230701266 - FDS LAB EXPERIMENTS

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Experiment-1a- Basic Practice Experiments

[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
0       Iris-setosa
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
..              …
145  Iris-virginica
```

```
146  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
---  ------         --------------  -----
 0   Id             150 non-null    int64
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

[5]:
```
data.describe()
```

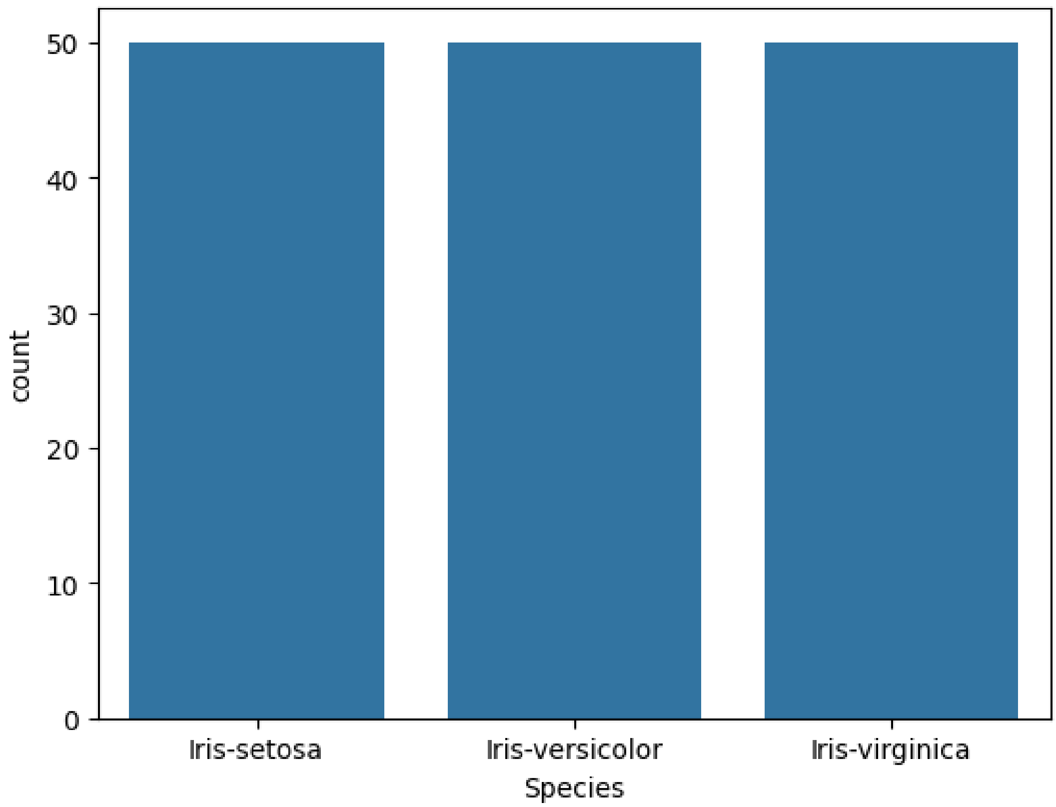
[5]:

	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)
```

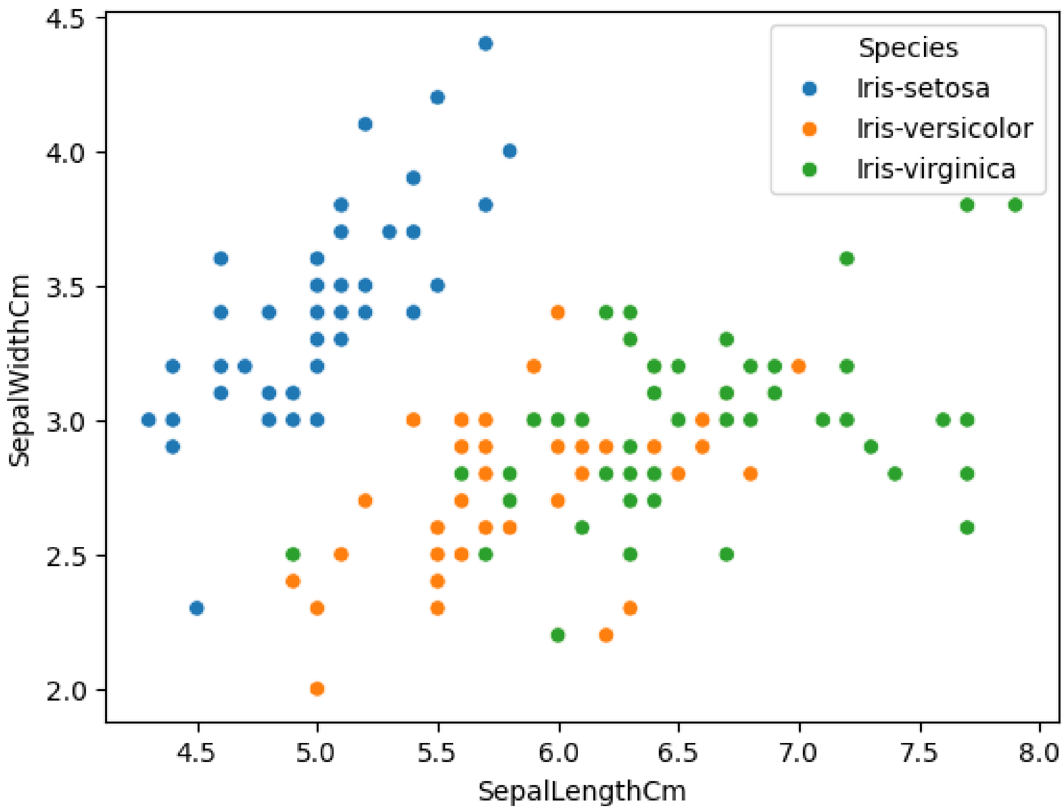
[10]:
```
FinalDataset.head()
```

[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
```

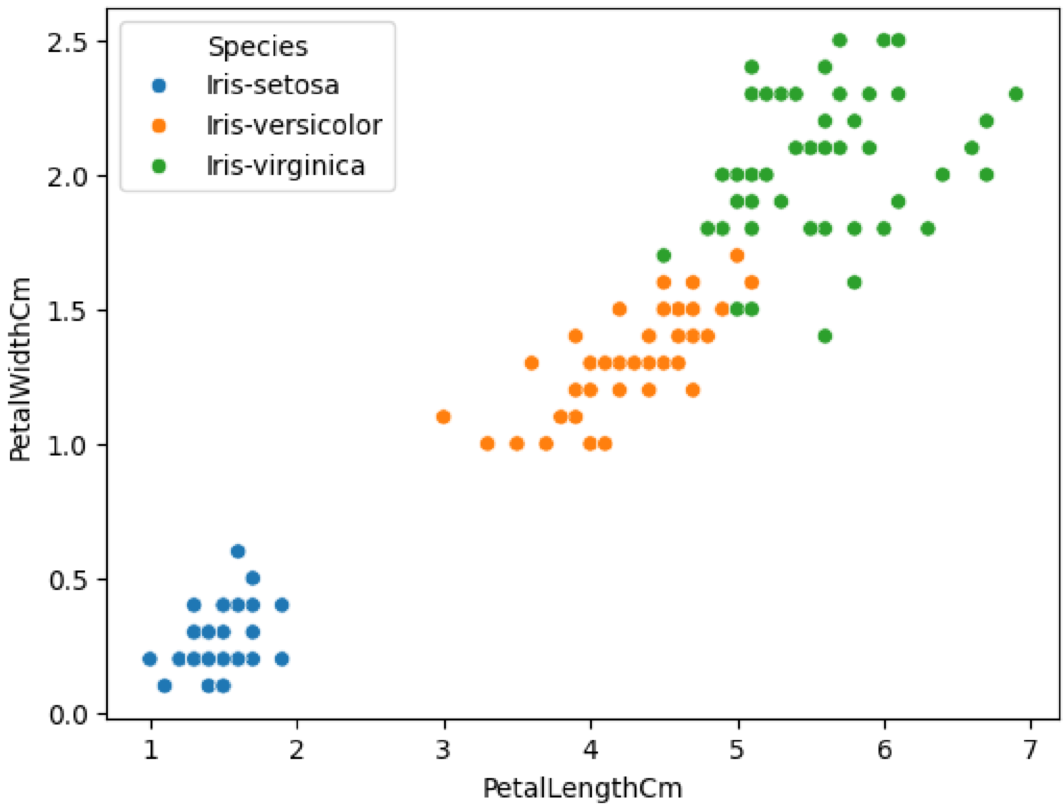
[11]:
```
sns.scatterplot(x='SepalLengthCm',y='SepalWidthCm',hue='Species',data=data,)
```

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

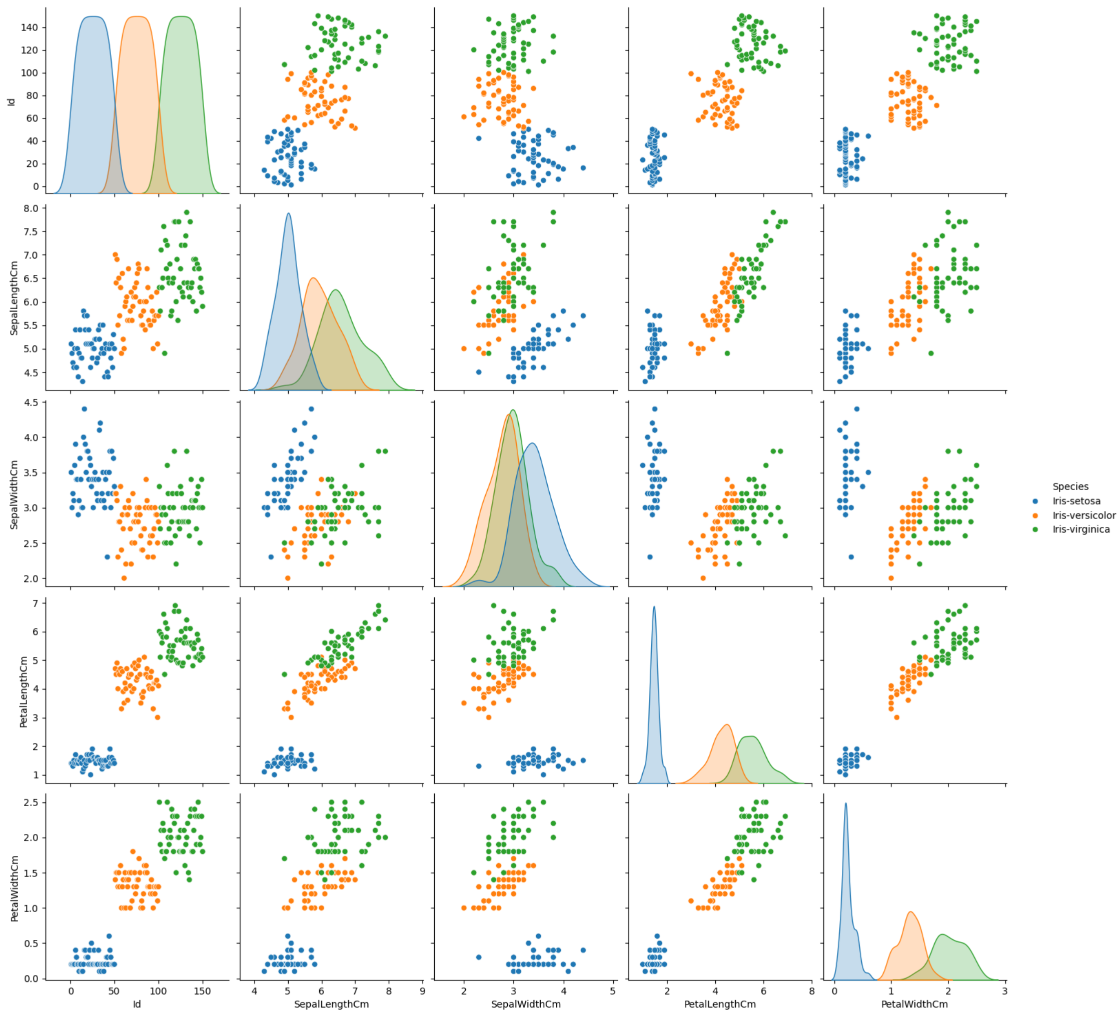


[12]:
```
sns.scatterplot(x='PetalLengthCm',y='PetalWidthCm',hue='Species',data=data,)
```

