230701268-fds-lab-manual

[ ]:
```
#EX.NO :1.a     Basic Practice Experiments(1 to
4)#DATA    :     30.07.2024

#NAME  :  ROHIT H
#ROLL  NO  :  230701268
#DEPARTMENT  :  B.E COMPUTER SCIENCE AND ENGINEERING - E
```

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

[3]:
```
data=pd.read_csv('Iris.csv')
data
```

[3]:
```
      Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
0      1            5.1           3.5            1.4           0.2
1      2            4.9           3.0            1.4           0.2
2      3            4.7           3.2            1.3           0.2
3      4            4.6           3.1            1.5           0.2
4      5            5.0           3.6            1.4           0.2
..   ...            ...           ...            ...           ...
145  146            6.7           3.0            5.2           2.3
146  147            6.3           2.5            5.0           1.9
147  148            6.5           3.0            5.2           2.0
148  149            6.2           3.4            5.4           2.3
149  150            5.9           3.0            5.1           1.8

            Species
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
5       Iris-setosa
..              ...
145  Iris-virginica
```

```
     Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]
```

[4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0  to  149 Data
columns  (total  6  columns):
 #    Column          Non-Null Count    Dtype
---   ------          ------------      -----
 1    Id              150 non-null      int64
 2    SepalLengthCm   150 non-null      float64
 3    SepalWidthCm    150 non-null      float64
 4    PetalLengthCm   150 non-null      float64
 5    PetalWidthCm    150 non-null      float64
 6    Species         150 non-null      object
```

146 dtypes: float64(4), int64(1), object(1) memory
usage: 7.2+ KB

[5]:

```
data.describe()
```

[5] :

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

[6]:

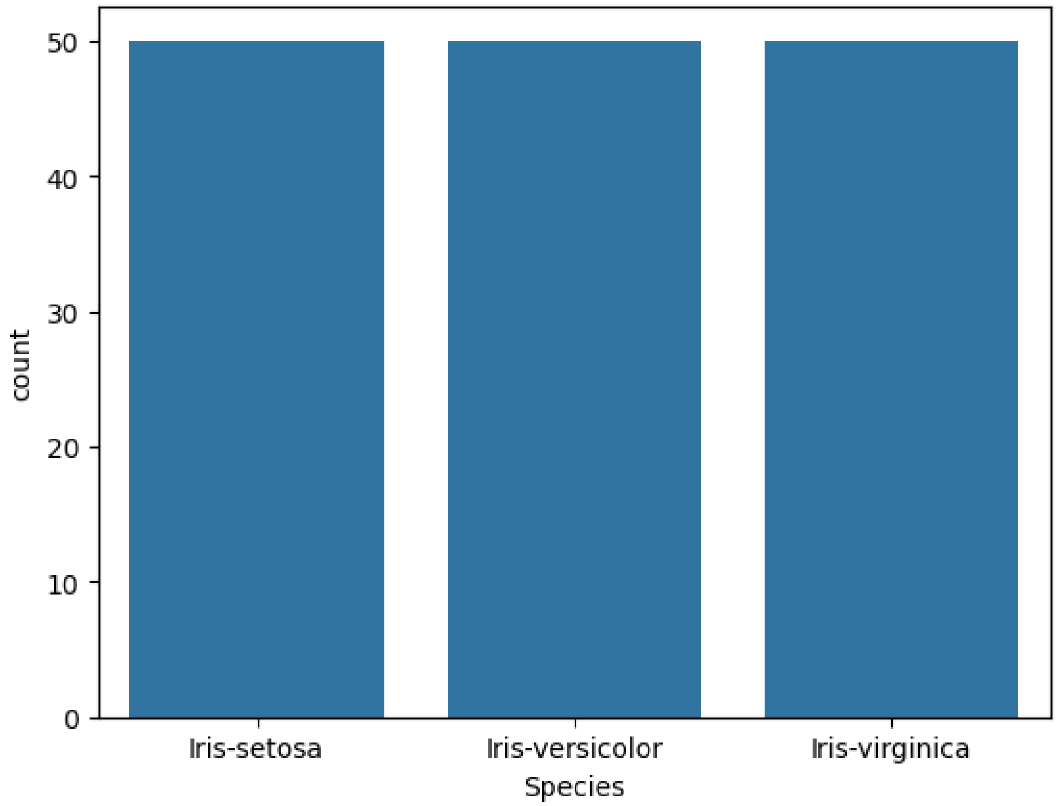
```
data.value_counts('Species')
```

[6] :

```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name:  count,  dtype:  int64
```

[7]:

```
sns.countplot(x='Species',data=data,)
plt.show()
```



[8]:
```
dummies=pd.get_dummies(data.Species)
```

[9]:
```
FinalDataset=pd.concat([pd.get_dummies(data.Species),data.iloc[:
 ↪,[0,1,2,3]]],axis=1)
```

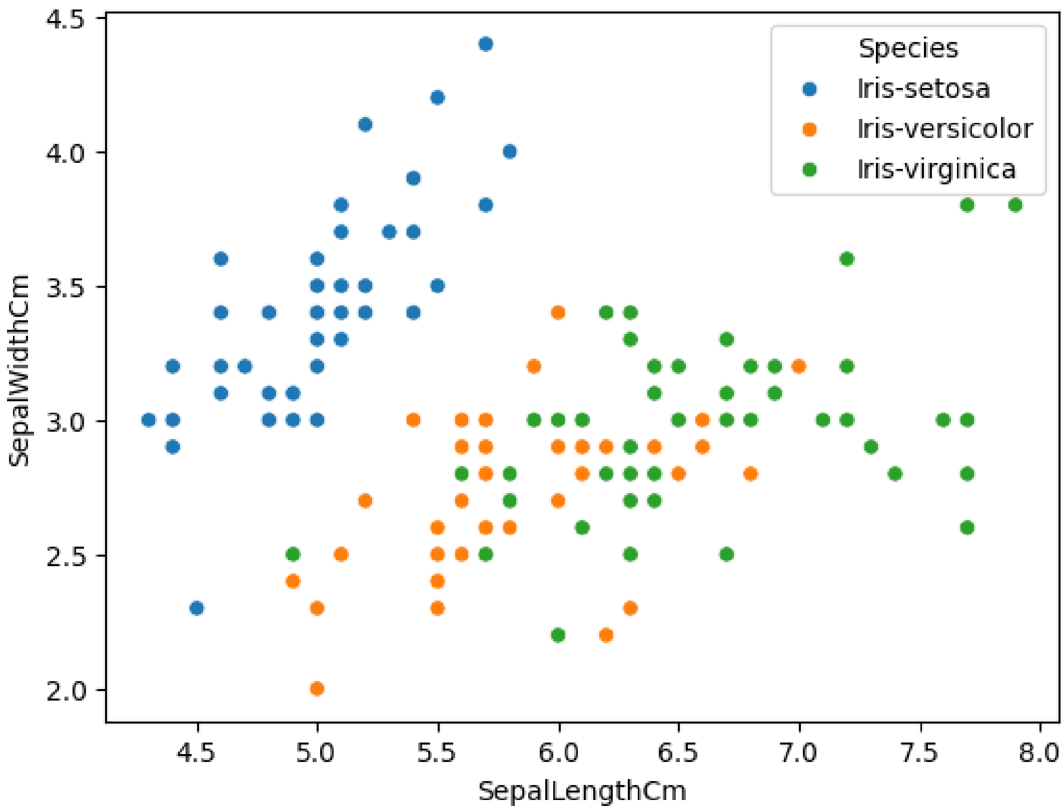
[10]:
```
FinalDataset.head()
```

[10]:
```
   Iris-setosa  Iris-versicolor  Iris-virginica  Id  SepalLengthCm  \
0         True            False           False   1            5.1
1         True            False           False   2            4.9
2         True            False           False   3            4.7
3         True            False           False   4            4.6
4         True            False           False   5            5.0

