1.Importing the headers

import in
import jumins as jud
import nummy on re
import nationalis.pyplot as pit
import insburn as ins
import statistics as at
import skimare

2.Downloading and loading the churn_modelling dataset

from google.colab import files
uploaded + files.upload()

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable. Saving Churn_Modelling.cov to Churn_Modelling.cov

[s] N() | dataset = pd_read_cxv(io.BytesIO(uploaded)'Churn_Modelling.cxv']))

To [72]) af a pd.yead_cav("thurn_flodetling.cav") cf.head()

RowNumber Customerid Surname CreditScore Geography Gender Age Tenure Belance NumOfProducts HasCrCard isActiveMember EstimatedSalary Exited MINI: 8.00 1 15634652 Hargrane 101340.00 3 15647311 166 (68 Spain Female 4) 5 81807.86 112542.58 2 15015404 France Female -42: E ISHGGRO 11393157 4 15701,354 Sun) 699 France Februio 39 1 EMACAT 1 15737999 Mischell 2 125510.82 79084.10

in [TT]: of a df.drep(columns]/Enduator*, 'ColumnEd', 'Lorente'])
df.head()

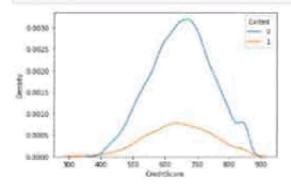
Dui[73]:		CreditScars	Geography	Gunder	Age	Tenure	Bulance	NumOfFroducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
	9	879	France	Person	42	2	0.00	7	1	1	10134526	7
	1	608	Spen	Pyrysie	41	1	8181720	1		1	HISADR	
	2	303	Francis	female	42	. 0	15960030)	1	0	11300 137	
	3	200	Frant	Terrain	.59	- 11	0.00	2.	10		1042643	0
	4	250	Spare	Service	43	2	125510.62	1		- 9	7909430	

2	302	Fearure Terroalie	4.0	6 159600.80	2	1	4	112841.57	- 1
3	Alley	Flance, Tenute	76	1 (000	2			61825.63	(4)
4	650.	Spain Female:	41.	2 12551042	1	1	1.0	79004.10	o

```
Tell'statiseMember'] = Of["IsactiseMember'].astype("(alegory")
df["Exited'] = Of["Exited"].astype("category")
df["HadrCard'] = Of["HadrCard'].astype("category")
```

3a.Univariate Analysis

```
t= [7]: sex_kdeplot(s='CreditScore', data = df , bur = 'Exited')
plt.show()
```



3b.Bivariate Analysis

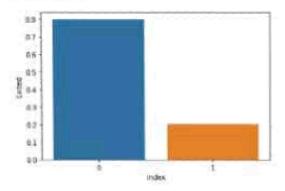
0 0 07901 1 1 0 0000



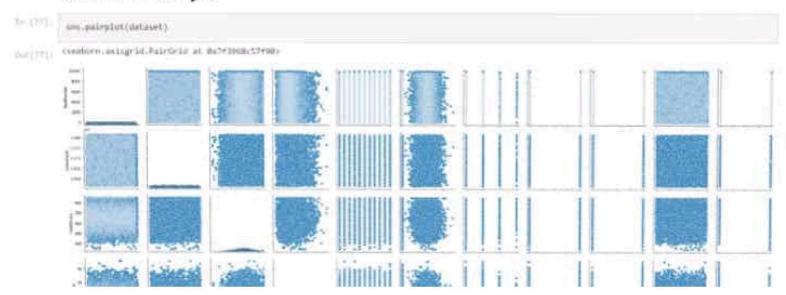
3b. Bivariate Analysis







3c.Multivariate Analysis





4. Discriptive Statistics bold text

```
To (78) Wh.linto()
           colass 'pandas.come.frame.bataFrame's
           Rangelnoss: 10000 entries, 0 to 9000
Data columns (total 11 columns):
            4. Collown
                                    Non-Null Count Diyer
               CreditScore 18000 non-mall intid
Geography 10000 non-mall object
Gender 10000 non-mall object
            e.
                \lambda g \pi
                                    20008 NUM-NALL INTER
                                   18000 non-mill 19554
                Balance
                                    18690 nos-sull float64
                NumOfFraducts.
                                    10000 non-null int64
                                    10000 rom-null category
                Hardecand
               IsactiveMember 10000 non-mult category
                fatinitedialary 18000 non-mull float64
                                    20000 non-null sategory
```

dtypes: category(3), float54(2), int64(4), seject(2)
memory usage: 654.8+ 82

in [70] sh.describe()