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

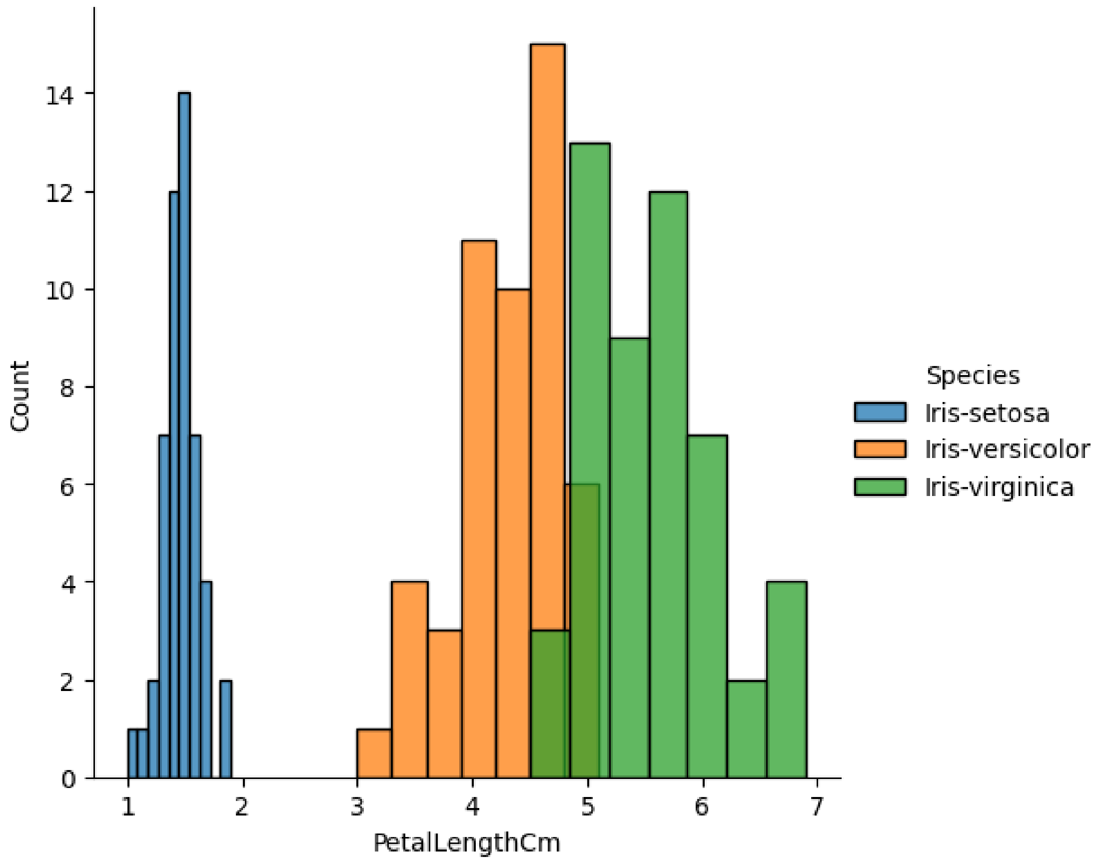


[13]:
```
sns.pairplot(data,hue='Species',height=3);
```

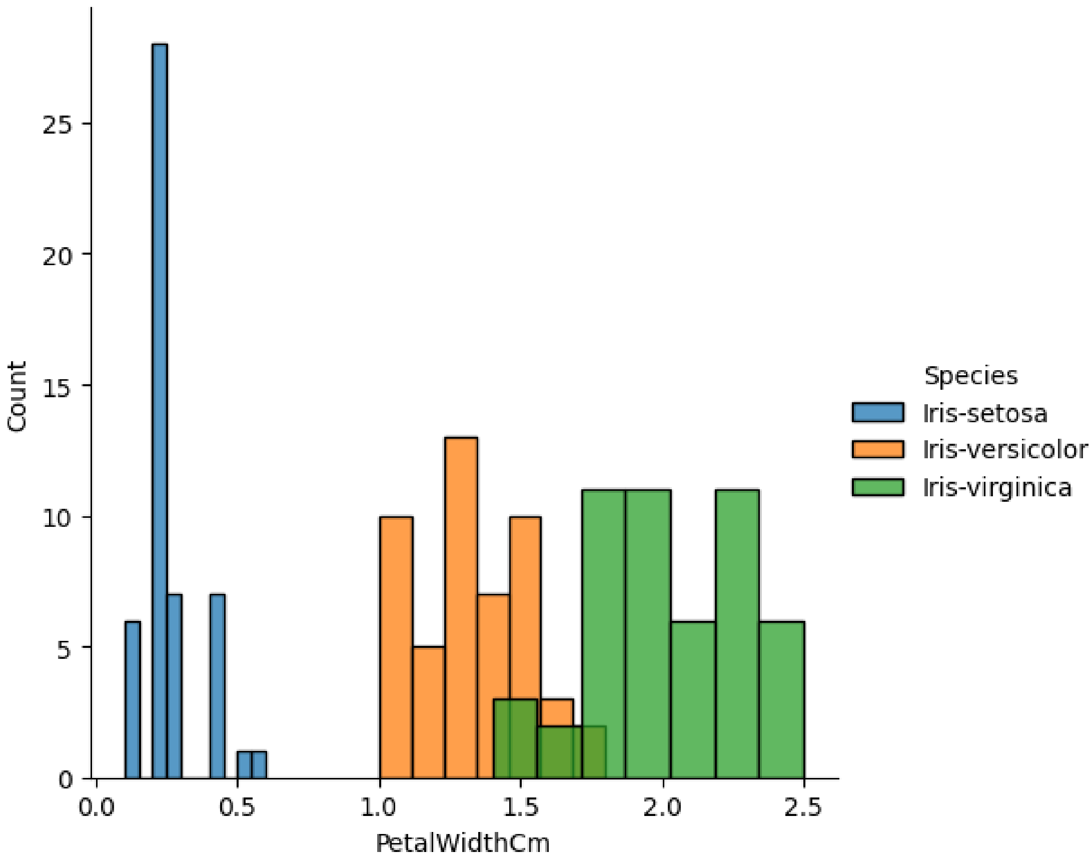


[14]:
```
plt.show()
```

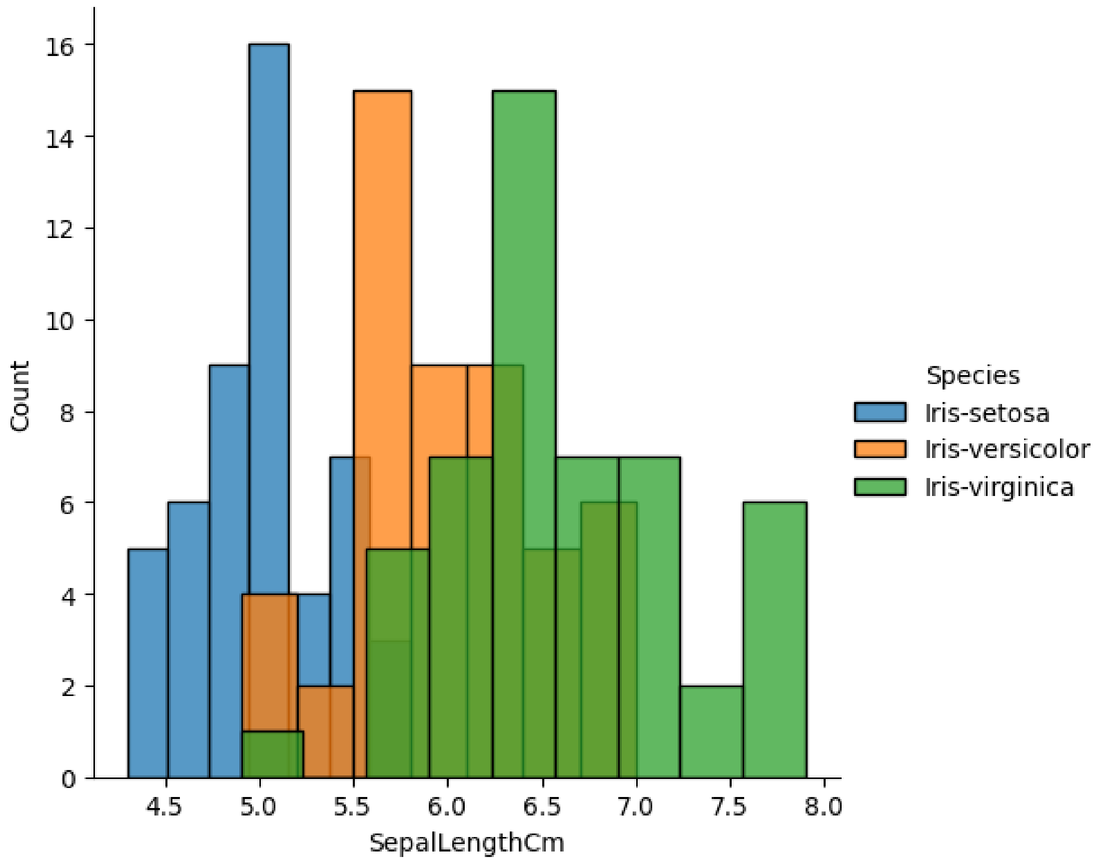
[15]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalLengthCm').
    ↪add_legend();
plt.show();
```



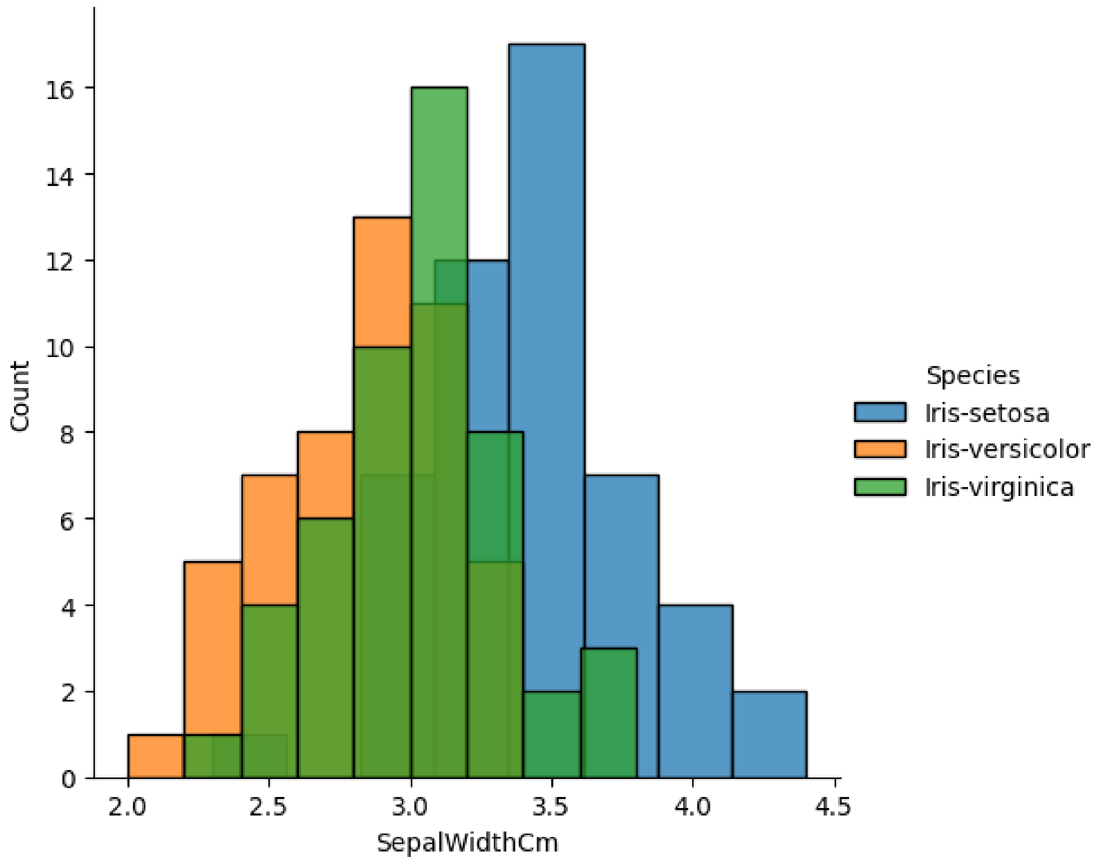
[16]:
```
sns.FacetGrid(data,hue='Species',height=5).map(sns.histplot,'PetalWidthCm').
  ↪add_legend();
plt.show();
```



[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();
```



