**Assignment -2**

Python Programming

| | |
|---|---|
| Assignment Date | 23 september 2022 |
| Student Name | KARTHICK.S |
| Student Roll Number | 311419205013 |
| Maximum Marks | 2 Marks |

# Data Visualization and Pre-processing

**Question-1:**

1. Load the dataset

**Solution:**

```
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)
```

In [2]:

```
df=pd.read_excel("/content/Churn_Modelling.xlsx")
```

In [1]:

```
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)
```

In [2]:

```
df=pd.read_excel("/content/Churn_Modelling.xlsx")
```

**Question-2:**

2. Perform Below Visualizations.

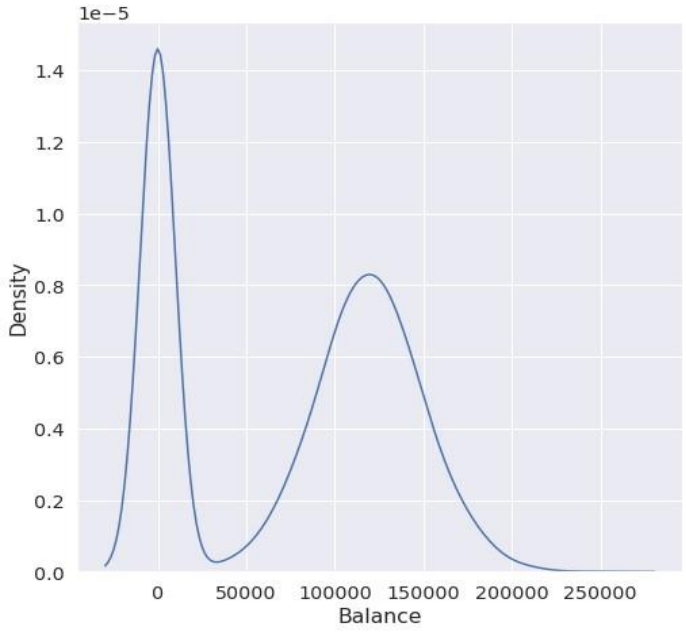
- Univariate Analysis
- Bi - Variate Analysis
- Multi - Variate Analysis

**Solution:**

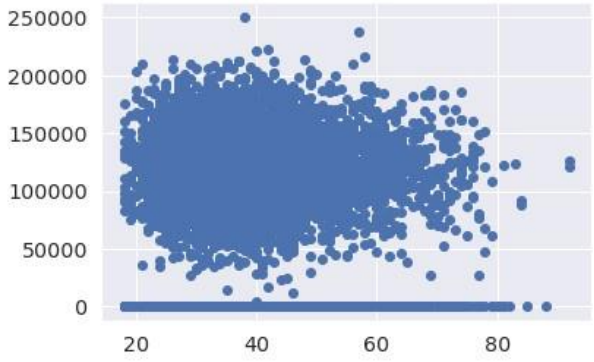
.

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

```
In [7]: #Perform Univariate Analysis
        plt.figure(figsize=(8,8))
        sns.kdeplot(x=df['Balance'])

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc3f3579c50>
```




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




```
#Perform Bivariate Analysis df.corr()
```

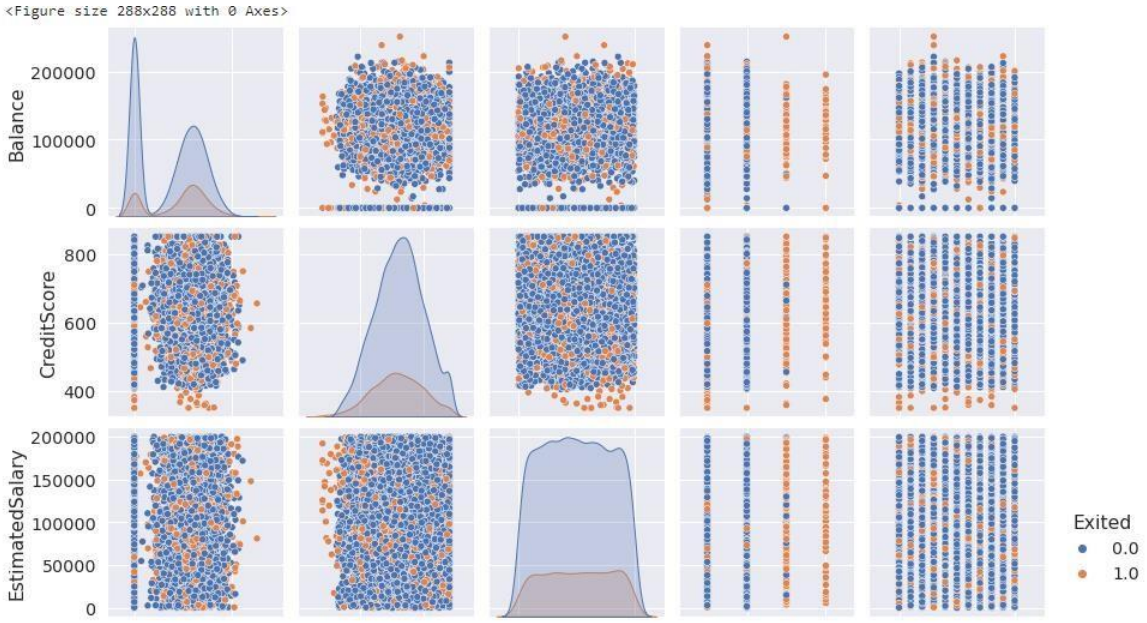
Out[9]:

