import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
sns.set\_style('darkgrid')
sns.set(font\_scale=1.3)

df=pd.read\_csv("/content/drive/MyDrive/IBM/Assignment - 2 /Churn\_Modelling.csv" df.head()

	Row Num ber	Cust omer Id	Sur na me	Cred itSco re	Geo grap hy	Ge nd er	A g e	Te nu re	Bal anc e	NumO fProdu cts	Has CrC ard	IsActiv eMemb er	Estima tedSala ry	Ex ite d
0	1	1563 4602	Har gra ve	619	Fran ce	Fe ma le	4 2	2	0.00	1	1	1	101348 .88	1
1	2	1564 7311	Hill	608	Spai n	Fe ma le	4	1	838 07.8 6	1	0	1	112542 .58	0
2	3	1561 9304	Oni o	502	Fran ce	Fe ma le	4 2	8	159 660. 80	3	1	0	113931 .57	1
3	4	1570 1354	Bon i	699	Fran ce	Fe ma le	3 9	1	0.00	2	0	0	93826. 63	0
4	5	1573 7888	Mit chel l	850	Spai n	Fe ma le	4 3	2	125 510. 82	1	1	1	79084. 10	0

 $df.drop(["RowNumber","CustomerId","Surname"], axis=1, inplace= \pmb{True})$ 

## df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 10000 entries, 0 to 9999 Data columns (total 11 columns):

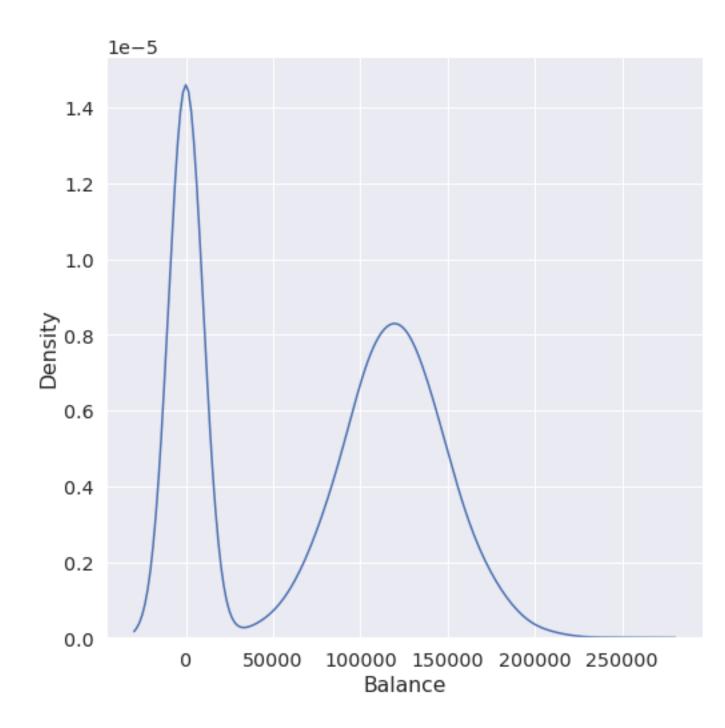
# Column Non-Null Count Dtype -----0 CreditScore 10000 non-null int64 1 Geography 10000 non-null object 2 Gender 10000 non-null object 3 Age 10000 non-null int64 4 Tenure 10000 non-null int64 5 Balance 10000 non-null float64 6 NumOfProducts 10000 non-null int64 7 HasCrCard 10000 non-null int64 8 IsActiveMember 10000 non-null int64 9 EstimatedSalary 10000 non-null float64 10 Exited 10000 non-null int64 dtypes: float64(2), int64(7), object(2)

memory usage: 859.5+ KB

#Perform Univariate Analysis
plt.figure(figsize=(8,8))
sns.countplot(x='Tenure',data=df)
plt.xlabel('0:Customers with Bank, 1: exited from bank')
plt.ylabel('No.of.Customers')
plt.title("Bank Customers viz")
plt.show()

