UNIVERSITY ADMIT ELIGIBILITY PREDICTOR

ASSIGNMENT - 2

Date	26th September 2022
Team ID	PNT2022TMID54388
Student Name	MOSIKARAN M (310619106083)
Domain Name	Education
Project Name	University Admit Eligibility Predictor
Maximum Marks	2 Marks

1.)IMPORT THE REQUIRED LIBRARIES

```
In [1]:
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2.)DOWNLOAD AND UPLOAD THE DATASET

	= pd.read_ .head()	csv(<mark>'Chu</mark> rn	_Modellir	ng.csv')									
	RowNumber	Customerld	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimated Salary
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

3.) HANDLE MISSING VALUES IN THE DATASET

```
Handle the Missing Values in the Dataset

In [3]: #Removing Unwanted Values df = df.drop(columns=['RowNumber','CustomerId','Surname'])

In [4]: df.isnull().sum()

Out[4]: CreditScore 0 Geography 0 Gender 0 Age 0 Tenure 0 Balance NumofProducts 0 HascrCard 0 IsActiveMember 0 Estimatedsalary 0 Exited 0 dtype: int64

In [5]: df.shape

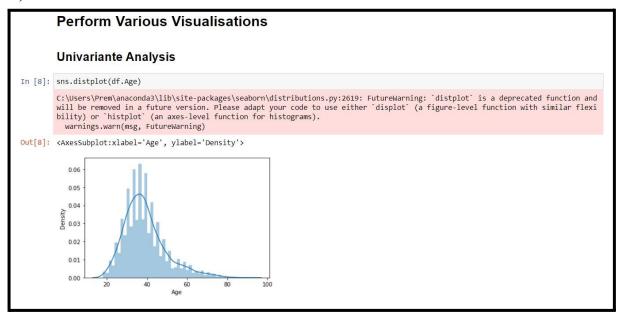
Out[5]: (10000, 11)
```

4.) PERFORM THE DESCRIPTIVE STATISTICS ON THE DATASET

:	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimated Salary	Exited
count	10000.000000	1000 - 100	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	96.653299	10.487806	2.892174	62397.405202	0.581654	0,45584	0.499797	57510.492818	0.402769
min	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000
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<clas Range Data #</clas 	s 'pandas.cor Index: 10000 columns (tota Column	entries, 0 l 11 column	to 9999	ype					
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<pre><clas #="" 0="" 1="" 2="" 3="" 4<="" data="" pre="" range=""></clas></pre>	yandas.cor Index: 10000 columns (tota Column CreditScore Geography Gender Age Tenure	entries, 0 l 11 column Non-Nul 10000 n 10000 n 10000 n	to 9999 s): l Count Dt on-null in on-null ob on-null in on-null in on-null in	t64 ject ject t64 t64					
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<pre><clas #="" 0="" 1="" 2="" 3="" 4="" 5="" 6="" 7<="" data="" pre="" range=""></clas></pre>	s 'pandas.cor Index: 10000 columns (tota Column CreditScore Geography Gender Age Tenure Balance NumOfProducts HasCrCard	entries, 0 1 11 column Non-Nul 10000 n 10000 n 10000 n 10000 n 10000 n 10000 n	to 9999 s): l Count Dty	t64 ject ject t64 t64 oat64 t64					
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5.) PERFORM VARIOUS VISUALISATIONS

a.) UNIVARIANTE ANALYSIS



```
In sns.lineplot(df.Age,df.Exited)

C:\users\Prem\anaconda3\lib\site-packages\seabOru\_decOrators.Dy:36:FutureWarniug:Passthe*OllOwi"9variablesaskeywOrdarg
s:x,y.Fromversion0.12,theonlyvalidpositionalargumentwillbe'data',audpassingotherargumentswithoutanexplicit
keywordwillresultinanerrorormisinterpretation.