   SepalWidthCm  PetalLengthCm
0           3.5            1.4
1           3.0            1.4
2           3.2            1.3
3           3.1            1.5
4           3.6            1.4
```

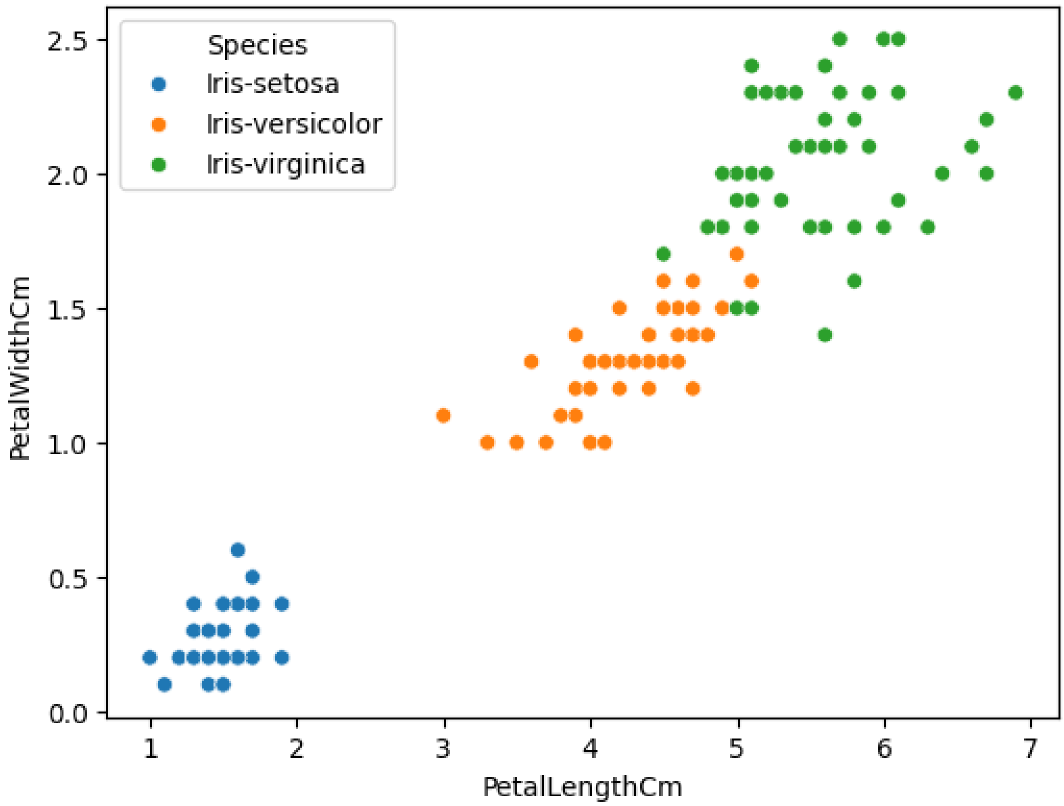
[11]:
```python
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=data,)
```

[11] : <Axes: xlabel='SepalLengthCm', ylabel='SepalWidthCm'>

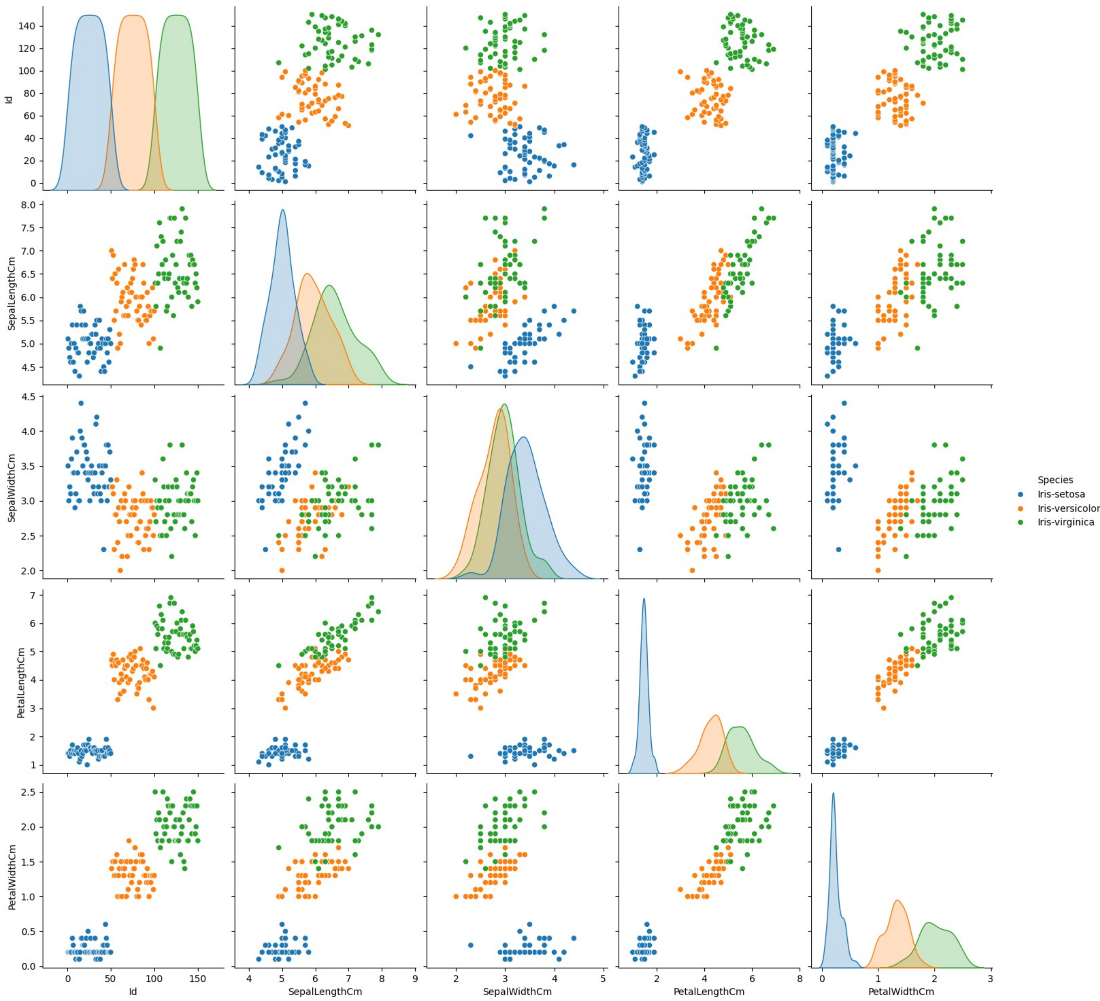


[12]:
```python
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=data,)
```

[12] : <Axes: xlabel='PetalLengthCm', ylabel='PetalWidthCm'>

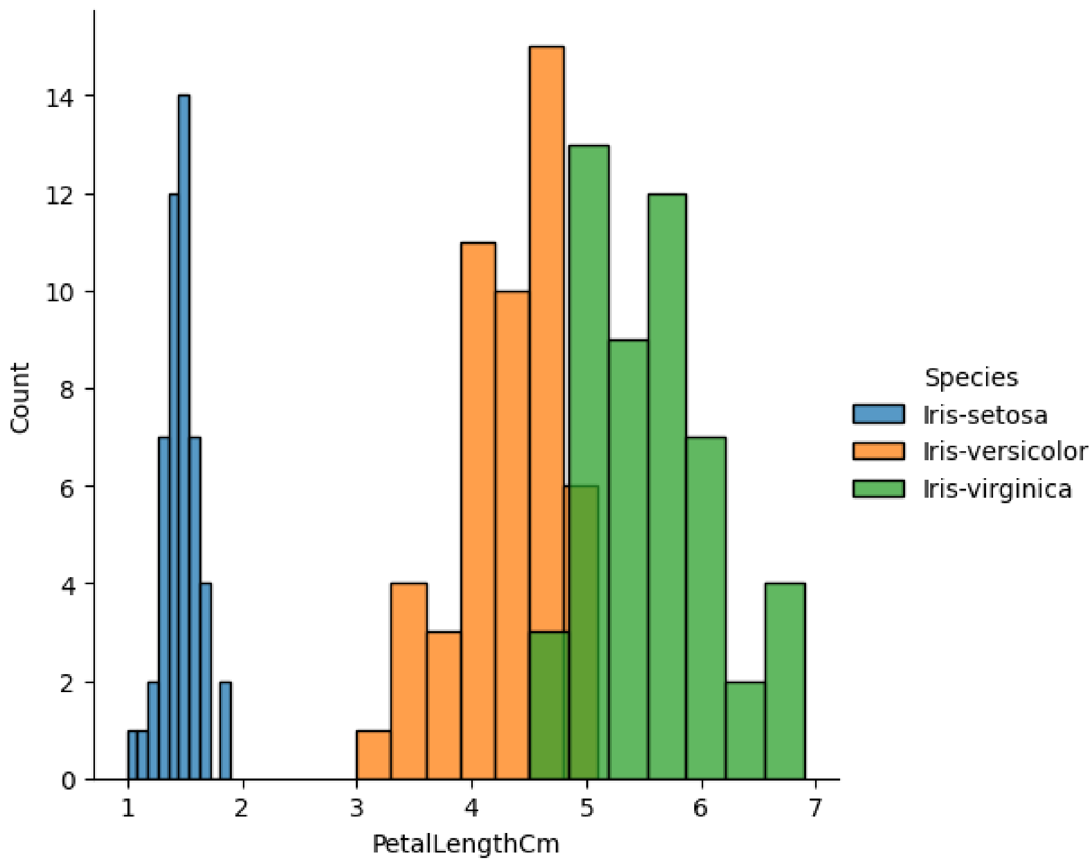


[13]:
```
sns.pairplot(data,hue='Species',height=3);
```

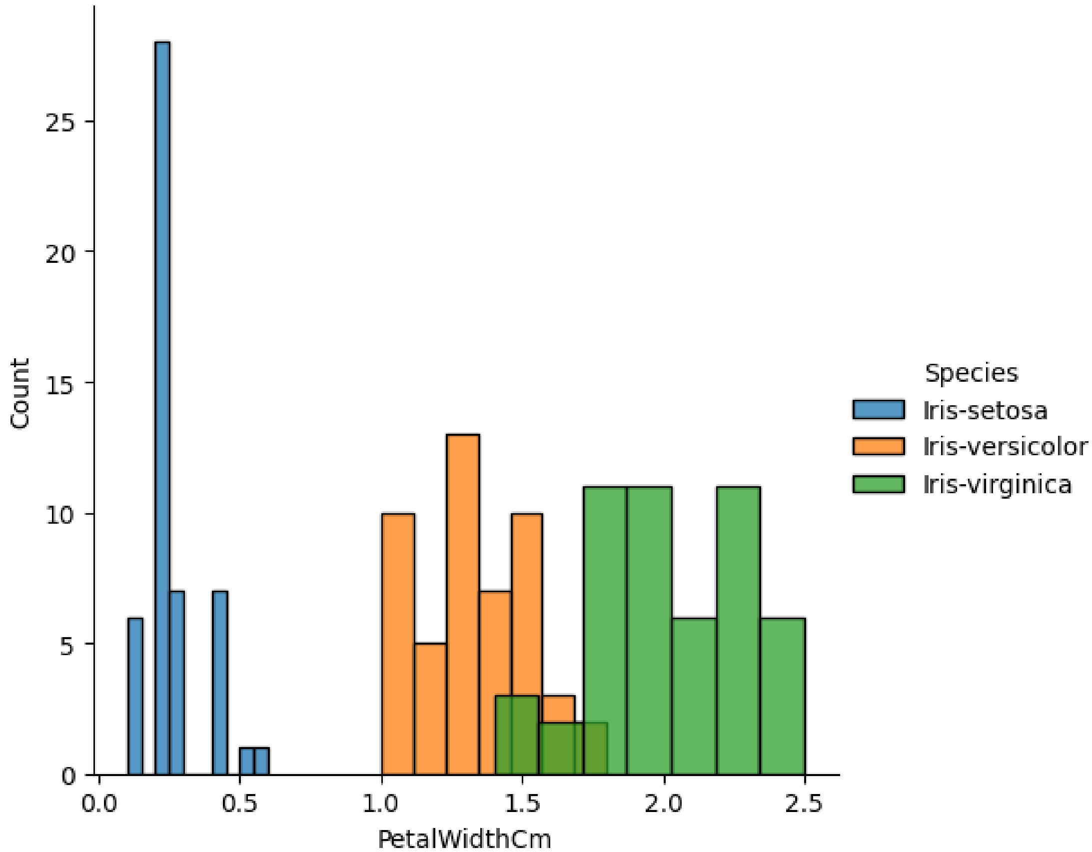


[14]:
```
plt.show()
```

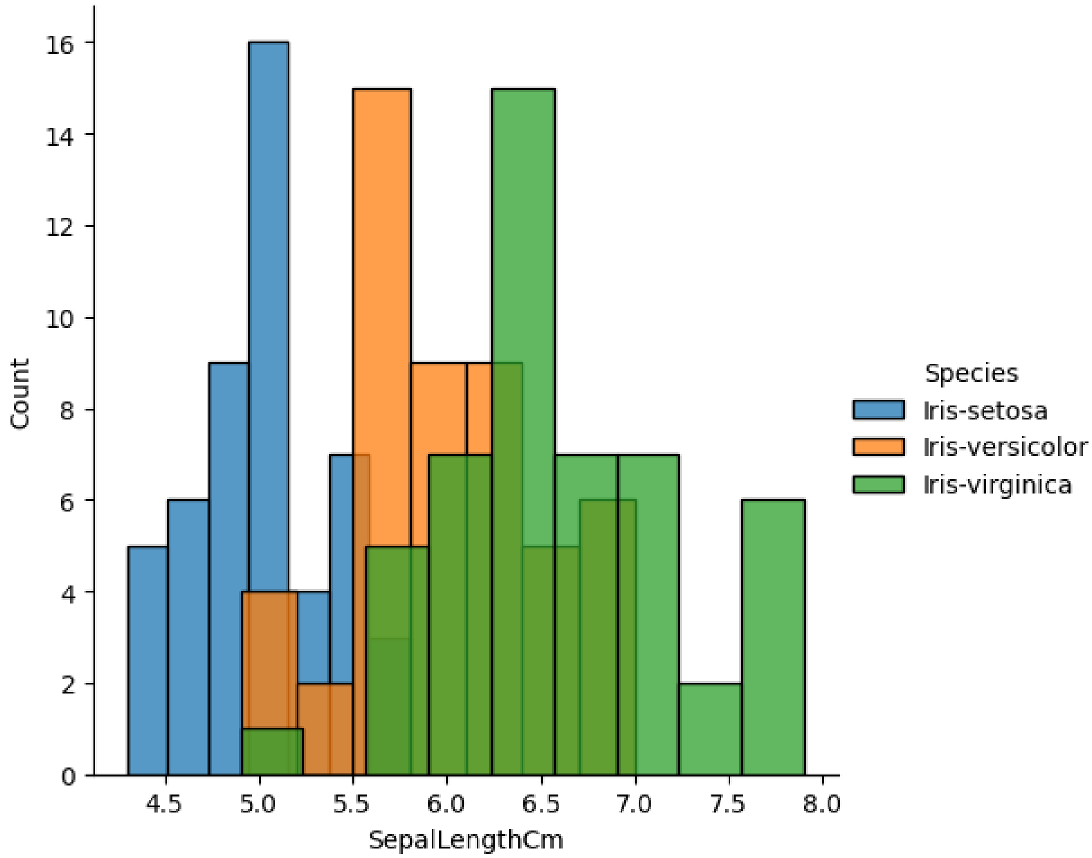
[15]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalLengthCm').
  ↪add_legend();
plt.show();
```



[16]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').
  ↪add_legend();
plt.show();
```

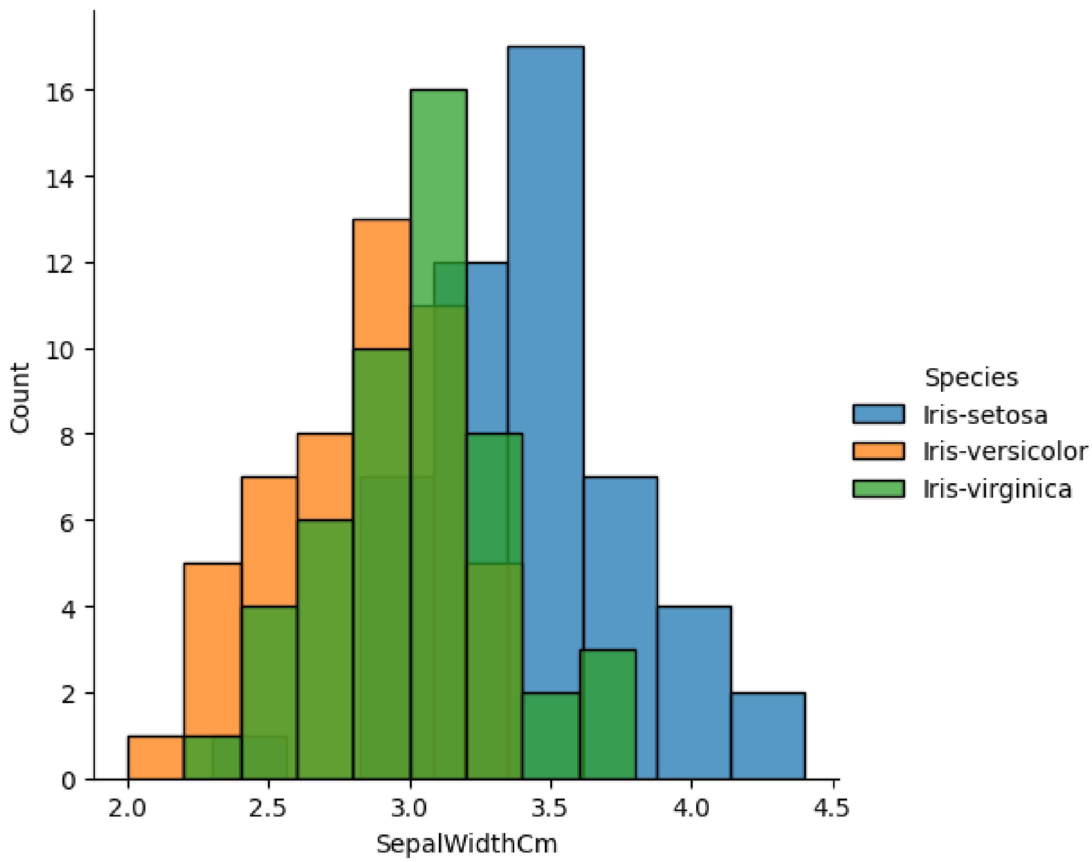


[17]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'SepalLengthCm').
↪add_legend();
plt.show();
```



[18]:

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



[ ]:

[ ]: #EX.NO :1.b Pandas Buit in function. Numpy Buit in fuction- Array slicing, Ravel,Reshape,ndim
#DATA : 06.08.2024

#NAME : PRASANNA KUMAR M#ROLL NO : 230701237

[20]:
```
array=np.random.randint(1,100,9)
array
```

[20]: array([39, 97, 88, 58, 29, 87, 27, 88, 91])

[21]:
```
np.sqrt(array)
```

[21]: array([6.244998 , 9.8488578 , 9.38083152, 7.61577311, 5.38516481,
9.32737905, 5.19615242, 9.38083152, 9.53939201])