Experiment 1b- Pandas Buit in function. Numpy Buit in fuction- Array slicing,

[20]:
```
import numpy as np
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]])

Experiment 2- Outlier detection

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

[34]:
```
array([37, 15, 49, 89, 30, 47,  2, 86, 53, 63, 41, 46, 42, 27,  5, 97])
```

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

[35]:
```
45.5625
```

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

[36]:
```
29.25
```

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

[37]:
```
44.0
```

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

[38]:
```
55.5
```

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

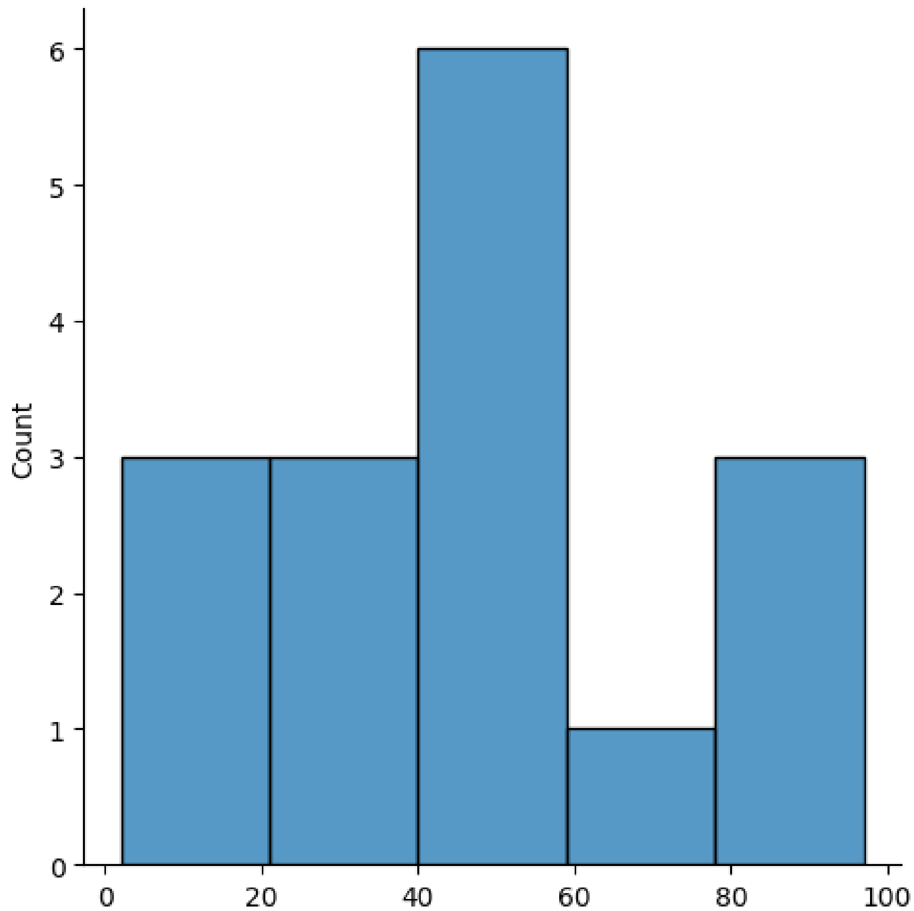
[39]:
```
97.0
```

[40]:
```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
```

[40]:
```
(-10.125, 94.875)
```

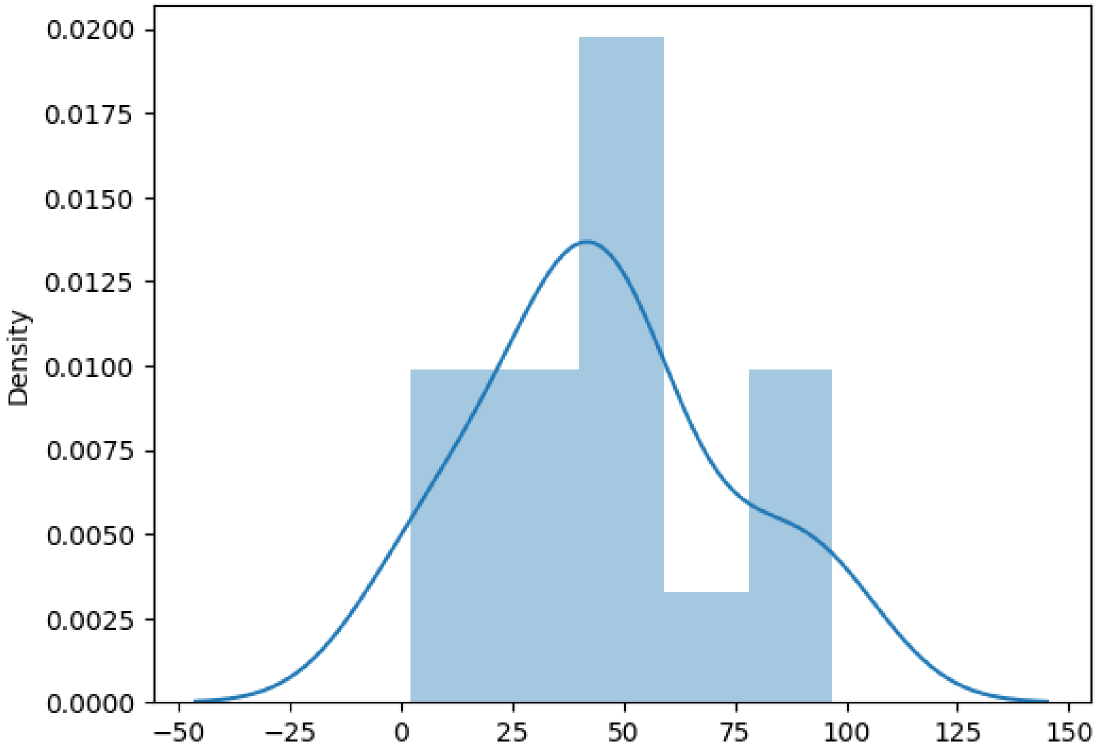
[41]:
```
import seaborn as sns
%matplotlib inline
sns.displot(array)
```

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



[42]:
```
sns.distplot(array)
```

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

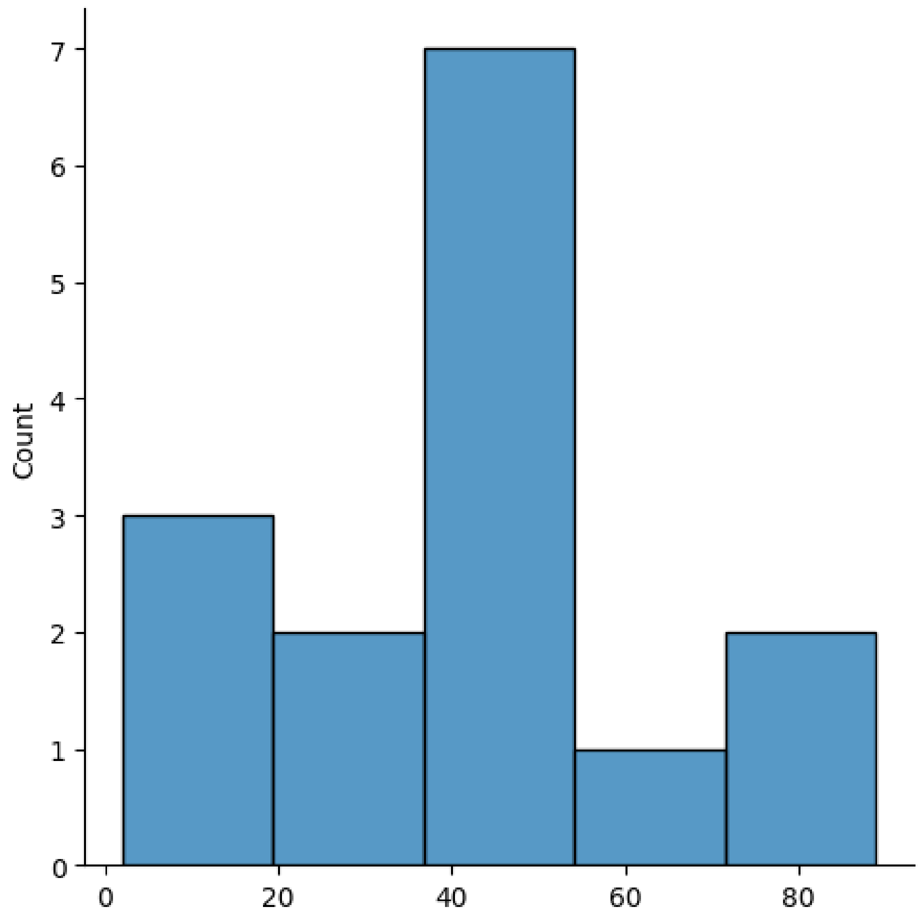


[43]:
```
new_array=array[(array>lr) & (array<ur)]
new_array
```

[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
```

