997	Fal	se	False	False	False		False	False
9998	Fals	se	False	False	False	e False	False	False
9999	Fal	se	False	False	False	e False	False	False
	Tenure	Balance	Nıım∩fl	Products	HasCrCard	IsActiveMemb	er \	
0	False	False	1,011.01.	False	False	Fal		
1	False	False		False	False	Fal		
2	False	False		False	False	Fal		
3	False	False		False	False	Fal		
4	False	False		False	False	Fal		
9995	False	False		False	False	Fal		
9996	False	False		False	False	Fal	.se	
9997	False	False		False	False	Fal	.se	
9998	False	False		False	False	Fal	.se	
9999	False	False		False	False	Fal	.se	
	Estimate	edSalary	Exited	d				
0		False	False	9				
1		False	False	9				
2		False	False	Э				
3		False	False	Э				
4		False	False	Э				
9995		False	False	9				

```
9996 False False
9997 False False
9998 False False
9998
                   False False
9999
                   False False
[10000 rows x 14 columns]
                                                                                            In [31]:
print(file_data.isnull().sum())
RowNumber
CustomerId
Surname
CreditScore 0
Geography
Gender
Age
Tenure
Balance
Balance
NumOfProducts
0
0
IsActiveMember 0
EstimatedSalary 0
Exited
dtype: int64
                                                                                            In [32]:
file data.isna().any()
                                                                                           Out[32]:
RowNumber False CustomerId False
Surname
                       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
```

## 6. Find the outliers and replace the outliers

```
In [33]:
x = sns.boxplot(x=file_data["Age"])
x

Out[33]:
<AxesSubplot:xlabel='Age'>

In [34]:
x = file_data.Age
sns.boxplot(x=x)
```

```
Out[34]:
<AxesSubplot:xlabel='Age'>

In [35]:
x = np.where(file_data['Age']>57,39, file_data['Age'])

In [36]:
sns.boxplot(x=x)

Out[36]:
<AxesSubplot:>
```

### 7. Check for Categorical columns and perform encoding.

```
In [37]:
pd.Categorical(file data["Geography"])
                                                                       Out[37]:
['France', 'Spain', 'France', 'France', 'Spain', ..., 'France', 'France', '
France', 'Germany', 'France']
Length: 10000
Categories (3, object): ['France', 'Germany', 'Spain']
                                                                       In [38]:
# One Hot Encoding
pd.get_dummies(file_data["Geography"]).head(10)
                                                                       Out[38]:
  France Germany Spain
     1
             0
      0
              0
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     1
              0
                    0
              0
      1
                    0
3
      0
              0
                    1
5
      0
              0
                    1
      1
              0
                    0
      0
              1
                    0
```

#### France Germany Spain

1 0 0

pd.get\_dummies(file\_data).head(10)

In [39]:

P	. · g c		anun	100	/ (	_		., • 1.	icaa	(10)										Out[	39]:
	R o w N u m b er	C u st o m er I d	C re di t S c o re	A g e	T e n u r	B a l a n c	N u m Of Pr od uc ts	H a s C r C a r d	Is Ac tiv e M e m be	Es ti m at ed Sa lar		Su rn am e_ Zu ba rev	Su rn am e_ Zu ba rev a	Su rn a m e_ Z ue v	Su rn a m e_ Z uy ev	Su rn a me _Z uy ev a	Ge og ra ph y_ Fr an ce	Ge ogr ap hy_ Ge rm any	Ge og ra ph y_ Sp ai n	G en de r_ Fe m al e	G en de r_ M al e
0	1	1 5 6 3 4 6 0 2	6 1 9	4 2	2	0 0 0	1	1	1	10 13 48 .8 8		0	0	0	0	0	1	0	0	1	0
1	2	1 5 6 4 7 3 1	6 0 8	4 1	1	8 3 8 0 7 8 6	1	0	1	11 25 42 .5 8	· ·	0	0	0	0	0	0	0	1	1	0
2	3	1 5 6 1 9 3 0 4	5 0 2	4 2	8	1 5 9 6 6 0 8	3	1	0	11 39 31 .5 7		0	0	0	0	0	1	0	0	1	0
3	4	1 5 7 0 1 3 5 4	6 9 9	3 9	1	0 0 0	2	0	0	93 82 6. 63		0	0	0	0	0	1	0	0	1	0