[22]:
```
array.ndim
```

[22]: 1

[23]:
```
new_array=array.reshape(3,3)
```

[24]:
```
new_array
```

[24]: array([[39, 97, 88],
[58, 29, 87],
[27, 88, 91]])

[25]:
```
new_array.ndim
```

[25]: 2

[26]:
```
new_array.ravel()
```

[26]: array([39, 97, 88, 58, 29, 87, 27, 88, 91])

[27]:
```
newm=new_array.reshape(3,3)
```

[28]:
```
newm
```

[28]: array([[39, 97, 88],
[58, 29, 87],
[27, 88, 91]])

[29]:
```
newm[2,1:3]
```

[29]: array([88, 91])

[30]:
```
newm[1:2,1:3]
```

[30]: array([[29, 87]])

[31]:
```
new_array[0:3,0:0]
```

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

[32]:
```
new_array[1:3]
```

[32]: array([[58, 29, 87],
[27, 88, 91]])

[ ]:
```
#EX.NO :2 Outlier
detection#DATA    :
13.08.2024

#NAME : PRASANNA KUMAR
```

[34]:
```
import numpy as np
import warnings
warnings.filterwarnings('ignore')
array=np.random.randint(1,100,16)
array
```

[34]: a

[35]:
```
array.mean()
```

[35]: 45.5625

[36]:
```
np.percentile(array,25)
```

[36]: 29.25

[37]:
```
np.percentile(array,50)
```

[37]: 44.0

[38]:
```
np.percentile(array,75)
```

[38]: 55.5

[39]:
```
np.percentile(array,100)
```

[39]: 97.0

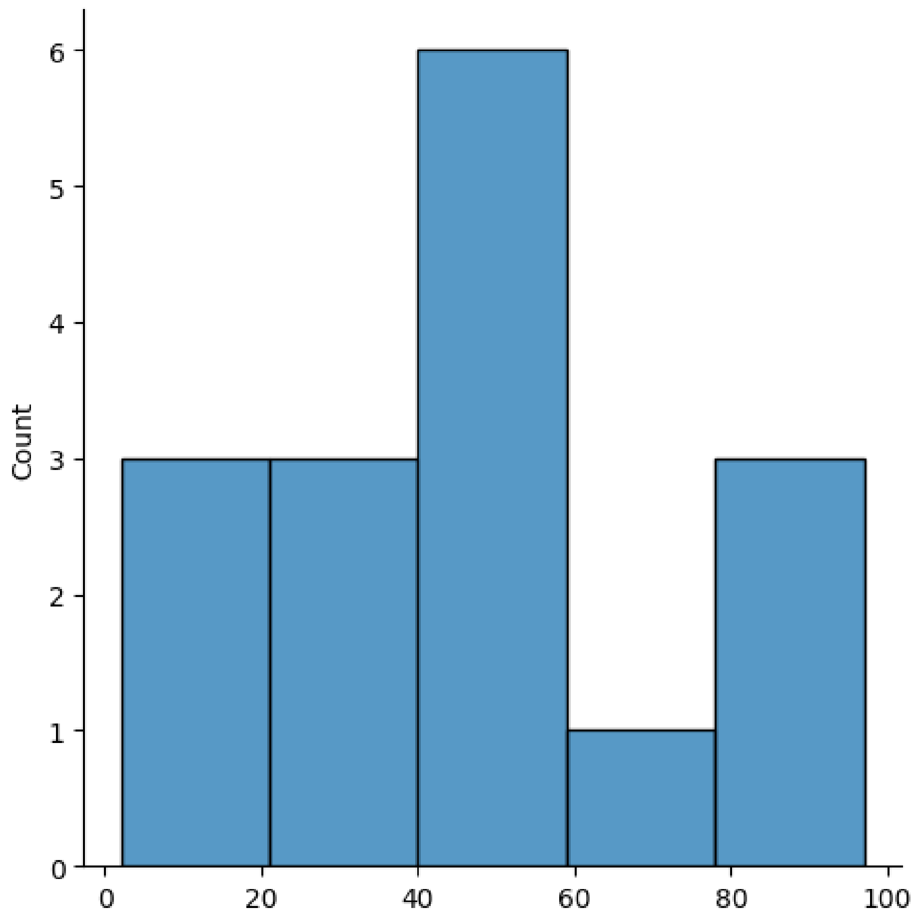
[40]:
```
#outliers detection
def outDetection(array):
	sorted(array)
	Q1,Q3=np.percentile(array,[25,75])
	IQR=Q3-Q1
	lr=Q1-(1.5*IQR)
	ur=Q3+(1.5*IQR)
	return lr,ur
lr,ur=outDetection(array)lr,ur
```

[40]: (-

[41]:

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

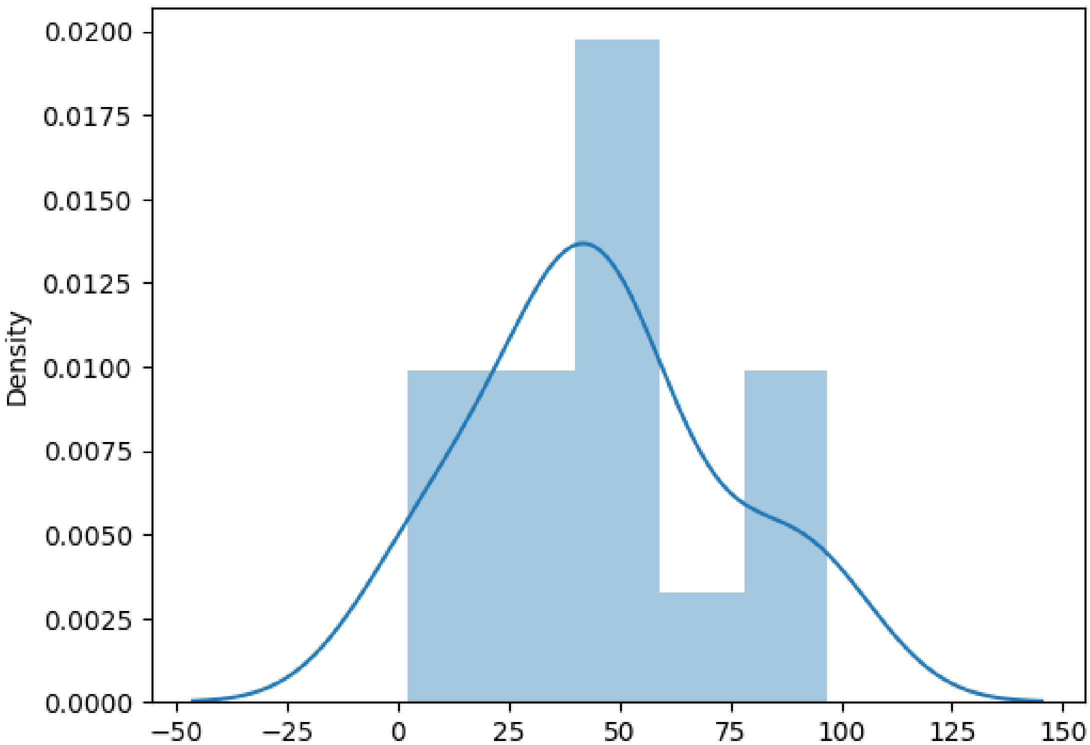
[41] : <seaborn.axisgrid.FacetGrid at 0x20d7cda3b50>



[42]:

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

[42] : <Axes: ylabel='Density'>



[43]:

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

[43]:

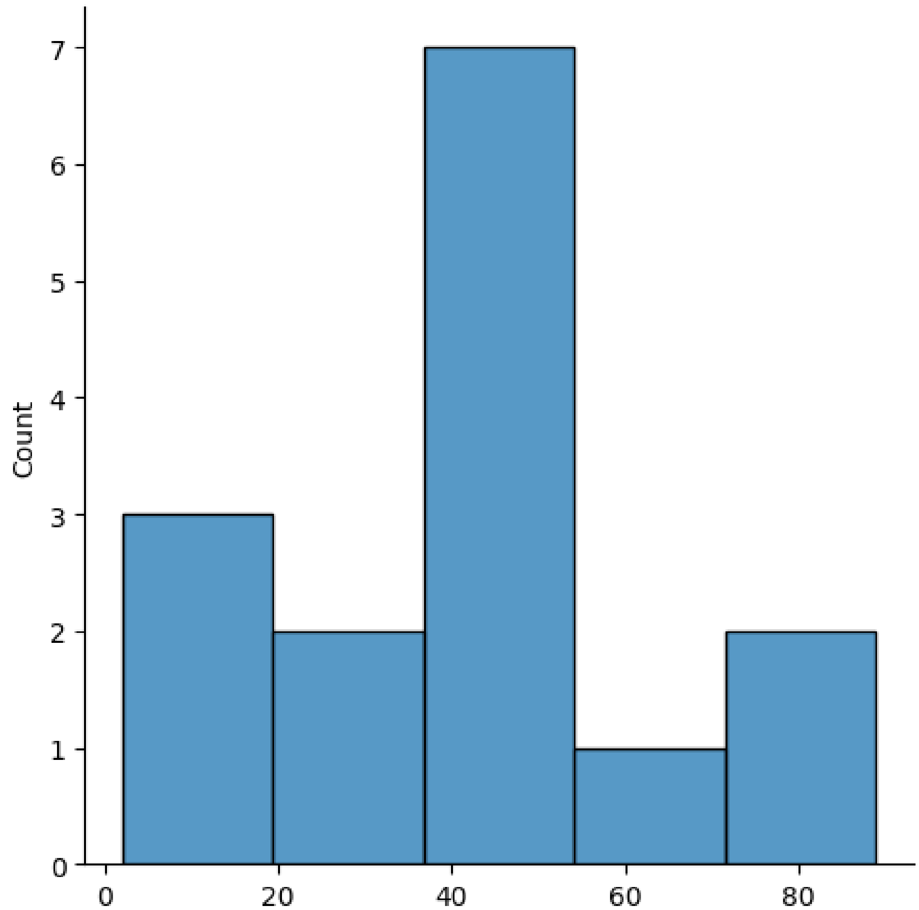
```
array([37, 15, 49, 89, 30, 47,          2, 86, 53, 63, 41, 46, 42, 27,          5])
```

[44]:

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

[44]:

```
<seaborn.axisgrid.FacetGrid at 0x20d7d02d950>
```



[45]:
```
lr1,ur1=outDetection(new_array)
lr1,ur1
```

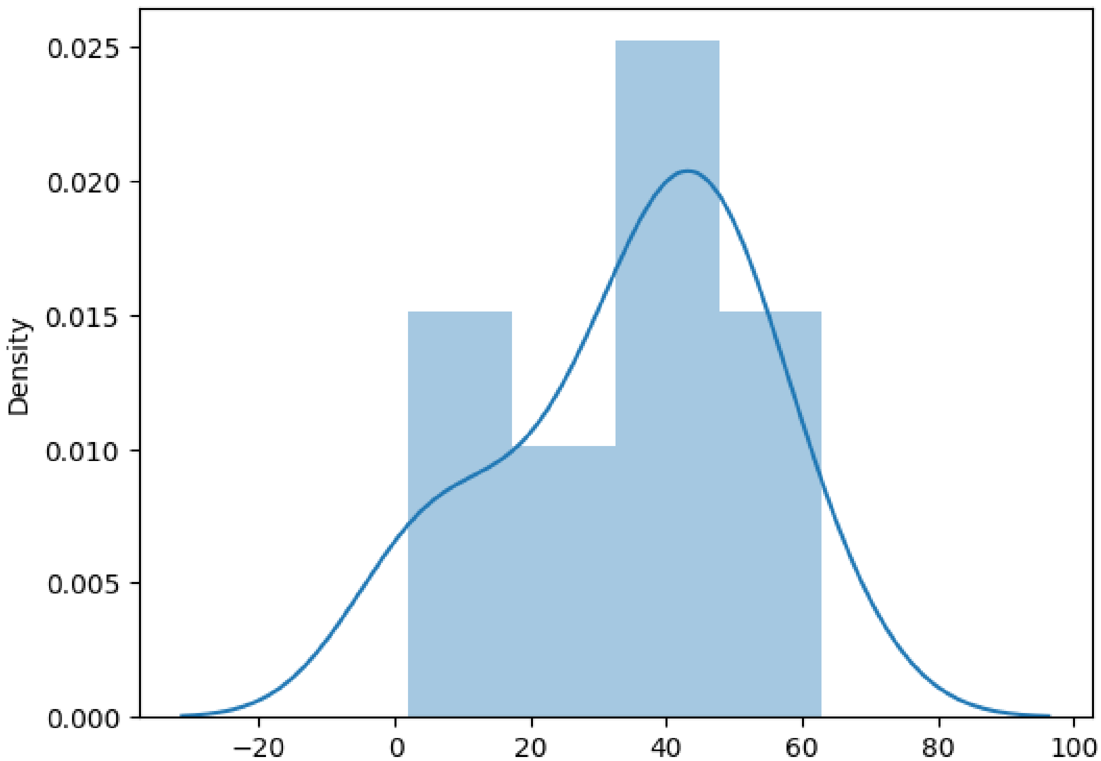
[45]: (-5.25, 84.75)

[46]:
```
final_array=new_array[(new_array>lr1) & (new_array<ur1)]
final_array
```

[46]: array([37, 15, 49, 30, 47, 2, 53, 63, 41, 46, 42, 27, 5])

[47]:
```
sns.distplot(final_array)
```

[47]: <Axes: ylabel='Density'>



[ ]:
```
#EX.NO :3  Missing and inappropriate
data#DATA: 20.08.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - B
```

[49]:
```
import numpy as np
import pandas as
pdimport warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("Hotel_Dataset.csv") df
```

[49] :

