RAJALAKSHMI ENGINEERING COLLEGE RAJALAKSHMI NAGAR, THANDALAM – 602 105

RAJALAKSHMI ENGINEERING COLLEGE
An AUTONOMOUS Institution
Affiliated to ANNA UNIVERSITY, Chennai

CS23334 – Fundamental of Data Science

Laboratory Record Notebook

Name: AAKASH V

Year / Branch / Section: 2nd year / B.E CSE – 'A'

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College Roll No: 230701002

Semester: 3rd Semester

Academic Year: 2023 - 2024

CS23334 – Fundamental of Data Science

NAME	**AAKASH V**
ROLL NO.	**2116230701002**
DEPT	**CSE**
SEC	**‘A’**

1.a Basic Practice Experiments(1 to 4)

DATE: 30.07.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
data=pd.read_csv('Iris.csv')
data
```

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Virginica
146	6.3	2.5	5.0	1.9	Virginica
147	6.5	3.0	5.2	2.0	Virginica
148	6.2	3.4	5.4	2.3	Virginica
149	5.9	3.0	5.1	1.8	Virginica

150 rows × 5 columns

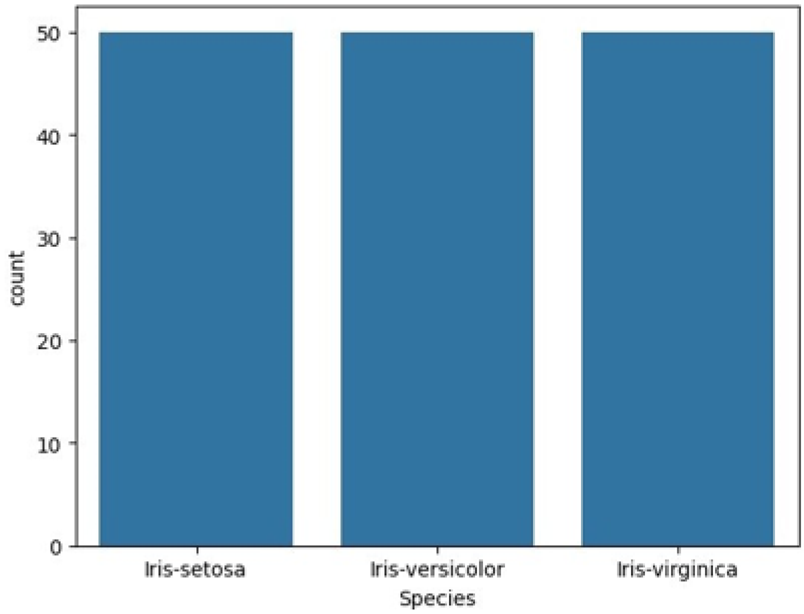
```python
data.info()
```

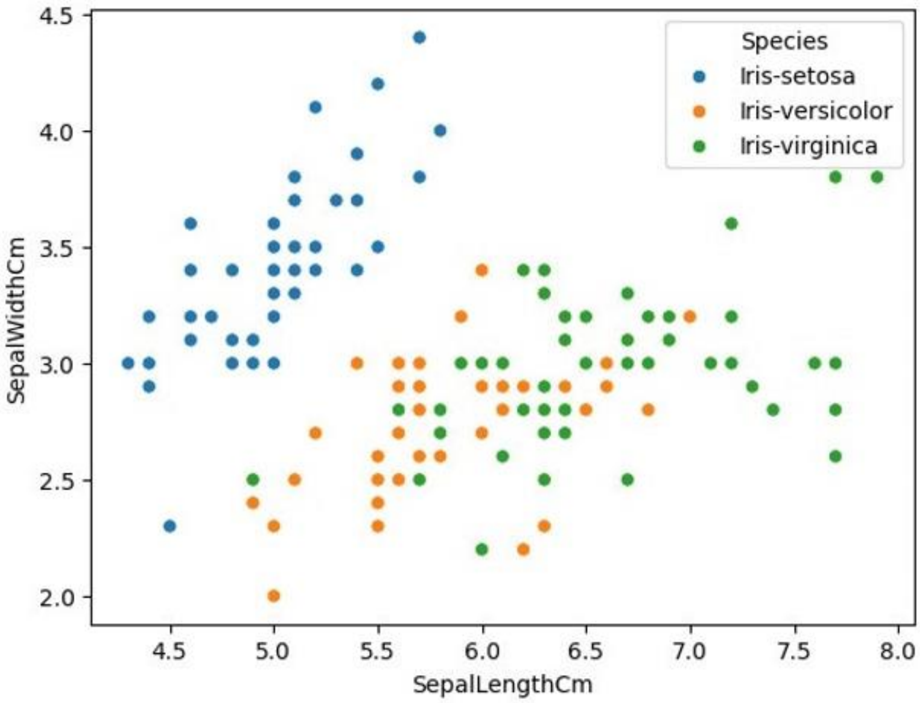
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal.length  150 non-null    float64
 1   sepal.width   150 non-null    float64
 2   petal.length  150 non-null    float64
 3   petal.width   150 non-null    float64
 4   variety       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```python
data.describe()
```

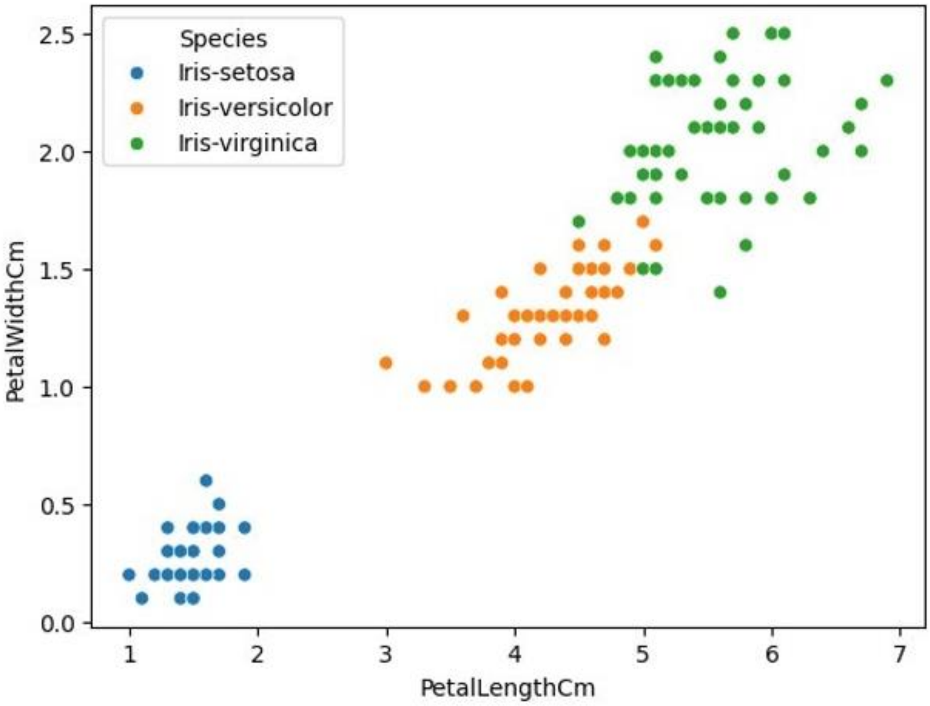
	sepal.length	sepal.width	petal.length	petal.width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333
std	0.828066	0.435866	1.765298	0.762238
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

```python
data.value_counts('Species')
```