0.J[9] <AxesSubplot:xlabel='Age', ylabel= Exited'>
```



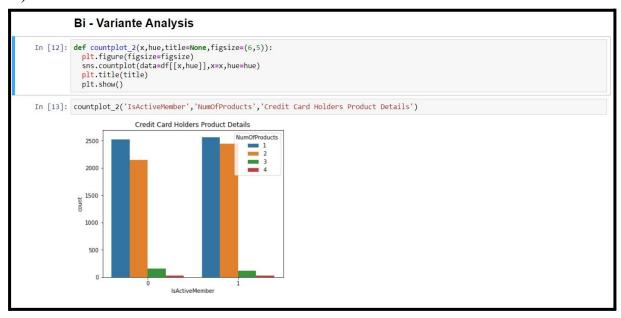
 $n\ [\]:sn\ s\ .\ be\ cplot(df\ .\ NumofP\ rod\ u\ ct\ s\ .\ va\ Inc\ con\ nts\ (\)\ .\ index,\ df\ .\ tlumO*Prod\ net\ s\ .\ val\ ue\ con\ nt\ s\ (\)\)$

c:\Users\Prem\anaconda3\lib\siteoaclages\seaborn\decorators.py:36:FutureNarning:Passthe*ollowingvariablesaskeywordargs:x, y. Frow verzlon a.12, The only valid positional argument will be dada', and oassing of aer arguments 191th out an explicit

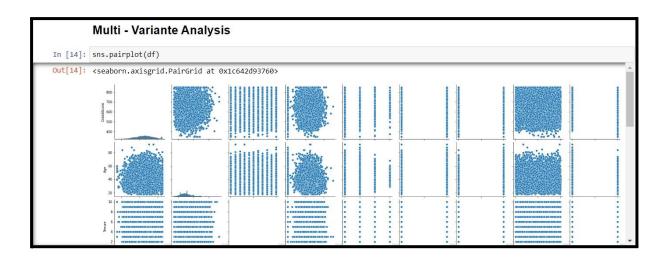
ma rnings . warn(

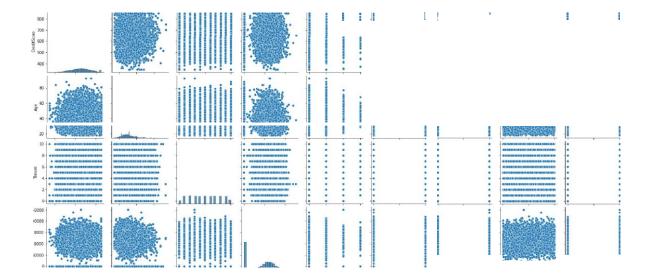
<AxesSubolot:ylabel='Num0*Produ<ts'>

b.) BI - VARIANTE ANALYSIS



c.) MULTI - VARIANTE ANALYSIS





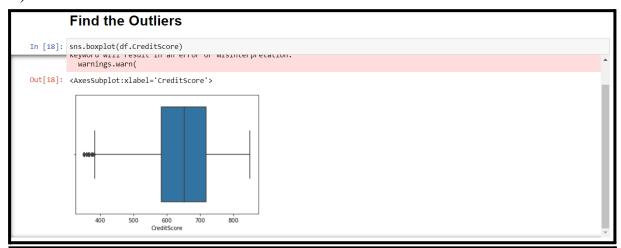


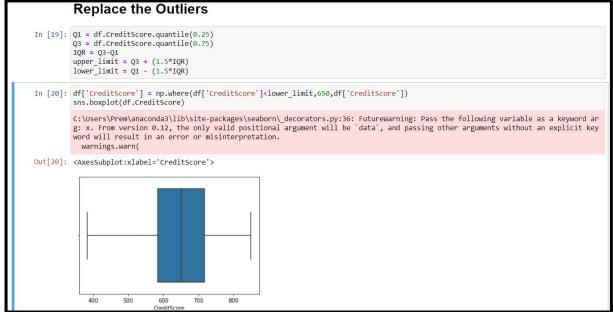
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In [1sj : df. com()

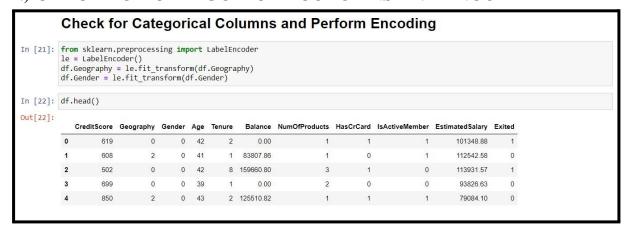
	AQe	Teuwe	Baauce	Num <mproduca< th=""><th>HasCrCard</th><th>lsAcivvMember</th><th>EsimaMdBaag</th><th>Exed</th></mproduca<>	HasCrCard	lsAcivvMember	EsimaMdBaag	Exed
Credit6core	1.000000 -0.0089b5	0.00D842	0.006268	0.012238	fi 00S45B	0.025654	0.00fi 384	-0.027094
Age	-0.003966 4 .0000D0	-0.00999Z	0.028308	-0.030680	-0.0fi 4 724	0.085472	-0.00720fi	0.285323
Tenure	0.000842 -0.009fi9J	fi.00D000	-0.04 2254	0.013^44	0.022583	-0.02B362	0.007Z84	-0.0 4 40D4
Balance	0 006268 0 02B3D8	-O 04 2Z54	4 000000	-0 304fi BO	-0 04 485B	-O D084	0 012 Z 97	4 B538
NuMGfProHHets	0 012288 —0 0306B0	0 04 344H	0 304fi 80	1 000000	0 83	0 0098fi 2	0 01^204	—0 0HT820
HasCrCaN	-0 005458 0 OU 721	0 022583	-0 04 4858	0 O03fi 88	fi 00000D	0 0fi 4 866	0 009983	-0 38
IsActiveMember	0.025651 0.085472	-0.028362	-0.010084	0.009612	-0.011866	1.000000	-0.011421 -0	0.156128
Estimate dSalary	-000fi -00072D100	0778H00279	7	001420A-0	009933	-00fi4424	100000000	42097
Exited	-0.027094 0.285323	-0.014001	0.118533	-0.047820	-0.007138	-0.156128	0.012097	1.000000

6.) FIND AND REPLACE THE OUTLIERS





7.) CHECK FOR CATEGORICAL COLUMNS AND ENCODE THEM



8.) SPLIT DATA INTO DEPENDENT AND INDEPENDENT VARIABLES

х.	<pre>x = df.drop(columns=['Exited']) x.head()</pre>									
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	0	0	42	2	0.00	1	1	1	101348.88
1	608	2	0	41	1	83807.86	1	0	1	112542.58
2	502	0	0	42	8	159660.80	3	1	0	113931.57
3	699	0	0	39	1	0.00	2	0	0	93826.63
4	850	2	0	43	2	125510.82	1	1	1	79084.10
	= df.Exited head()	i								
0	1									
1 2	0									

9.) SCALE THE INDEPENDENT VARIABLES

```
Scale the Independent Variables

In [25]: from sklearn.preprocessing import MinMaxScaler scale = MinMaxScaler()
X_scaled = pd.DataFrame(scale.fit_transform(X),columns=X.columns)
```

10.) SPLIT THE DATA INTO TRAINING AND TESTING