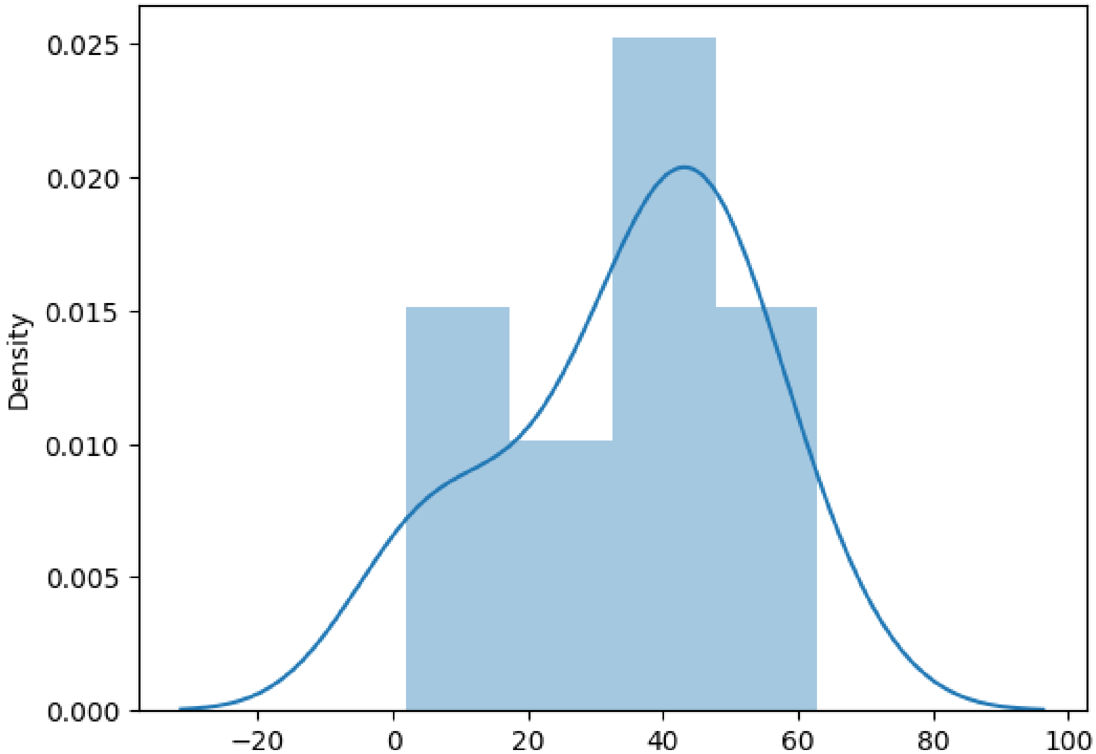
[45]: (-5.25, 84.75)

[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'>



Experiment 3 - Missing and inappropriate data

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

[49]:
```
   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
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
---  ------           --------------  -----
 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
```

[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.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
```

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

[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]:
```
   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
```

Experiment 4- Data Preprocessing

[65]:

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

[65]:

	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

[66]:

```
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
```

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

[67]:
```
0    France
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
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
```

[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
---  ------     --------------  -----
 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
```

[74]:
```
updated_dataset.Purchased.replace(['No','Yes'],[0,1],inplace=True)