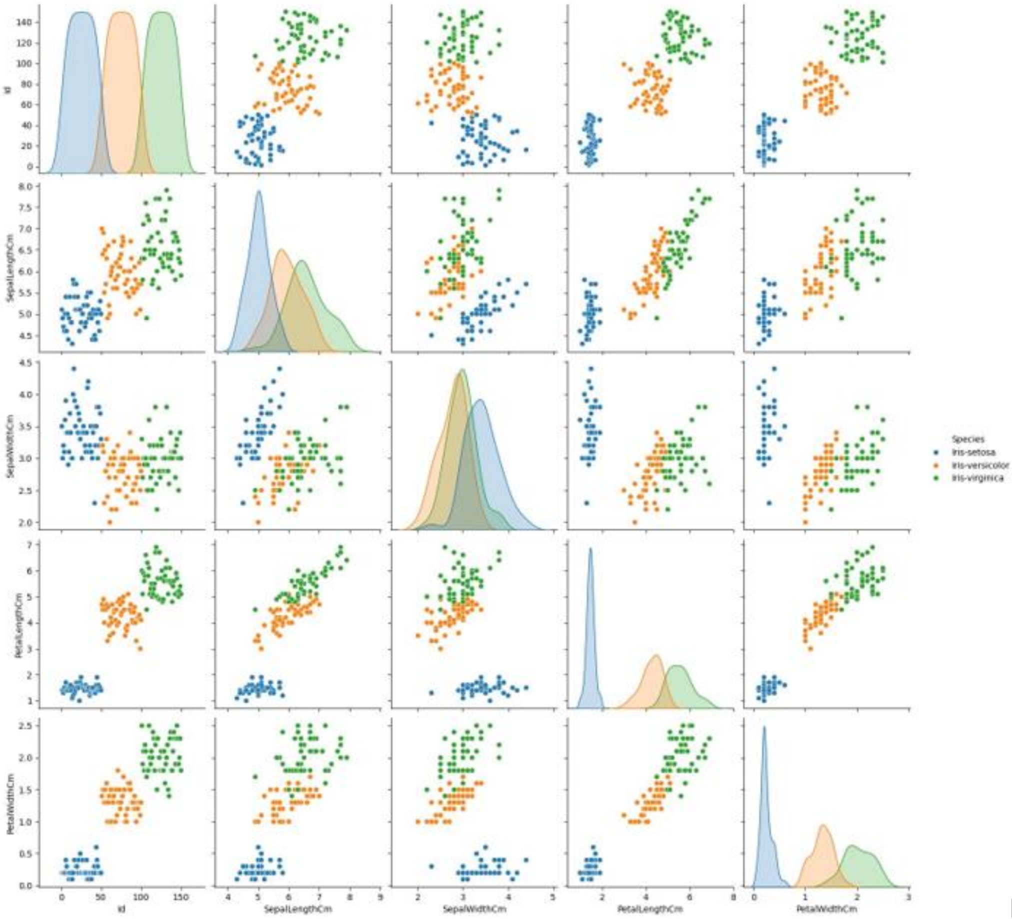




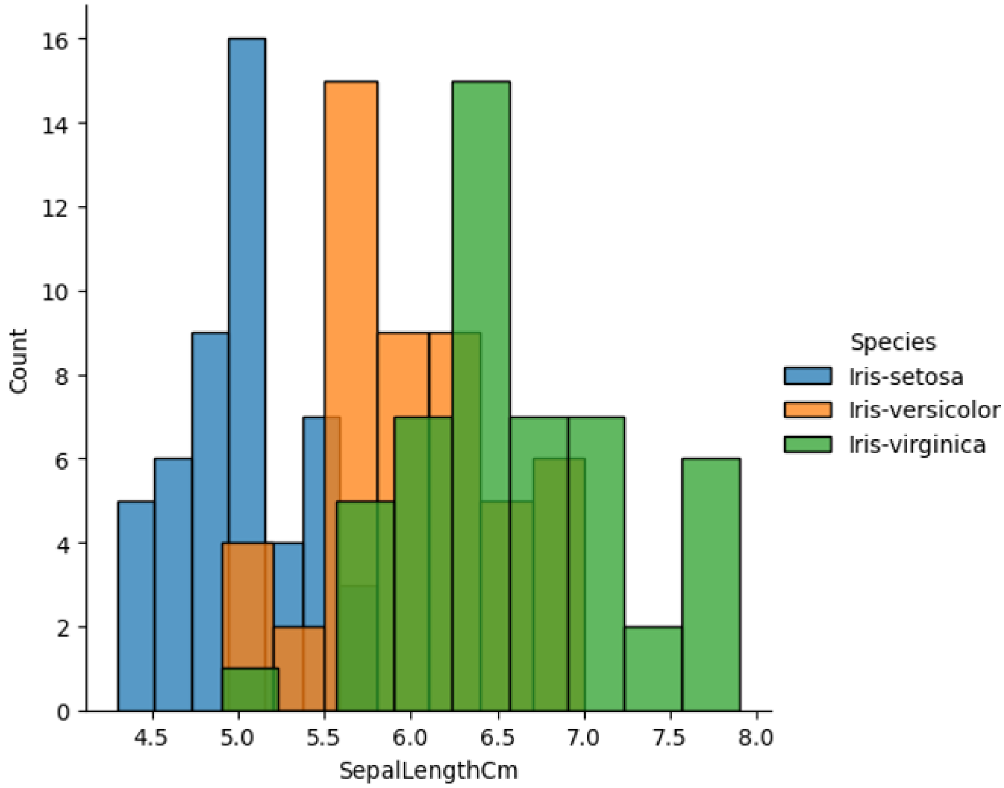

```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data= data,)
<Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>
```



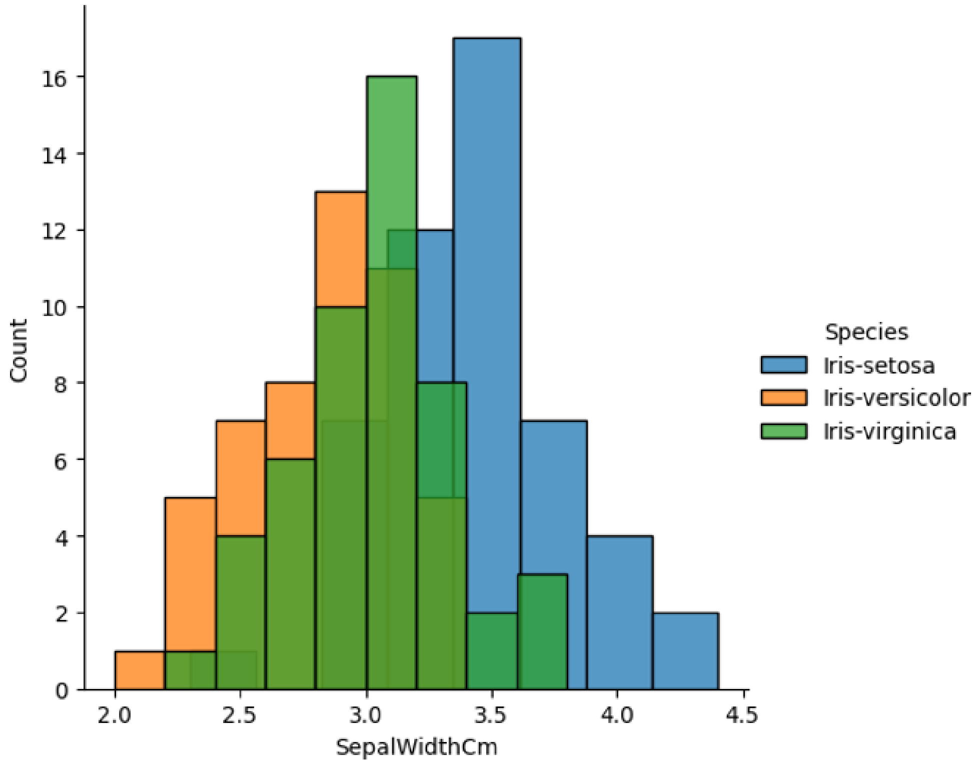

```
sns.pairplot(data,hue='Species',height=3);
```




```
plt.show()
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalLeng thCm').add_legend();
plt.show();
```




```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalWidt hCm').add_legend();
plt.show();
```



Count
SepalWidthCm
0
2
4
6
8
10
12
14
16
2.0
2.5
3.0
3.5
4.0
4.5
Species
Iris-setosa
Iris-versicolor
Iris-virginica

1.b Pandas Buit in function. Numpy Buit in fuction

DATE: 06.08.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
array=np.random.randint(1,100,9)
array
```

```
array([ 7, 55, 95, 60, 89,  2, 29, 40, 74], dtype=int32)
```

```
np.sqrt(array)
```

```
array([2.64575131, 7.41619849, 9.74679434, 7.74596669, 9.43398113,
       1.41421356, 5.38516481, 6.32455532, 8.60232527])
```

```
array.ndim
```

```
1
```

```
new_array=array.reshape(3,3)
new_array
```

```
array([[ 7, 55, 95],
       [60, 89,  2],
       [29, 40, 74]], dtype=int32)
```

```
new_array.ndim
```

```
2
```

```
new_array.ravel()
```

```
array([ 7, 55, 95, 60, 89,  2, 29, 40, 74], dtype=int32)
```

```
newm=new_array.reshape(3,3)
newm
```

```
array([[ 7, 55, 95],
       [60, 89,  2],
       [29, 40, 74]], dtype=int32)
```

```
newm[2,1:3]
```

```
array([40, 74], dtype=int32)
```

```
newm[1:2,1:3]
```

```
array([[89,  2]], dtype=int32)
```

```
new_array[0:3,0:0]
```

```
array([], shape=(3, 0), dtype=int32)
```

```
new_array[1:3]
```

```
array([[60, 89,  2],
       [29, 40, 74]], dtype=int32)
```

2. Outlier detection

DATE: 13.08.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import warnings
warnings.filterwarnings('ignore')
array=np.random.randint(1,100,16)
array
```

```
array([28, 58, 91, 94, 43, 93, 91, 86, 61, 33, 42, 91, 13, 52, 23, 61],
      dtype=int32)
```

```
array.mean()
```

```
np.float64(60.0)
```

```
np.percentile(array,25)
```

```
np.float64(39.75)
```

```
np.percentile(array,50)
```

```
np.float64(59.5)
```

```
np.percentile(array,75)
```

```
np.float64(91.0)
```

```
np.percentile(array,100)
```

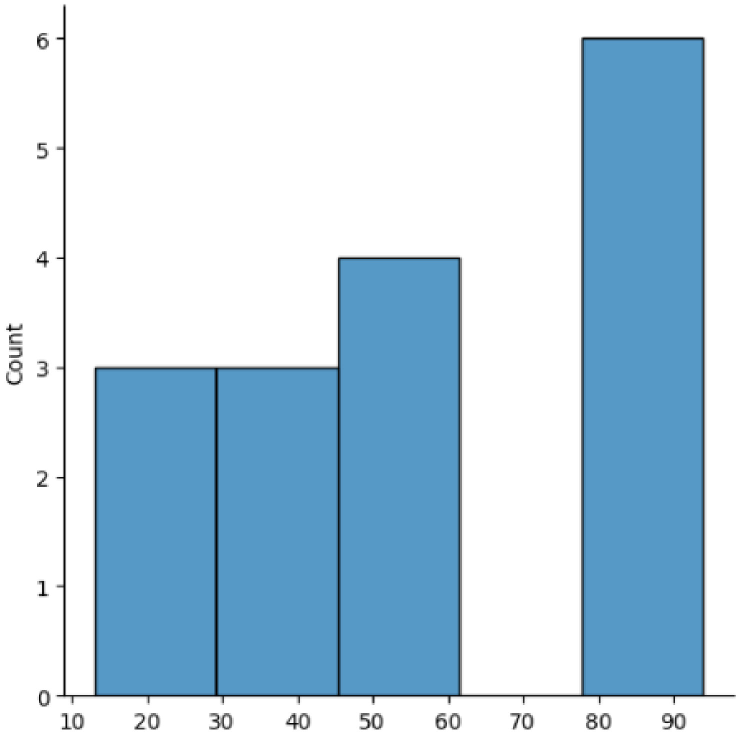
```
np.float64(94.0)
```

```python
#outliers detection
def outDetection(array):
    sorted(array)
    Q1,Q3=np.percentile(array,[25,75])
    IQR=Q3-Q1
    lr=Q1-(1.5*IQR)
    ur=Q3+(1.5*IQR)
    return lr,ur
lr,ur=outDetection(array)
lr,ur
```

```
(np.float64(-37.125), np.float64(167.875))
```