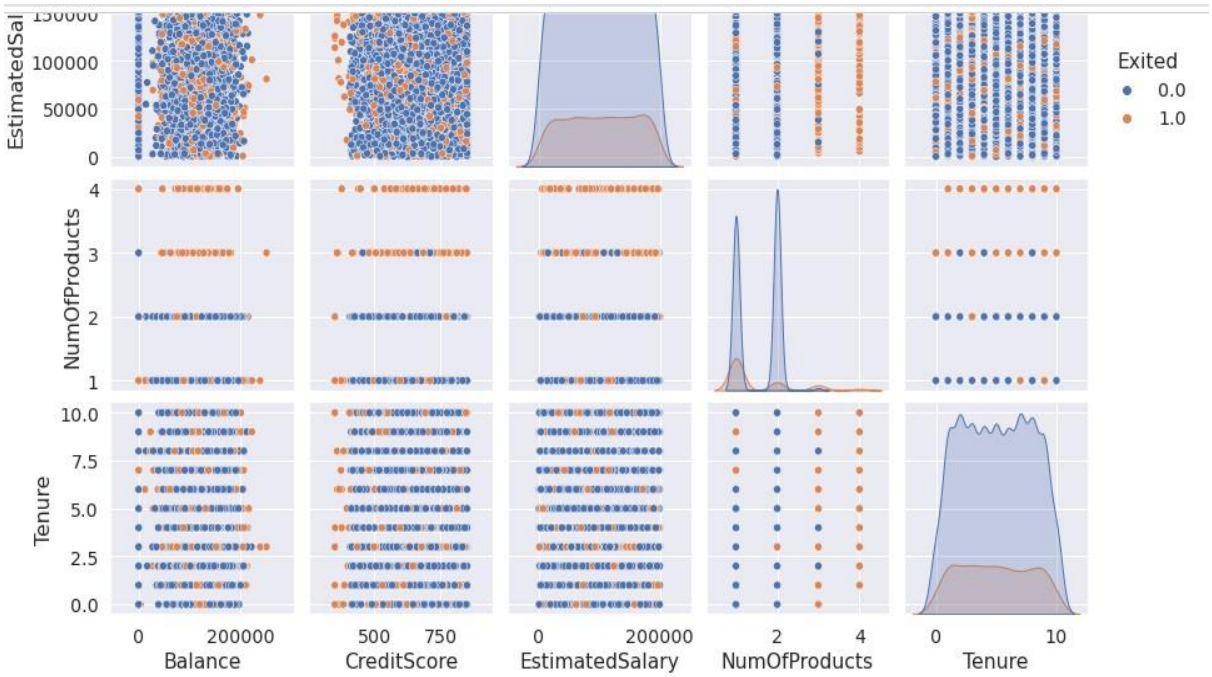
| | CreditScore | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|
| CreditScore | 1.000000 | -0.003965 | 0.000842 | 0.006268 | 0.012238 | -0.005458 | 0.025651 | -0.001384 | -0.027094 |
| Age | -0.003965 | 1.000000 | -0.009997 | 0.028308 | -0.030680 | -0.011721 | 0.085472 | -0.007201 | 0.285323 |
| Tenure | 0.000842 | -0.009997 | 1.000000 | -0.012254 | 0.013444 | 0.022583 | -0.028362 | 0.007784 | -0.014001 |
| Balance | 0.006268 | 0.028308 | -0.012254 | 1.000000 | -0.304180 | -0.014858 | -0.010084 | 0.012797 | 0.118533 |
| NumOfProducts | 0.012238 | -0.030680 | 0.013444 | -0.304180 | 1.000000 | 0.003183 | 0.009612 | 0.014204 | -0.047820 |
| HasCrCard | -0.005458 | -0.011721 | 0.022583 | -0.014858 | 0.003183 | 1.000000 | -0.011866 | -0.009933 | -0.007138 |
| IsActiveMember | 0.025651 | 0.085472 | -0.028362 | -0.010084 | 0.009612 | -0.011866 | 1.000000 | -0.011421 | -0.156128 |
| EstimatedSalary | -0.001384 | -0.007201 | 0.007784 | 0.012797 | 0.014204 | -0.009933 | -0.011421 | 1.000000 | 0.012097 |
| Exited | -0.027094 | 0.285323 | -0.014001 | 0.118533 | -0.047820 | -0.007138 | -0.156128 | 0.012097 | 1.000000 |

```
                                        #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:            CreditScore   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.01916
Date:                Thu, 29 Sep 2022   Prob (F-statistic):              0.890
Time:                        14:58:55   Log-Likelihood:                -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]
------------------------------------------------------------------------------
const            650.7617      1.940    335.407      0.000     646.958     654.565
EstimatedSalary -2.326e-06   1.68e-05     -0.138      0.890   -3.53e-05    3.06e-05
==============================================================================
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")
```