```

Experiment 5- EDA-Quantitative and Qualitative plots

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

[76]:

	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
```

[77]:
```python
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
```

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

[78]:
```
0    France
Name: Country, dtype: object
```

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

[79]: 'France'

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

[80]: pandas.core.series.Series

[81]:
```python
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
---  ------     --------------  -----
 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
```

[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

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

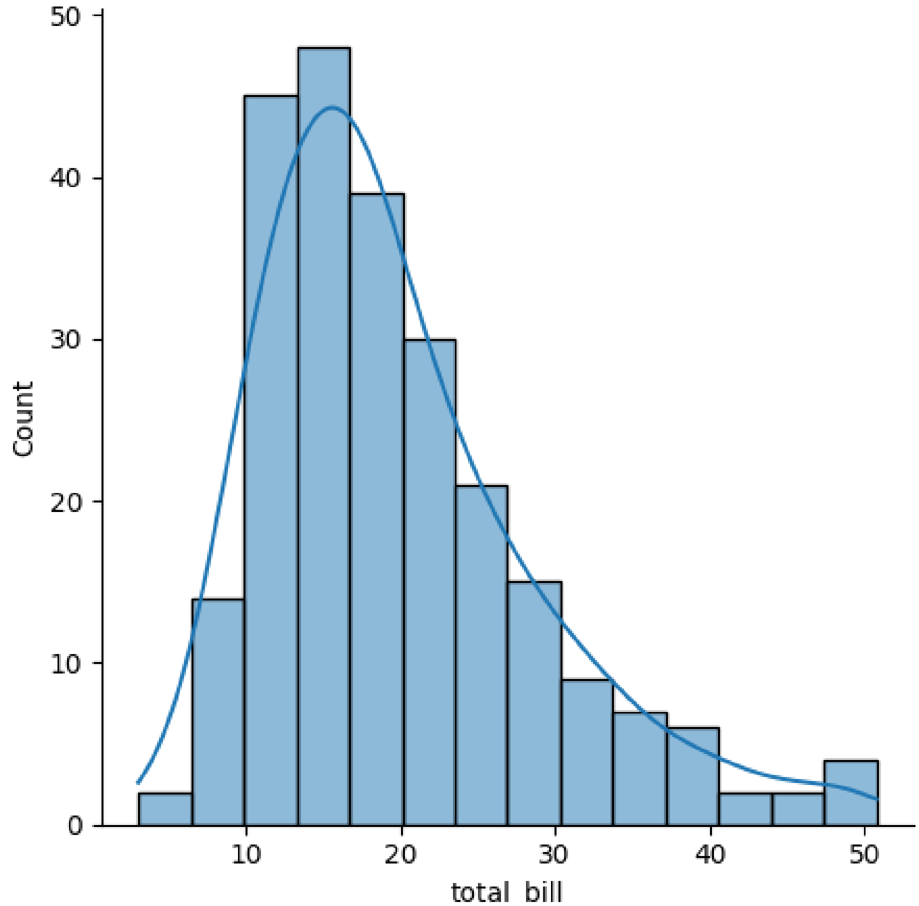
[88]:
```
tips=sns.load_dataset('tips')
tips.head()
```

[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

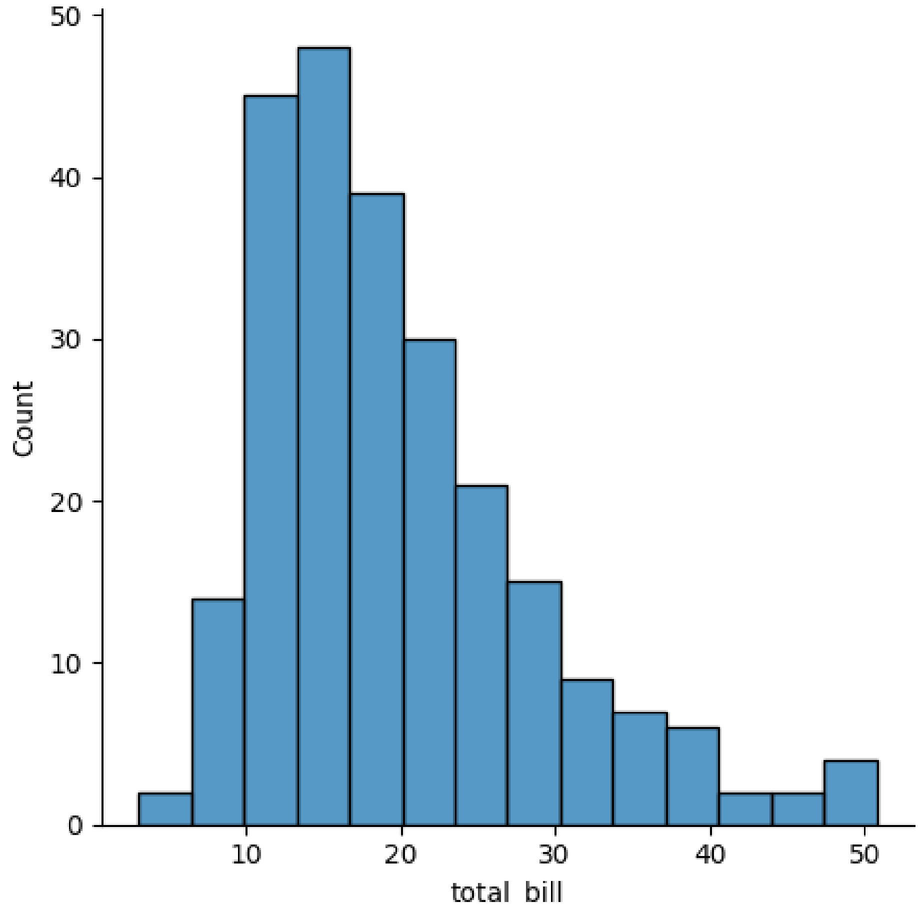
[89]:
```
sns.displot(tips.total_bill,kde=True)
```

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



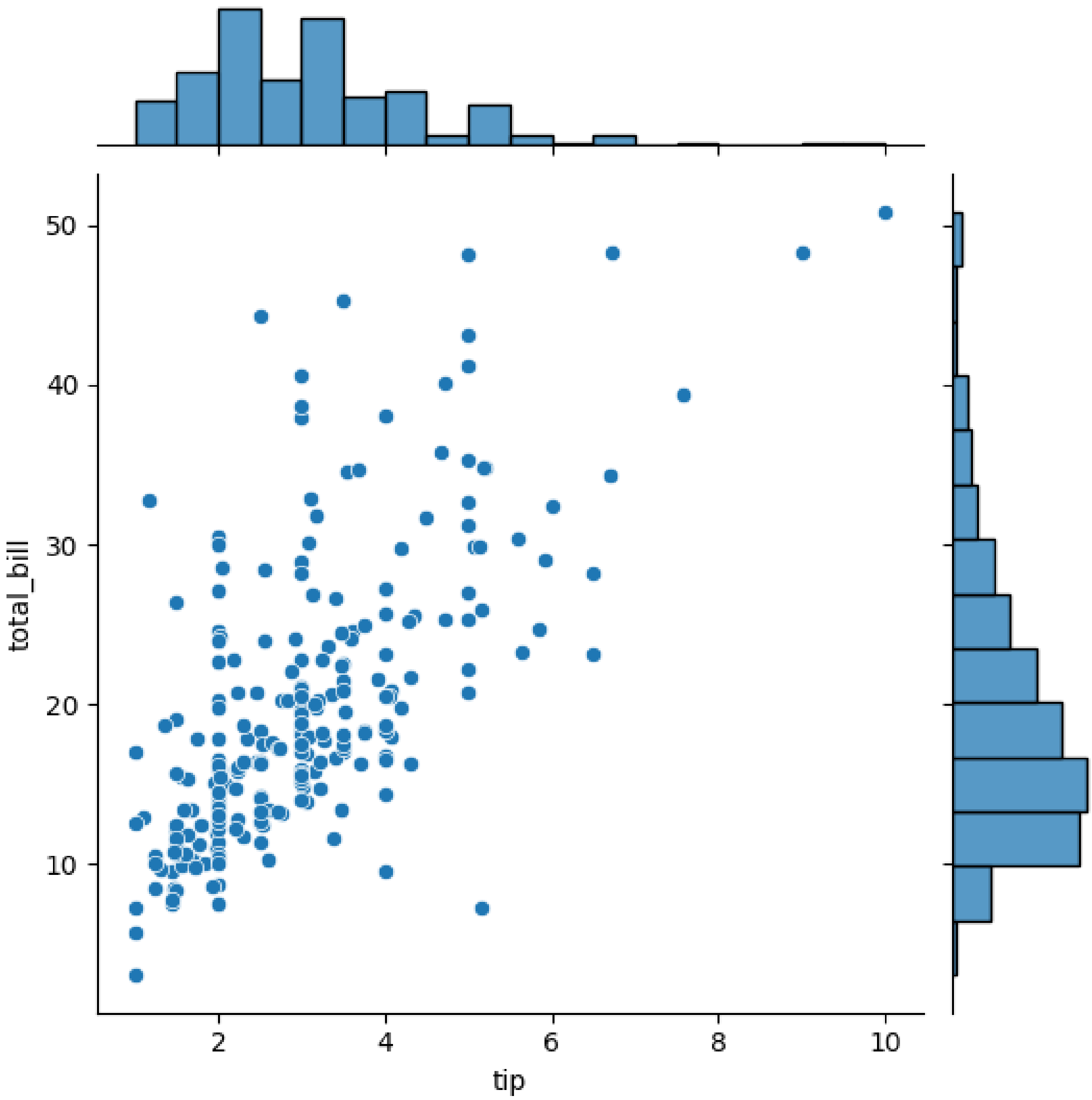
[90]:
```
sns.displot(tips.total_bill,kde=False)
```

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



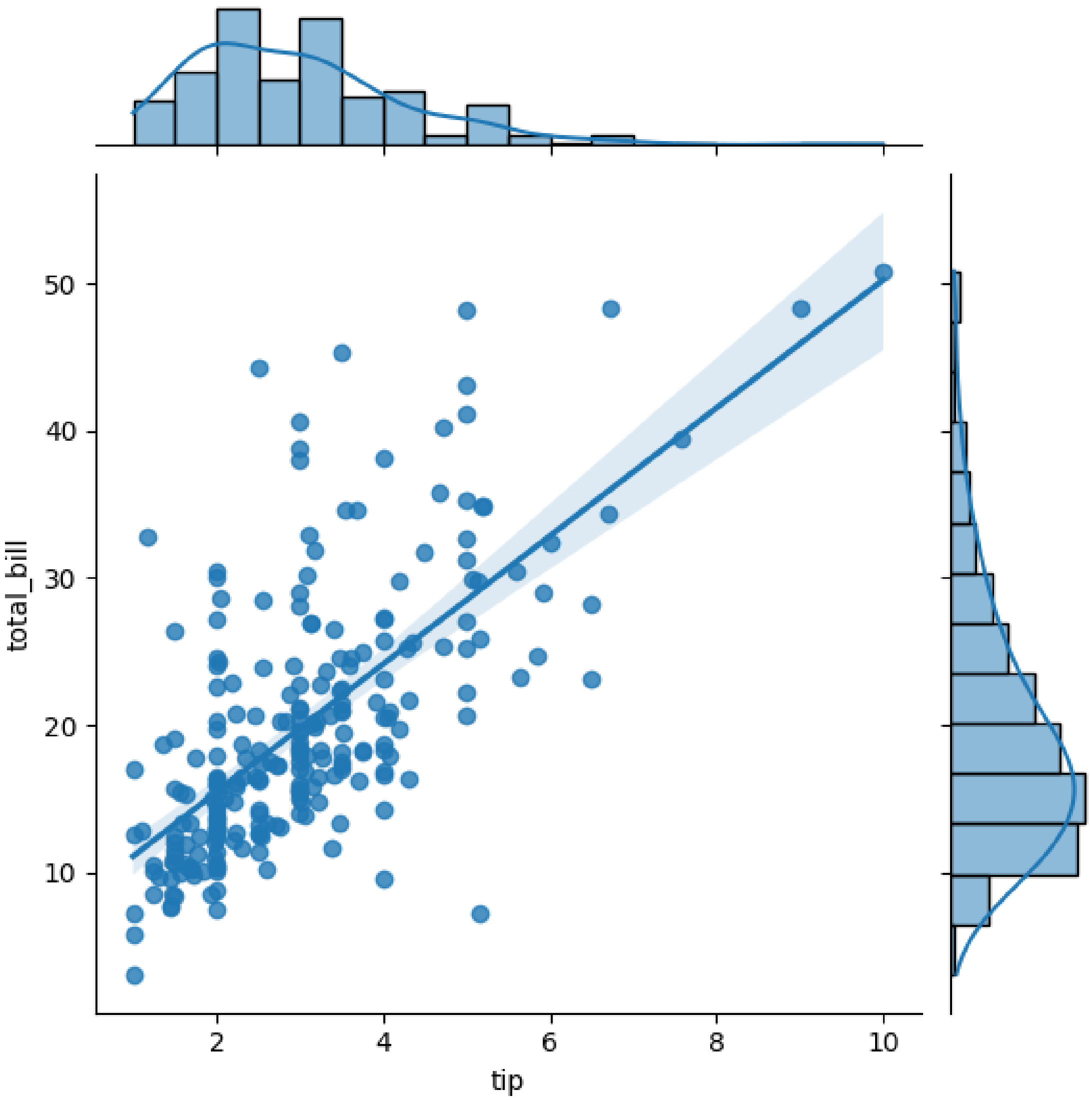
[91]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill)
```