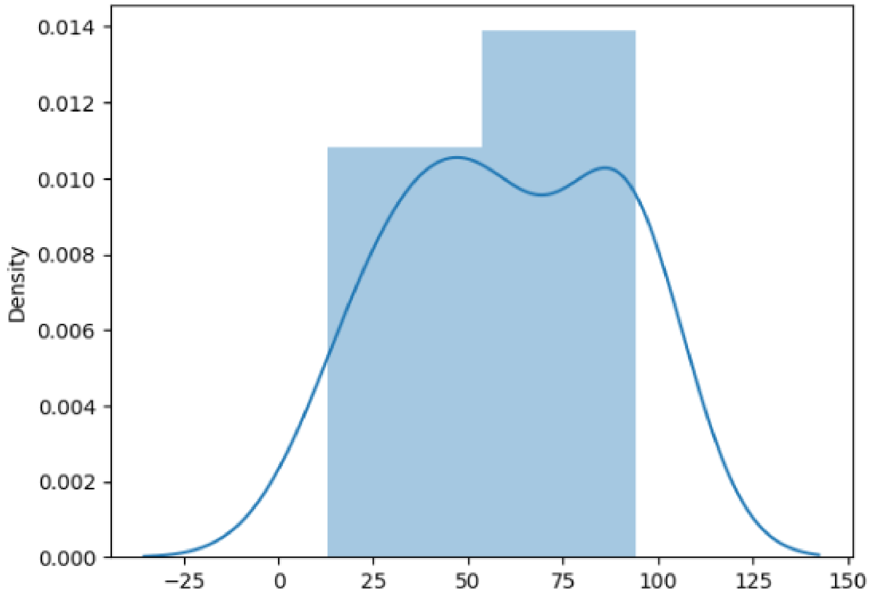
```python
import seaborn as sns
%matplotlib inline
sns.displot(array)
```

```
<seaborn.axisgrid.FacetGrid at 0x2a0f48d7750>
```



```python
sns.distplot(array)
```

```
<Axes: ylabel='Density'>
```

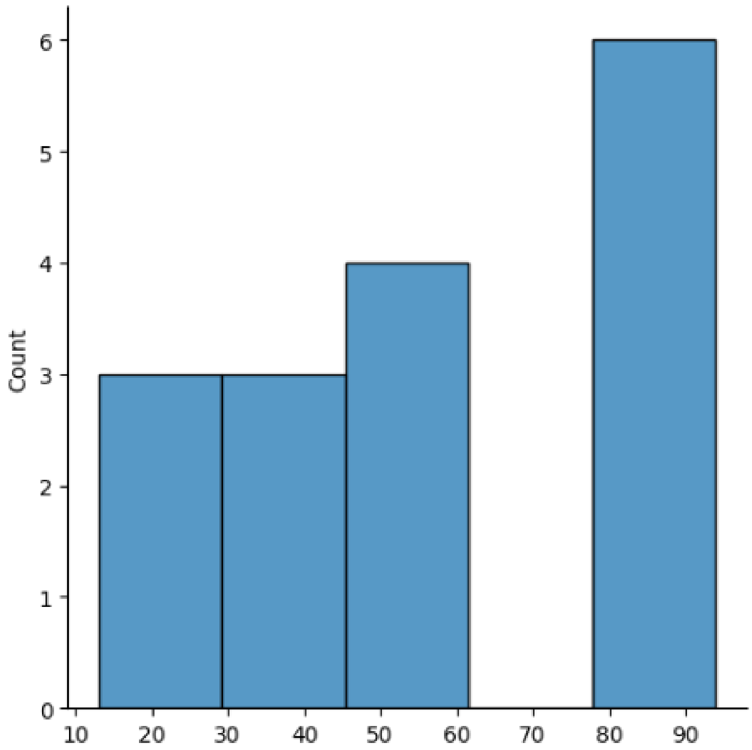



```python
new_array=array[(array>lr) & (array<ur)]
new_array
```

```
array([28, 58, 91, 94, 43, 93, 91, 86, 61, 33, 42, 91, 13, 52, 23, 61],
      dtype=int32)
```

```python
sns.displot(new_array)
```

```
<seaborn.axisgrid.FacetGrid at 0x2a0f4951550>
```




```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

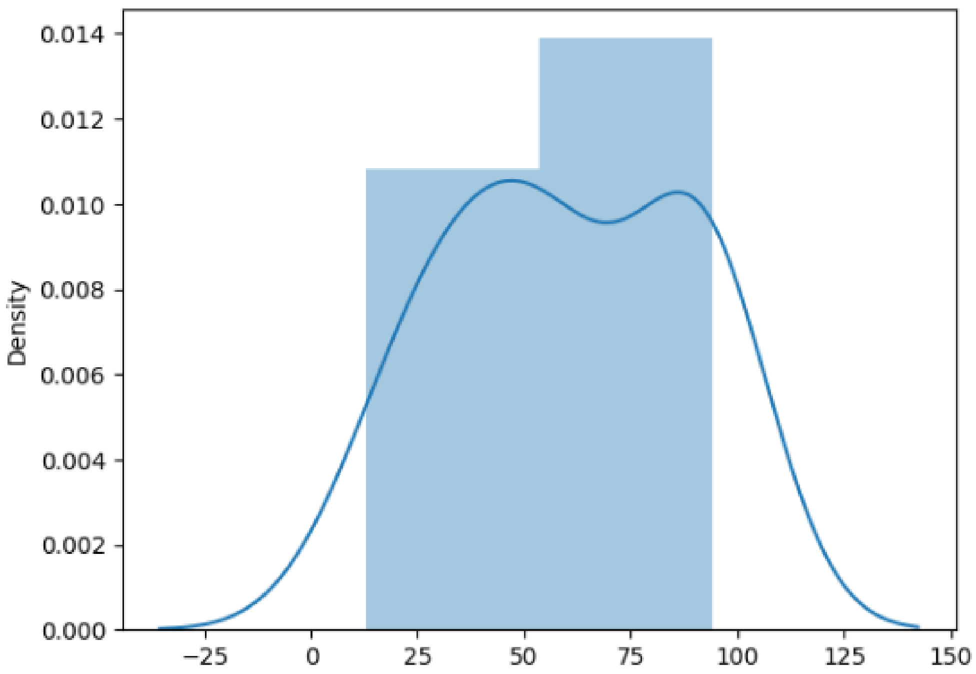
```
(np.float64(-37.125), np.float64(167.875))
```

```
final_array=new_array[(new_array>lr1) & (new_array<ur1)]
final_array
```

```
array([28, 58, 91, 94, 43, 93, 91, 86, 61, 33, 42, 91, 13, 52, 23, 61],
      dtype=int32)
```

```
sns.distplot(final_array)
```

```
<Axes: ylabel='Density'>
```


Density
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
−25
0
25
50
75
100
125
150

3. Missing and inappropriate data

DATA : 20.08.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("Hotel_Dataset.csv")
df
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

```
5           6     35+        3      Ibys     Non-Veg   1909
6           7     35+        4    RedFox  Vegetarian   1000
7           8   20-25        7 LemonTree        Veg   2999
8           9   25-30        2      Ibis     Non-Veg   3456
9           9   25-30        2      Ibis     Non-Veg   3456
10         10   30-35        5    RedFox     non-Veg  -6755
```

```
    NoOfPax  EstimatedSalary Age Group.1
0         2            40000       20-25
1         3            59000       30-35
2         2            30000       25-30
3         2           120000       20-25
4         2            45000         35+
5         2           122220         35+
6        -1            21122         35+
7       -10           345673       20-25
8         3           -99999       25-30
9         3           -99999       25-30
10        4            87777       30-35
```

```
df.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
5      False
6      False
7      False
8      False
9       True
10     False
dtype: bool
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 9 columns):
 #   Column            Non-Null Count   Dtype
---  ----------------------------------  ------
 0   CustomerID        11 non-null      int64
 1   Age Group         11 non-null      object
 2   Rating(1-5)       11 non-null      int64
```

```
 3   Hotel             11 non-null     object
 4   FoodPreference    11 non-null     object
 5   Bill              11 non-null     int64
 6   NoOfPax           11 non-null     int64
 7   EstimatedSalary   11 non-null     int64
 8   Age_Group.1       11 non-null     object
dtypes: int64(5), object(4)
memory usage: 924.0+ bytes
```

```
df.drop_duplicates(inplace=True)
df
```

```
    CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference  Bill  \
0            1     20-25            4       Ibis           veg  1300

1            2     30-35            5  LemonTree       Non-Veg  2000

2            3     25-30            6     RedFox           Veg  1322

3            4     20-25           -1  LemonTree           Veg  1234

4            5       35+            3       Ibis    Vegetarian   989

5            6       35+            3       Ibys       Non-Veg  1909

6            7       35+            4     RedFox    Vegetarian  1000

7            8     20-25            7  LemonTree           Veg  2999

8            9     25-30            2       Ibis       Non-Veg  3456

10          10     30-35            5     RedFox       non-Veg -6755


    NoOfPax  EstimatedSalary Age_Group.1
0         2            40000       20-25
1         3            59000       30-35
2         2            30000       25-30
3         2           120000       20-25
4         2            45000         35+
5         2           122220         35+
6        -1            21122         35+
7       -10           345673       20-25
8         3           -99999       25-30
10        4            87777       30-35
```

```
len(df)
```

```
10
```

```
index=np.array(list(range(0,len(df))))
df.set_index(index,inplace=True)
index
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
df
```

```
   CustomerID Age_Group  Rating(1-5)       Hotel FoodPreference  Bill
NoOfPax  \
0           1     20-25            4        Ibis            veg  1300
2
1           2     30-35            5  LemonTree        Non-Veg  2000
3
2           3     25-30            6      RedFox            Veg  1322
2
3           4     20-25           -1  LemonTree            Veg  1234
2
4           5       35+            3        Ibis     Vegetarian   989
2
5           6       35+            3        Ibys        Non-Veg  1909
2
6           7       35+            4      RedFox     Vegetarian  1000
-1
7           8     20-25            7  LemonTree            Veg  2999
-10
8           9     25-30            2        Ibis        Non-Veg  3456
3
9          10     30-35            5      RedFox        non-Veg -6755
4

