# Assignment -2

## Data Visualization and Pre-processing

| | |
|---|---|
| Assignment Date | 27 September 2022 |
| Student Name | VIGNESH.P |
| Student Roll Number | 310619205305 |
| Maximum Marks | 2 Marks |

## Task 1:

1. Download the dataset: [Dataset]


### Assignment-2

1. Download the dataset: [Dataset]


## Task 2:

2.Loading the Churn_Modelling dataset

**Solution:**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```


### 2.Loading the Churn_Modelling dataset

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```


```
from google.colab import drive
drive.mount('/content/drive')
```

```
[ ] from google.colab import drive
    drive.mount('/content/drive')

    Mounted at /content/drive
```

data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/Churn_Modelling.csv")

data.info()

```
[ ] data = pd.read_csv("/content/drive/MyDrive/Churn_Modelling.csv")
```

```
[ ] data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
```

data.head()

```
[ ] data.head()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0.00 | 1 | 1 | 1 | 101348.88 | 1 |
| **1** | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 | 0 |
| **2** | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.80 | 3 | 1 | 0 | 113931.57 | 1 |
| **3** | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0.00 | 2 | 0 | 0 | 93826.63 | 0 |
| **4** | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 | 0 |

data.head()

```
[ ] data.tail()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **9995** | 9996 | 15606229 | Obijiaku | 771 | France | Male | 39 | 5 | 0.00 | 2 | 1 | 0 | 96270.64 | 0 |
| **9996** | 9997 | 15569892 | Johnstone | 516 | France | Male | 35 | 10 | 57369.61 | 1 | 1 | 1 | 101699.77 | 0 |
| **9997** | 9998 | 15584532 | Liu | 709 | France | Female | 36 | 7 | 0.00 | 1 | 0 | 1 | 42085.58 | 1 |
| **9998** | 9999 | 15682355 | Sabbatini | 772 | Germany | Male | 42 | 3 | 75075.31 | 2 | 1 | 0 | 92888.52 | 1 |
| **9999** | 10000 | 15628319 | Walker | 792 | France | Female | 28 | 4 | 130142.79 | 1 | 1 | 0 | 38190.78 | 0 |

data.shape

```
[ ] data.shape

(10000, 14)
```

# Task 3:

3. Visualization of Dataset

Univariate Analysis

- Distribution Plot

**Solution:**

sns.displot(data['Age'], color ='skyblue')

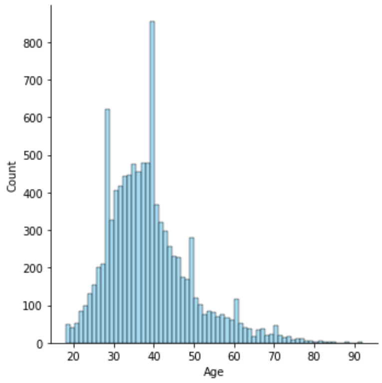
**3.Visualization of Dataset**

Univariate Analysis

Distriution Plot

```
[ ] sns.displot(data['Age'], color ='skyblue')
```

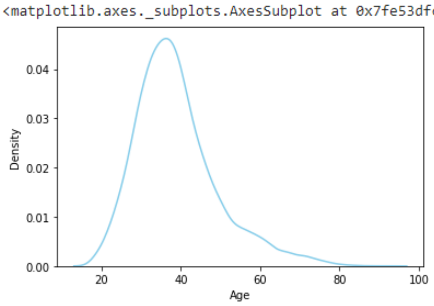
```
&lt;seaborn.axisgrid.FacetGrid at 0x7fe54134b650&gt;
```




sns.distplot(data["Age"],hist=False,color='skyblue')

```
sns.distplot(data["Age"],hist=False,color='skyblue')
```

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x7fe53dfc9b50&gt;
```




- Histograms

data['Geography'].value_counts()

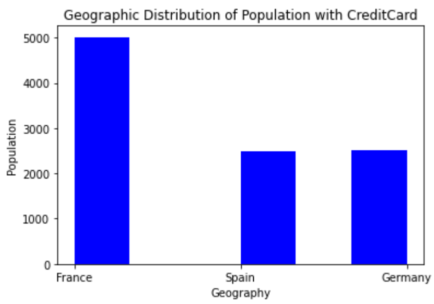
Histograms