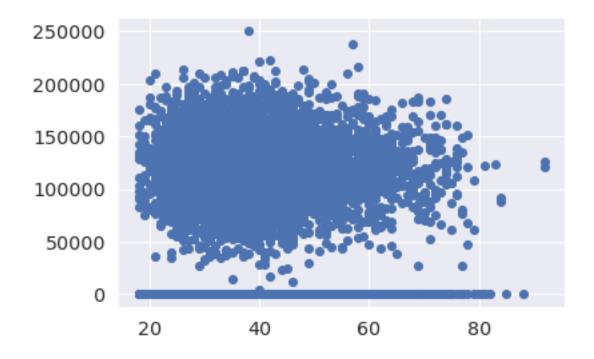
#Perform Univariate Analysis
plt.figure(figsize=(8,8))
sns.kdeplot(x=df['Balance'])

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fa0c03906d0>



#Perform Bivariate Analysis plt.scatter(df.Age,df.Balance)

<matplotlib.collections.PathCollection at 0x7fa0d35a7dd0>



#Perform Bivariate Analysis df.corr()

	Credit Score	Gen der	Age	Tenu re	Bala nce	NumOfPr oducts	HasCr Card	IsActive Member	Estimated Salary	Exite d
CreditSco re	1.0000	0.007 888	0.003 965	0.000 842	0.006 268	0.012238	0.0054 58	0.025651	-0.001384	0.027 094
Gender	0.0078 88	1.000	0.022 812	0.003 739	0.069 408	0.003972	0.0085	0.006724	-0.001369	0.035 943
Age	0.0039 65	0.022 812	1.000 000	0.009 997	0.028 308	-0.030680	0.0117 21	0.085472	-0.007201	0.285 323
Tenure	0.0008 42	0.003 739	0.009 997	1.000	0.012 254	0.013444	0.0225 83	-0.028362	0.007784	0.014 001
Balance	0.0062 68	0.069 408	0.028 308	0.012 254	1.000	-0.304180	0.0148 58	-0.010084	0.012797	0.118 533

	Credit Score	Gen der	Age	Tenu re	Bala nce	NumOfPr oducts	HasCr Card	IsActive Member	Estimated Salary	Exite d
NumOfPr oducts	0.0122 38	0.003 972	0.030 680	0.013 444	0.304 180	1.000000	0.0031 83	0.009612	0.014204	0.047 820
HasCrCa rd	0.0054 58	0.008 523	0.011 721	0.022 583	0.014 858	0.003183	1.0000	-0.011866	-0.009933	0.007 138
IsActive Member	0.0256 51	0.006 724	0.085 472	0.028 362	0.010 084	0.009612	0.0118 66	1.000000	-0.011421	0.156 128
Estimated Salary	0.0013 84	0.001 369	0.007 201	0.007 784	0.012 797	0.014204	0.0099	-0.011421	1.000000	0.012 097
Exited	0.0270 94	0.035 943	0.285 323	0.014 001	0.118 533	-0.047820	0.0071 38	-0.156128	0.012097	1.000

#Perform Bivariate Analysis import statsmodels.api as sm

#define response variable y = df['CreditScore']

#define explanatory variable x = df[['EstimatedSalary']]

#add constant to predictor variables
x = sm.add\_constant(x)

#fit linear regression model model = sm.OLS(y, x).fit()

#view model summary
print(model.summary())

## **OLS Regression Results**

Dep. Variable: 0.000 CreditScore R-squared: Model: OLS Adj. R-squared: -0.000Method: Least Squares F-statistic: 0.01916 Sat, 24 Sep 2022 Prob (F-statistic): 0.890 Date: 05:06:19 Log-Likelihood: Time: -59900. No. Observations: 10000 AIC: 1.198e+05 Df Residuals: 9998 BIC: 1.198e+05

Df Model: 1

Covariance Type: nonrobust

===

coef std err t P>|t| [0.025 0.975]

-----

 Omnibus:
 132.939 Durbin-Watson:
 2.014

 Prob(Omnibus):
 0.000 Jarque-Bera (JB):
 84.242

 Skew:
 -0.072 Prob(JB):
 5.10e-19

 Kurtosis:
 2.574 Cond. No.
 2.32e+05

\_\_\_\_\_\_

## Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.32e+05. This might indicate that there are strong multicollinearity or other numerical problems.