   EstimatedSalary Age_Group.1
0            40000       20-25
1            59000       30-35
2            30000       25-30
3           120000       20-25
4            45000         35+
5           122220         35+
6            21122         35+
7           345673       20-25
8           -99999       25-30
9            87777       30-35
```

```
df.drop(['Age_Group.1'],axis=1,inplace=True)
df
```

```
   CustomerID Age_Group  Rating(1-5)       Hotel FoodPreference Bill
NoOfPax  \
0           1     20-25            4        Ibis            veg  1300
2
```

```
6          7.0        35+                4       RedFox      Vegetarian   1000.0

7          8.0      20-25                7    LemonTree             Veg   2999.0

8          9.0      25-30                2         Ibis         Non-Veg   3456.0

9         10.0      30-35                5       RedFox         non-Veg      NaN


   NoOfPax  EstimatedSalary
0        2          40000.0
1        3          59000.0
2        2          30000.0
3        2         120000.0
4        2          45000.0
5        2         122220.0
6       -1          21122.0
7      -10         345673.0
8        3              NaN
9        4          87777.0
```

```
df['NoOfPax'].loc[(df['NoOfPax']<1) | (df['NoOfPax']>20)]=np.nan
df
```

```
   CustomerID Age_Group  Rating(1-5)       Hotel FoodPreference    Bill
\
0         1.0     20-25            4        Ibis            veg  1300.0

1         2.0     30-35            5   LemonTree        Non-Veg  2000.0

2         3.0     25-30            6      RedFox            Veg  1322.0

3         4.0     20-25           -1   LemonTree            Veg  1234.0

4         5.0       35+            3        Ibis     Vegetarian   989.0

5         6.0       35+            3        Ibys        Non-Veg  1909.0

6         7.0       35+            4      RedFox     Vegetarian  1000.0

7         8.0     20-25            7   LemonTree            Veg  2999.0

8         9.0     25-30            2        Ibis        Non-Veg  3456.0

9        10.0     30-35            5      RedFox        non-Veg     NaN


   NoOfPax  EstimatedSalary
0      2.0          40000.0
1      3.0          59000.0
2      2.0          30000.0
```

```
3       2.0          120000.0
4       2.0           45000.0
5       2.0          122220.0
6       NaN           21122.0
7       NaN          345673.0
8       3.0               NaN
9       4.0           87777.0
```

```
df.Age_Group.unique()
```

```
array(['20-25', '30-35', '25-30', '35+'], dtype=object)
```

```
df.Hotel.unique()
```

```
array(['Ibis', 'LemonTree', 'RedFox', 'Ibys'], dtype=object)
```

```
df.Hotel.replace(['Ibys'],'Ibis',inplace=True)
df.FoodPreference.unique
```

```
<bound method Series.unique of 0           veg
1        Non-Veg
2            Veg
3            Veg
4     Vegetarian
5        Non-Veg
6     Vegetarian
7            Veg
8        Non-Veg
9        non-Veg
Name: FoodPreference, dtype: object>
```

```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=True)
df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
```

```
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=Tru
e)
df.NoOfPax.fillna(round(df.NoOfPax.median()),inplace=True)
df['Rating(1-5)'].fillna(round(df['Rating(1-5)'].median()),
inplace=True)
df.Bill.fillna(round(df.Bill.mean()),inplace=True)
df
```

```
   CustomerID Age_Group  Rating(1-5)       Hotel FoodPreference    Bill
\
0         1.0     20-25            4        Ibis            Veg  1300.0

1         2.0     30-35            5   LemonTree        Non-Veg  2000.0

2         3.0     25-30            6      RedFox            Veg  1322.0

3         4.0     20-25           -1   LemonTree            Veg  1234.0
```

4	5.0	35+	3	Ibis	Veg	989.0
5	6.0	35+	3	Ibis	Non-Veg	1909.0
6	7.0	35+	4	RedFox	Veg	1000.0
7	8.0	20-25	7	LemonTree	Veg	2999.0
8	9.0	25-30	2	Ibis	Non-Veg	3456.0
9	10.0	30-35	5	RedFox	Non-Veg	1801.0

	NoOfPax	EstimatedSalary
0	2.0	40000.0
1	3.0	59000.0
2	2.0	30000.0
3	2.0	120000.0
4	2.0	45000.0
5	2.0	122220.0
6	2.0	21122.0
7	2.0	345673.0
8	3.0	96755.0
9	4.0	87777.0

4. Data Preprocessing

DATA:27.08.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv")
df
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Country    10 non-null     object 
 1   Age        9 non-null      float64
 2   Salary     9 non-null      float64
 3   Purchased  10 non-null     object 
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

```
df.Country.mode()
```

```
0    France
Name: Country, dtype: object
```

```
df.Country.mode()[0]
```

```
'France'
```

```
type(df.Country.mode())
```

```
pandas.core.series.Series
```

```
df.Country.fillna(df.Country.mode()[0],inplace=True)
df.Age.fillna(df.Age.median(),inplace=True)
df.Salary.fillna(round(df.Salary.mean()),inplace=True)
df
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	63778.0	Yes
5	France	35.0	58000.0	Yes
6	Spain	38.0	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

```
pd.get_dummies(df.Country)
```

	France	Germany	Spain
0	True	False	False
1	False	False	True
2	False	True	False
3	False	False	True
4	False	True	False
5	True	False	False
6	False	False	True
7	True	False	False
8	False	True	False
9	True	False	False

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Country    10 non-null     object 
 1   Age        10 non-null     float64
 2   Salary     10 non-null     float64
 3   Purchased  10 non-null     object 
dtypes: float64(2), object(2)
memory usage: 452.0+ bytes
```

```
updated_dataset.Purchased.replace(['No','Yes'],[0,1],inplace=True)
```

5 .EDA-Quantitative and Qualitative plots

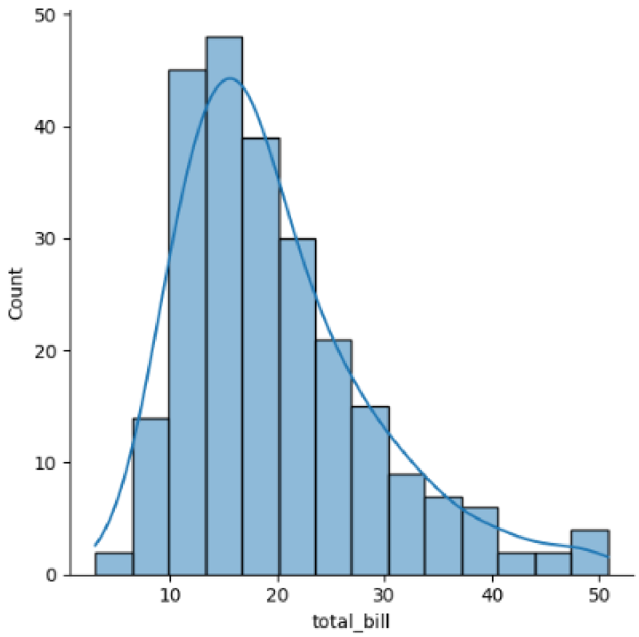
DATA : 03.09.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
tips=sns.load_dataset('tips')
tips.head()
```

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

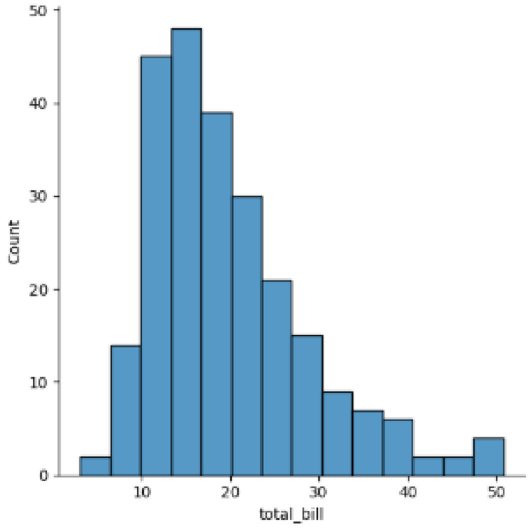
```
sns.displot(tips.total_bill,kde=True)
```

<seaborn.axisgrid.FacetGrid at 0x2a0f86e0990>



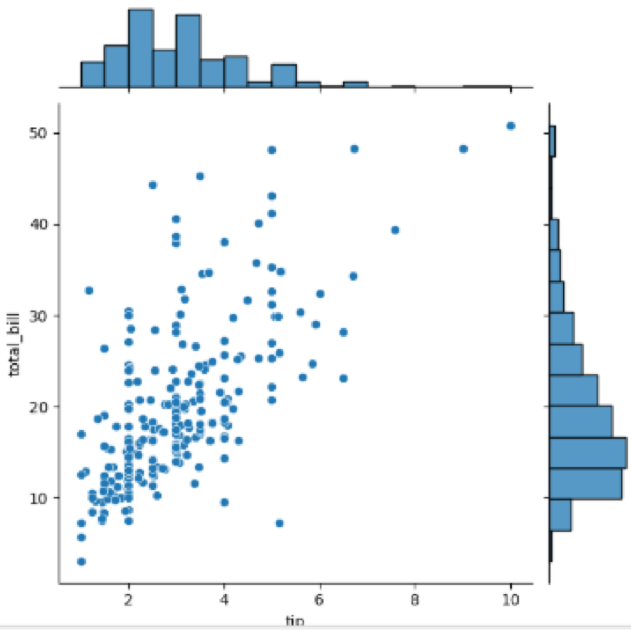
```
sns.displot(tips.total_bill,kde=False)
```