```
[ ] data['Geography'].value_counts()
```

```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

plt.hist(x=data.Geography, bins=6, color='blue')
plt.title("Geographic Distribution of Population with CreditCard")
plt.xlabel("Geography")
plt.ylabel("Population")
plt.show()

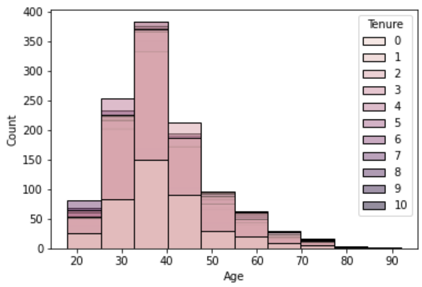
```
[ ] plt.hist(x=data.Geography, bins=6, color='blue')
    plt.title("Geographic Distribution of Population with CreditCard")
    plt.xlabel("Geography")
    plt.ylabel("Population")
    plt.show()
```




sns.histplot(x=data.Age,hue=data['Tenure'], bins =10,)

```
[ ] sns.histplot(x=data.Age,hue=data['Tenure'], bins =10,)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53dad19d0>
```




- Bar Plot

data['Gender'].value_counts()

Bar Plot

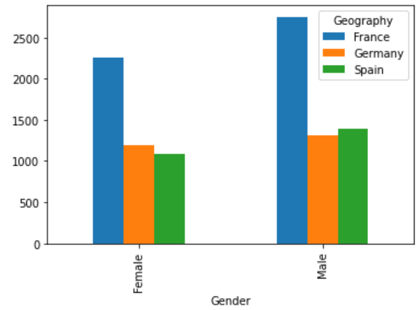
```
[ ] data['Gender'].value_counts()
```

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

pd.crosstab(data['Gender'],data['Geography']).plot(kind='bar')

```
[ ] pd.crosstab(data['Gender'],data['Geography']).plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d858ad0>
```

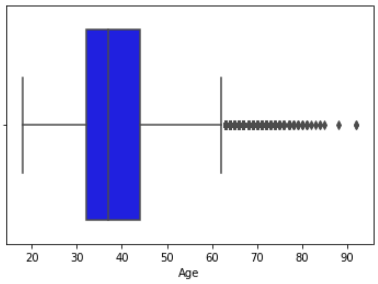



- Box Plot

sns.boxplot(data["Age"],color='blue')

```
[ ] sns.boxplot(data["Age"],color='blue')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d76ab90>
```



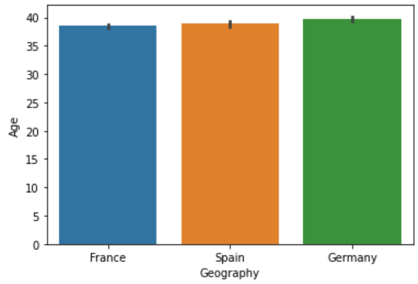

Bivariate Analysis

sns.barplot(data['Geography'], data["Age"])

## Bivariate Analysis

```
[ ] sns.barplot(data['Geography'], data["Age"])
```

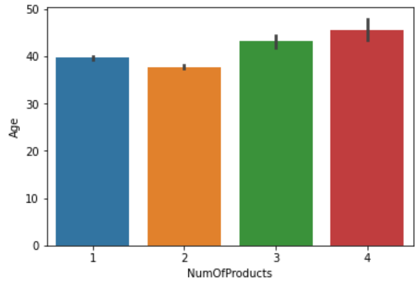
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d757ed0>
```




sns.barplot(data["NumOfProducts"],data["Age"])

```
sns.barplot(data["NumOfProducts"],data["Age"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d6e0d10>
```




data['HasCrCard'].value_counts()

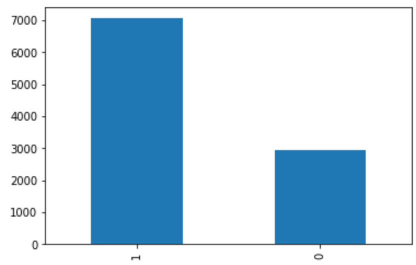
```
[ ] data['HasCrCard'].value_counts()
```