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
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
```

[50]:
```
df.duplicated()
```

[50] :
```
0     False
1     False
2     False
3     False
4     False
5     False
6     False
7     False
8     False
9      True
10    False
dtype: bool
```

[51]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  -----            --------------  -----
 1   CustomerID       11 non-null     int64
 2   Age_Group        11 non-null     object
 3   Rating(1-5)      11 non-null     int64
 4   Hotel            11 non-null     object
 5   FoodPreference   11 non-null     object
 6   Bill             11 non-null     int64
 7   NoOfPax          11 non-null     int64
```

```
    EstimatedSalary    11 non-null    int64
 9  Age_Group.1        11 non-null    object
dtypes: int64(5), object(4)
memory usage: 924.0+ bytes
```

[52]:

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

[52]:

```
    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.10    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
```

[53]:

```
len(df)
```

[53]: 10

[54]:

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

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

[55]:

```
df
```

[55]:

```
   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
```

[56]:
```python
df.drop(['Age_Group.1'],axis=1,inplace=True) df
```

[56]:
```
   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
0            40000
1            59000
2            30000
3           120000
4            45000
5           122220
6            21122
7           345673
8           -99999
9            87777
```

[57]:

```
df.CustomerID.loc[df.CustomerID<0]=np.nan
df.Bill.loc[df.Bill<0]=np.nan
df.EstimatedSalary.loc[df.EstimatedSalary<0]=np.nan df
```

[57]:

	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	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

[58]:

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

[58]:

	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

[59]:
```
df.Age_Group.unique()
```

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

[60]:
```
df.Hotel.unique()
```

[60] : array(['Ibis', 'LemonTree', 'RedFox', 'Ibys'], dtype=object)[61]:

[61] : <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>

[62]:
```
df.FoodPreference.replace(['Vegetarian','veg'],'Veg',inplace=True)
df.FoodPreference.replace(['non-Veg'],'Non-Veg',inplace=True)
```

[63]:
```
df.EstimatedSalary.fillna(round(df.EstimatedSalary.mean()),inplace=True)
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
```

[63]:

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

[ ]:
```
#EX.NO :4   Data
Preprocessing#DATA        :
27.08.2024

#NAME : PRASANNA KUMAR
```

[65]:
```
import numpy as np
import pandas as
pdimport warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv") df
```

[65]:

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

[66]:
```
df.info()
```

<class 'pandas.core.frame.DataFrame'>

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

[67]:

[67]:
```
df.Country.mode()
```

[67] :

Name: Country, dtype: object

[68]:
```
df.Country.mode()[0]
```

[68] : 'France'

[69]:
```
type(df.Country.mode())
```

[69] : pandas.core.series.Series

[70]:
```
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
```

[70]:

	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

[71]:
```
pd.get_dummies(df.Country)
```

[71]:

	France	Germany	Spain
1	True	False	False
2	False	False	True
3	False	True	False

	False	False	True
5	False	True	False
6	True	False	False
7	False	False	True
8	True	False	False
9	False	True	False

[72]:
```
updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:
↪,[1,2,3]]],axis=1)
```

[73]:
```
df.info()
```

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

[74]:

[ ]:
```
#EX.NO :5  EDA-Quantitative and Qualitative
plots#DATA: 27.08.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[76]:
```
import numpy as np
import pandas as
pdimport warnings
warnings.filterwarnings('ignore')
df=pd.read_csv("pre_process_datasample.csv") df
```

[76]:

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

[77]:
```
df.info()
```

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

[78]:

[78] :
```
df.Country.mode()
```

Name: Country, dtype: object

[79]:
```
df.Country.mode()[0]
```

[79] : 'France'

[80]:
```
type(df.Country.mode())
```

[80] : pandas.core.series.Series

[81]:
```
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
```

[81]:

	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

[82]:
```
pd.get_dummies(df.Country)
```

[82]:

	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

[83]:
```
updated_dataset=pd.concat([pd.get_dummies(df.Country),df.iloc[:
↪,[1,2,3]]],axis=1)
updated_dataset
```

[83]:

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

[84]:
```
df.info()
```

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

[85]:
```
updated_dataset
```

[85]:

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

[ ]:
```
#EX.NO :5  EDA-Quantitative and Qualitative
plots#DATA: 03.09.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
```

[87]:
```
import seaborn as sns
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

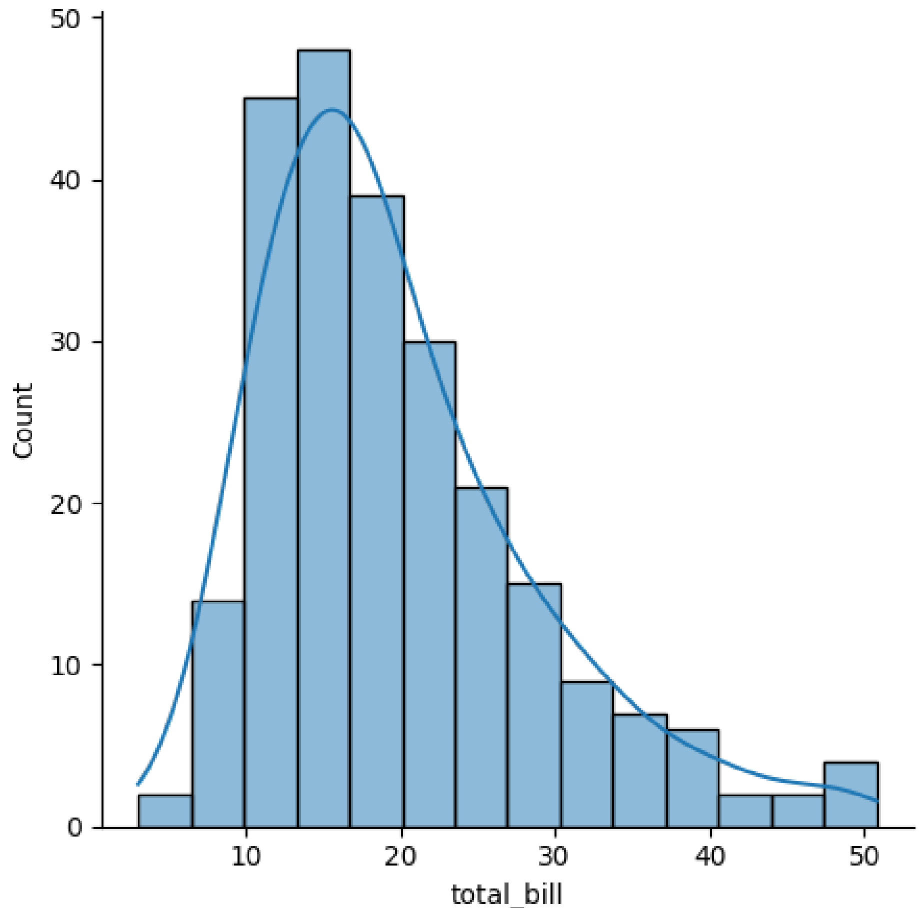
[88]:
```
tips=sns.load_dataset('tips')
tips.head()
```

[88] :

	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

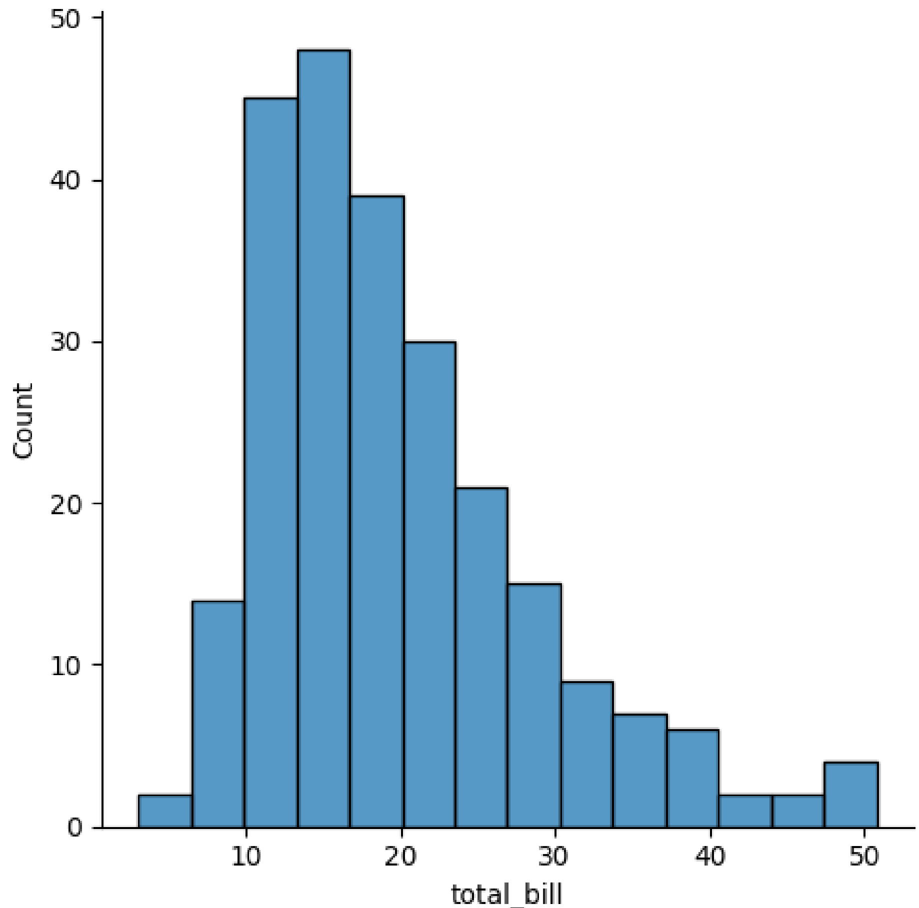
[89]:
```
sns.displot(tips.total_bill,kde=True)
```

[89] : <seaborn.axisgrid.FacetGrid at 0x20d7dc69390>



[90]:
```
sns.displot(tips.total_bill,kde=False)
```

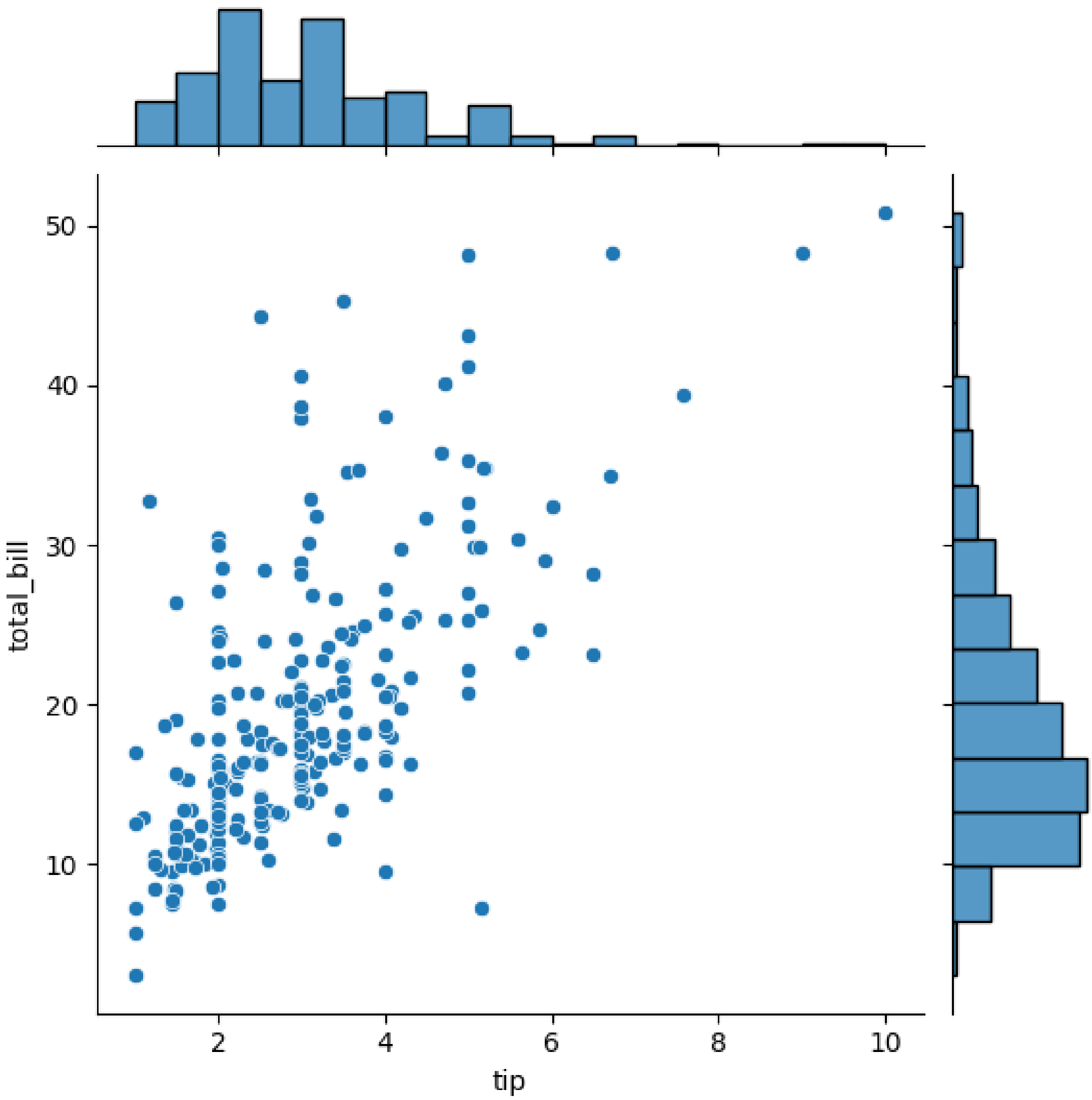
[90] : <seaborn.axisgrid.FacetGrid at 0x20d7dc22790>