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



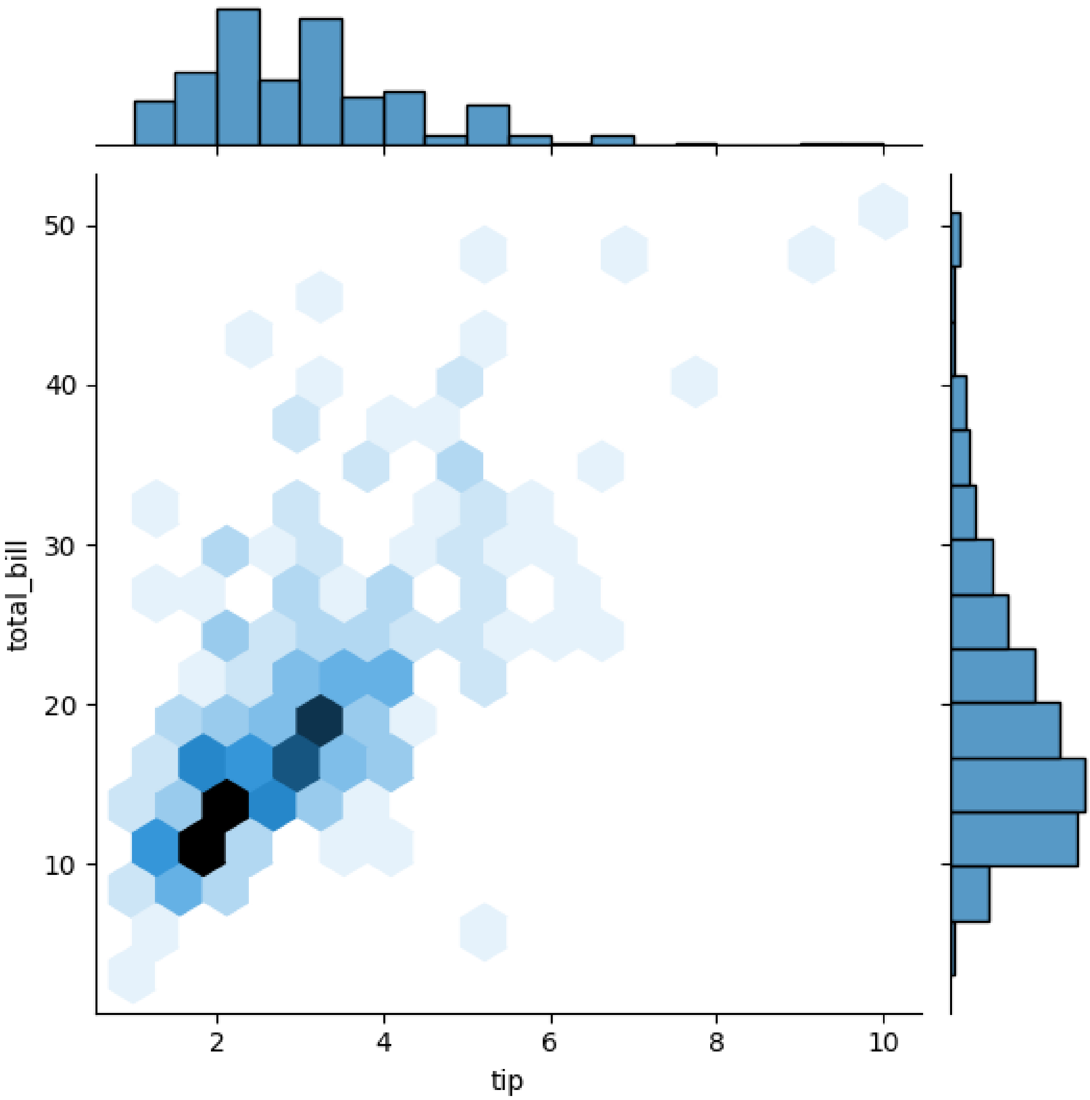
[92]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="reg")
```

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



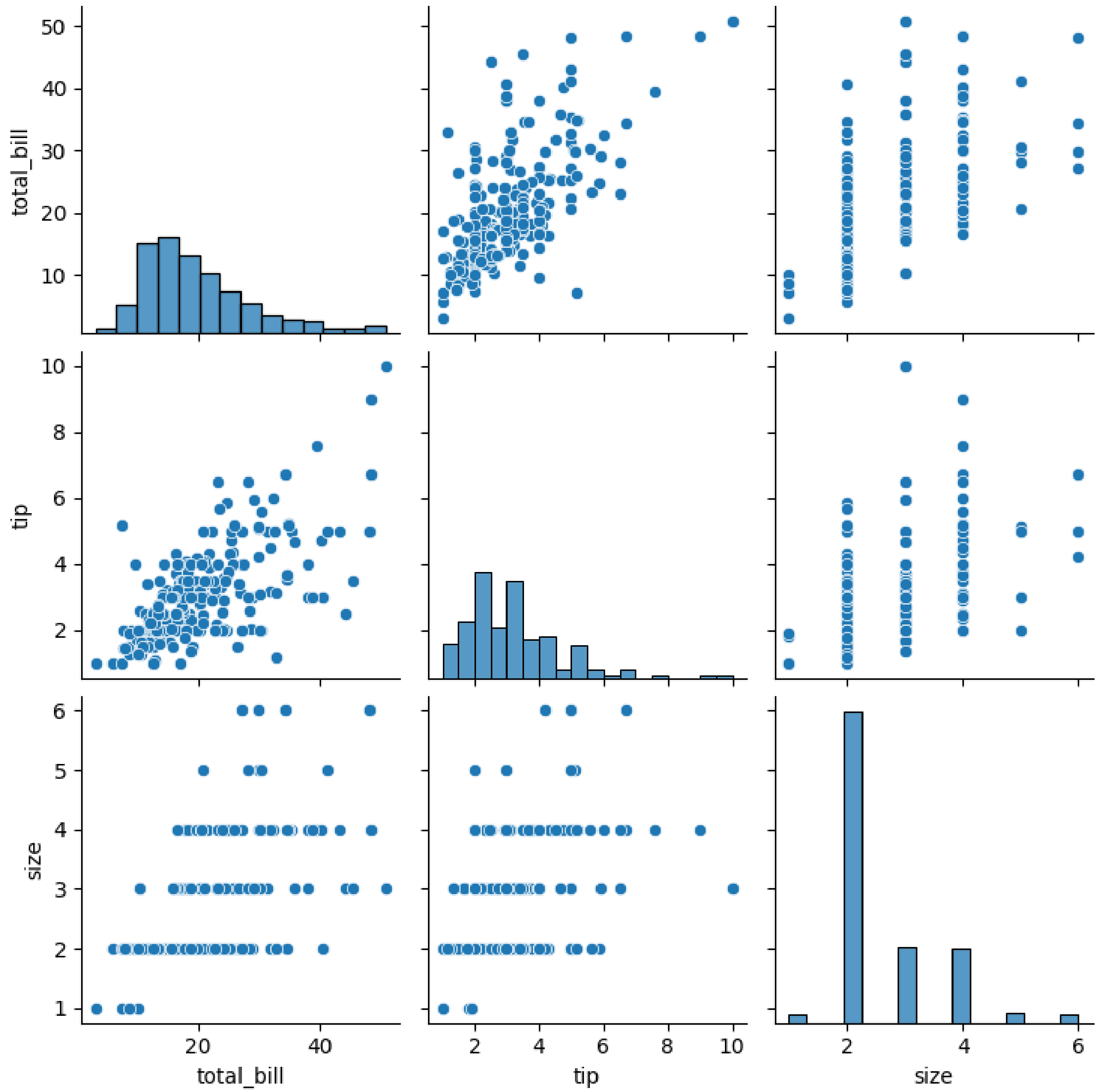
[93]:
```
sns.jointplot(x=tips.tip,y=tips.total_bill,kind="hex")
```

[93]: <seaborn.axisgrid.JointGrid at 0x20d7ed7d350>




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

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

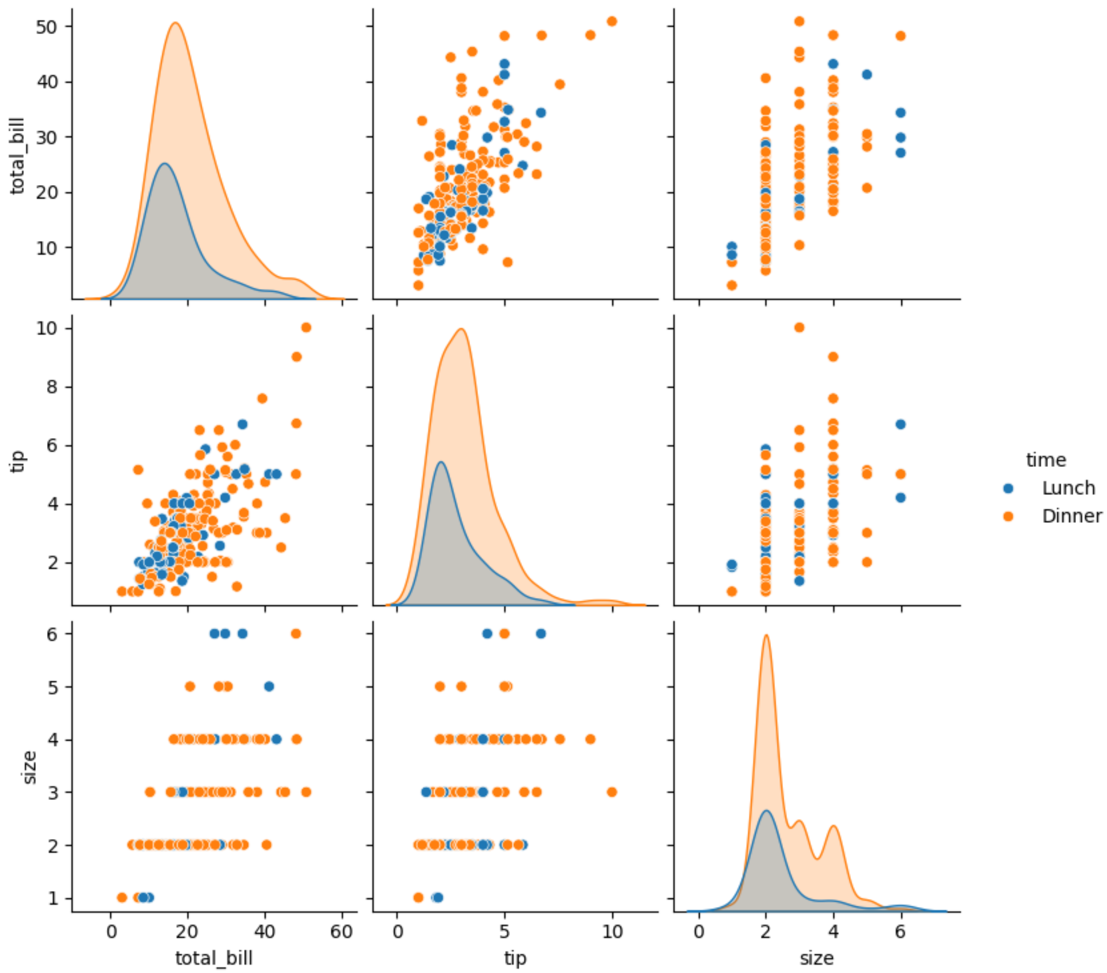


[95]:
```
tips.time.value_counts()
```

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

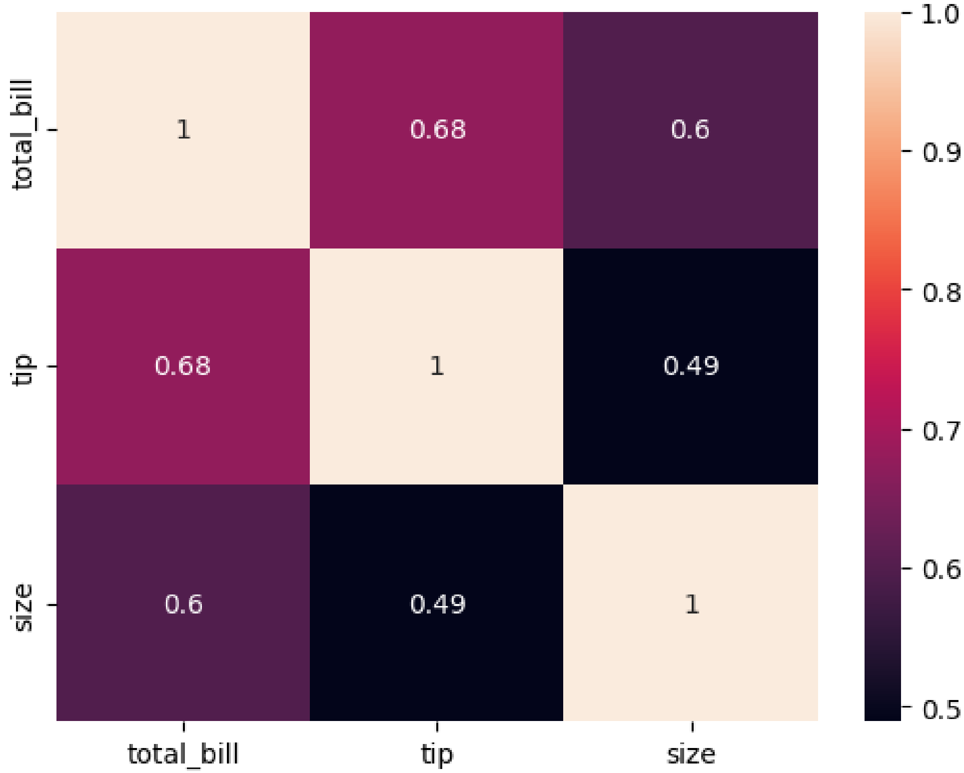
[96]:
```
sns.pairplot(tips,hue='time')
```

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



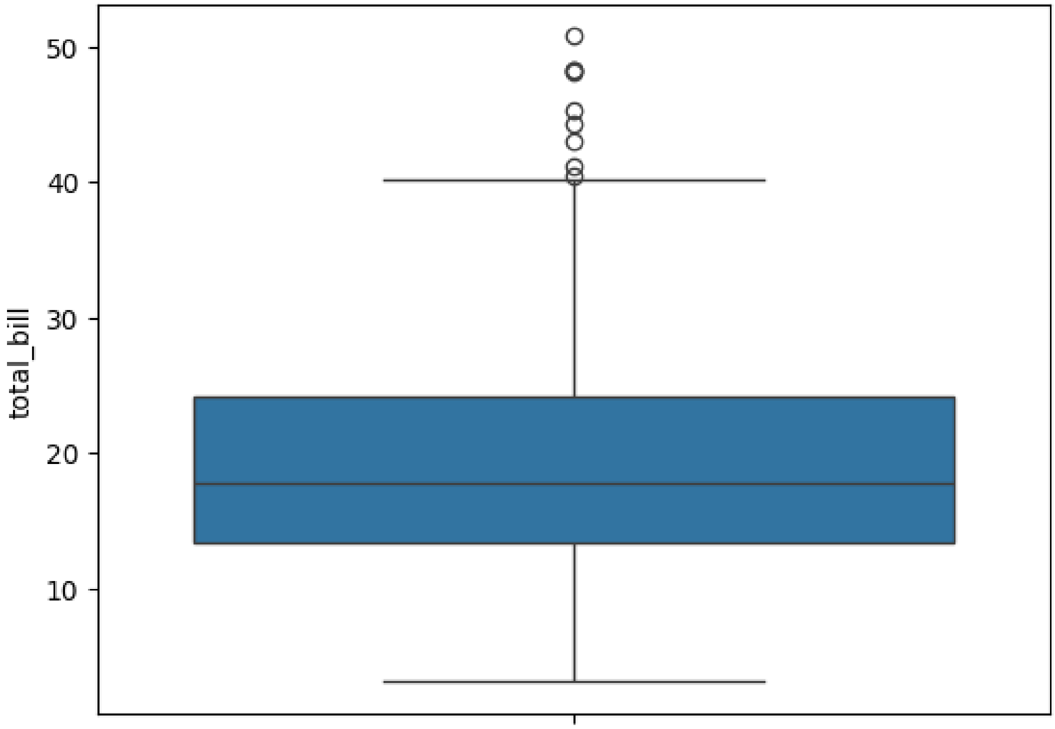