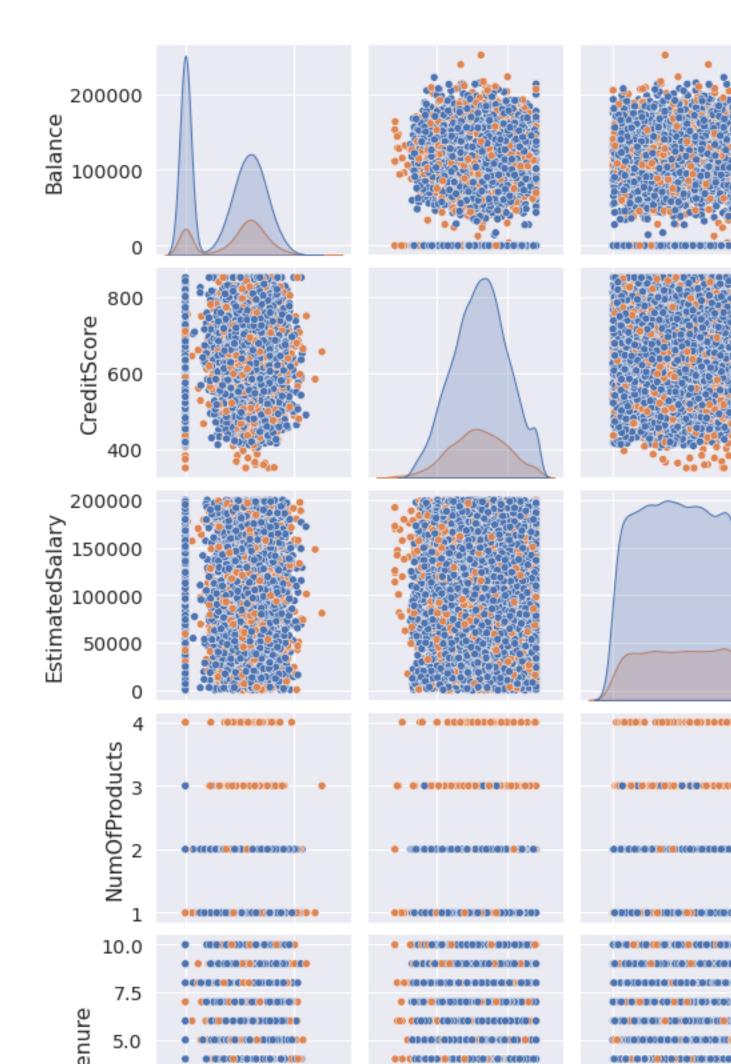
#Perform Multivariate Analysis

plt.figure(figsize=(4,4))

sns.pairplot(data=df[["Balance","CreditScore","EstimatedSalary","NumOfProducts","Tenure","Exited"]],hue="Exited")