**Question-3:**

3. Perform descriptive statistics on the dataset.

**Solution:**

```
#Perform Descriptive Statistics
df=pd.DataFrame(df) print(df.sum())
```

```
CreditScore                                          6505288.0
Geography          FranceSpainFranceFranceSpainSpainFranceGermany...
Gender             FemaleFemaleFemaleFemaleFemaleMaleMaleFemaleMa...
Age                                                  389218.0
Tenure                                               50128.0
Balance                                          764858892.88
NumOfProducts                                        15302.0
HasCrCard                                            7055.0
IsActiveMember                                       5151.0
EstimatedSalary                                  1000902398.81
Exited                                               2037.0
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
1       197002.44
2       274149.37
3        94567.63
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        inf
Age                inf
Tenure             0.0
Balance            0.0
NumOfProducts      inf
HasCrCard          0.0
IsActiveMember     0.0
EstimatedSalary    inf
Exited             0.0
dtype: float64
---------------------------------
```

```
#Perform Descriptive Statistics print("---------
-Mean Value-----------") print(df.mean())
print("---------------------------------")
print("----------Median Value---------")
print(df.median()) print("----------------------
---------") print("----------Mode Value---------
---") print(df.mode())
print("---------------------------------")
```

```
----------Mean Value-----------
CreditScore           650.528800
Age                    38.921800
Tenure                  5.012800
Balance             76485.889288
NumOfProducts           1.530200
HasCrCard               0.705500
IsActiveMember          0.515100
EstimatedSalary    100090.239881
Exited                  0.203700
dtype: float64
--------------------------------
----------Median Value---------
CreditScore           652.000
Age                    37.000
Tenure                  5.000
Balance             97198.540
NumOfProducts           1.000
HasCrCard               1.000
IsActiveMember          1.000
EstimatedSalary    100193.915
Exited                  0.000
dtype: float64
--------------------------------
----------Mode Value------------
   CreditScore Geography Gender   Age  Tenure  Balance  NumOfProducts
0        850.0    France   Male  37.0     2.0      0.0            1.0

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0        1.0             1.0         24924.92     0.0
--------------------------------
```

**Question-4:**

4.Handle the Missing values

**Solution:**

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


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

Out[16]:

| | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | True | True | True | True | True | True | True | True | True | True | True |
| 1 | True | True | True | True | True | True | True | True | True | True | True |
| 2 | True | True | True | True | True | True | True | True | True | True | True |
| 3 | True | True | True | True | True | True | True | True | True | True | True |
| 4 | True | True | True | True | True | True | True | True | True | True | True |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 9995 | True | True | True | True | True | True | True | True | True | True | True |
| 9996 | True | True | True | True | True | True | True | True | True | True | True |
| 9997 | True | True | True | True | True | True | True | True | True | True | True |
| 9998 | True | True | True | True | True | True | True | True | True | True | True |
| 9999 | True | True | True | True | True | True | True | True | True | True | True |