<seaborn.axisgrid.FacetGrid at 0x2a0f87643d0>



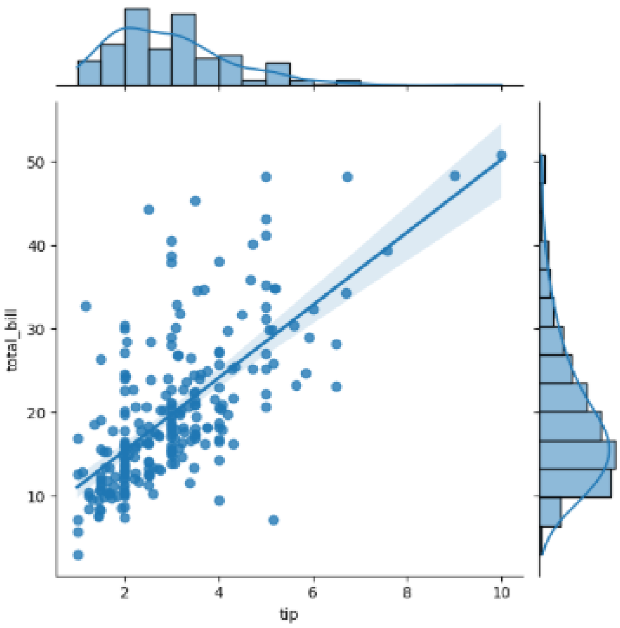

```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

<seaborn.axisgrid.JointGrid at 0x2a0f87ace10>



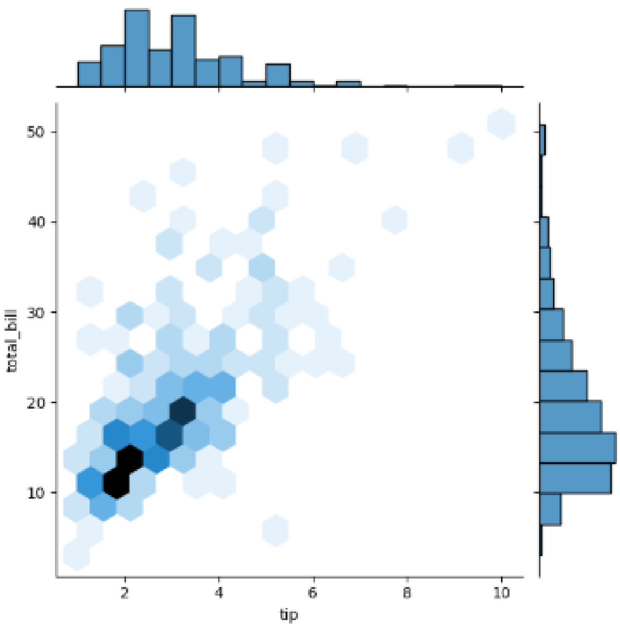
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

<seaborn.axisgrid.JointGrid at 0x2a0f891d910>



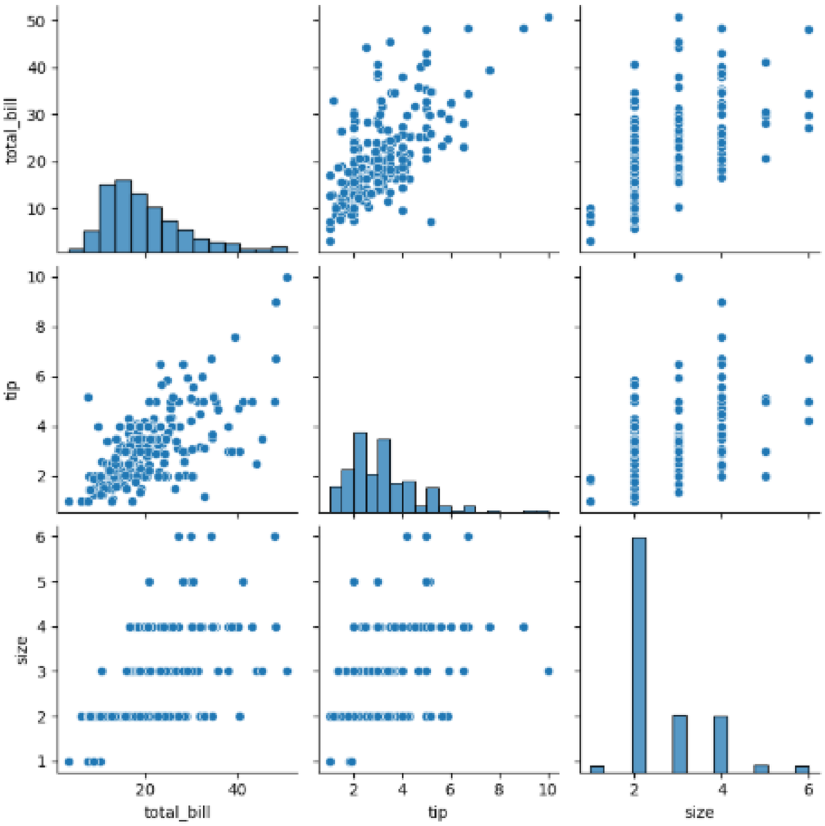

```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

<seaborn.axisgrid.JointGrid at 0x2a0f8b720d0>




```
sns.pairplot(tips)
```

```
<seaborn.axisgrid.PairGrid at 0x2a0f8f3cd90>
```

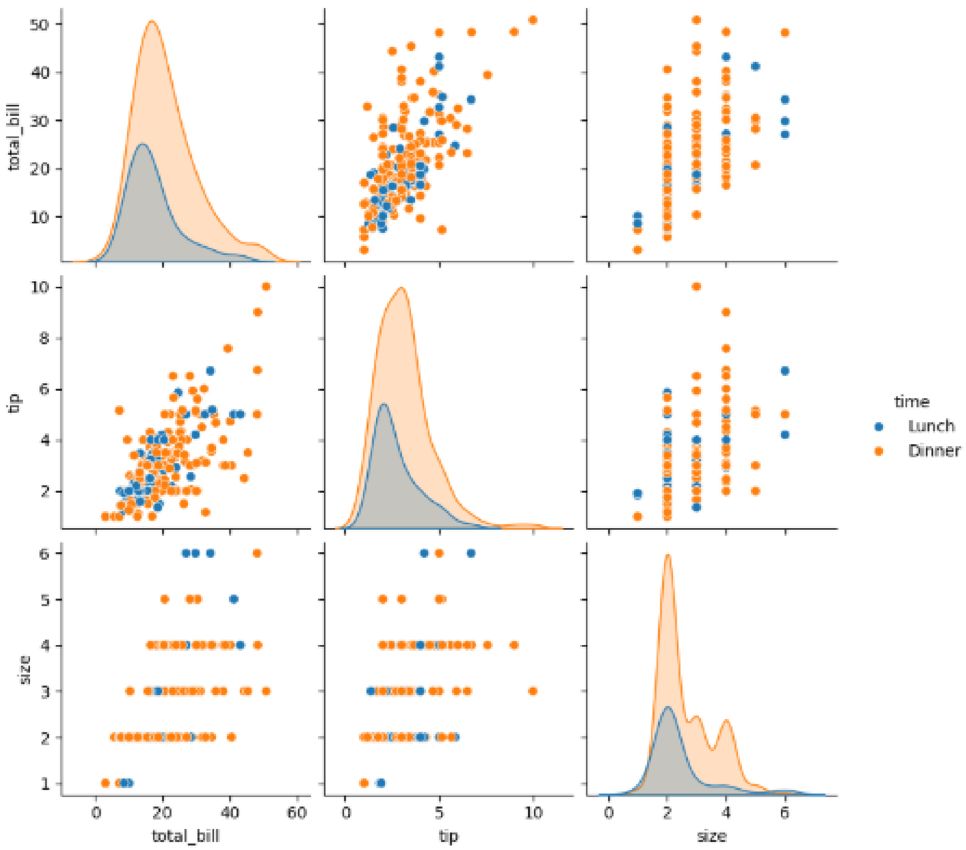



```python
tips.time.value_counts()
```

```
time
Dinner    176
Lunch      68
Name: count, dtype: int64
```

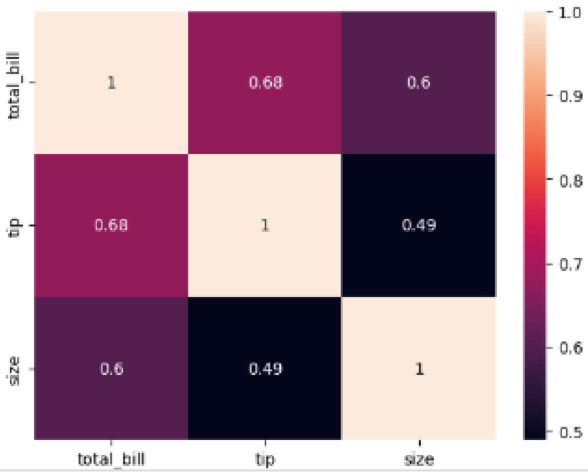
```python
sns.pairplot(tips,hue='time')
```

<seaborn.axisgrid.PairGrid at 0x2a0f8b8e210>



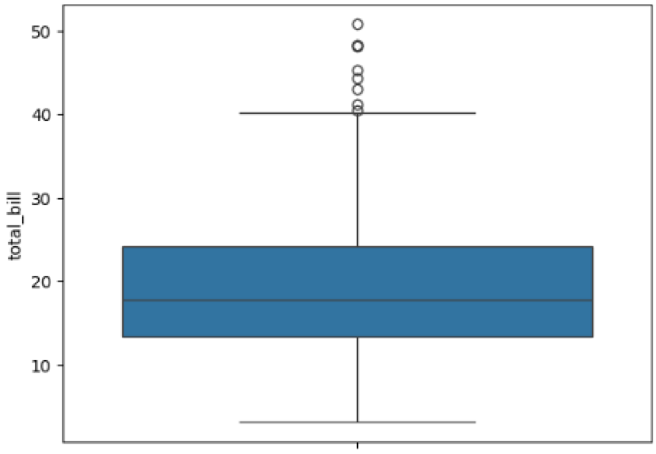

```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

<Axes: >



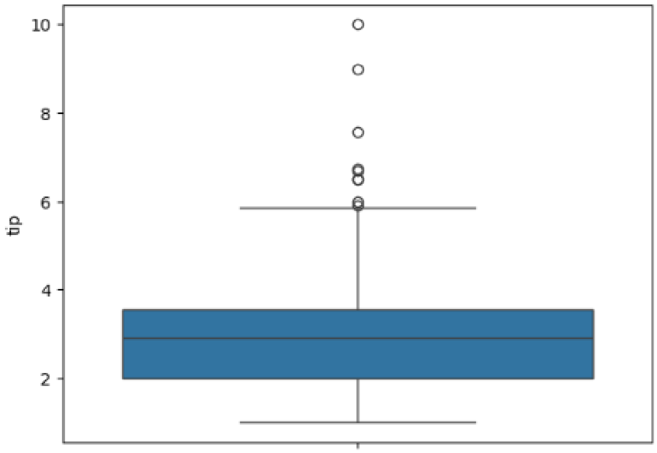
```
sns.boxplot(tips.total_bill)
```