<sup>&</sup>lt;seaborn.axisgrid.PairGrid at 0x7fa0b00a1b10>

<sup>&</sup>lt;Figure size 288x288 with 0 Axes>



```
#Perform Descriptive Statistics
df=pd.DataFrame(df)
print(df.sum())
CreditScore
                                   6505288
              FranceSpainFranceFranceSpainSpainFranceGermany...
Geography
Gender
            FemaleFemaleFemaleFemaleMaleMaleFemaleMa... \\
Age
                                 389218
Tenure
                                  50128
Balance
                               764858892.88
NumOfProducts
                                      15302
HasCrCard
                                     7055
IsActiveMember
                                       5151
EstimatedSalary
                                 1000902398.81
Exited
                                  2037
dtype: object
#Perform Descriptive Statistics
print("----Sum Value-----")
print(df.sum(1))
print("----")
print("----Product Value----")
print(df.prod())
print("-----")
----Sum Value-----
0
    102015.88
    197002.44
1
2
    274149.37
     94567.63
3
4
    205492.92
9995 97088.64
9996 159633.38
9997
     42840.58
9998 168784.83
9999 169159.57
Length: 10000, dtype: float64
_____
----Product Value----
CreditScore
             0.0
           0.0
Age
Tenure
            0.0
Balance
            0.0
NumOfProducts
                0.0
HasCrCard
              0.0
IsActiveMember 0.0
EstimatedSalary inf
Exited
           0.0
dtype: float64
_____
#Perform Descriptive Statistics
print("-----")
```

print(df.mean())

#Handling with missing Values df.isnull()#Checking values are null

	CreditS core	Geogr aphy		Ag e			NumOfPr oducts				Exit ed
0	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
1	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e

	CreditS core	Geogr aphy	Gen der	Ag e	Ten ure	Bala nce	NumOfPr oducts	HasCr Card	IsActiveM ember	Estimated Salary	Exit ed
2	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
3	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
4	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
99 95	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
99 96	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
99 97	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
99 98	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e
99 99	False	False	Fals e	Fal se	Fals e	False	False	False	False	False	Fals e

 $10000 \; rows \times 11 \; columns$ 

#Handling with missing Values df.notnull()#Checking values are not null

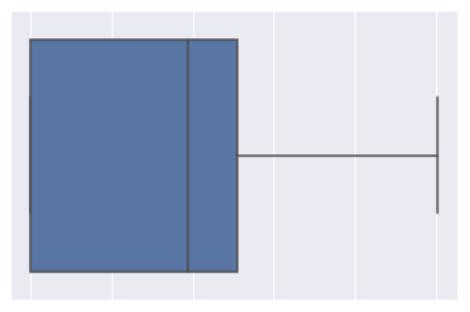
	CreditS core	Geogr aphy		Ag e					IsActiveM ember		
0	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
1	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
2	True	True	True	Tr ue	True	True	True	True	True	True	Tru e

	CreditS core	Geogr aphy	Gen der	Ag e	Ten ure	Bala nce	NumOfPr oducts	HasCr Card	IsActiveM ember	Estimated Salary	Exit ed
3	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
4	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
•••											
99 95	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
99 96	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
99 97	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
99 98	True	True	True	Tr ue	True	True	True	True	True	True	Tru e
99 99	True	True	True	Tr ue	True	True	True	True	True	True	Tru e

 $10000 \; rows \times 11 \; columns$ 

#Find outliers & replace the outliers sns.boxplot(df['Balance'])

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fa0af6dcf90>



## 0 50000 100000 150000 200000 250000 Balance

```
#Find outliers & replace the outliers
print(np.where(df['Balance']>100000))
(array([ 2, 4, 5, ..., 9987, 9993, 9999]),)
#Find outliers & replace the outliers
from scipy import stats
import numpy as np
z = np.abs(stats.zscore(df["EstimatedSalary"]))
print(z)
0
     0.021886
     0.216534
1
2
     0.240687
3
     0.108918
4
     0.365276
9995 0.066419
9996 0.027988
9997 1.008643
9998 0.125231
9999 1.076370
Name: EstimatedSalary, Length: 10000, dtype: float64
#Check for categorical columns & performs encoding
```

from sklearn.preprocessing import LabelEncoder

array(['Female', 'Male'], dtype=object)

df['Gender'].unique()

#Check for categorical columns & performs encoding df['Gender'].value\_counts()

Male 5457 Female 4543

Name: Gender, dtype: int64

#Check for categorical columns & performs encoding encoding=LabelEncoder()