```
1    7055
0    2945
Name: HasCrCard, dtype: int64
```

data['HasCrCard'].value_counts().head(20).plot.bar()

```
[ ] data['HasCrCard'].value_counts().head(20).plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d658f90>
```



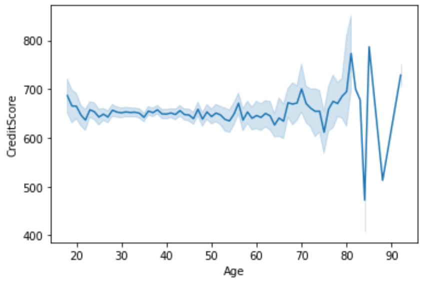

- Line Chart

sns.lineplot(data['Age'], data['CreditScore'])

Line Chart

```
[ ] sns.lineplot(data['Age'], data['CreditScore'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d61e7d0>
```



# Multi-Variate Analysis

- Scatter Plot

data['IsActiveMember'].value_counts()

## Multi-Variate Analysis

Scatter Plot

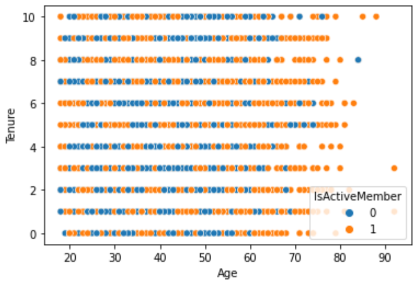
```
[ ] data['IsActiveMember'].value_counts()
```

```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

sns.scatterplot(data['Age'],data['Tenure'], hue=data['IsActiveMember'] )

```
[ ] sns.scatterplot(data['Age'],data['Tenure'], hue=data['IsActiveMember'] )
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d6fa790>
```



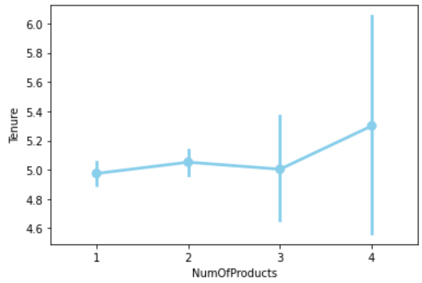
- Point Plot

sns.pointplot(x=data['NumOfProducts'],y=data['Tenure'],color='skyblue')

Point Plot

```
[ ] sns.pointplot(x=data['NumOfProducts'],y=data['Tenure'],color='skyblue')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53dae2a90>
```




- HeatMap

data.head()

HeatMap

```
[ ] data.head()
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0.00 | 1 | 1 | 1 | 101348.88 | 1 |
| 1 | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 | 0 |
| 2 | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.80 | 3 | 1 | 0 | 113931.57 | 1 |
| 3 | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0.00 | 2 | 0 | 0 | 93826.63 | 0 |
| 4 | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 | 0 |

data_cor = data.iloc[:,3:].corr()
data_cor

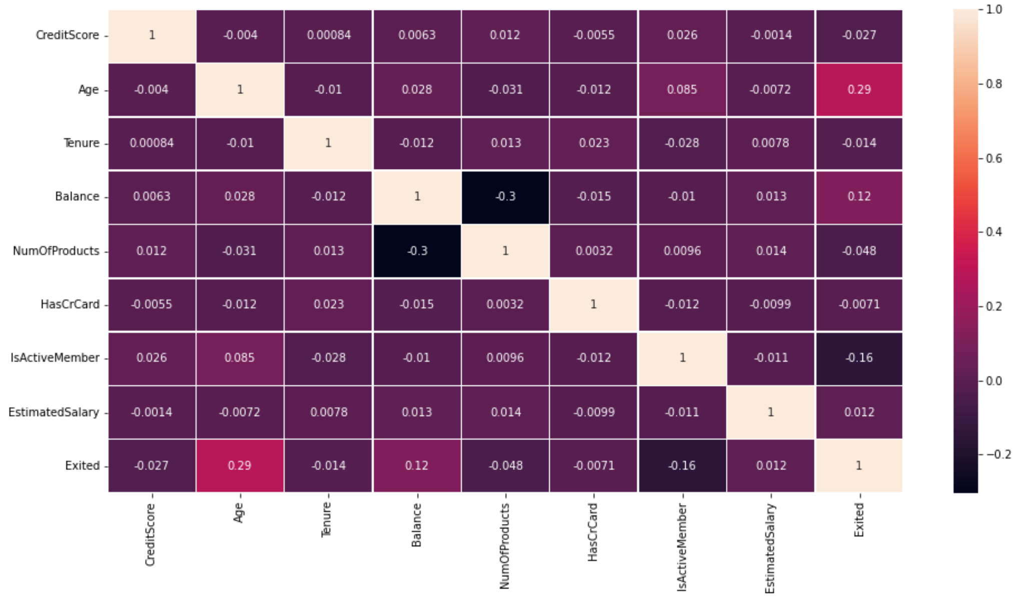
```
[ ] data_cor = data.iloc[:,3:].corr()
    data_cor
```

| | 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 |

plt.figure(figsize = (16,8))
sns.heatmap(data_cor,linecolor='white',linewidth=0.5, annot=True)