```
[97]: sns.heatmap(tips.corr(numeric_only=True),annot=True)
```

[97]: <Axes: >



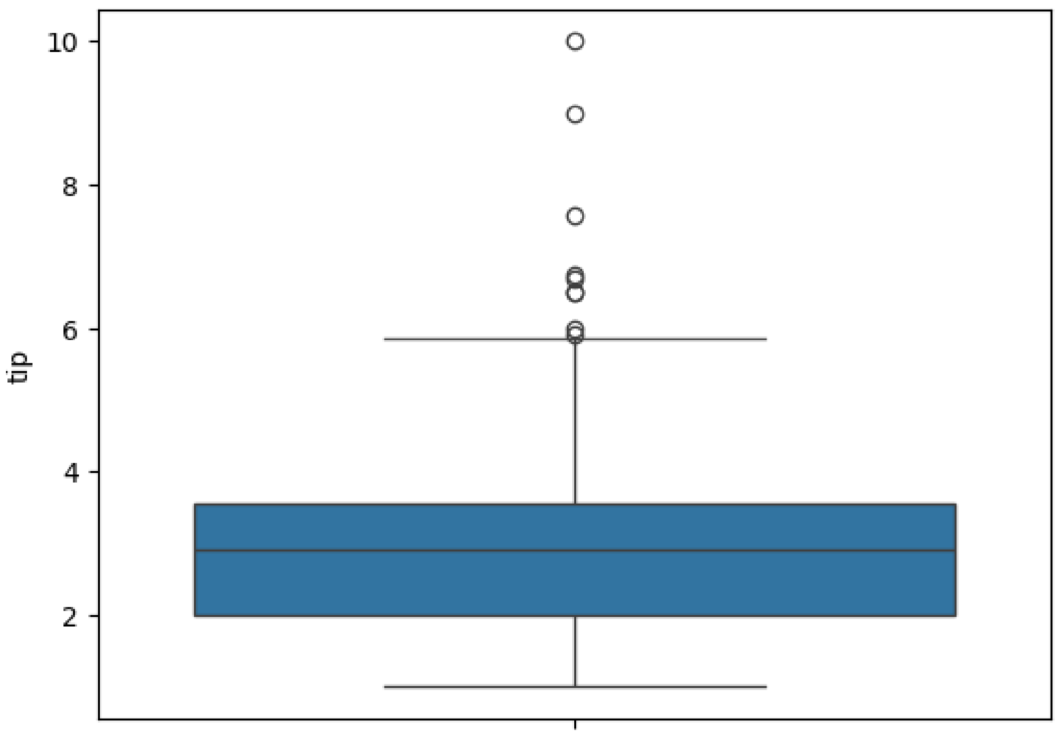
[98]:
```
sns.boxplot(tips.total_bill)
```

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



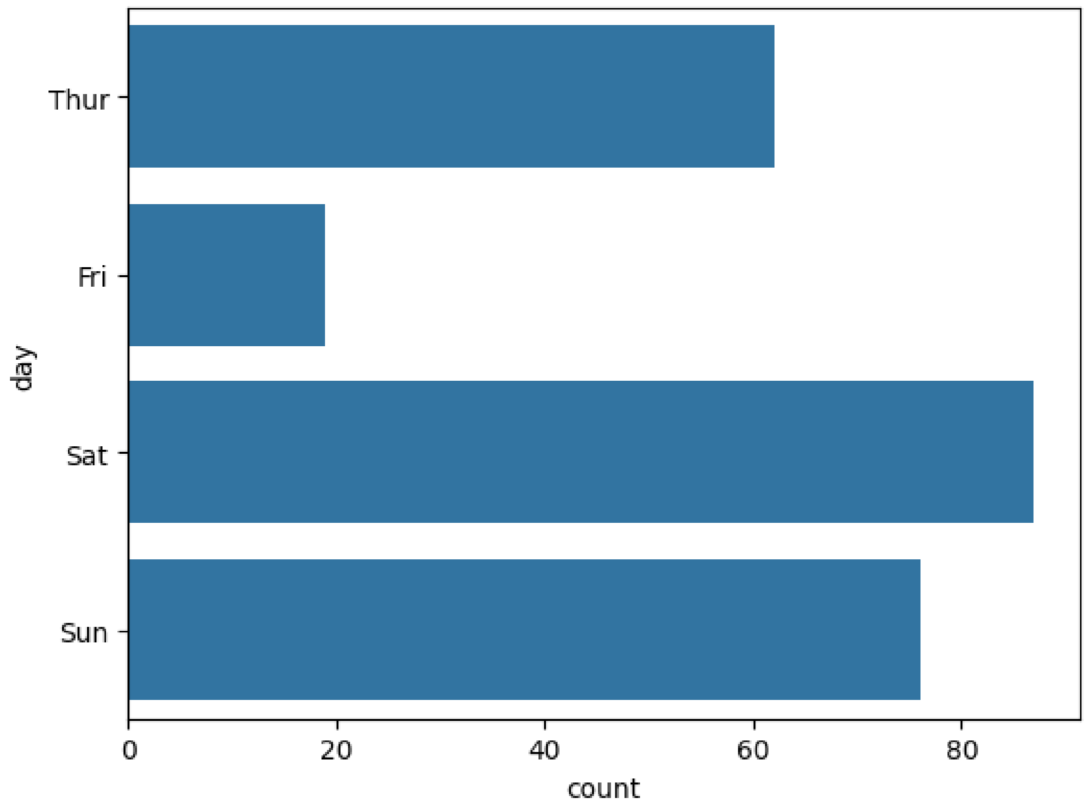
[99]:
```
sns.boxplot(tips.tip)
```

[99]: <Axes: ylabel='tip'>



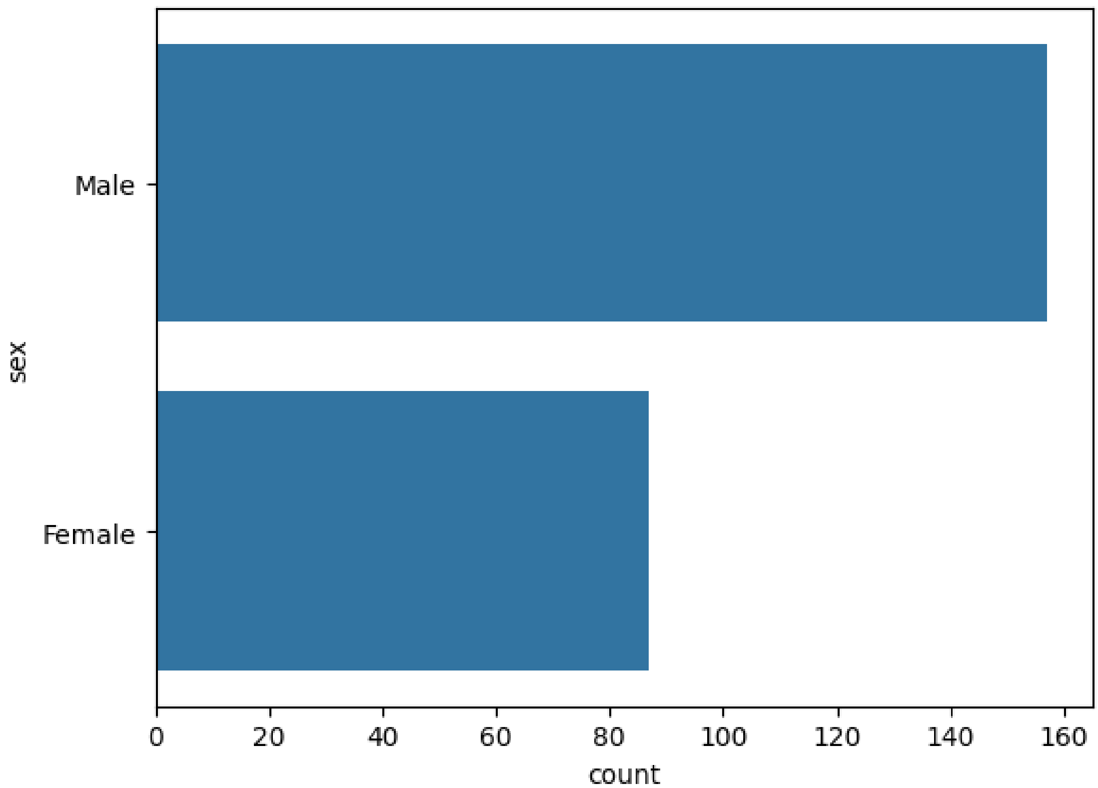
[100]:
```
sns.countplot(tips.day)
```

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



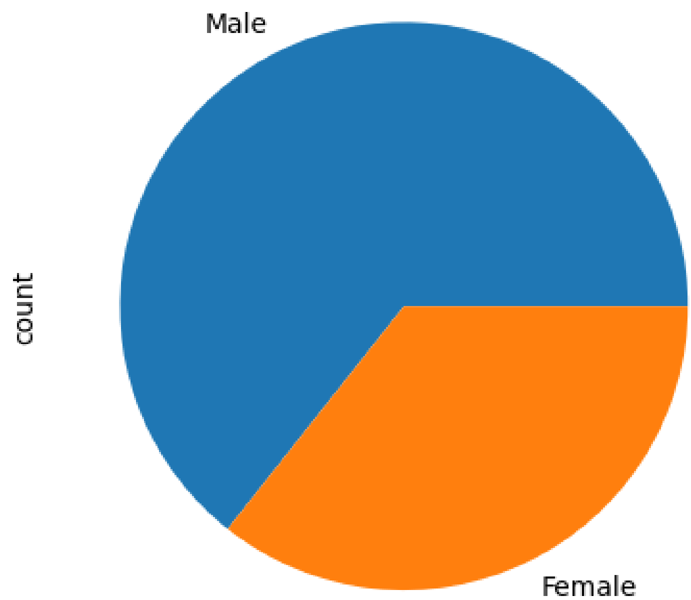
[101]:
```
sns.countplot(tips.sex)
```

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



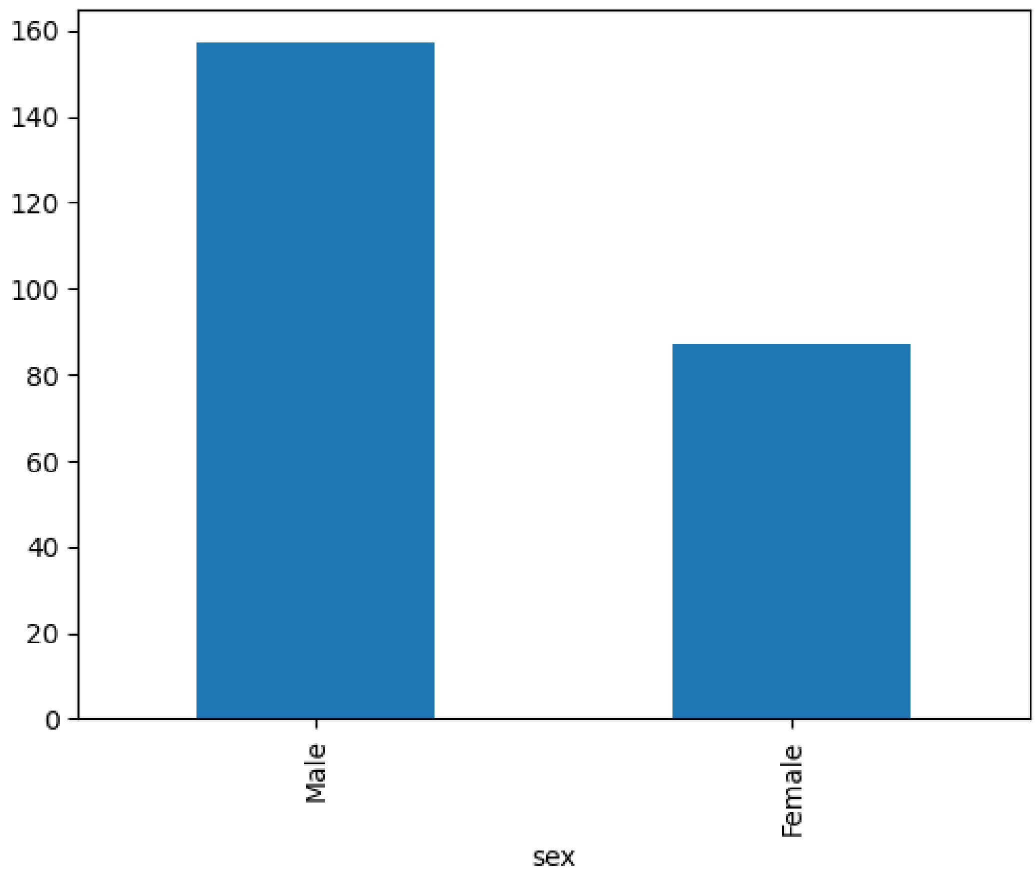
[102]:
```
tips.sex.value_counts().plot(kind='pie')
```

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



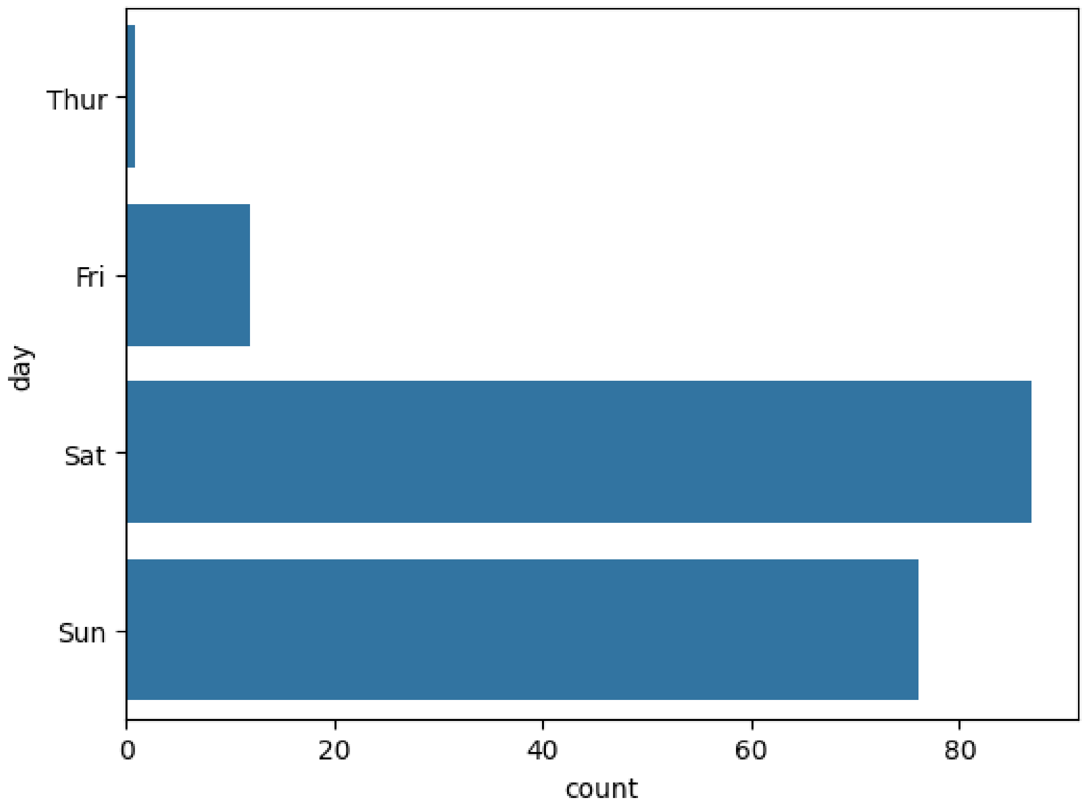