 $df["Gender"] = encoding.fit\_transform(df.iloc[:,1].values)$ 

df

	Credit Score	Geogr aphy	Gen der	A ge	Ten ure	Balan ce	NumOfPr oducts	HasCr Card	IsActiveM ember	Estimated Salary	Exit ed
0	619	France	0	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	2	41	1	83807 .86	1	0	1	112542.58	0
2	502	France	0	42	8	15966 0.80	3	1	0	113931.57	1
3	699	France	0	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	2	43	2	12551 0.82	1	1	1	79084.10	0
•••											
99 95	771	France	0	39	5	0.00	2	1	0	96270.64	0
99 96	516	France	0	35	10	57369 .61	1	1	1	101699.77	0
99 97	709	France	0	36	7	0.00	1	0	1	42085.58	1
99 98	772	Germa ny	1	42	3	75075 .31	2	1	0	92888.52	1
99 99	792	France	0	28	4	13014 2.79	1	1	0	38190.78	0

 $10000 \text{ rows} \times 11 \text{ columns}$ 

```
#Split the data into Dependent & Independent Variables
print("-----")
X=df.iloc[:,1:4]
print(X)
print("----")
print("-----")
Y=df.iloc[:,4]
print(Y)
print("-----")
-----Dependent Variables-----
   Age Tenure Balance
   42
        2 0.00
  41 1 83807.86
1
2 42 8 159660.80
3
  39 1 0.00
4
  43 2 125510.82
... ... ...
9995 39 5 0.00
9996 35 10 57369.61
9997 36 7 0.00
9998 42 3 75075.31
9999 28 4 130142.79
[10000 rows x 3 columns]
-----Independent Variables-----
0
   1
1
    1
2
    3
3
    2
4
    1
9995 2
9996 1
9997
9998 2
9999 1
Name: NumOfProducts, Length: 10000, dtype: int64
#Scale the independent Variables
from sklearn.preprocessing import StandardScaler
object= StandardScaler()
# standardization
scale = object.fit_transform(df)
print(scale)
 [[-0.32622142 \ 0.29351742 \ -1.04175968 \ ... \ 0.97024255 \ 0.02188649 
 1.97716468]
[-0.44003595 \ 0.19816383 \ -1.38753759 \ ... \ 0.97024255 \ 0.21653375
 -0.50577476]
[-1.53679418 \ 0.29351742 \ 1.03290776 \dots -1.03067011 \ 0.2406869
 1.97716468]
 \lceil \ 0.60498839 \ \hbox{-}0.27860412 \ \ 0.68712986 \ ... \ \ 0.97024255 \ \hbox{-}1.00864308
```

```
1.97716468]
[1.25683526 0.29351742 -0.69598177 ... -1.03067011 -0.12523071 1.97716468]
[1.46377078 -1.04143285 -0.35020386 ... -1.03067011 -1.07636976 -0.50577476]]
```

#Split the data into training & testing from sklearn.model\_selection import train\_test\_split

#Split the data into training & testing
x\_train, x\_test, y\_train, y\_test = train\_test\_split(x, y, test\_size=4,random\_state=4)
x\_train

	const	EstimatedSalary
2558	1.0	137903.54
7642	1.0	121765.00
8912	1.0	109470.34
3319	1.0	2923.61
6852	1.0	7312.25
•••		
456	1.0	7666.73
6017	1.0	9085.00
709	1.0	147794.63
8366	1.0	102515.42
1146	1.0	54776.64

9996 rows  $\times$  2 columns

 $\#Split\ the\ data\ into\ training\ \&\ testing\ x\_test$ 

	const	EstimatedSalary						
1603	1.0	23305.85						
8713	1.0	41248.80						
4561	1.0	143317.42						
6600	1.0	174123.16						
#Split the data into training & te								

#Split the data into training & testing y\_train

8366 637 1146 614

Name: CreditScore, Length: 9996, dtype: int64

#Split the data into training & testing y\_test

1603 576 8713 786 4561 562

6600 505

Name: CreditScore, dtype: int64