[91]:

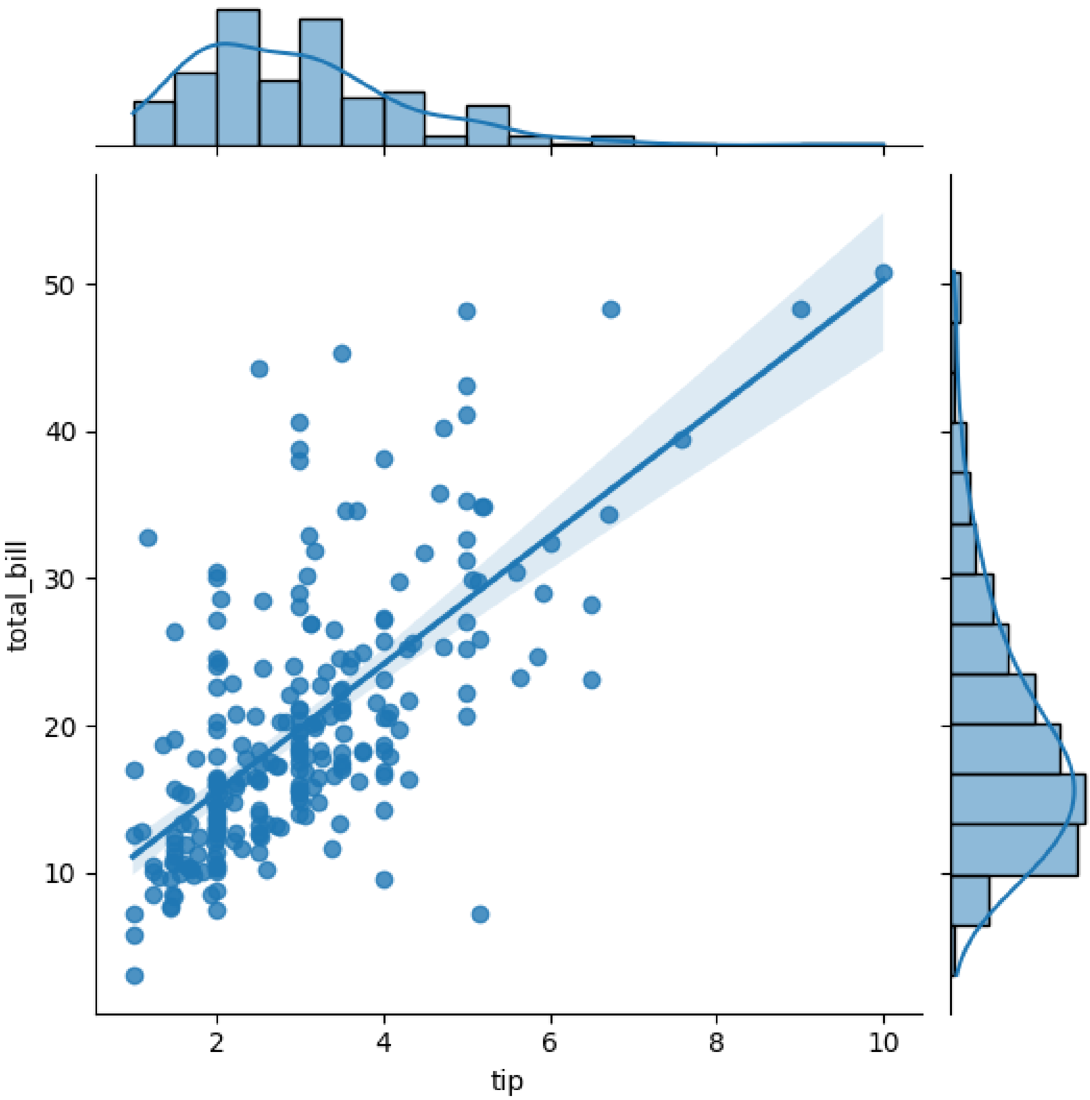
```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

[91] : <seaborn.axisgrid.JointGrid at 0x20d7dc2f2d0>

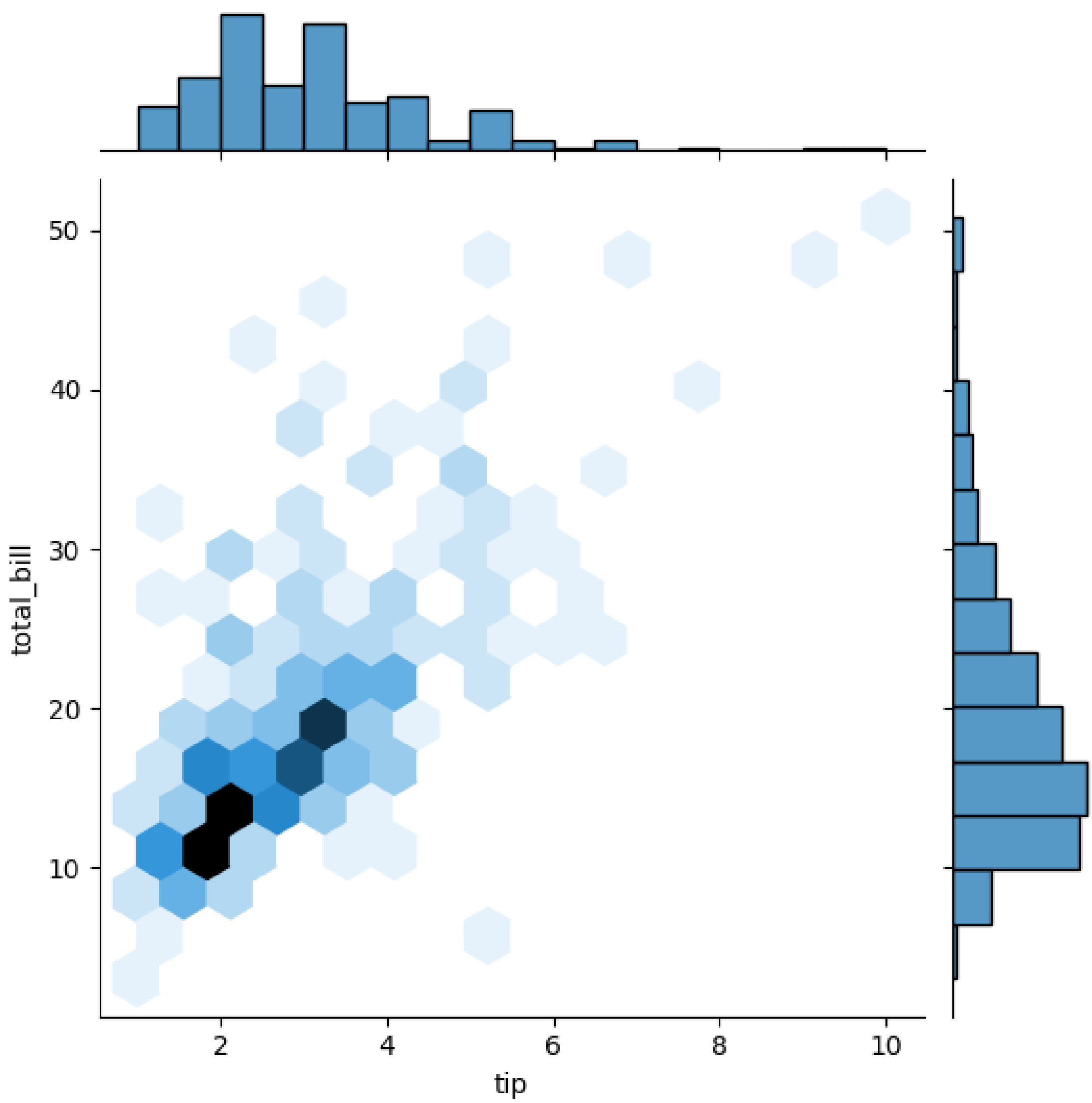



```
[92]: sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

```
[92]: <seaborn.axisgrid.JointGrid at 0x20d7ed32450>
```

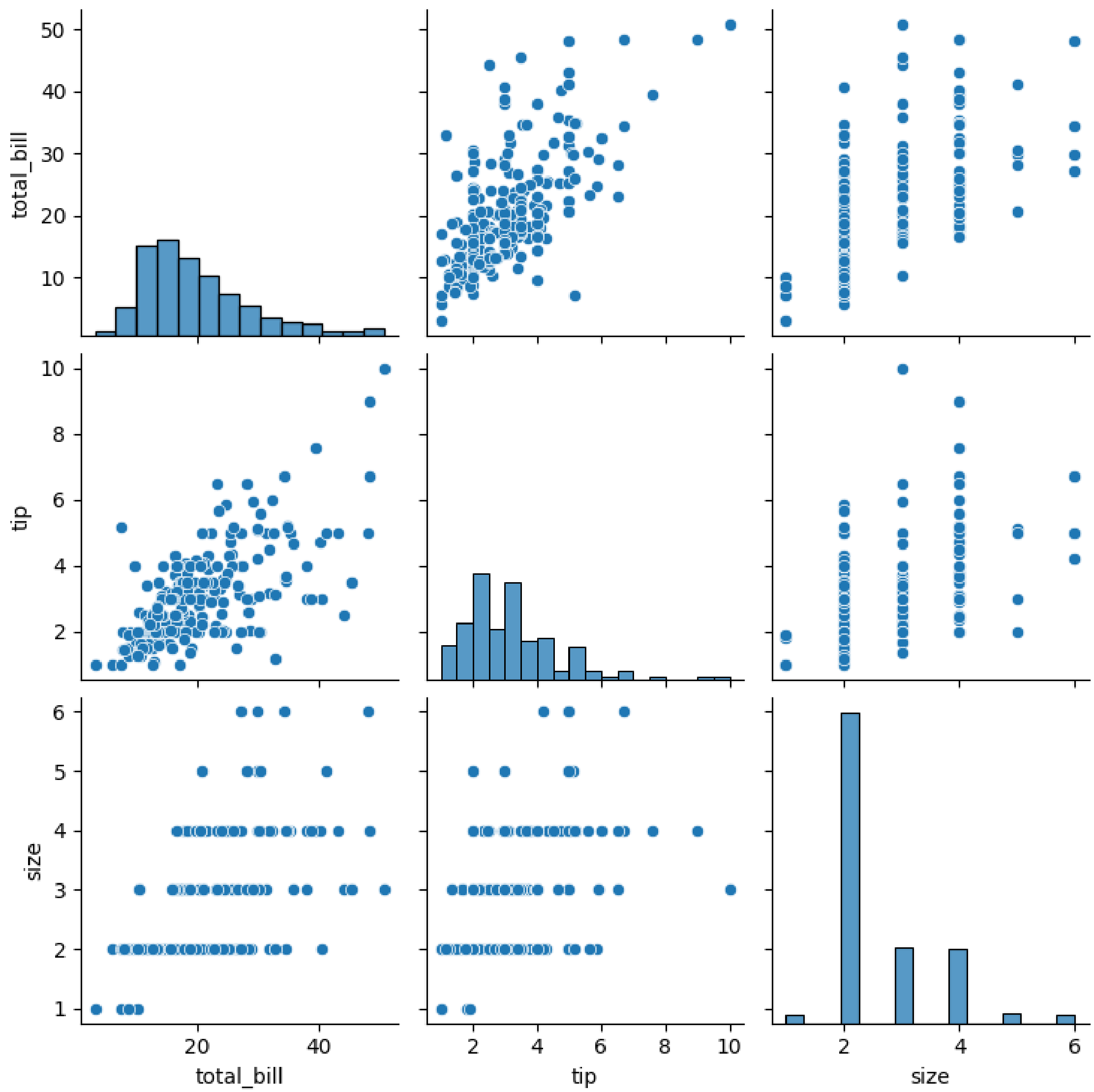


[93]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```
[93] : <seaborn.axisgrid.JointGrid at 0x20d7ed7d350>



[94]:
```
sns.pairplot(tips)
```

[94] : <seaborn.axisgrid.PairGrid at 0x20d7f1c9cd0>

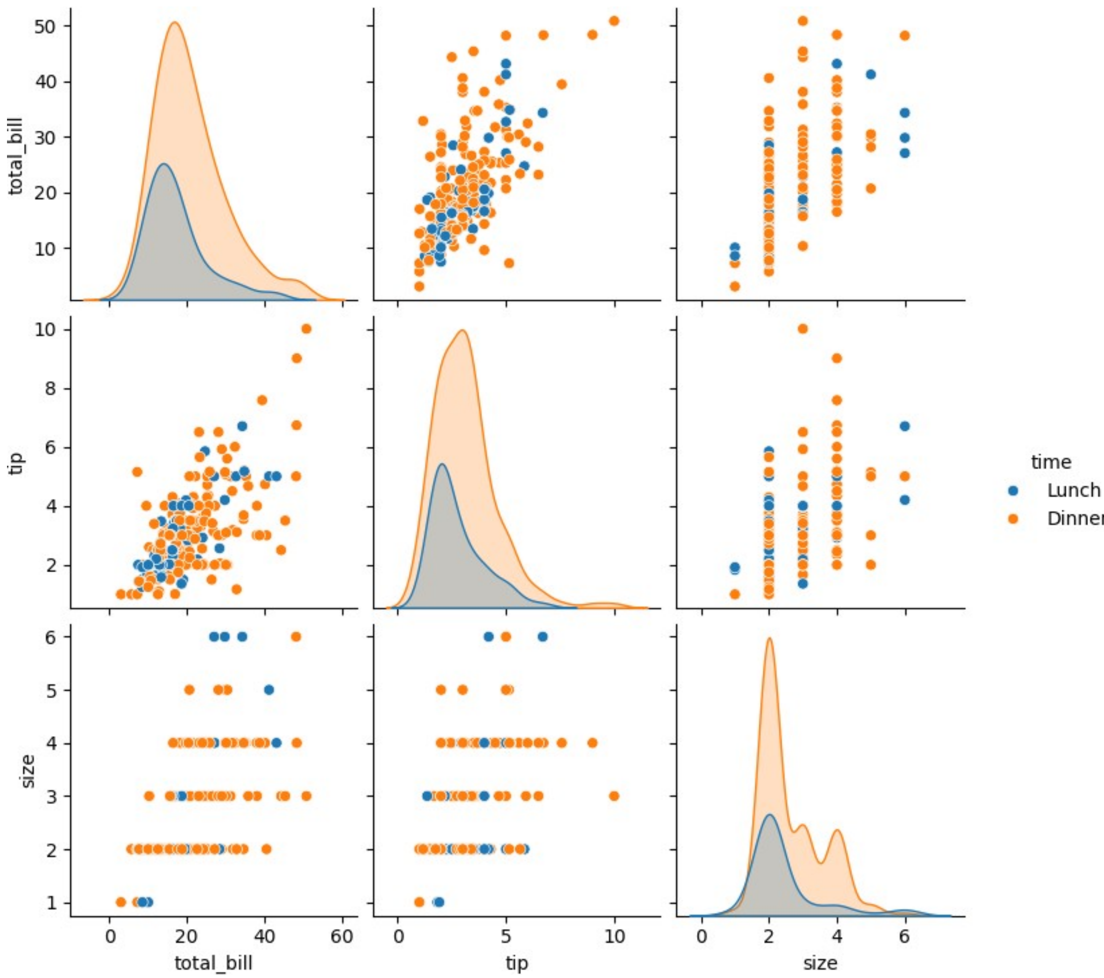



```
[95]: tips.time.value_counts()
```