```
[103]: tips.sex.value_counts().plot(kind='bar')
```

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




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

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



Experiment- 6 - Random Sampling and Sampling Distribution

[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] = []
```

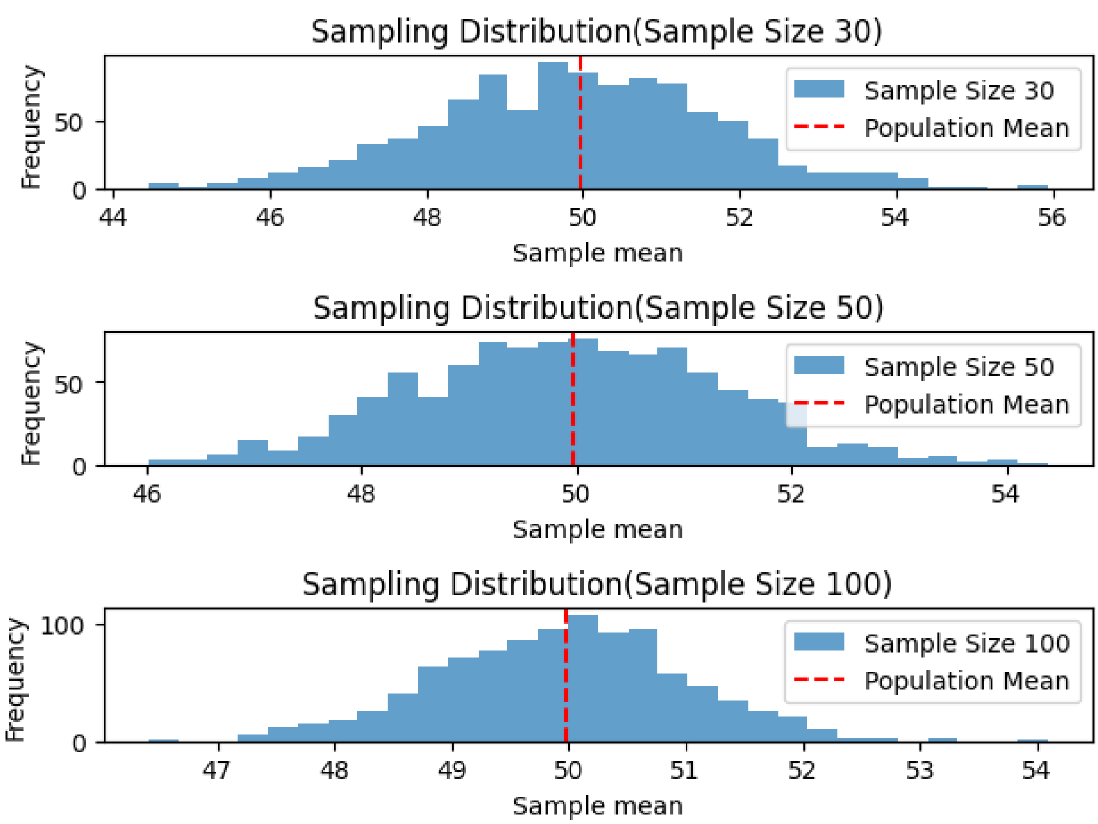
```
    for _ in range(num_samples):
        sample = np.random.choice(population, size=size, replace=False)
        sample_means[size].append(np.mean(sample))
```

[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()
```



Experiment-7- Z-Test

[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.")
```

```
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.
```

Experiment 8: T-Test

```
[119]: 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)
```

```
[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.")
```

```
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.
```

EX.NO :9 Annova TEST

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

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

[125]:
```python
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]:
```python
all_data = np.concatenate([growth_A, growth_B, growth_C])
```

[127]:
```python
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]:
```python
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
---------------------------------------------------
```

EX.NO :10 Feature Scaling

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

[131]:
```python
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]:
```python
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 OneHotEncoder
oh = 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.],
       [1., 0., 0.]])
```

[139]:
```
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]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(final_set)
feat_standard_scaler=sc.transform(final_set)
```

[141]:
```
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]:
```
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]])
```

EX.NO :11 Linear Regression

[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]:
```python
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
```

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

[146]:
```
    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
```

[147]:

```
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
```

[148]:

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

[148]:

	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

[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],
       [121872]], dtype=int64)
```

[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]:
```
'\ny is depenent ouput\n0.2 allocate test for 20 % automatically train for 80
%\n'
```

[152]:
```
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
'''
```

[152]:
```
'\nsk - size kit \nlinear means using linear regression \nfit means add data \n'
```

[153]:
```
model.score(x_train,y_train)
'''
accuracy calculating
96 %
```

```
'''
```

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

[154]:
```
model.score(x_test,y_test)
'''
accuracy calculating
91 %
'''
```

[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]: '\npickle momory obj to file\n\n'

[158]:
```
model = pickle.load(open('SalaryPred.model','rb'))
```

[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))
```

```
Enter years of expreience:  24
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

[162]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('Social_Network_Ads.csv.csv')
df
```

[162]:

	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 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]].values
label = 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],
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[    41,  72000],
[    51, 146000],
```

```
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[    36, 144000],
[    55, 125000],
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[    48,  90000],
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[    37,  78000],
[    39, 134000],
[    49,  89000],
[    55,  39000],
```

```
[     37,  77000],
[     35,  57000],
[     36,  63000],
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[     43, 112000],
[     45,  79000],
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[     48,  74000],
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[     40,  60000],
[     42,  54000],
[     51, 134000],
[     47, 113000],
[     36, 125000],
[     38,  50000],
[     42,  70000],
[     39,  96000],
[     38,  50000],
[     49, 141000],
[     39,  79000],
[     39,  75000],
[     54, 104000],
[     35,  55000],
[     45,  32000],
[     36,  60000],
[     52, 138000],
[     53,  82000],
[     41,  52000],
[     48,  30000],
[     48, 131000],
[     41,  60000],
[     41,  72000],
[     42,  75000],
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[     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],
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[    37,  57000],
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[    41,  72000],
[    40,  71000],
[    42,  54000],
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[    58,  47000],
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[    38,  71000],
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[    60,  46000],
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[    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],
```

```
       [    39,  71000],
       [    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]:
```
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]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

[168]:
```
# 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
```