```
[ ] plt.figure(figsize = (16,8))
    sns.heatmap(data_cor,linecolor='white',linewidth=0.5, annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53d4a2e10>
```



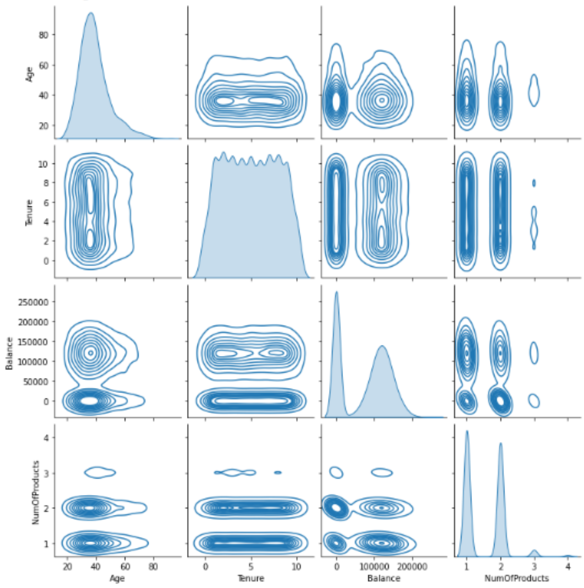

- Pair Plot

  data.head()sns.pairplot(data=data[["Age","Tenure","Balance","NumOfProducts"]],kind="kde",)

Pair Plot

```
[ ] sns.pairplot(data=data[["Age","Tenure","Balance","NumOfProducts"]],kind="kde",)
```

```
<seaborn.axisgrid.PairGrid at 0x7fe53da59b90>
```




# Task 4:

4. Descriptive Statistic Analysis

1. Mean
2. Medium
3. Mode
4. Standard Deviation
5. Variance

## Solution:

data.describe().T

### 4.Descriptive Statistic Analysis

1. Mean
2. Medium
3. Mode
4. Standard Deviation
5. Variance

```
[ ] data.describe().T
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| RowNumber | 10000.0 | 5.000500e+03 | 2886.895680 | 1.00 | 2500.75 | 5.000500e+03 | 7.500250e+03 | 10000.00 |
| CustomerId | 10000.0 | 1.569094e+07 | 71936.186123 | 15565701.00 | 15628528.25 | 1.569074e+07 | 1.575323e+07 | 15815690.00 |
| CreditScore | 10000.0 | 6.505288e+02 | 96.653299 | 350.00 | 584.00 | 6.520000e+02 | 7.180000e+02 | 850.00 |
| Age | 10000.0 | 3.892180e+01 | 10.487806 | 18.00 | 32.00 | 3.700000e+01 | 4.400000e+01 | 92.00 |
| Tenure | 10000.0 | 5.012800e+00 | 2.892174 | 0.00 | 3.00 | 5.000000e+00 | 7.000000e+00 | 10.00 |
| Balance | 10000.0 | 7.648589e+04 | 62397.405202 | 0.00 | 0.00 | 9.719854e+04 | 1.276442e+05 | 250898.09 |
| NumOfProducts | 10000.0 | 1.530200e+00 | 0.581654 | 1.00 | 1.00 | 1.000000e+00 | 2.000000e+00 | 4.00 |
| HasCrCard | 10000.0 | 7.055000e-01 | 0.455840 | 0.00 | 0.00 | 1.000000e+00 | 1.000000e+00 | 1.00 |
| IsActiveMember | 10000.0 | 5.151000e-01 | 0.499797 | 0.00 | 0.00 | 1.000000e+00 | 1.000000e+00 | 1.00 |
| EstimatedSalary | 10000.0 | 1.000902e+05 | 57510.492818 | 11.58 | 51002.11 | 1.001939e+05 | 1.493882e+05 | 199992.48 |
| Exited | 10000.0 | 2.037000e-01 | 0.402769 | 0.00 | 0.00 | 0.000000e+00 | 0.000000e+00 | 1.00 |