```
<Axes: ylabel='total_bill'>
```



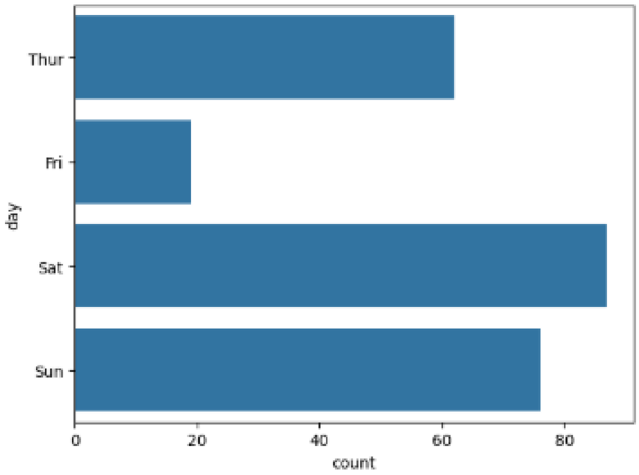

```
sns.boxplot(tips.tip)
```

```
<Axes: ylabel='tip'>
```



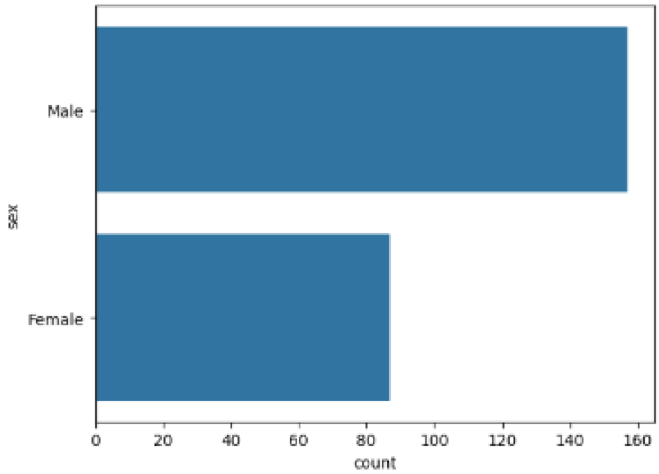
```
sns.countplot(tips.day)
```

<Axes: xlabel='count', ylabel='day'>



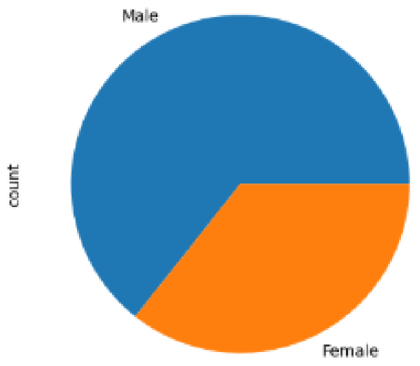

```
sns.countplot(tips.sex)
```

<Axes: xlabel='count', ylabel='sex'>



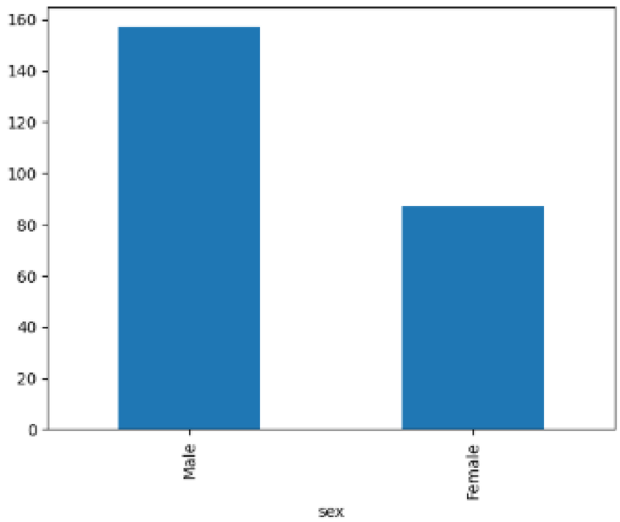
```
tips.sex.value_counts().plot(kind='pie')
```

```
<Axes: ylabel='count'>
```



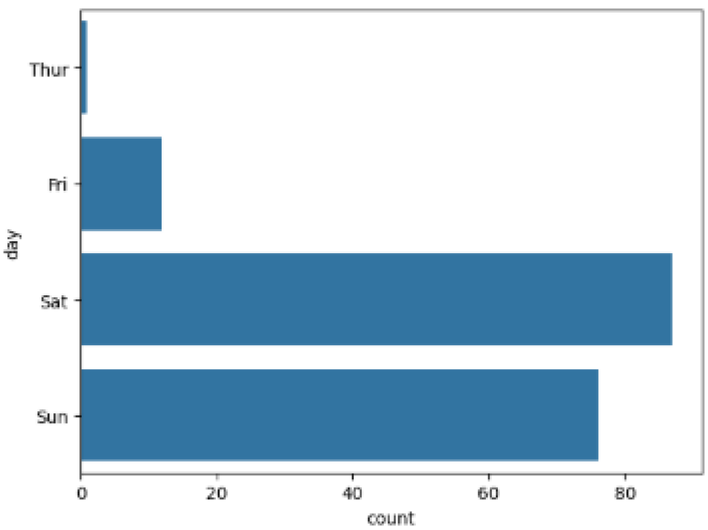

```
tips.sex.value_counts().plot(kind='bar')
```

```
<Axes: xlabel='sex'>
```




```
sns.countplot(tips[tips.time=='Dinner']['day'])
```

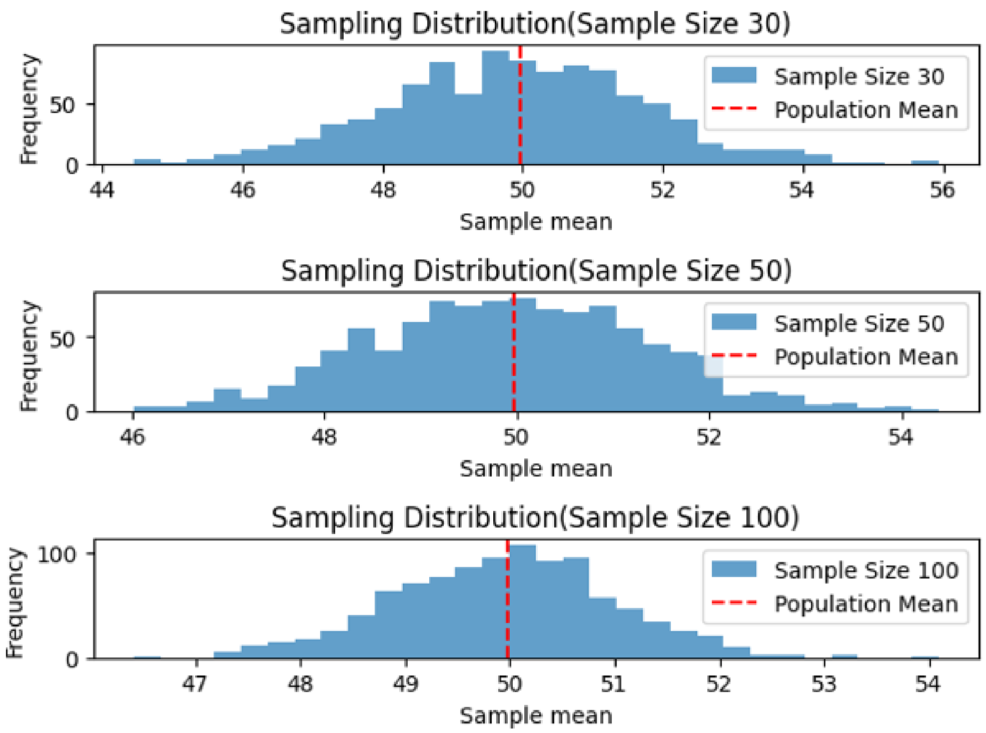
```
<Axes: xlabel='count', ylabel='day'>
```



6 . Random Sampling and Sampling Distribution

DATA : 10.09.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import matplotlib.pyplot as plt
population_mean = 50
population_std = 10
population_size = 100000
population = np.random.normal(population_mean, population_std, population_size)
sample_sizes = [30, 50, 100]
num_samples = 1000
sample_means = {}
for size in sample_sizes:
    sample_means[size] = []
    for _ in range(num_samples):
        sample = np.random.choice(population, size=size, replace=False)
        sample_means[size].append(np.mean(sample))
        plt.figure(figsize=(12, 8))
for i, size in enumerate(sample_sizes):
    plt.subplot(len(sample_sizes), 1, i+1)
    plt.hist(sample_means[size], bins=30, alpha=0.7, label=f'Sample Size {size}')
    plt.axvline(np.mean(population), color='red', linestyle= 'dashed', linewidth=1.5,
label= 'Population Mean')
    plt.title(f'Sampling Distribution(Sample Size {size})')
    plt.xlabel('Sample mean')
    plt.ylabel('Frequency')
    plt.legend()
plt.tight_layout()
plt.show()
```



7. Z-Test

DATA : 10.09.2024

```python
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import scipy.stats as stats
sample_data = np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,
149,151, 150, 149, 152, 151, 148, 150, 152, 149, 150,148, 153, 151,
150, 149, 152, 148, 151, 150, 153])
population_mean = 150
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)
n = len(sample_data)
z_statistic = (sample_mean - population_mean) / (sample_std / np.sqrt(n))
p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic)))
# Assuming sample_mean, z_statistic, and p_value have already been calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"Z-Statistic: {z_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")
# Significance level
alpha = 0.05

# Decision based on p-value
if p_value < alpha:
    print("Reject the null hypothesis: The average weight is significantly different from 150 grams.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in average weight from 150 grams.")
```

```
Sample Mean: 150.20

Z-Statistic: 0.6406

P-Value: 0.5218

Fail to reject the null hypothesis: There is no significant difference in average weight from 150 grams.
```

