Assignment -2

Data Visualization and Pre-processing

Assignment Date	:	15 October 2022
Student Name	:	Rithika R
Student Roll Number	:	73771914158
Maximum Marks	:	2 Marks

Task 1:

Download the dataset: [Dataset]

Assignment-2

1. Download the dataset: Dataset

Task 2:

Question-`1:

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")
```

Output:

1.Loading the Churn_Modelling dataset

In [1]:

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

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

Solution:

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

Output:

In [2]:

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

```
Mounted at /content/drive
```

Solution:

```
data = pd.read_csv("/content/Churn_Modelling.csv")
```

Output:

In [3]:

```
data = pd.read_csv("/content/Churn_Modelling.csv")
```

Solution:

```
data.info()
```

Output:

In [4]:
```
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
```

Solution:

data.head()

Output:

In [5]:
```
data.head()
```

Out[5]:

	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

Solution:

```
data.tail()
```

Output:

In [6]:

```
data.tail()
```

Out[6]:

	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

Solution:

```
data.shape
```

In [7]:

```
data.shape
```

Out[7]: (10000, 14)

Task 3:

Question-2:

Visualization of Dataset

Univariate Analysis

- Distribution Plot

Solution:

```
penguins = sns.load_dataset("penguins")
sns.displot(penguins, x="flipper_length_mm")
```

Output:

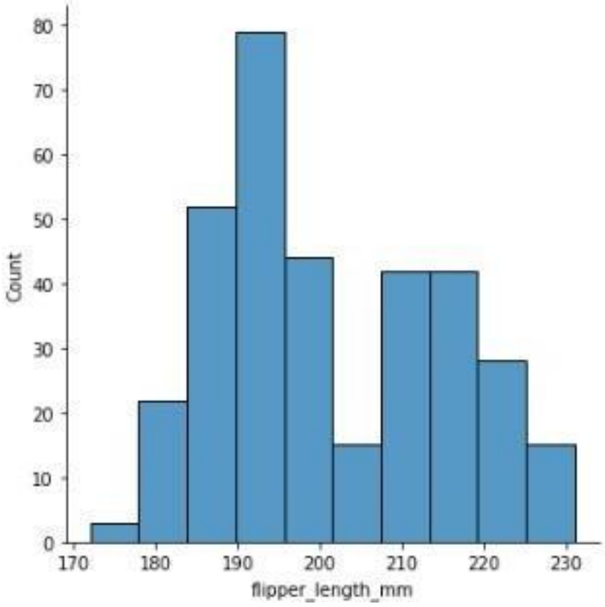
2.Vizualization of Dataset

Univariate Analysis

> Distriution Plot

In [17]:
```
penguins = sns.load_dataset("penguins")
sns.displot(penguins, x="flipper_length_mm")
```

Out[17]: <seaborn.axisgrid.FacetGrid at 0x7f3961965990>



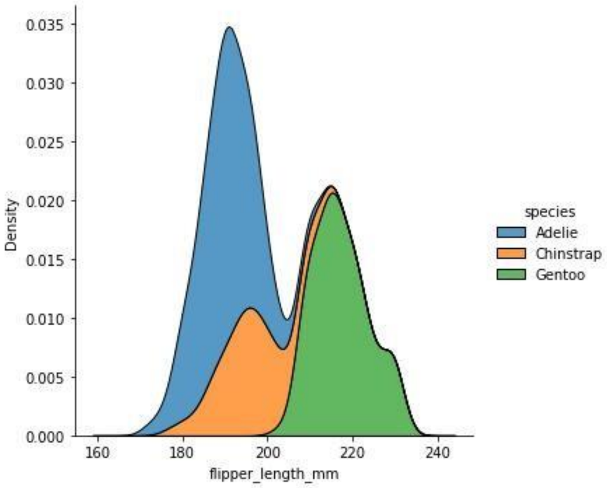
Solution:

```
sns.displot(penguins, x="flipper_length_mm", hue="species", kind="kde", multiple="stack")
```

Output:

In [23]:
```
sns.displot(penguins, x="flipper_length_mm", hue="species", kind="kde", multiple="stack")
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x7f395f278650>