data['Age'].mean()

```
[ ] data['Age'].mean()

38.9218
```

data['Age'].median()

```
[ ] data['Age'].median()

37.0
```

data['Age'].mode()

```
[ ] data['Age'].mode()

0    37
dtype: int64
```

data['EstimatedSalary'].mean()

```
[ ] data['EstimatedSalary'].mean()

100090.239881
```

data['EstimatedSalary'].median(),)

```
[ ] data['EstimatedSalary'].median()

    100193.915
```

data['EstimatedSalary'].mode())

```
[ ] data['EstimatedSalary'].mode()

    0    24924.92
    dtype: float64
```

data['Balance'].mean()

```
[ ] data['Balance'].mean()

    76485.889288
```

data['CreditScore'].std()

```
[ ] data['CreditScore'].std()

    96.65329873613035
```

data['Tenure'].var()

```
[ ] data['Tenure'].var()

    8.364672627262726
```

# Task 5:

5.Handling Missing Values

## Solution:

data.isna().any()

**5.Handling Missing Values**

```
[ ] data.isna().any()

    RowNumber          False
    CustomerId         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
```

data.isnull().sum()

```
[ ] data.isnull().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

# Task 6:

6. Finding Outliers and Replacing Them

## Solution:

outliers = data.quantile(q=(0.25,0.75))
outliers

### 6. Finding Outliers and Replacing Them

```
[ ] outliers = data.quantile(q=(0.25,0.75))
```

```
[ ] outliers
```

| | RowNumber | CustomerId | CreditScore | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0.25** | 2500.75 | 15628528.25 | 584.0 | 32.0 | 3.0 | 0.00 | 1.0 | 0.0 | 0.0 | 51002.1100 | 0.0 |
| **0.75** | 7500.25 | 15753233.75 | 718.0 | 44.0 | 7.0 | 127644.24 | 2.0 | 1.0 | 1.0 | 149388.2475 | 0.0 |

iqr = outliers.loc[0.75]-outliers.loc[0.25]
iqr[2:]

```
[ ] iqr = outliers.loc[0.75]-outliers.loc[0.25]
```

```
[ ] iqr[2:]
```

```
CreditScore           134.0000
Age                    12.0000
Tenure                  4.0000
Balance            127644.2400
NumOfProducts           1.0000
HasCrCard               1.0000
IsActiveMember          1.0000
EstimatedSalary     98386.1375
Exited                  0.0000
dtype: float64
```

upper = outliers.loc[0.75] + 1.5 * iqr

upper[2:]

```
[ ] upper = outliers.loc[0.75] + 1.5 * iqr
```

```
[ ] upper[2:]
```

```
CreditScore           919.00000
Age                    62.00000
Tenure                 13.00000
Balance            319110.60000
NumOfProducts           3.50000
HasCrCard               2.50000
IsActiveMember          2.50000
EstimatedSalary    296967.45375
Exited                  0.00000
dtype: float64
```

lower = outliers.loc[0.25] - 1.5 * iqr
lower[2:]

```
[ ] lower = outliers.loc[0.25] - 1.5 * iqr
```

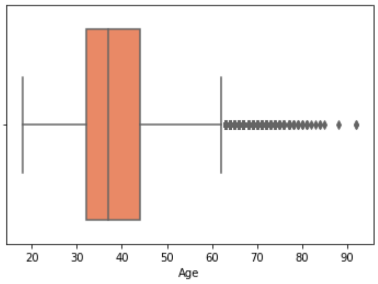
```
[ ] lower[2:]
```