10000 rows × 11 columns

**Question-5:**

5. Find the outliers and replace the outliers

**Solution:**

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

Out[17]:


```
#Find outliers & replace the outliers
print(np.where(df['Balance']>100000))
```

```
(array([   2,    4,    5, ..., 9987, 9993, 9999]),)
```

In [19]:

```
#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
1       0.216534
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
```

**Question-6:**

6. Check for Categorical columns and perform encoding

**Solution:**

```
#Check for categorical columns & performs encoding from
sklearn.preprocessing import LabelEncoder

df['Gender'].unique()
df['Gender'].value_counts()
 encoding=LabelEncoder()
df["Gender"]=encoding.fit_transform(df.iloc[:,1].values)
df
```

```
]:
#Check for categorical columns & performs encoding
from sklearn.preprocessing import LabelEncoder
df['Gender'].unique()
```

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

```
]:
#Check for categorical columns & performs encoding
df['Gender'].value_counts()
```

```
]:
Male      5457
Female    4543
Name: Gender, dtype: int64
```

Out[22]:

| | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 619.0 | France | 0 | 42.0 | 2.0 | 0.00 | 1.0 | 1.0 | 1.0 | 101348.88 | 1.0 |
| 1 | 608.0 | Spain | 2 | 41.0 | 1.0 | 83807.86 | 1.0 | 0.0 | 1.0 | 112542.58 | 0.0 |
| 2 | 502.0 | France | 0 | 42.0 | 8.0 | 159660.80 | 3.0 | 1.0 | 0.0 | 113931.57 | 1.0 |
| 3 | 699.0 | France | 0 | 39.0 | 1.0 | 0.00 | 2.0 | 0.0 | 0.0 | 93826.63 | 0.0 |
| 4 | 850.0 | Spain | 2 | 43.0 | 2.0 | 125510.82 | 1.0 | 1.0 | 1.0 | 79084.10 | 0.0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 9995 | 771.0 | France | 0 | 39.0 | 5.0 | 0.00 | 2.0 | 1.0 | 0.0 | 96270.64 | 0.0 |
| 9996 | 516.0 | France | 0 | 35.0 | 10.0 | 57369.61 | 1.0 | 1.0 | 1.0 | 101699.77 | 0.0 |
| 9997 | 709.0 | France | 0 | 36.0 | 7.0 | 0.00 | 1.0 | 0.0 | 1.0 | 42085.58 | 1.0 |
| 9998 | 772.0 | Germany | 1 | 42.0 | 3.0 | 75075.31 | 2.0 | 1.0 | 0.0 | 92888.52 | 1.0 |
| 9999 | 792.0 | France | 0 | 28.0 | 4.0 | 130142.79 | 1.0 | 1.0 | 0.0 | 38190.78 | 0.0 |

10000 rows × 11 columns

**Question-7:**

**7.**Split the data into dependent and independent variables.

**Solution:**

```
#Split the data into Dependent & Independent Variables
print("----------Dependent Variables----------")
X=df.iloc[:,1:4] print(X) print("---------------------
------------------") print("---------Independent
Variables---------") Y=df.iloc[:,4] print(Y)
print("----------------------------------------")
```

**Question-8:**

8. Scale the independent variables

**Solution:**

```
        #Split the data into Dependent & Independent Variables
print("----------Dependent Variables----------")
X=df.iloc[:,1:4] print(X) print("---------------
------------------------") print("---------
Independent Variables---------") Y=df.iloc[:,4]
print(Y)
print("----------------------------------------")
```

**Question-9:**

9. Split the data into training and testing

**Solution:**

```
#Split the data into training & testing from
sklearn.model_selection import train_test_split
```

In [34]:

```
#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 x_test y_train y_test
```

Out[31]:

| | const | EstimatedSalary |
|---|---|---|
| **1603** | 1.0 | 23305.85 |
| **8713** | 1.0 | 41248.80 |
| **4561** | 1.0 | 143317.42 |
| **6600** | 1.0 | 174123.16 |

In [32]:

```
#Split the data into training & testing
y_train
```

Out[32]:

```
2558    727.0
7642    811.0
8912    623.0
3319    430.0
6852    600.0
        ...
456     733.0
6017    487.0
709     686.0
8366    637.0
1146    614.0
Name: CreditScore, Length: 9996, dtype: float64
```

Out[34]:

| | 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 × 2 columns