8. T-Test

DATA : 08.10.2024

```python
#Name:AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import scipy.stats as stats
np.random.seed(42)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)
population_mean = 100
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)
n = len(sample_data)
t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)
# Assuming sample_mean, t_statistic, and p_value have already been calculated:
print(f"Sample Mean: {sample_mean:.2f}\n")
print(f"T-Statistic: {t_statistic:.4f}\n")
print(f"P-Value: {p_value:.4f}\n")
# Significance level
alpha = 0.05

# Decision based on p-value
if p_value < alpha:
    print("Reject the null hypothesis: The average IQ score is significantly different from 100.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.")
```

```
Sample Mean: 99.55

T-Statistic: -0.1577

P-Value: 0.8760

Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.
```

9. ANNOVA TEST

DATA : 08.10.2024

```python
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import scipy.stats as stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd
np.random.seed(42)
n_plants = 25
growth_A = np.random.normal(loc=10, scale=2, size=n_plants)
growth_B = np.random.normal(loc=12, scale=3, size=n_plants)
growth_C = np.random.normal(loc=15, scale=2.5, size=n_plants)
all_data = np.concatenate([growth_A, growth_B, growth_C])
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] * n_plants
f_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)
mean_A = np.mean(growth_A)
mean_B = np.mean(growth_B)
mean_C = np.mean(growth_C)
print(f"Treatment A Mean Growth: {mean_A:.4f}")
print(f"Treatment B Mean Growth: {mean_B:.4f}")
print(f"Treatment C Mean Growth: {mean_C:.4f}")
print(f"F-Statistic: {f_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference in mean growth rates among the three treatments.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference in mean growth rates among the three treatments.")

if p_value < alpha:

    tukey_results = pairwise_tukeyhsd(all_data, treatment_labels, alpha=0.05)

    print("\nTukey's HSD Post-hoc Test:")
    print(tukey_results)
```

```
Treatment A Mean Growth: 9.6730
Treatment B Mean Growth: 11.1377
Treatment C Mean Growth: 15.2652
F-Statistic: 36.1214
P-Value: 0.0000
Reject the null hypothesis: There is a significant difference in mean growth rates among the three treatments.

Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
===================================================
group1 group2 meandiff p-adj  lower  upper  reject
---------------------------------------------------
     A      B   1.4647 0.0877 -0.1683 3.0977  False
     A      C   5.5923    0.0  3.9593 7.2252   True
     B      C   4.1276    0.0  2.4946 5.7605   True
---------------------------------------------------
```

10. Feature Scaling

DATA : 22.10.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('pre_process_datasample.csv')
df.head()
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes

```
df.Country.fillna(df.Country.mode()[0],inplace=True)
features=df.iloc[:,:-1].values
features
```

```
array([['France', 44.0, 72000.0],
       ['Spain', 27.0, 48000.0],
       ['Germany', 30.0, 54000.0],
       ['Spain', 38.0, 61000.0],
       ['Germany', 40.0, nan],
       ['France', 35.0, 58000.0],
       ['Spain', nan, 52000.0],
       ['France', 48.0, 79000.0],
       ['Germany', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)
```

```
label=df.iloc[:,-1].values
from sklearn.impute import SimpleImputer
age=SimpleImputer(strategy="mean",missing_values=np.nan)
Salary=SimpleImputer(strategy="mean",missing_values=np.nan)
age.fit(features[:,[1]])
SimpleImputer()
Salary.fit(features[:,[2]])
SimpleImputer()
SimpleImputer()
SimpleImputer()
features[:,[1]]=age.transform(features[:,[1]])
features[:,[2]]=Salary.transform(features[:,[2]])
features
```

```
array([['France', 44.0, 72000.0],
       ['Spain', 27.0, 48000.0],
       ['Germany', 30.0, 54000.0],
       ['Spain', 38.0, 61000.0],
       ['Germany', 40.0, 63777.77777777778],
       ['France', 35.0, 58000.0],
       ['Spain', 38.77777777777778, 52000.0],
       ['France', 48.0, 79000.0],
       ['Germany', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)
```

```
from sklearn.preprocessing import OneHotEncoder
oh = OneHotEncoder(sparse_output=False)
Country=oh.fit_transform(features[:,[0]])
Country
```

```
array([[1., 0., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 1., 0.],
       [1., 0., 0.]])
```

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(final_set)
feat_standard_scaler=sc.transform(final_set)

feat_standard_scaler

array([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
          7.58874362e-01,  7.49473254e-01],
        [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         -1.71150388e+00, -1.43817841e+00],
        [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         -1.27555478e+00, -8.91265492e-01],
        [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         -1.13023841e-01, -2.53200424e-01],
        [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
          1.77608893e-01,  6.63219199e-16],
        [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         -5.48972942e-01, -5.26656882e-01],
        [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
          0.00000000e+00, -1.07356980e+00],
        [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
          1.34013983e+00,  1.38753832e+00],
        [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
          1.63077256e+00,  1.75214693e+00],
        [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         -2.58340208e-01,  2.93712492e-01]])

from sklearn.preprocessing import MinMaxScaler
mms=MinMaxScaler(feature_range=(0,1))
mms.fit(final_set)
feat_minmax_scaler=mms.transform(final_set)
feat_minmax_scaler
```

```
from sklearn.preprocessing import MinMaxScaler
mms=MinMaxScaler(feature_range=(0,1))
mms.fit(final_set)
feat_minmax_scaler=mms.transform(final_set)
feat_minmax_scaler

array([[1.        , 0.        , 0.        , 0.73913043, 0.68571429],
       [0.        , 0.        , 1.        , 0.        , 0.        ],
       [0.        , 1.        , 0.        , 0.13043478, 0.17142857],
       [0.        , 0.        , 1.        , 0.47826087, 0.37142857],
       [0.        , 1.        , 0.        , 0.56521739, 0.45079365],
       [1.        , 0.        , 0.        , 0.34782609, 0.28571429],
       [0.        , 0.        , 1.        , 0.51207729, 0.11428571],
       [1.        , 0.        , 0.        , 0.91304348, 0.88571429],
       [0.        , 1.        , 0.        , 1.        , 1.        ],
       [1.        , 0.        , 0.        , 0.43478261, 0.54285714]])
```

11. Linear Regression

DATA : 29.10.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE - A

import numpy as np
import pandas as pd
df = pd.read_csv('Salary_data.csv')
df
```

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088

18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302
23	8.2	113812
24	8.7	109431
25	9.0	105582
26	9.5	116969
27	9.6	112635
28	10.3	122391
29	10.5	121872

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     int64  
dtypes: float64(1), int64(1)
memory usage: 612.0 bytes
```

```
df.dropna(inplace=True);
df
```

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642

6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088
18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302
23	8.2	113812
24	8.7	109431
25	9.0	105582
26	9.5	116969
27	9.6	112635
28	10.3	122391
29	10.5	121872

```
df.describe()
```

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.429785
min	1.100000	37731.000000
25%	3.200000	56720.750000
50%	4.700000	65237.000000
75%	7.700000	100544.750000
max	10.500000	122391.000000

```
features = df.iloc[:,[0]].values # : - > all row , 0 -> first column #iloc index based selection loc location based sentence
label = df.iloc[:,[1]].values

features
```

```
array([[ 1.1],
       [ 1.3],
       [ 1.5],
       [ 2. ],
       [ 2.2],
       [ 2.9],
       [ 3. ],
       [ 3.2],
       [ 3.2],
       [ 3.7],
       [ 3.9],
       [ 4. ],
       [ 4. ],
       [ 4.1],
       [ 4.5],
       [ 4.9],
       [ 5.1],
       [ 5.3],
       [ 5.9],
       [ 6. ],
       [ 6.8],
       [ 7.1],
       [ 7.9],
       [ 8.2],
       [ 8.7],
       [ 9. ],
       [ 9.5],
       [ 9.6],
       [10.3],
       [10.5]])
```

```
label
```

```
array([[ 39343],
       [ 46205],
       [ 37731],
       [ 43525],
       [ 39891],
       [ 56642],
       [ 60150],
       [ 54445],
       [ 64445],
       [ 57189],
       [ 63218],
       [ 55794],
       [ 56957],
       [ 57081],
       [ 61111],
       [ 67938],
       [ 66029],
       [ 83088],
       [ 81363],
       [ 93940],
       [ 91738],
       [ 98273],
       [101302],
       [113812],
       [109431],
       [105582],
       [116969],
       [112635],
       [122391],
       [121872]])
```

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train,y_train)
'''
sk - size kit
linear means using linear regression
fit means add data
'''
```

```
'\nsk - size kit \nlinear means using linear regression \nfit means
add data \n'
```

```
model.score(x_train,y_train)
'''
accuracy calculating
96 %
'''
```

```
'\naccuracy calculating\n96 %\n'
```

```
model.score(x_test,y_test)
'''
accuracy calculating
91 %
'''
```

```
'\naccuracy calculating\n91 %\n'
```

```
model.coef_
```

```
array([[9281.30847068]])
```

```
model.intercept_
```

```
array([27166.73682891])
```

```
import pickle
pickle.dump(model,open('SalaryPred.model','wb'))
'''
pickle momory obj to file

'''
```

```
'\npickle momory obj to file\n\n'
```

```
model = pickle.load(open('SalaryPred.model','rb'))
```

```
yr_of_exp = float(input("Enter years of expreience: "))
yr_of_exp_NP = np.array([[yr_of_exp]])
salary = model.predict(yr_of_exp_NP)
print("Estimated salary for {} years of expreience is {} .
".format(yr_of_exp,salary))
```

```
Enter years of expreience:  24

Estimated salary for 24.0 years of expreience is [[249918.14012525]] .
```

```
print(f" Estimated salary for {yr_of_exp} years of expreience is
{salary} . ")
```

```
 Estimated salary for 24.0 years of expreience is
[[249918.14012525]] .
```