```
CreditScore           383.00000
Age                    14.00000
Tenure                 -3.00000
Balance           -191466.36000
NumOfProducts          -0.50000
HasCrCard              -1.50000
IsActiveMember         -1.50000
EstimatedSalary    -96577.09625
Exited                  0.00000
dtype: float64
```

sns.boxplot(data['Age'], color= 'Coral',)

```
[ ] sns.boxplot(data['Age'], color= 'Coral',)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53b08d1d0>
```




upper['Age']

```
[ ] upper['Age']
```

```
62.0
```

data['Age'].mode()

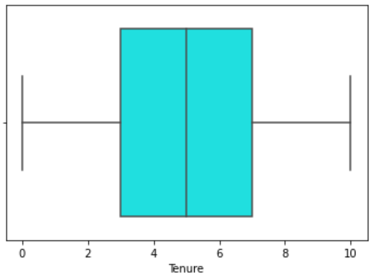
```
[ ] data['Age'].mode()
```

```
0    37
dtype: int64
```

sns.boxplot(data['Tenure'], color= 'cyan',)

```
[ ] sns.boxplot(data['Tenure'], color= 'cyan',)
```

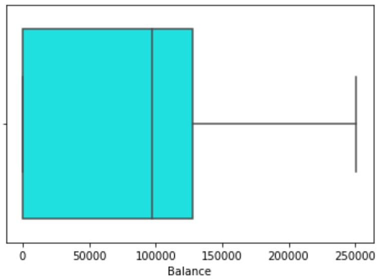
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53b061b50>
```




sns.boxplot(data['EstimatedSalary'], color= 'cyan',)

```
[ ] sns.boxplot(data['Balance'], color= 'cyan',)
```

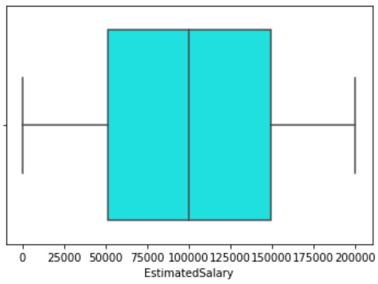
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53afd6050>
```




sns.boxplot(data['CreditScore'], color= 'cyan',)

```
sns.boxplot(data['EstimatedSalary'], color= 'cyan',)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53afb8d50>
```




data['CreditScore'].mode()

```
[ ] data['CreditScore'].mode()
```

```
0    850
dtype: int64
```

lower['CreditScore']

```
[ ] lower['CreditScore']
```

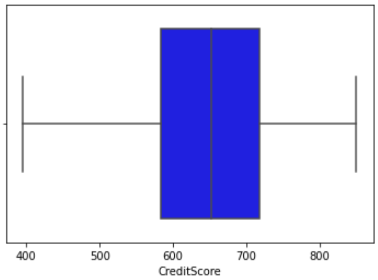
```
383.0
```

data["CreditScore"] = np.where(data["CreditScore"]<390,850,data["CreditScore"]) sns.boxplot(data['CreditScore'], color= 'blue',)

```
[ ] data["CreditScore"] = np.where(data["CreditScore"]<390,850,data["CreditScore"])
```

```
[ ] sns.boxplot(data['CreditScore'], color= 'blue',)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe53ae93ad0>
```




# Task 7:

7. Checking for categorical columns and perform encoding

## Solution:

data.info()

### 7. Checking for categorical columns and perform encoding

```
[ ] data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 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
```

data.dtypes.value_counts()

```
[ ] data.dtypes.value_counts()
```

```
int64      9
object     3
float64    2
dtype: int64
```

# Encoding Categorical variables into numerical variables'

```
# Label Encoding

from sklearn.preprocessing import LabelEncode
label = LabelEncoder()

data['Gender'] = label.fit_transform(data['Gender'])
data['Geography'] = label.fit_transform(data['Geography'])
data.head(8)
```

```
[ ] # Encoding Categorical variables into numerical variables
    # Label Encoding

    from sklearn.preprocessing import LabelEncoder
    label = LabelEncoder()
```

```
[ ] data['Gender'] = label.fit_transform(data['Gender'])
    data['Geography'] = label.fit_transform(data['Geography'])
```