Del[78]: CreditScore Balanca NumOfFreducts EstimatedSalary Age Tenues count. 10000,000000 10000,000000 10000,000000 10000,000000 100000000 10000.000000 WILL STREET 36.921506 5.012800 THAIS DESCRIP 5 530300 500006,229881 ad 90.653299 111-617506 2.892174 . 62397.405202 0.501054 17110,40218 250.000000 13.0000000 0.000000 0.000000 E.0000000 11,560000 25% 384.000000 32,000,000 3,700000 h-botmie 1,000000 51002310000 853.000008 27.300000E \$100000 9719E34000 1.000000 100161915000 75% 718.000000 44.000000 7.560000 127644.240000 2.2900000 149388,247500 850.600000 62:000000 10.0000001 -2508HE390000 4:500000 199992.450000 100.00

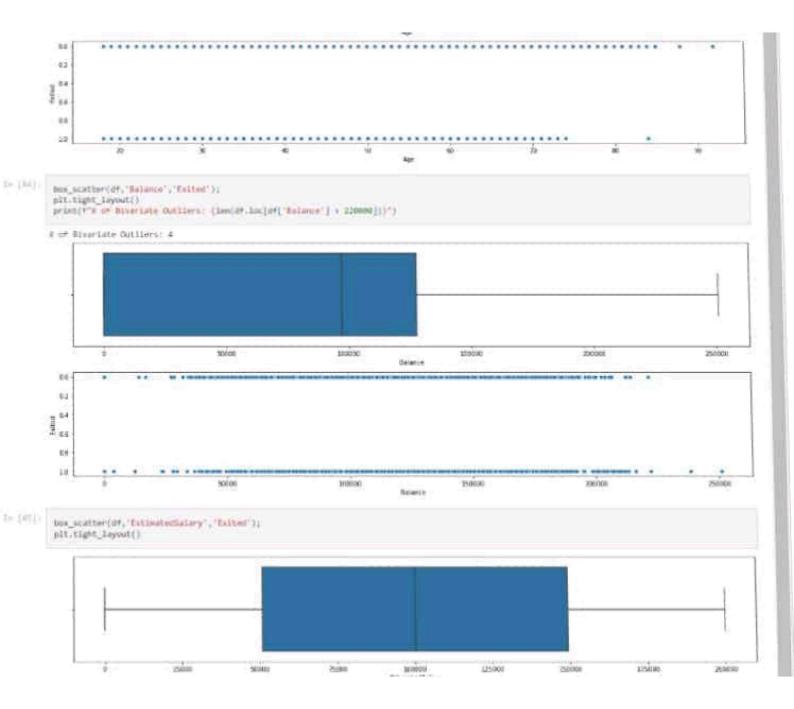
5. Haldle Missing Values

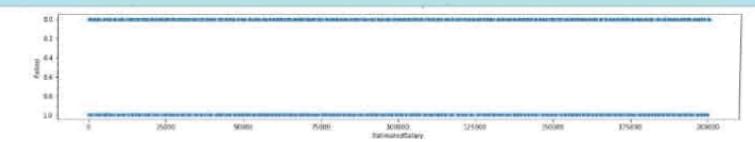
Tenure di Balance di NumOffroducts di HasCrCerd di IsActiveNember di Estimaterialary di

6. Find the Outliers and Replace the Outlier

Finding outliers

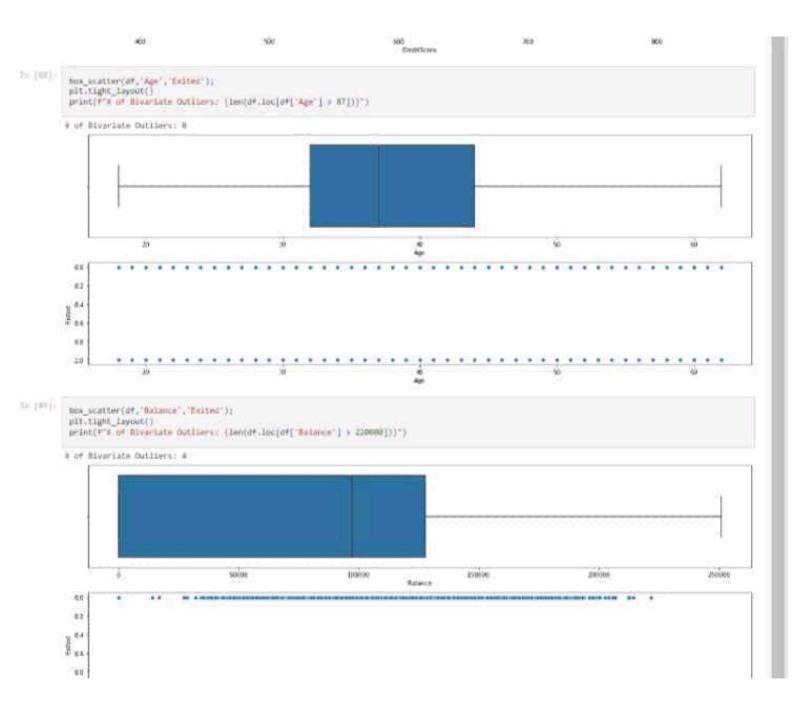
```
20 [81]
               def tox_scatter(data, x, y):
   fig, (ax1, ax2) = plt.subplots(pross=2, ecols=1, figsize=(16,6))
   ses.toxplot(data=data, xxx, asxax1)
   ses.scatterplot(data=data, x=x,y=y,ax=ax2)
Jul [E2]:
                box_scatter(df,'CreditScore','Esited');
plt.tight_layout()
print(f'& of Riveriage Outliers: (len(df,loc[df('CreditScore') < 400)))*)</pre>
               8 of Riverlate Outliers: 19
                                                    100
                                                                                                                                001
Contrictors
                                                                                            500
                   DE
                   67
                   64
                1 nd
                   41
                                                                                                                                     600
                                                                                             100
                                                                                                                                                                                                                     NOC:
 TH [HT]:
                  bus_ication(of, 'Age', 'Exited');
                  pit.tight_layout()
print(FTG of Blvariate Outliers: {lem(df.loc[df['Age'] > 87])}")
                 A of Rivertate Dutliers; 3
```