12. Logistic Regression

DATA : 05.11.2024

```
#NAME : AAKASH V
#ROLL NO : 230701002
#DEPARTMENT : B.E CSE- A
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('Social_Network_Ads.csv.csv')
df
```

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
...	...	...	...	...	...
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

400 rows × 5 columns

```
df.tail(20)
```

	User ID	Gender	Age	EstimatedSalary	Purchased
380	15683758	Male	42	64000	0
381	15670615	Male	48	33000	1
382	15715622	Female	44	139000	1
383	15707634	Male	49	28000	1
384	15806901	Female	57	33000	1
385	15775335	Male	56	60000	1
386	15724150	Female	49	39000	1
387	15627220	Male	39	71000	0
388	15672330	Male	47	34000	1
389	15668521	Female	48	35000	1
390	15807837	Male	48	33000	1
391	15592570	Male	47	23000	1
392	15748589	Female	45	45000	1
393	15635893	Male	60	42000	1
394	15757632	Female	39	59000	0
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

```
df.head(25)
```

[102]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1
8	15600575	Male	25	33000	0
9	15727311	Female	35	65000	0
10	15570769	Female	26	80000	0
11	15606274	Female	26	52000	0
12	15746139	Male	20	86000	0
13	15704987	Male	32	18000	0
14	15628972	Male	18	82000	0
15	15697686	Male	29	80000	0
16	15733883	Male	47	25000	1
17	15617482	Male	45	26000	1
18	15704583	Male	46	28000	1
19	15621083	Female	48	29000	1
20	15649487	Male	45	22000	1
21	15736760	Female	47	49000	1
22	15714658	Male	48	41000	1
23	15599081	Female	45	22000	1
24	15705113	Male	46	23000	1

```
[103]: features = df.iloc[:,[2,3]].values
       label = df.iloc[:,4].values
       features
```

```
       [    22,  63000],
       [    31,  68000],
       [    25,  80000],
       [    24,  27000],
       [    20,  23000],
       [    33, 113000],
       [    32,  18000],
       [    34, 112000],
       [    18,  52000],
       [    22,  27000],
       [    28,  87000],
       [    26,  17000],
       [    30,  80000],
       [    39,  42000],
       [    20,  49000],
       [    35,  88000],
       [    30,  62000],
       [    31, 118000],
```

```
[104]: label
```

```
[104]: array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0,
       1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0,
       1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1,
       0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
       1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1,
       0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 0, 1])
```

```
from sklearn.model_selection import train_test_split from sklearn.linear_model import LogisticRegression
# Assuming `features` and `label` are already defined

for i in range(1, 401):

x_train, x_test, y_train, y_test = train_test_split(features, label, test_size=0.2, random_state=i)
model = LogisticRegression() model.fit(x_train, y_train)

train_score = model.score(x_train, y_train) test_score = model.score(x_test, y_test)

if test_score > train_score:
print(f"Test Score: {test_score:.4f} | Train Score:
{train_score:.4f} | Random State: {i}")
```

```
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 4
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 5
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 6
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 7
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 9
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 10
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 14
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 15
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 16
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 18
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 19
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 20
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 21
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 22
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 24
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 26
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 27
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 30
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 31
Test Score: 0.8750 | Train Score: 0.8531 | Random State: 32
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 33
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 35
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 36
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 38
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 39
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 42
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 46
Test Score: 0.9125 | Train Score: 0.8313 | Random State: 47
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 51
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 54
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 57
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 58
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 61
```

```
Test Score: 0.8875 | Train Score: 0.8344 | Random State: 65
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 68
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 72
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 75
Test Score: 0.9250 | Train Score: 0.8250 | Random State: 76
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 77
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 81
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 82
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 83
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 84
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 85
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 87
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 88
Test Score: 0.9125 | Train Score: 0.8375 | Random State: 90
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 95
Test Score: 0.8750 | Train Score: 0.8500 | Random State: 99
Test Score: 0.8500 | Train Score: 0.[illegible]dom State: 101
Test Score: 0.8500 | Train Score: 0.[illegible]dom State: 102
Test Score: 0.9000 | Train Score: 0.8[illegible]dom State: 106
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 107
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 109
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 111
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 112
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 115
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 116
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 119
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 120
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 125
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 128
Test Score: 0.8750 | Train Score: 0.8500 | Random State: 130
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 133
Test Score: 0.9250 | Train Score: 0.8344 | Random State: 134
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 135
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 138
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 141
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 143
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 146
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 147
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 148
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 150
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 151
Test Score: 0.9250 | Train Score: 0.8438 | Random State: 152
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 153
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 154
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 155
Test Score: 0.8875 | Train Score: 0.8469 | Random State: 156
Test Score: 0.8875 | Train Score: 0.8344 | Random State: 158
Test Score: 0.8750 | Train Score: 0.8281 | Random State: 159
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 161
```

```
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 163
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 164
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 169
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 171
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 172
Test Score: 0.9000 | Train Score: 0.8250 | Random State: 180
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 184
Test Score: 0.9250 | Train Score: 0.8219 | Random State: 186
Test Score: 0.9000 | Train Score: 0.8313 | Random State: 193
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 195
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 196
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 197
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 198
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 199
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 200
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 202
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 203
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 206
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 211
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 212
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 214
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 217
Test Score: 0.9625 | Train Score: 0.8187 | Random State: 220
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 221
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 222
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 223
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 227
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 228
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 229
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 232
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 233
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 234
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 235
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 236
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 239
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 241
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 242
Test Score: 0.8875 | Train Score: 0.8250 | Random State: 243
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 244
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 245
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 246
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 247
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 248
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 250
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 251
Test Score: 0.8875 | Train Score: 0.8438 | Random State: 252
Test Score: 0.8625 | Train Score: 0.8469 | Random State: 255
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 257
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 260
```

```
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 266
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 268
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 275
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 276
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 277
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 282
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 283
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 285
Test Score: 0.9125 | Train Score: 0.8344 | Random State: 286
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 290
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 291
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 292
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 294
Test Score: 0.8875 | Train Score: 0.8281 | Random State: 297
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 300
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 301
Test Score: 0.8875 | Train Score: 0.[illegible] | [illegible]dom State: 302
Test Score: 0.8750 | Train Score: 0.[illegible] | [illegible]dom State: 303
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 305
Test Score: 0.9125 | Train Score: 0.8375 | Random State: 306
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 308
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 311
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 313
Test Score: 0.9125 | Train Score: 0.8344 | Random State: 314
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 315
Test Score: 0.9000 | Train Score: 0.8469 | Random State: 317
Test Score: 0.9125 | Train Score: 0.8219 | Random State: 319
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 321
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 322
Test Score: 0.8500 | Train Score: 0.8469 | Random State: 328
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 332
Test Score: 0.8875 | Train Score: 0.8531 | Random State: 336
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 337
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 343
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 346
Test Score: 0.8875 | Train Score: 0.8313 | Random State: 351
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 352
Test Score: 0.9500 | Train Score: 0.8187 | Random State: 354
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 356
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 357
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 358
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 362
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 363
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 364
Test Score: 0.9375 | Train Score: 0.8219 | Random State: 366
Test Score: 0.9125 | Train Score: 0.8406 | Random State: 369
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 371
Test Score: 0.9250 | Train Score: 0.8344 | Random State: 376
Test Score: 0.9125 | Train Score: 0.8281 | Random State: 377
```

```
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 378
Test Score: 0.8875 | Train Score: 0.8500 | Random State: 379
Test Score: 0.8625 | Train Score: 0.8406 | Random State: 382
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 386
Test Score: 0.8500 | Train Score: 0.8375 | Random State: 387
Test Score: 0.8750 | Train Score: 0.8281 | Random State: 388
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 394
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 395
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 397
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 400

'\n\n\n'
```

```
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 4
Test Score: 0.8625 | Train Score: 0.8500 | Random State: 5
Test Score: 0.8625 | Train Score: 0.8594 | Random State: 6
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 7
Test Score: 0.8625 | Train Score: 0.8375 | Random State: 9
Test Score: 0.9000 | Train Score: 0.8406 | Random State: 10
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 14
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 15
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 16
Test Score: 0.8750 | Train Score: 0.8344 | Random State: 18
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 19
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 20
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 21
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 22
Test Score: 0.8750 | Train Score: 0.8406 | Random State: 24
Test Score: 0.8500 | Train Score: 0.8344 | Random State: 26
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 27
Test Score: 0.8625 | Train Score: 0.8344 | Random State: 30
Test Score: 0.8625 | Train Score: 0.8562 | Random State: 31
Test Score: 0.8750 | Train Score: 0.8531 | Random State: 32
Test Score: 0.8625 | Train Score: 0.8438 | Random State: 33
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 35
Test Score: 0.8625 | Train Score: 0.8531 | Random State: 36
Test Score: 0.8875 | Train Score: 0.8406 | Random State: 38
Test Score: 0.8750 | Train Score: 0.8375 | Random State: 39
Test Score: 0.8875 | Train Score: 0.8375 | Random State: 42
Test Score: 0.8750 | Train Score: 0.8469 | Random State: 46
Test Score: 0.9125 | Train Score: 0.8313 | Random State: 47
Test Score: 0.8750 | Train Score: 0.8313 | Random State: 51
Test Score: 0.9000 | Train Score: 0.8438 | Random State: 54
Test Score: 0.8500 | Train Score: 0.8438 | Random State: 57
Test Score: 0.8750 | Train Score: 0.8438 | Random State: 58
Test Score: 0.9250 | Train Score: 0.8375 | Random State: 61
```

```
x_train,x_test,y_train,y_test=train_test_split(features,label,test_siz e=0.2,random_state=209)
finalModel=LogisticRegression() finalModel.fit(x_train,y_train)
LogisticRegression()
print(finalModel.score(x_train,y_train)) print(finalModel.score(x_train,y_train))
0.85
0.85
from sklearn.metrics import classification_report print(classification_report(label,finalModel.predict(features)))
```

	precision	recall	f1-score	support
0	0.86	0.91	0.89	257
1	0.83	0.73	0.77	143
accuracy			0.85	400
macro avg	0.84	0.82	0.83	400
weighted avg	0.85	0.85	0.85	400