	R o w N u m b er	C u st o m er I d	C re di t S c o re	A g e	T e n u r	B a l a n c	N u m Of Pr od uc ts	H a s C r C a r d	Is Ac tiv e M e m be r	Es ti m at ed Sa lar y	 Su rn am e_ Zu ba rev	Su rn am e_ Zu ba rev a	Su rn a m e_ Z ue v	Su rn a m e_ Z uy ev	Su rn a me _Z uy ev a	Ge og ra ph y_ Fr an ce	Ge ogr ap hy_ Ge rm any	Ge og ra ph y_ Sp ai n	G en de r_ Fe m al e	G en de r_ M al e
4	5	1 5 7 3 7 8 8 8	8 5 0	4 3	2	1 2 5 5 1 0 8 2	1	1	1	79 08 4. 10	 0	0	0	0	0	0	0	1	1	0
5	6	1 5 5 7 4 0 1 2	6 4 5	4 4	8	1 1 3 7 5 5	2	1	0	14 97 56 .7	 0	0	0	0	0	0	0	1	0	1
6	7	1 5 5 9 2 5 3 1	8 2 2	5 0	7	0 0 0	2	1	1	10 06 2. 80	 0	0	0	0	0	1	0	0	0	1
7	8	1 5 6 5 6 1 4 8	3 7 6	2 9	4	1 1 5 0 4 6	4	1	0	11 93 46 .8 8	 0	0	0	0	0	0	1	0	1	0
8	9	1 5 7 9 2 3 6 5	5 0 1	4 4	4	1 4 2 0 5 1	2	0	1	74 94 0. 50	 0	0	0	0	0	1	0	0	0	1

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```

 $10 \text{ rows} \times 2948 \text{ columns}$ 

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

```
In [40]:
# Splitting the Dataset into the Independent

X = file_data.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]]

# Extracting the Dataset to Get the Dependent

Y = file_data.iloc[:, -1].values
print(Y)

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

### 9. Scale the independent variables

# 10. Split the data into training and testing

In [44]:

from sklearn.model\_selection import train\_test\_split

In [45]:

x = file\_data.drop("EstimatedSalary", axis=1)
x

				Out	[45]:	
on	Rala	NumOf	HacC	Ic Activo	Fvi	

	RowN umber	Custo merId	Surn ame	Credit Score	Geog raphy	Ge nde r	A g e	Ten ure	Bala nce	NumOf Product s	HasC rCard	IsActive Member	Exi ted
0	1	15634 602	Harg rave	619	Franc e	Fe mal e	4 2	2	0.00	1	1	1	1
1	2	15647 311	Hill	608	Spain	Fe mal e	4	1	8380 7.86	1	0	1	0
2	3	15619 304	Onio	502	Franc e	Fe mal e	4 2	8	1596 60.80	3	1	0	1
3	4	15701 354	Boni	699	Franc e	Fe mal e	3 9	1	0.00	2	0	0	0
4	5	15737 888	Mitc hell	850	Spain	Fe mal e	4 3	2	1255 10.82	1	1	1	0
•••							•••						
99 95	9996	15606 229	Obiji aku	771	Franc e	Mal e	3	5	0.00	2	1	0	0
99 96	9997	15569 892	John stone	516	Franc e	Mal e	3 5	10	5736 9.61	1	1	1	0
99 97	9998	15584 532	Liu	709	Franc e	Fe mal e	3 6	7	0.00	1	0	1	1
99	9999	15682	Sabb	772	Germ	Mal	4	3	7507	2	1	0	1

	RowN umber	Custo merId	Surn ame	Credit Score	Geog raphy	Ge nde r	A g e	Ten ure	Bala nce	NumOf Product s	HasC rCard	IsActive Member	Exi ted	
98		355	atini		any	e	2		5.31					
99 99	10000	15628 319	Wal ker	792	Franc e	Fe mal e	2 8	4	1301 42.79	1	1	0	0	
$10000 \text{ rows} \times 13 \text{ columns}$														
<pre>y = file_data.EstimatedSalary</pre>											In	In [46]:		
Y  0											Out	[46]:		
Name: EstimatedSalary, Length: 10000, dtype: float64										In	[47]:			
<pre>x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)</pre>										)				
<pre>print(x_train.shape, x_test.shape)</pre>										111	[48]:			

(8000, 13) (2000, 13)