Removing the Outliers

```
$4 [80]:
                              \frac{d^2[1] \exp \operatorname{iders}(d^2[1] \text{ supper, upper, } d^2[1])}{d^2[1] \operatorname{upp.ubers}(d^2[1] \leq 1 \operatorname{ouer, } 1 \operatorname{upper, } d^2[1])} 
In [B7]
                box_scatter(of, 'Crediticore', 'Esited');
pit,tight_Lapont()
print(f'S of Sinariate Outliers: {len(of,loc[of['Crediticore'] < 400]))')</pre>
               & of Elvariate Outliers: 18
                                                                                   300
                                                                                                                                500
Overfore
                                                                                                                                                                             203
                                                                                                                                                                                                                         200
                  8.0
                  63
               7 64
2 54
                  20
                  10
                                                                                                                               600
CrestScore
```



Balance

7.Categorical Encoding

8.Split the data into dependent and indipendent variables

9.Scale and independent variables

print (nervalland VV

```
[[1.]
[0.]
[1.]
             [1.]
[1.]
[n.])
De LISE.
             standard V = Y.copy()
             from skinary import preprocessing
             ss = preprocessing-StandardScaler()
             Es-Fit(standard Y)
             print (standard, Y)
                    California
             39.94
             9997
             9994
             [10000 rows s 1 columns]
             10.Perform Train Test Split
 In Jane.
              from sklears.model_selection import train_test_split s_train, s_test, y_train, y_test = train_test_split (X,\,Y)
              a truly
```

58

06

34

35

375

Alpin 17

0.00

10.000

9.00

0.00

88129.58

W 311577.05

9 54502536

Balanca NumOfFreducts HasCrCard IsActiveMember ExtmatedSalary Exted

B.

ġ.

幸

١.

0

1

25951.91

170705.53

188271.90

(2916.52)

563 191 62

(740/06.78

12100107

B

Sumame CreditScore Geography Gender Age Tenure

100

185

575

616

480

799

15771322 Oguminhir

Larren

Would

Shih

15746731

15000149

15782096

15579017

15.720.702

04/1/24%

6831

2974

952

5643

4653

1317

4812

2975

853

3644

4054

1318

a test Det[100. Rentweber Customerid Surname CreditScore Balance NumOfProducts HasCrCard InActiveMember EstimatedSalary Exits 7220 1221 15700637 Oung 718 8.00 2 ô. 0 521537.61 Span 1154 7155 15764887 Notice to part of the last of 538 2. 122773.50 16467.00 3156 £ 190701.29 ò 2157 15509641 Sorrg 642 39354,24 4554 4515 15658670 Chine 664 0.00 84041.16 2017 2018 15702244 538 4 41192.95 Macketel 0,00 1 3444 1443 15686715 Moretii 190 Spain Semale: 1 Ü 58607.16 0.00 712× 7121 1560016 Chulsiumeitz 722 0.00 16798A.72 1997 1991 15624785 Monete 672 1 142151.75 2 1 1 153753.34 5735 5736 15756070 585 005 101728.66 4148 15574367 625 79064.85 9 11.5291.75 2500 rows = 14 columns 4:直 TH JANK. y_train dut(tet. Exited 1150 4 2974 q 952 5643 7061 Ŋ. 4653 1217 3661 1002 5967 ٥

7500 rows × 1 columns

y_test

2h [188.

.0 5643 1 . . 7500 rows - 1 columns 10,1196,y_test 040 100 Lained 1154 F 2500 rows = 1 columns MIR