- Histograms

Solution:

data['Geography'].value_counts()

Output:

In [12]:
```
data['Geography'].value_counts()
```

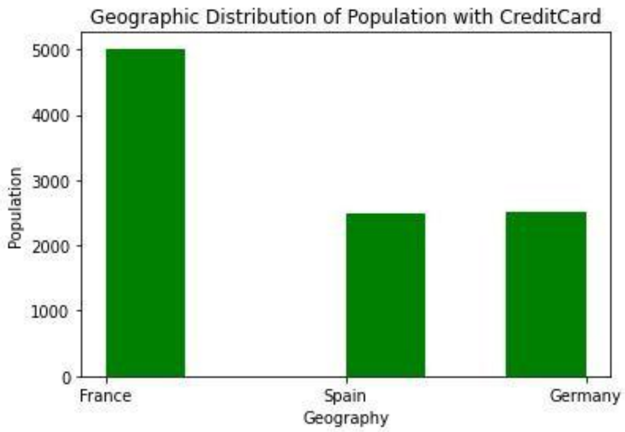
Out[12]:
```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

Solution:

```
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()
```

Output:

```
In [21]: plt.hist(x=data.Geography, bins=6, color='green')
         plt.title("Geographic Distribution of Population with CreditCard")
         plt.xlabel("Geography")
         plt.ylabel("Population")
         plt.show()
```

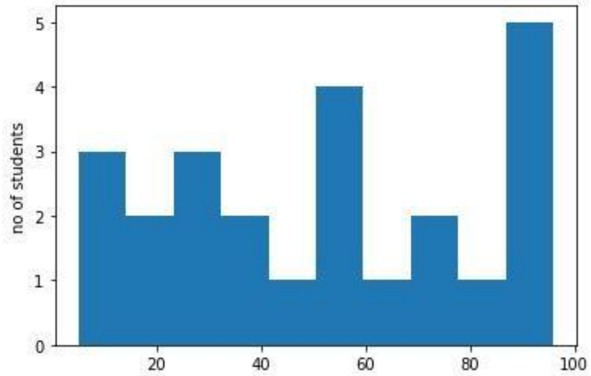


Solution:

```
fig,ax = plt.subplots(1,1)
a = np.array([22,87,5,43,56,73,55,54,11,20,51,5,79,31,27,63,71,90,92,95,96,
    32,37,40])
plt.hist(a)
ax.set_ylabel('no of students')
plt.show()
```

Output:

In [14]:
```
fig,ax = plt.subplots(1,1)
a = np.array([22,87,5,43,56,73,55,54,11,20,51,5,79,31,27,63,71,90,92,95,96,32,37,40])
plt.hist(a)
ax.set_ylabel('no of students')
plt.show()
```



- **Bar Plot**

Solution:

data['Gender'].value_counts()

Output:

Bar Plot

In [15]:
```
data['Gender'].value_counts()
```

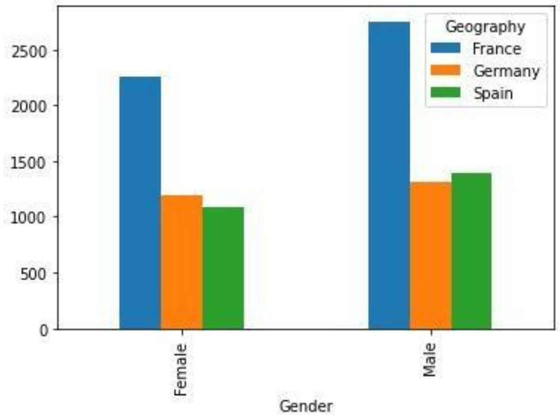
Out[15]:
```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

Solution:

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

Output:

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

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4178be81d0>
```



Pie charts

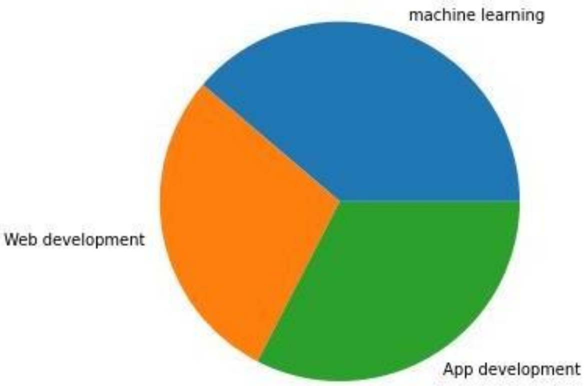
- **Pie charts**

Solution:

```
fig=plt.figure()
ax=fig.add_axes([0,0,1,1])
courses=['machine learning','Web development','App
development']
students_enrolled=[50,37,42]
ax.pie(students_enrolled,labels=courses)
plt.show()
```

Output:

```
In [16]:
fig=plt.figure()
ax=fig.add_axes([0,0,1,1])
courses=['machine learning','Web development','App development']
students_enrolled=[50,37,42]
ax.pie(students_enrolled,labels=courses)
plt.show()
```



●Box plot

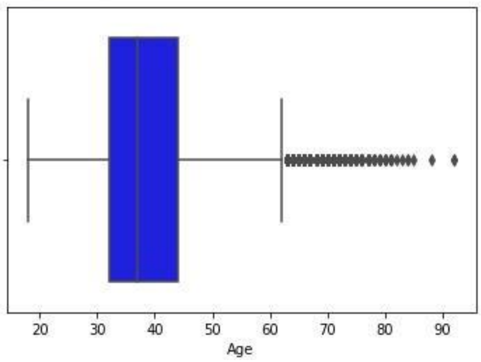
Solution:

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

Output:

Box pLot

```
In [ ]: sns.boxplot(data["Age"],color='blue')
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4178b5f650>
```



Bivariate Analysis

Solution:

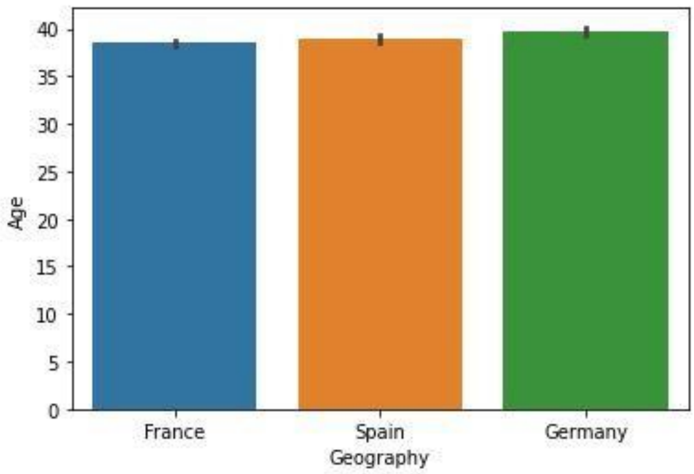
sns.barplot(data[‘Geographgy’],data[″Age″])

Output:

Bivariate Analysis

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

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4178ae1190>

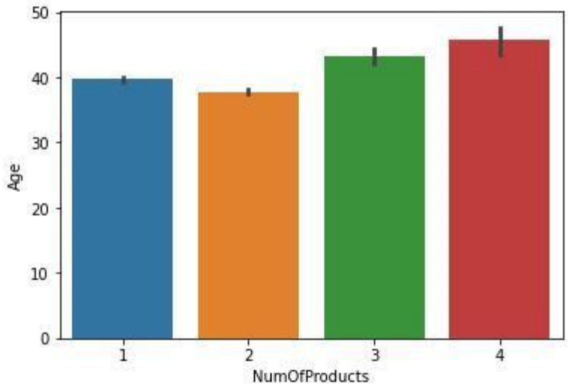


Solution:

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

Output:

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

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4178ac6f10>
```



Solution:

data['HasCrCard'].value_counts()

Output:

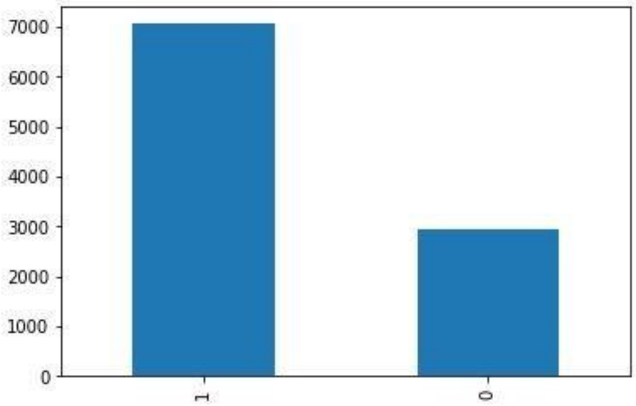
```
In [ ]: data['HasCrCard'].value_counts()

Out[ ]: 1    7055
        0    2945
        Name: HasCrCard, dtype: int64
```

Solution:

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

Output:

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

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f41789d3ad0>
```



- **Line Chart**

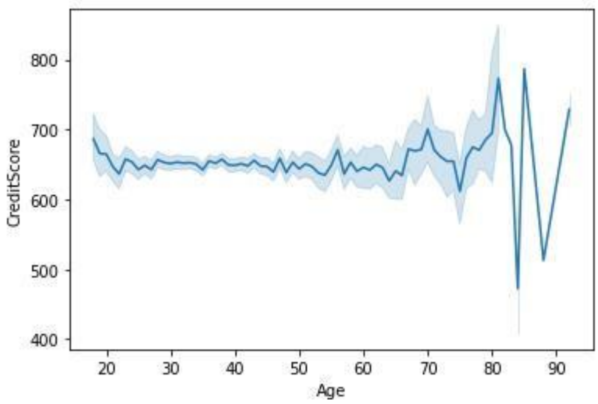
Solution:

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

Output:

Line Chart

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

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f41789a3290>
```



Multi-Variate Analysis

- **Scatter Plot**

Solution:

data['IsActiveMember'].value_counts()

Output:

Multi-Variate Analysis

> Scatter Plot

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

Out[ ]:
```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

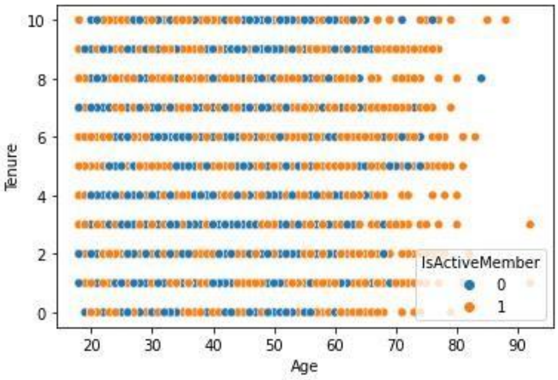
Solution:

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

Output:

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

Out[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4178ae1f10>
```



- **Point Plot**

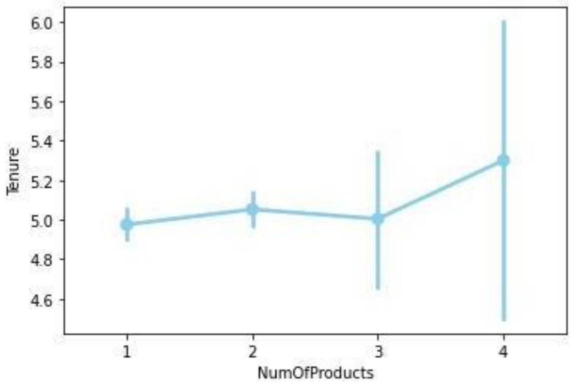
Solution:

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

Output:

Point Plot

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

Out[ ]: &lt;matplotlib.axes._subplots.AxesSubplot at 0x7f4178c806d0&gt;
```



- **HeatMap**

Solution:

```
data.head()
```

Output:

HeatMap

In [ ]:

```
data.head()
```

Out[ ]:

	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

Solution:

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

Output:

In [ ]:

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

Out[ ]:

	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

Solution:

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

Output:

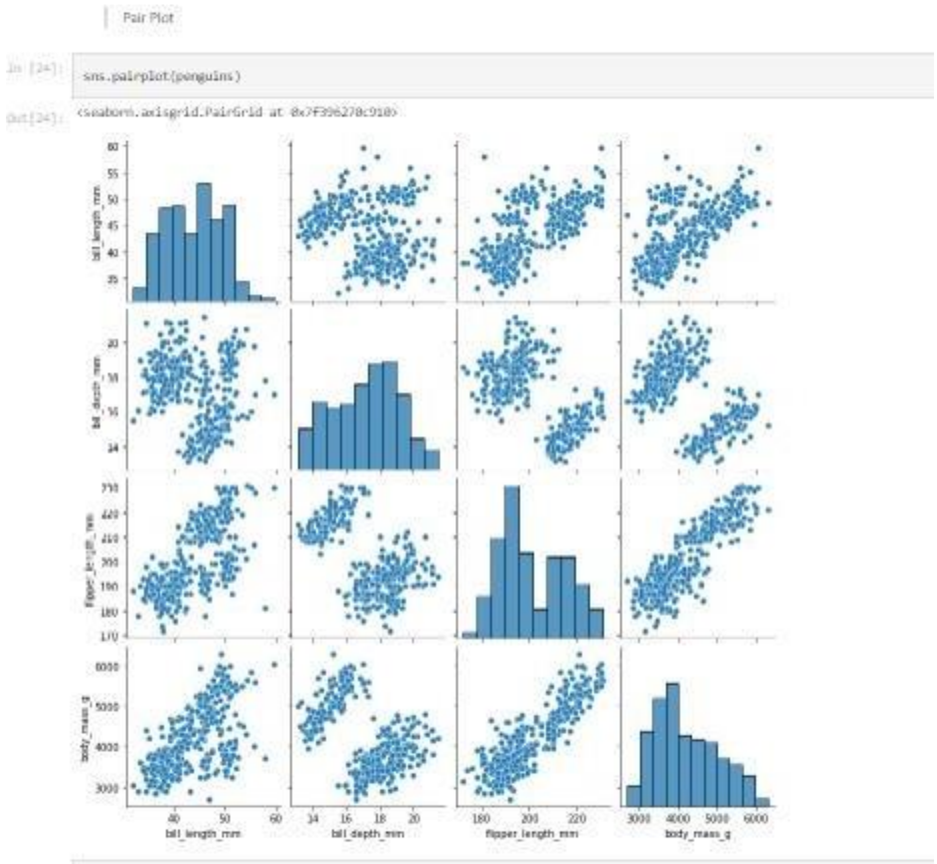
```
In [ ]: plt.figure(figsize = (16,8))
        sns.heatmap(data_cor,linecolor='white',linewidth=0.5, annot=True)

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f41788d03d0>
```

- **Pair Plot**

Solution:

```
sns.pairplot(penguins)
```

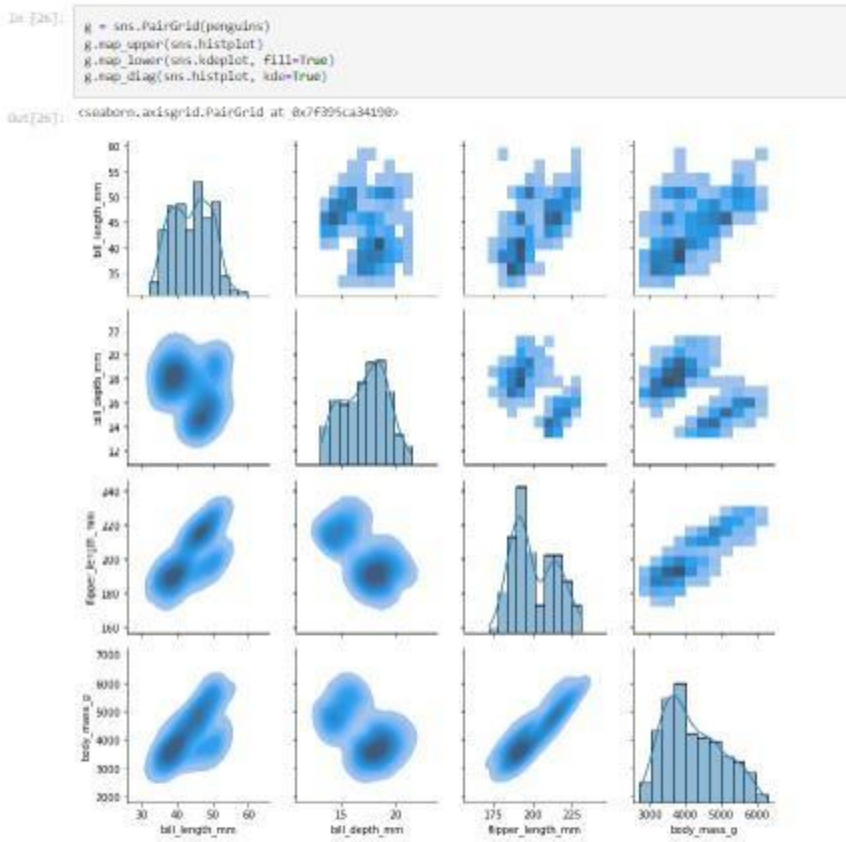
Output:



Solution:

```
g = sns.PairGrid(penguins)
g.map_upper(sns.histplot)
g.map_lower(sns.kdeplot, fill=True)
g.map_diag(sns.histplot, kde=True)
```

Output:



Task 4:

Question-3:

Descriptive Statistic Analysis

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

Solution:

```
data.describe().T
```

Output:

In [27]:

```
data.describe().T
```

Out[27]:

	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

Solution:

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

Output:

In [35]:

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

Out[35]: 38.9218

Solution:

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

Output:

```
In [36]: data['Age'].median()

Out[36]: 37.0
```

Solution:

data['Age'].mode()

Output:

```
In [34]: data['Age'].mode()

Out[34]: 0    37
         dtype: int64
```

Solution:

data['EstimatedSalary'].mean()

Output:

```
In [33]: data['EstimatedSalary'].mean()

Out[33]: 100090.239881
```

Solution:

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

Output:

```
In [32]: data['EstimatedSalary'].median()

Out[32]: 100193.915
```

Solution:

data['EstimatedSalary'].mode())

Output:

```
In [31]: data['EstimatedSalary'].mode()

Out[31]: 0    24924.92
         dtype: float64
```

Solution:

data['Balance'].mean()

Output:

```
In [30]: data['Balance'].mean()

Out[30]: 76485.889288
```

Solution:

data['CreditScore'].std()

Output:

```
In [29]: data['CreditScore'].std()

Out[29]: 96.65329873613035
```

Solution:

data['Tenure'].var()

Output:

```
In [28]: data['Tenure'].var()

Out[28]: 8.364672627262726
```

Task 5:

Question-4:

Handling Missing Values

Solution:

data.isna().any()

Output:

4.Handling Missing Values

In [38]:
```
data.isna().any()
```

Out[38]:
```
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
```

Solution:

```
data.dropna(inplace = True)
data.isnull().sum()
```

Output:

In [42]:
```
data.dropna(inplace = True)
data.isnull().sum()
```

Out[42]:
```
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
```

Solution:

```
data.isnull().sum()
```

Output:

```
In [37]: data.isnull().sum()

Out[37]: 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:

Question-5:

Finding Outliers and Replacing Them

Solution:

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

Output:

5. Finding Outliers and Replacing Them

```
In [43]: outliers = data.quantile(q=(0.25,0.75))
```

Solution:

Outliers

Output:

In [44]:
```
outliers
```

Out[44]:

	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

Solution:

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

Output:

In [47]:
```
iqr = outliers.loc[0.75]-outliers.loc[0.25]
```

Solution:

iqr[2:]

Output:

In [48]:
```
iqr[2:]
```

Out[48]:
```
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
```

Solution:

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

Output:

```
In [49]: upper = outliers.loc[0.75] + 1.5 * iqr
```

Solution:

upper[2:]

Output:

```
In [51]: upper[2:]

Out[51]: 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
```

Solution:

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

Output:

```
In [50]: lower = outliers.loc[0.25] - 1.5 * iqr
```

Solution:

```
lower[2:]
```

Output:

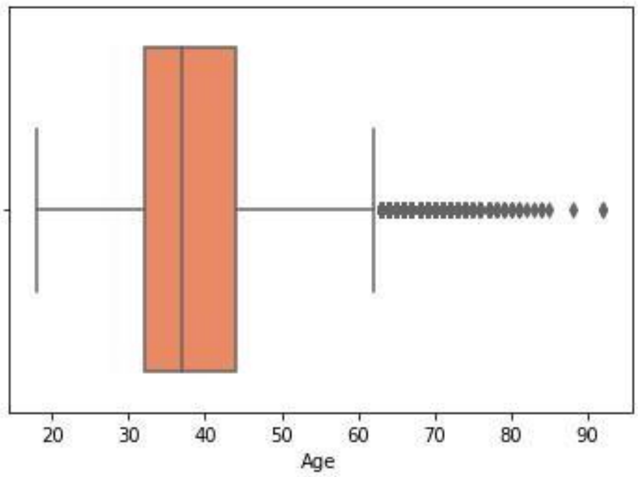
```
In [52]: lower[2:]

Out[52]: 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
```

Solution:

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

Output:

```
In [53]: sns.boxplot(data['Age'], color= 'Coral',)

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7f395c0522d0>
```



Solution:

upper['Age']

Output:

```
In [54]: upper['Age']

Out[54]: 62.0
```

Solution:

data['Age'].mode()

Output:

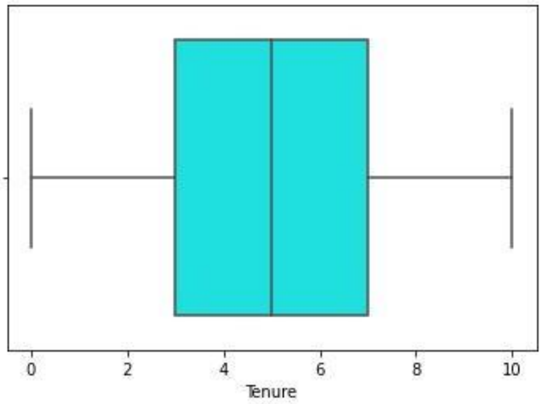
```
In [55]: data['Age'].mode()

Out[55]: 0    37
         dtype: int64
```

Solution:

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

Output:

```
In [56]: sns.boxplot(data['Tenure'], color= 'cyan',)

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7f395bfdd350>
```

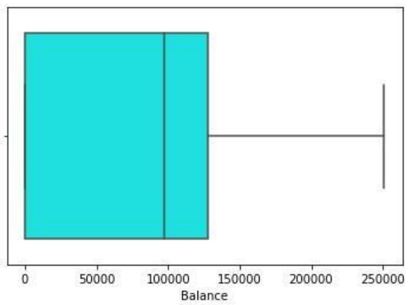


Solution:

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

Output:

```
In [57]: sns.boxplot(data['Balance'], color= 'cyan',)

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7f395bfd8610>
```



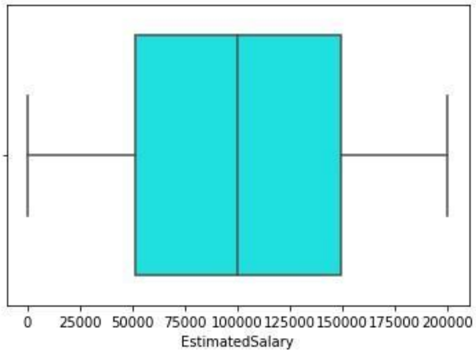
Solution:

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

Output:

In [58]:
```
sns.boxplot(data['EstimatedSalary'], color= 'cyan',)
```

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x7f395bf14350>



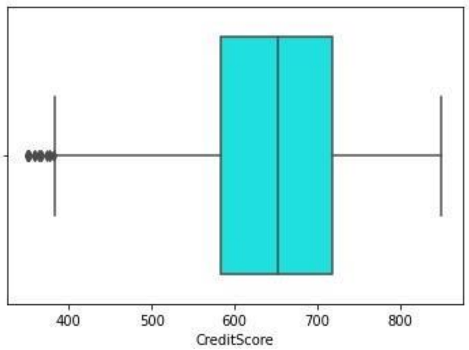
Solution:

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

Output:

In [59]:
```
sns.boxplot(data['CreditScore'], color= 'cyan',)
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7f395bea7d90>



Solution:

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

Output:

```
In [60]: data['CreditScore'].mode()

Out[60]: 0    850
         dtype: int64
```

Solution:

lower['CreditScore']

Output:

```
In [61]: lower['CreditScore']

Out[61]: 383.0
```

Solution:

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

Output:

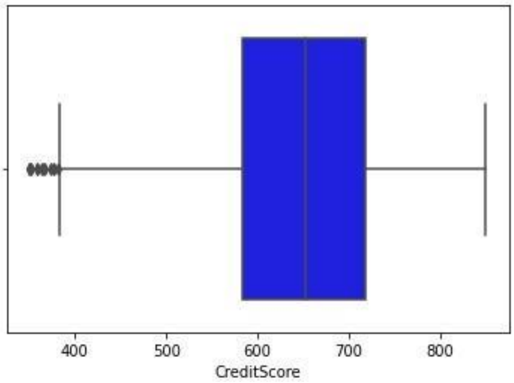
```
In [ ]: data["CreditScore"] = np.where(data["CreditScore"]<390,850,data["CreditScore"])
```

Solution:

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

Output:

```
In [62]: sns.boxplot(data['CreditScore'], color= 'blue',)

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x7f395be0b2d0>
```



Task 7:

Question-6:

Checking for categorical columns and perform encoding

Solution:

```
data.info()
```

Output:

6. Checking for categorical columns and perform encoding

In [63]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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
```

Solution:

```
data.dtypes.value_counts()
```

Output:

In [64]:
```
data.dtypes.value_counts()
```

Out[64]:
```
int64      9
object     3
float64    2
dtype: int64
```

Solution:

```
# Encoding Categorical variables into numerical variables'
# Label Encoding

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

Output:

In [65]:
```
# Encoding Categorical variables into numerical variables
# Label Encoding

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

Solution:

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

Output:

In [66]:
```
data['Gender'] = label.fit_transform(data['Gender'])
data['Geography'] = label.fit_transform(data['Geography'])
```

Solution:

```
data.head(8)
```

Output:

In [67]:
```
data.head(8)
```

Out[67]:

	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	376	1	0	29	4	115046.74	4	1	0	119346.88	1

Task 8:

Question-7:

Split the data into dependent and independent variables

Solution:

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

Output:

7.Split the data into dependent and independent variables

In [72]:
```
data_new = data.drop(['CustomerId', 'Surname', 'RowNumber'], axis = 1)
data_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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  int64
 2   Gender           10000 non-null  int64
 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(9)
memory usage: 937.5 KB
```

Solution:

```
data_new.shape
```

Output:

In [73]:
```
data_new.shape
```

Out[73]:
```
(10000, 11)
```

Solution:

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

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

print(x.columns)
```

Output:

```
In [75]: 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')
```

Solution:

```
x.head(8)
```

Output:

```
In [74]: x.head(8)
```

Out[74]:

	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	376	1	0	29	4	115046.74	4	1	0	119346.88

Task 9:

Question-8:

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)
```

Output:

8. Split the data into training and testing

In [76]:

```
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:

Question-9:

Scale the independent variables

Solution:

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

Output:

9. Scale the independent variables

In [77]:

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

Solution:

```
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()
```

Output:

In [79]:

```
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()
```

Out[79]:

	0	1	2	3	4	5	6	7	8	9
0	0.169582	1.519198	-1.091687	-0.464608	0.006661	-1.215717	0.809503	0.642595	-1.032270	1.106432
1	-2.304559	0.313126	0.916013	0.301026	-1.377440	-0.006312	-0.921591	0.642595	0.968738	-0.748664
2	-1.191196	-0.892945	-1.091687	-0.943129	-1.031415	0.579935	-0.921591	0.642595	-1.032270	1.485335
3	0.035566	1.519198	0.916013	0.109617	0.006661	0.473128	-0.921591	0.642595	-1.032270	1.276528
4	2.056114	1.519198	-1.091687	1.736588	1.044737	0.810193	0.809503	0.642595	0.968738	0.558378