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

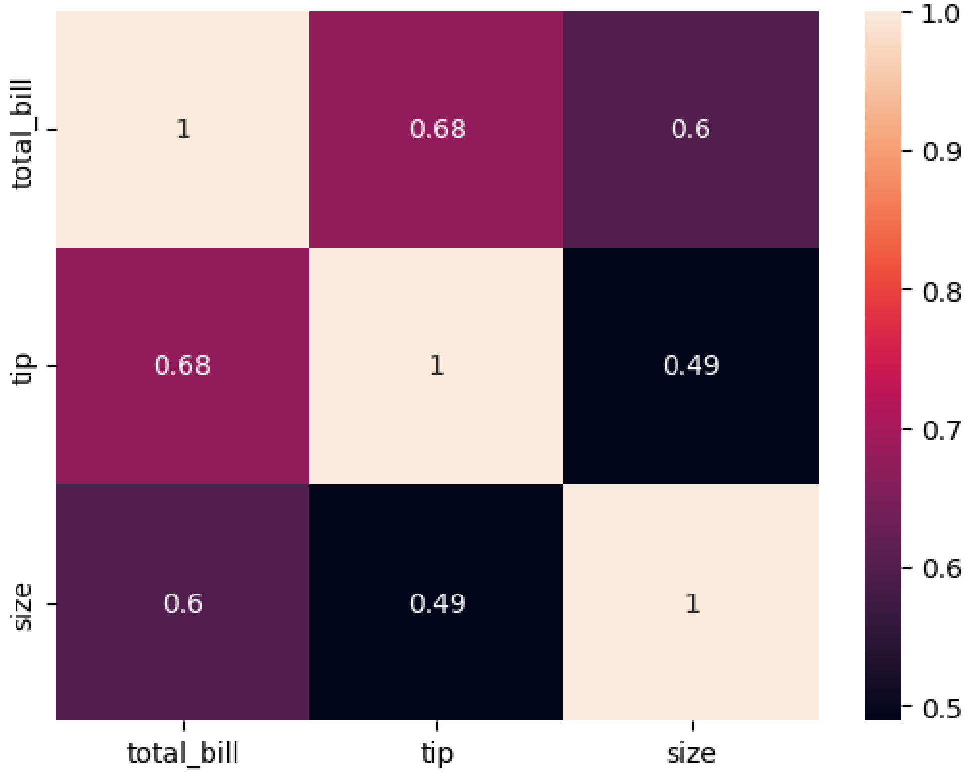
```
[96]: sns.pairplot(tips,hue='time')
```

```
[96] : <seaborn.axisgrid.PairGrid at 0x20d7cc27990>
```