```
[ ] data.head(8)
```

| | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 15634602 | Hargrave | 619 | 0 | 0 | 42 | 2 | 0.00 | 1 | 1 | 1 | 101348.88 | 1 |
| 1 | 2 | 15647311 | Hill | 608 | 2 | 0 | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 | 0 |
| 2 | 3 | 15619304 | Onio | 502 | 0 | 0 | 42 | 8 | 159660.80 | 3 | 1 | 0 | 113931.57 | 1 |
| 3 | 4 | 15701354 | Boni | 699 | 0 | 0 | 39 | 1 | 0.00 | 2 | 0 | 0 | 93826.63 | 0 |
| 4 | 5 | 15737888 | Mitchell | 850 | 2 | 0 | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.10 | 0 |
| 5 | 6 | 15574012 | Chu | 645 | 2 | 1 | 44 | 8 | 113755.78 | 2 | 1 | 0 | 149756.71 | 1 |
| 6 | 7 | 15592531 | Bartlett | 822 | 0 | 1 | 50 | 7 | 0.00 | 2 | 1 | 1 | 10062.80 | 0 |
| 7 | 8 | 15656148 | Obinna | 850 | 1 | 0 | 29 | 4 | 115046.74 | 4 | 1 | 0 | 119346.88 | 1 |

# Task 8:

8. Split the data into dependent and independent variables

**Solution:**

```
data_new = data.drop(['CustomerId', 'Surname', 'RowNumber'], axis = 1)
data_new.info()

data_new.shape

x = data_new.iloc[:,0:10]
y = data_new.iloc[:,10
print(x.shape)
print(y.shape)
print(x.columns)

x.head(8)
```

```
[ ] x = data_new.iloc[:,0:10]
    y = data_new.iloc[:,10]

    print(x.shape)
    print(y.shape)

    print(x.columns)

    (10000, 10)
    (10000,)
    Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
           'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary'],
          dtype='object')
```

```
[ ] x.head(8)
```

| | 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 |
| **5** | 645 | 2 | 1 | 44 | 8 | 113755.78 | 2 | 1 | 0 | 149756.71 |
| **6** | 822 | 0 | 1 | 50 | 7 | 0.00 | 2 | 1 | 1 | 10062.80 |
| **7** | 850 | 1 | 0 | 29 | 4 | 115046.74 | 4 | 1 | 0 | 119346.88 |

# Task 9:

9. Split the data into training and testing

**Solution:**

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.20, random_state = 0)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)

## 9. Split the data into training and testing

```
[ ] from sklearn.model_selection import train_test_split
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.20, random_state = 0)

    print(x_train.shape)
    print(y_train.shape)
    print(x_test.shape)
    print(y_test.shape)

    (8000, 10)
    (8000,)
    (2000, 10)
    (2000,)
```

# Task 10:

10. Scale the independent variables

**Solution:**

from sklearn.preprocessing import StandardScaler
ss = StandardScaler

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)

x_train = pd.DataFrame(x_train)
x_train.head()

### 10. Scale the independent variables

```
[ ] from sklearn.preprocessing import StandardScaler
    ss = StandardScaler
```

```
[ ] from sklearn.preprocessing import StandardScaler

    sc = StandardScaler()
    x_train = sc.fit_transform(x_train)
    x_test = sc.fit_transform(x_test)

    x_train = pd.DataFrame(x_train)
    x_train.head()
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.160295 | 1.519198 | -1.091687 | -0.464608 | 0.006661 | -1.215717 | 0.809503 | 0.642595 | -1.032270 | 1.106432 |
| 1 | -2.325224 | 0.313126 | 0.916013 | 0.301026 | -1.377440 | -0.006312 | -0.921591 | 0.642595 | 0.968738 | -0.748664 |
| 2 | -1.206740 | -0.892945 | -1.091687 | -0.943129 | -1.031415 | 0.579935 | -0.921591 | 0.642595 | -1.032270 | 1.485335 |
| 3 | 0.025663 | 1.519198 | 0.916013 | 0.109617 | 0.006661 | 0.473128 | -0.921591 | 0.642595 | -1.032270 | 1.276528 |
| 4 | 2.055504 | 1.519198 | -1.091687 | 1.736588 | 1.044737 | 0.810193 | 0.809503 | 0.642595 | 0.968738 | 0.558378 |