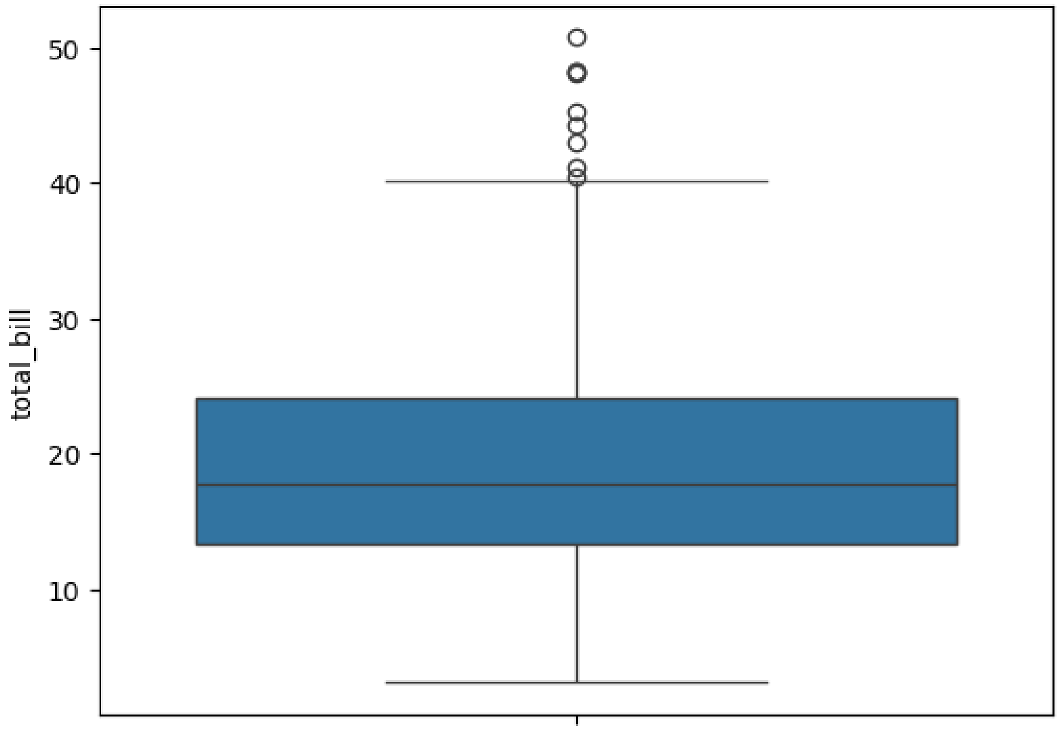
[97]:
```
sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

[97] : <Axes: >

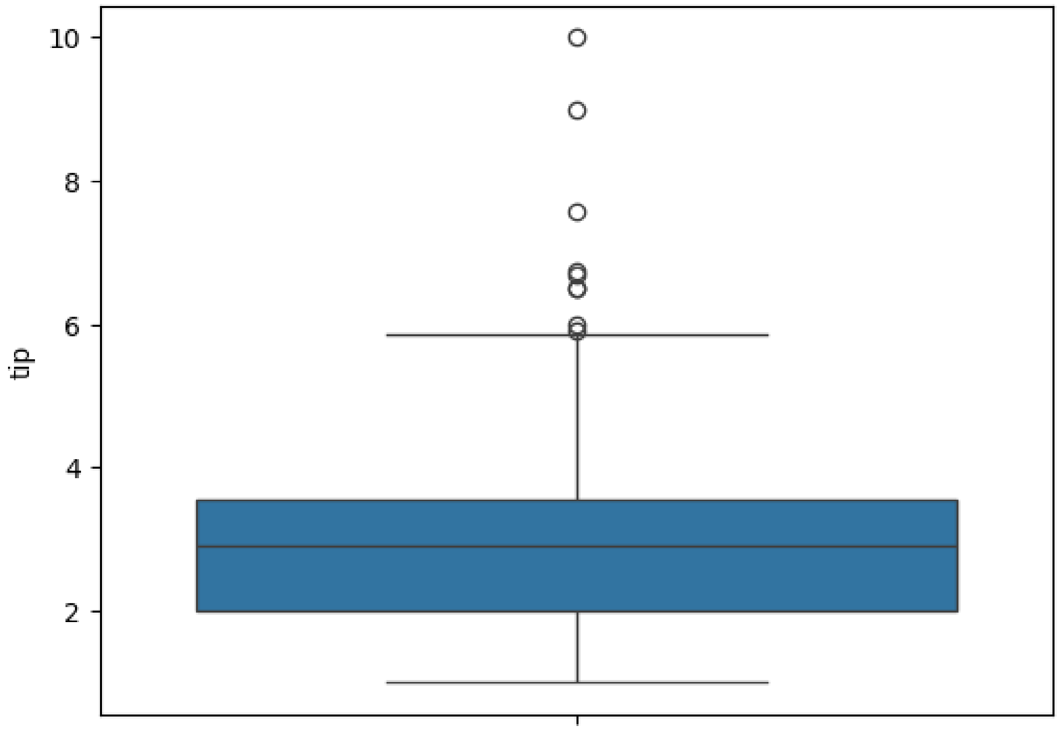


[98]:
```
sns.boxplot(tips.total_bill)
```

[98] : <Axes: ylabel='total_bill'>

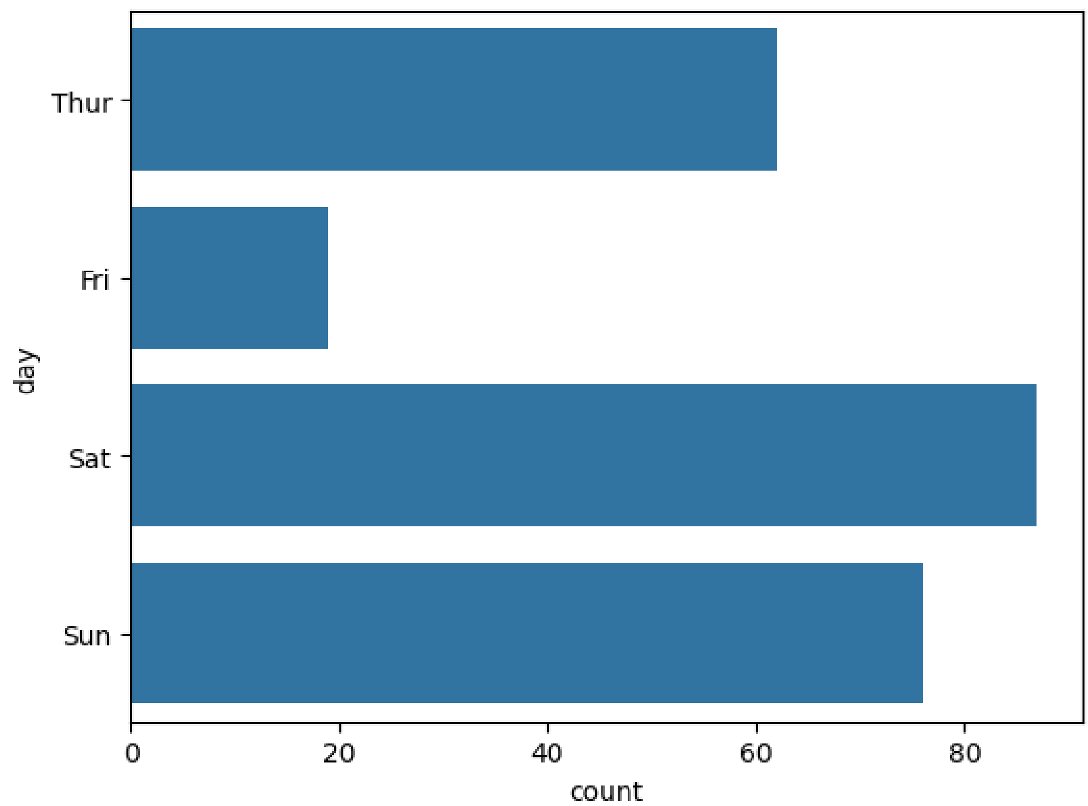


[99]:
```
sns.boxplot(tips.tip)
```
[99] : <Axes: ylabel='tip'>



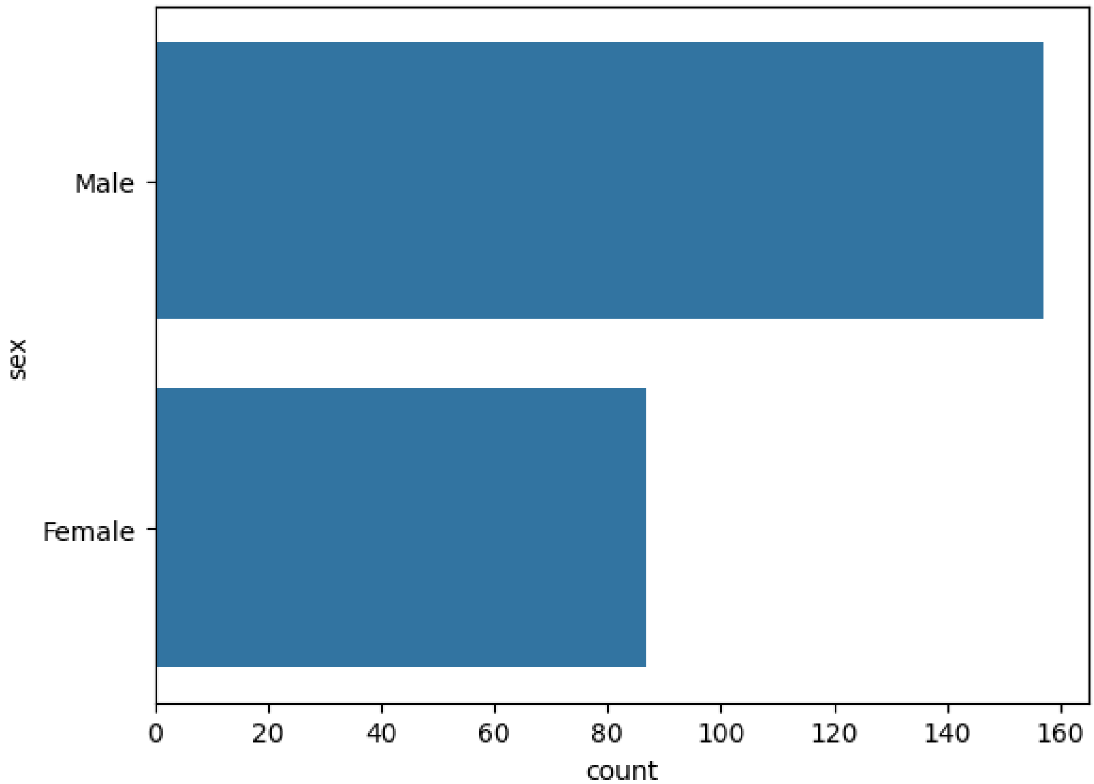
[100]:
```
sns.countplot(tips.day)
```

[100] : <Axes: xlabel='count', ylabel='day'>



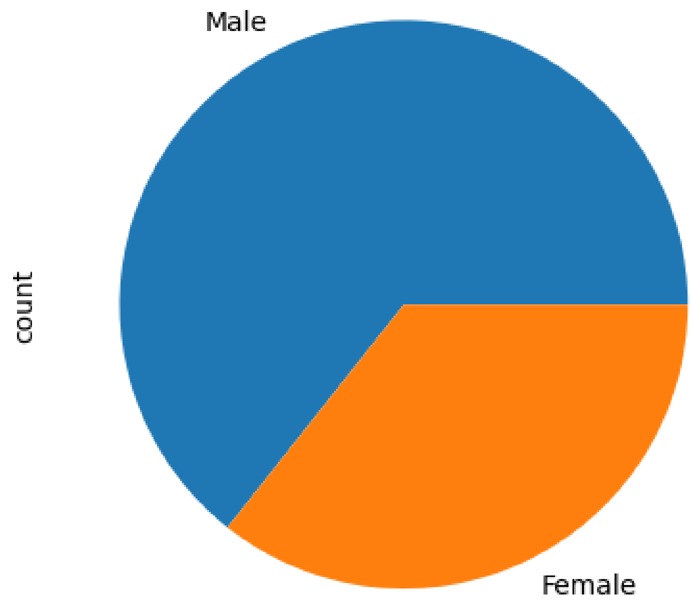
[101]:
```
sns.countplot(tips.sex)
```

[101] : <Axes: xlabel='count', ylabel='sex'>



[102]:
```
tips.sex.value_counts().plot(kind='pie')
```

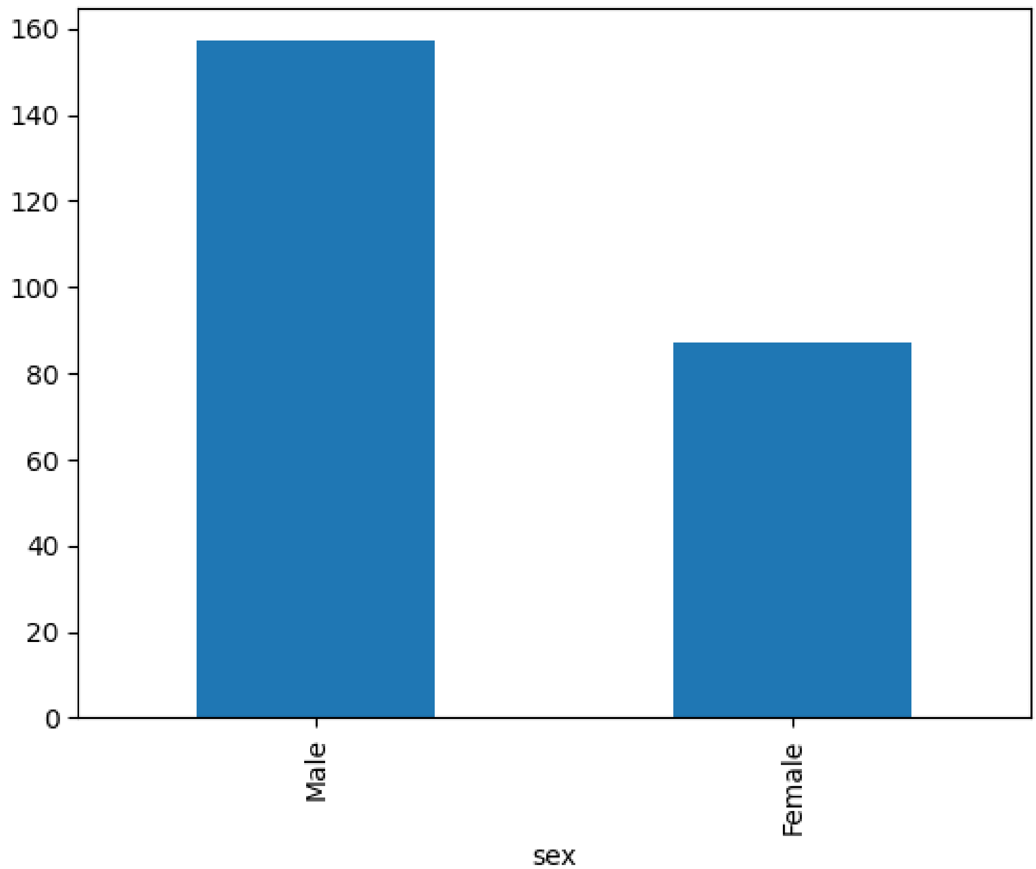
[102] : <Axes: ylabel='count'>



[103]:

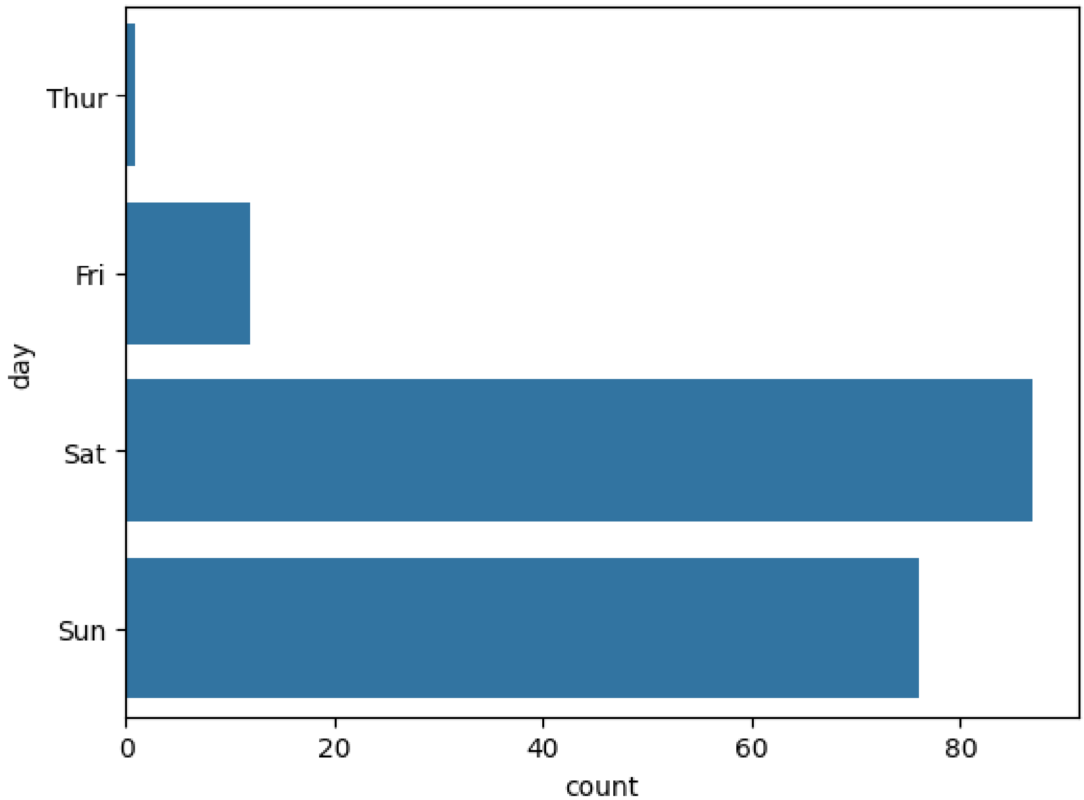
```
tips.sex.value_counts().plot(kind='bar')
```

[103] : <Axes: xlabel='sex'>



[104]:
```
sns.countplot(tips[tips.time=='Dinner']['day'])
```

[104] : <Axes: xlabel='count', ylabel='day'>



[ ]:
```
#EX.NO :6  Random Sampling and Sampling
Distribution#DATA  :  10.09.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
```

[106]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[107]:
```
population_mean = 50
population_std = 10
population_size = 100000
population = np.random.normal(population_mean, population_std, population_size)
```

[108]:
```
sample_sizes = [30, 50, 100]
num_samples = 1000
```

[109]:
```
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))
```

[110]:

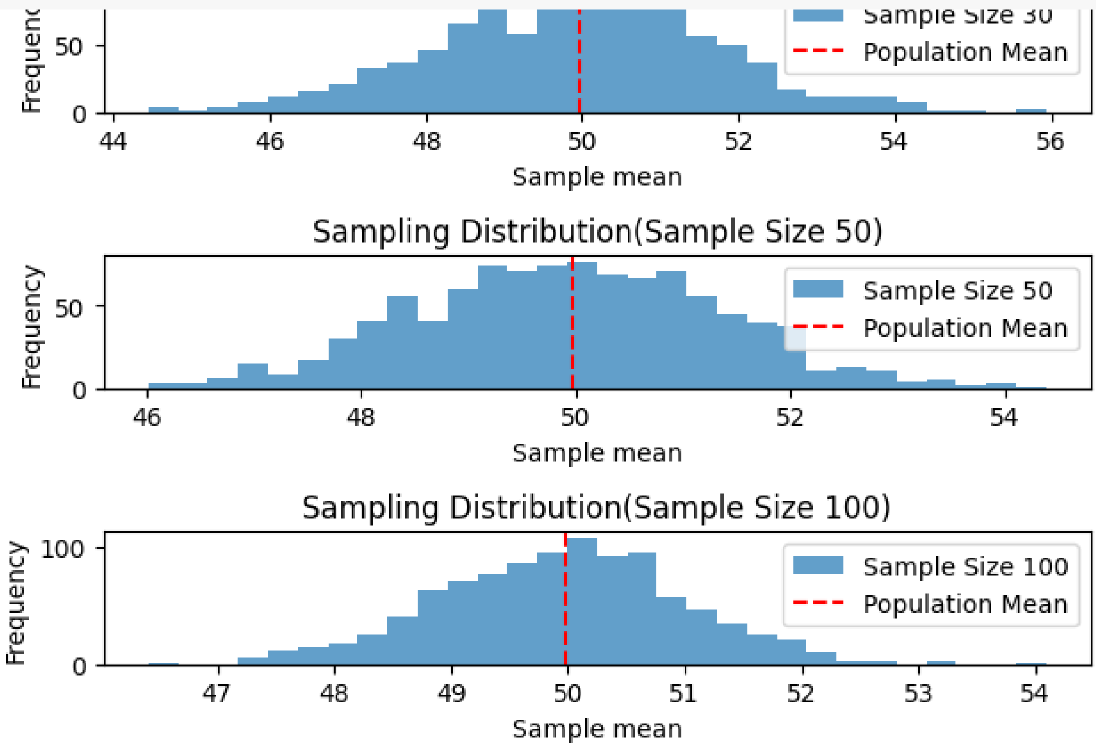
```
plt.figure(figsize=(12, 8))
```

[110]: <Figure size 1200x800 with 0 Axes>

<Figure size 1200x800 with 0 Axes>

[111]:

```
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()
```



[ ]:

```
#EX.NO :7  Z-Test
#DATA  :  10.09.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
```

[113]:

```
import numpy as np
import scipy.stats as stats
```

[114]:

```
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])
```

[115]:

```
population_mean = 150
sample_mean = np.mean(sample_data) sample_std =
np.std(sample_data, ddof=1)
```

[116]:

```
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)))
```

[117]:

```
# 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.")
```

P-Value: 0.5218

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

[ ]:

```
#EX.NO :8  T-Test
#DATA  :  08.10.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
```

[119]:

```
import numpy as np
import scipy.stats as
statsnp.random.seed(42)
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)
```

[120]:

```
population_mean = 100
sample_mean = np.mean(sample_data) sample_std =
np.std(sample_data, ddof=1)
```

[121]:

```
n = len(sample_data)
t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)
```

[122]:

```
# 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.")
```

P-Value: 0.8760

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

[ ]:

```
#EX.NO :9  Annova
TEST#DATA :
```

```
#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[124]:
```
import numpy as np
import scipy.stats as stats
from statsmodels.stats.multicomp import pairwise_tukeyhsd

np.random.seed(42)
n_plants = 25
```

[125]:
```
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)
```

[126]:
```
all_data = np.concatenate([growth_A, growth_B, growth_C])
```

[127]:
```
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] * n_plants f_statistic, p_value
= stats.f_oneway(growth_A, growth_B, growth_C)
```

[128]:
```
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 growthrates
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
```

[ ]:
```
#EX.NO :10 Feature
Scaling#DATA        :
22.10.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
```

[130]:
```
import numpy as np
import pandas as
pdimport warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('pre_process_datasample.csv')
```

[131]:
```
df.head()
```

[131]:

	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

[132]:
```
df.Country.fillna(df.Country.mode()[0],inplace=True)
features=df.iloc[:,:-1].values
features
```

[132]:
```
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)
```

[133]:
```
label=df.iloc[:,-1].values
```

[134]:
```
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]])
```

[134] : SimpleImputer()

[135]:
```
Salary.fit(features[:,[2]])
```

[135] : SimpleImputer()

[136]:
```
SimpleImputer()
```

[136] : SimpleImputer()

[137]:
```
features[:,[1]]=age.transform(features[:,[1]])
features[:,[2]]=Salary.transform(features[:,[2]])
features
```

[137]:
```
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)
```

[138]:
```
from sklearn.preprocessing import
OneHotEncoderoh =
OneHotEncoder(sparse_output=False)
Country=oh.fit_transform(features[:,[0]]) Country
```

[138]:
```
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.],
```

[139]:

```python
final_set=np.concatenate((Country,features[:,[1,2]]),axis=1)
final_set
```

[139]:

```
array([[1.0, 0.0, 0.0, 44.0, 72000.0],
       [0.0, 0.0, 1.0, 27.0, 48000.0],
       [0.0, 1.0, 0.0, 30.0, 54000.0],
       [0.0, 0.0, 1.0, 38.0, 61000.0],
       [0.0, 1.0, 0.0, 40.0, 63777.77777777778],
       [1.0, 0.0, 0.0, 35.0, 58000.0],
       [0.0, 0.0, 1.0, 38.77777777777778, 52000.0],
       [1.0, 0.0, 0.0, 48.0, 79000.0],
       [0.0, 1.0, 0.0, 50.0, 83000.0],
       [1.0, 0.0, 0.0, 37.0, 67000.0]], dtype=object)
```

[140]:

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

[141]:

```python
feat_standard_scaler
```

[141]:

```
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]])
```

[142]:

```python
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
```

[142]:

```
       [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]])
```

[ ]:

```python
#EX.NO :11 Linear Regression
#DATA  :  29.10.2024

#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
```

[144]:

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

[144]:

	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

[145]:
```
df.info()
```

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

[146]:

[146]:
```
df.dropna(inplace=True);
df
```

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

[147]:

```
df.info()
```

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

[148]:

[148]:

```
df.describe()   #descripte statical report# find out IYER FOR BELOW META DATA
```

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

[149]:

```
features = df.iloc[:,[0]].values # : - > all row , 0 -> first column

#iloc index based selection loc location based sentence

label = df.iloc[:,[1]].values
```

```
features
```

```
[149]: 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]])
```

```
[150]: label
```

```
[150]: 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],
```

[151]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(features,label,test_size=0.
 ↪2,random_state=23)
# x independent input train 80 % test
20 %'''
y is depenent ouput
0.2 allocate test for 20 % automatically train for
80 %'''
```

[151] :

```
%\n'
```

[152]:

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

[152] : '

```
model.score(x_train,y_train)
'''
accuracy
calculating96 %
```

```
'''
```

[153] : '\naccuracy calculating\n96 %\n'

[154]:

```
```

[154] : '\naccuracy calculating\n91 %\n'

[155]:

```
model.coef_
```

[155]: array([[9281.30847068]])

[156]:

```
model.intercept_
```

[156]: array([27166.73682891])

[157]:

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

'''
```

[157]: '\

[159]:

```
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))
```

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

[160]:

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

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

[ ]:

```
#EX.NO :12    Logistic
Regression#DATA  :  05.11.2024
```

```
#NAME : PRASANNA KUMAR
M#ROLL NO : 230701237
#DEPARTMENT : B.E COMPUTER SCIENCE AND ENGINEERING - D
```

[162]:

```
import numpy as np
import pandas as
pdimport warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('Social_Network_Ads.csv.csv') df
```

[162]:

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 x 5 columns]

[163]:

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

[163]:

	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

[164]:
```
df.head(25)
```

[164]:

	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

[165]:
```
features = df.iloc[:,[2,3]].valueslabel
= df.iloc[:,4].values features
```

[165]:
```
array([[      19,   19000],
       [      35,   20000],
       [      26,   43000],
       [      27,   57000],
       [      19,   76000],
       [      27,   58000],
       [      27,   84000],
       [      32,  150000],
       [      25,   33000],
       [      35,   65000],
       [      26,   80000],
```

```
[     26,  52000],
[     20,  86000],
[     32,  18000],
[     18,  82000],
[     29,  80000],
[     47,  25000],
[     45,  26000],
[     46,  28000],
[     48,  29000],
[     45,  22000],
[     47,  49000],
[     48,  41000],
[     45,  22000],
[     46,  23000],
[     47,  20000],
[     49,  28000],
[     47,  30000],
[     29,  43000],
[     31,  18000],
[     31,  74000],
[     27, 137000],
[     21,  16000],
[     28,  44000],
[     27,  90000],
[     35,  27000],
[     33,  28000],
[     30,  49000],
[     26,  72000],
[     27,  31000],
[     27,  17000],
[     33,  51000],
[     35, 108000],
[     30,  15000],
[     28,  84000],
[     23,  20000],
[     25,  79000],
[     27,  54000],
[     30, 135000],
[     31,  89000],
[     24,  32000],
[     18,  44000],
[     29,  83000],
[     35,  23000],
[     27,  58000],
[     24,  55000],
[     23,  48000],
[     28,  79000],
```

```
[       22,   18000],
[       32,  117000],
[       27,   20000],
[       25,   87000],
[       23,   66000],
[       32,  120000],
[       59,   83000],
[       24,   58000],
[       24,   19000],
[       23,   82000],
[       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],
[       24,   55000],
[       28,   85000],
[       26,   81000],
[       35,   50000],
[       22,   81000],
[       30,  116000],
[       26,   15000],
[       29,   28000],
[       29,   83000],
[       35,   44000],
[       35,   25000],
[       28,  123000],
[       35,   73000],
[       28,   37000],
[       27,   88000],
[       28,   59000],
[       32,   86000],
[       33,  149000],
[       19,   21000],
```

```
[       21,    72000],
[       26,    35000],
[       27,    89000],
[       26,    86000],
[       38,    80000],
[       39,    71000],
[       37,    71000],
[       38,    61000],
[       37,    55000],
[       42,    80000],
[       40,    57000],
[       35,    75000],
[       36,    52000],
[       40,    59000],
[       41,    59000],
[       36,    75000],
[       37,    72000],
[       40,    75000],
[       35,    53000],
[       41,    51000],
[       39,    61000],
[       42,    65000],
[       26,    32000],
[       30,    17000],
[       26,    84000],
[       31,    58000],
[       33,    31000],
[       30,    87000],
[       21,    68000],
[       28,    55000],
[       23,    63000],
[       20,    82000],
[       30,   107000],
[       28,    59000],
[       19,    25000],
[       19,    85000],
[       18,    68000],
[       35,    59000],
[       30,    89000],
[       34,    25000],
[       24,    89000],
[       27,    96000],
[       41,    30000],
[       29,    61000],
[       20,    74000],
[       26,    15000],
[       41,    45000],
```

```
[      31,   76000],
[      36,   50000],
[      40,   47000],
[      31,   15000],
[      46,   59000],
[      29,   75000],
[      26,   30000],
[      32,  135000],
[      32,  100000],
[      25,   90000],
[      37,   33000],
[      35,   38000],
[      33,   69000],
[      18,   86000],
[      22,   55000],
[      35,   71000],
[      29,  148000],
[      29,   47000],
[      21,   88000],
[      34,  115000],
[      26,  118000],
[      34,   43000],
[      34,   72000],
[      23,   28000],
[      35,   47000],
[      25,   22000],
[      24,   23000],
[      31,   34000],
[      26,   16000],
[      31,   71000],
[      32,  117000],
[      33,   43000],
[      33,   60000],
[      31,   66000],
[      20,   82000],
[      33,   41000],
[      35,   72000],
[      28,   32000],
[      24,   84000],
[      19,   26000],
[      29,   43000],
[      19,   70000],
[      28,   89000],
[      34,   43000],
[      30,   79000],
[      20,   36000],
[      26,   80000],
```

```
[       35,    22000],
[       35,    39000],
[       49,    74000],
[       39,   134000],
[       41,    71000],
[       58,   101000],
[       47,    47000],
[       55,   130000],
[       52,   114000],
[       40,   142000],
[       46,    22000],
[       48,    96000],
[       52,   150000],
[       59,    42000],
[       35,    58000],
[       47,    43000],
[       60,   108000],
[       49,    65000],
[       40,    78000],
[       46,    96000],
[       59,   143000],
[       41,    80000],
[       35,    91000],
[       37,   144000],
[       60,   102000],
[       35,    60000],
[       37,    53000],
[       36,   126000],
[       56,   133000],
[       40,    72000],
[       42,    80000],
[       35,   147000],
[       39,    42000],
[       40,   107000],
[       49,    86000],
[       38,   112000],
[       46,    79000],
[       40,    57000],
[       37,    80000],
[       46,    82000],
[       53,   143000],
[       42,   149000],
[       38,    59000],
[       50,    88000],
[       56,   104000],
[       41,    72000],
[       51,   146000],
```

```
[      35,   50000],
[      57,  122000],
[      41,   52000],
[      35,   97000],
[      44,   39000],
[      37,   52000],
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[      37,  146000],
[      50,   44000],
[      52,   90000],
[      41,   72000],
[      40,   57000],
[      58,   95000],
[      45,  131000],
[      35,   77000],
[      36,  144000],
[      55,  125000],
[      35,   72000],
[      48,   90000],
[      42,  108000],
[      40,   75000],
[      37,   74000],
[      47,  144000],
[      40,   61000],
[      43,  133000],
[      59,   76000],
[      60,   42000],
[      39,  106000],
[      57,   26000],
[      57,   74000],
[      38,   71000],
[      49,   88000],
[      52,   38000],
[      50,   36000],
[      59,   88000],
[      35,   61000],
[      37,   70000],
[      52,   21000],
[      48,  141000],
[      37,   93000],
[      37,   62000],
[      48,  138000],
[      41,   79000],
[      37,   78000],
[      39,  134000],
[      49,   89000],
[      55,   39000],
```

```
[     37,   77000],
[     35,   57000],
[     36,   63000],
[     42,   73000],
[     43,  112000],
[     45,   79000],
[     46,  117000],
[     58,   38000],
[     48,   74000],
[     37,  137000],
[     37,   79000],
[     40,   60000],
[     42,   54000],
[     51,  134000],
[     47,  113000],
[     36,  125000],
[     38,   50000],
[     42,   70000],
[     39,   96000],
[     38,   50000],
[     49,  141000],
[     39,   79000],
[     39,   75000],
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[     36,   60000],
[     52,  138000],
[     53,   82000],
[     41,   52000],
[     48,   30000],
[     48,  131000],
[     41,   60000],
[     41,   72000],
[     42,   75000],
[     36,  118000],
[     47,  107000],
[     38,   51000],
[     48,  119000],
[     42,   65000],
[     40,   65000],
[     57,   60000],
[     36,   54000],
[     58,  144000],
[     35,   79000],
[     38,   55000],
[     39,  122000],
```

```
[      53,  104000],
[      35,   75000],
[      38,   65000],
[      47,   51000],
[      47,  105000],
[      41,   63000],
[      53,   72000],
[      54,  108000],
[      39,   77000],
[      38,   61000],
[      38,  113000],
[      37,   75000],
[      42,   90000],
[      37,   57000],
[      36,   99000],
[      60,   34000],
[      54,   70000],
[      41,   72000],
[      40,   71000],
[      42,   54000],
[      43,  129000],
[      53,   34000],
[      47,   50000],
[      42,   79000],
[      42,  104000],
[      59,   29000],
[      58,   47000],
[      46,   88000],
[      38,   71000],
[      54,   26000],
[      60,   46000],
[      60,   83000],
[      39,   73000],
[      59,  130000],
[      37,   80000],
[      46,   32000],
[      46,   74000],
[      42,   53000],
[      41,   87000],
[      58,   23000],
[      42,   64000],
[      48,   33000],
[      44,  139000],
[      49,   28000],
[      57,   33000],
[      56,   60000],
[      49,   39000],
```

```
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[       47,  34000],
[       48,  35000],
[       48,  33000],
[       47,  23000],
[       45,  45000],
[       60,  42000],
[       39,  59000],
[       46,  41000],
[       51,  23000],
[       50,  20000],
[       36,  33000],
[       49,  36000]], dtype=int64)
```

[166]:

```python
label
```

[166]:

```
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], dtype=int64)
```

[167]:

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

[168]:

```python
# 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: 0.8406 | Random State: 101
Test Score: 0.8500 | Train Score: 0.8406 | Random State: 102
Test Score: 0.9000 | Train Score: 0.8250 | Random 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: 0.8500 | Random State: 302
Test Score: 0.8750 | Train Score: 0.8469 | Random 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
```

[168]: '\n\n\n'

[169]:

```
x_train,x_test,y_train,y_test=train_test_split(features,label,test_size=0.
  ↪2,random_state=209)
finalModel=LogisticRegression()
finalModel.fit(x_train,y_train)
```

[169]: LogisticRegression()

[170]:

```
print(finalModel.score(x_train,y_train))
print(finalModel.score(x_train,y_train))
```

```
0.85
0.85
```

[171]:

```
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