Machine Learning:

Machine Learning Procedure:-

- Dataset Reading and Studying
- Data Cleaning and Analysis
- Data Visualization or EDA (Exploratory Data Analysis)
- Encoding (converting of string columns to integer columns)
- ip/op Creation (separating input data and output/target data)
- Train Test Split (separate the training data and testing data)
- Standard Scaler Transform (standardizing all the input datas)
- Machine Learning Algorithm
- Prediction
- Accuracy

Regression Model:-

Linear Regression:-

In [1]:
```
# Importing the packages:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Reading the Dataset:-
adv = pd.read_csv(r"C:\Users\lab25\Downloads\archive (9)\advertising.csv")
adv
```

Out[2]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9
...	...	...	...	...
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	18.4

200 rows × 4 columns

In [3]:
```
# Data Cleaning:-
# Checking null values:
adv.isnull().sum()
```

Out[3]:
```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

In [4]:
```
# checking the datatypes:
adv.dtypes
```

Out[4]:
```
TV           float64
Radio        float64
Newspaper    float64
Sales        float64
dtype: object
```

In [5]:
```
# checking the unique values:
for i in adv.columns:
    print(f"{i}:\n {adv[i].unique()}\n")
```

```
TV:
 [230.1  44.5  17.2 151.5 180.8   8.7  57.5 120.2   8.6 199.8  66.1 214.7
  23.8  97.5 204.1 195.4  67.8 281.4  69.2 147.3 218.4 237.4  13.2 228.3
  62.3 262.9 142.9 240.1 248.8  70.6 292.9 112.9  97.2 265.6  95.7 290.7
 266.9  74.7  43.1 228.  202.5 177.  293.6 206.9  25.1 175.1  89.7 239.9
 227.2  66.9 100.4 216.4 182.6 262.7 198.9   7.3 136.2 210.8 210.7  53.5
 261.3 239.3 102.7 131.1  69.   31.5 139.3 216.8 199.1 109.8  26.8 129.4
 213.4  16.9  27.5 120.5   5.4 116.   76.4 239.8  75.3  68.4 213.5 193.2
  76.3 110.7  88.3 134.3  28.6 217.7 250.9 107.4 163.3 197.6 184.9 289.7
 135.2 222.4 296.4 280.2 187.9 238.2 137.9  25.   90.4  13.1 255.4 225.8
 241.7 175.7 209.6  78.2  75.1 139.2 125.7  19.4 141.3  18.8 224.  123.1
 229.5  87.2   7.8  80.2 220.3  59.6   0.7 265.2   8.4 219.8  36.9  48.3
  25.6 273.7  43.   73.4 193.7 220.5 104.6  96.2 140.3 243.2  38.   44.7
 280.7 121.  171.3 187.8   4.1  93.9 149.8  11.7 131.7 172.5  85.7 188.4
 163.5 117.2 234.5  17.9 206.8 215.4 284.3  50.  164.5  19.6 168.4 276.9
 248.4 170.2 276.7 165.6 156.6 218.5  56.2 287.6 253.8 205.  139.5 191.1
 286.   18.7  39.5  75.5 166.8 149.7  38.2  94.2 283.6 232.1]

Radio:
 [37.8 39.3 45.9 41.3 10.8 48.9 32.8 19.6  2.1  2.6  5.8 24.  35.1  7.6
 32.9 47.7 36.6 39.6 20.5 23.9 27.7  5.1 15.9 16.9 12.6  3.5 29.3 16.7
 27.1 16.  28.3 17.4  1.5 20.   1.4  4.1 43.8 49.4 26.7 37.7 22.3 33.4
  8.4 25.7 22.5  9.9 41.5 15.8 11.7  3.1  9.6 41.7 46.2 28.8 28.1 19.2
 49.6 29.5  2.  42.7 15.5 29.6 42.8  9.3 24.6 14.5 27.5 43.9 30.6 14.3
 33.   5.7 43.7  1.6 28.5 29.9  7.7 20.3 44.5 43.  18.4 40.6 25.5 47.8
  4.9 33.5 36.5 14.  31.6 21.  42.3  4.3 36.3 10.1 17.2 34.3 46.4 11.
  0.3  0.4 26.9  8.2 38.  15.4 20.6 46.8 35.   0.8 36.9 26.8 21.7  2.4
 34.6 32.3 11.8 38.9  0.  49.  12.   2.9 27.2 38.6 47.  39.  28.9 25.9
 17.  35.4 33.2 14.8  1.9  7.3 40.3 25.8 13.9 23.3 39.7 21.1 11.6 43.5
  1.3 18.1 35.8 36.8 14.7  3.4 37.6  5.2 23.6 10.6 20.9 20.1  7.1 30.2
  7.8  2.3 10.   5.4 21.3 45.1 28.7 12.1 41.1 42.  35.6  3.7  8.6]

Newspaper:
 [ 69.2  45.1  69.3  58.5  58.4  75.   23.5  11.6   1.   21.2  24.2   4.
  65.9   7.2  46.   52.9 114.   55.8  18.3  19.1  53.4  49.6  26.2  19.5
  12.6  22.9  40.8  43.2  38.6  30.    0.3   7.4   8.5   5.   45.7  35.1
  32.   31.6  38.7   1.8  26.4  43.3  31.5  35.7  18.5  49.9  36.8  34.6
   3.6  39.6  58.7  15.9  60.   41.4  16.6  37.7   9.3  21.4  54.7  27.3
   8.4  28.9   0.9   2.2  10.2  11.   27.2  31.7  19.3  31.3  13.1  89.4
  20.7  14.2   9.4  23.1  22.3  36.9  32.5  35.6  33.8  65.7  16.   63.2
  73.4  51.4  33.   59.   72.3  10.9   5.9  22.   51.2  45.9  49.8 100.9
  17.9   5.3  29.7  23.2  25.6   5.5  56.5   2.4  10.7  34.5  52.7  14.8
  79.2  46.2  50.4  15.6  12.4  74.2  25.9  50.6   9.2   3.2  43.1   8.7
  43.    2.1  65.6  59.7  20.5   1.7  12.9  75.6  37.9  34.4  38.9   9.
  44.3  11.9  20.6  37.   48.7   9.5   5.7  50.5  24.3  45.2  30.7  49.3
   5.4  84.8  21.6  19.4  57.6   6.4  18.4  47.4  17.   12.8  41.8  20.3
  35.2  23.7  17.6   8.3  27.4  71.8  19.6  26.6  18.2   3.7  23.4   5.8
   6.   13.8   8.1  66.2]

Sales:
 [22.1 10.4 12.  16.5 17.9  7.2 11.8 13.2  4.8 15.6 12.6 17.4  9.2 13.7
 19.  22.4 12.5 24.4 11.3 14.6 18.  17.5  5.6 20.5  9.7 17.  15.  20.9
 18.9 10.5 21.4 11.9 17.8 25.4 14.7 10.1 21.5 16.6 17.1 20.7  8.5 16.1
 10.6 23.2 19.8 16.4 10.7 22.6 21.2 20.2 23.7  5.5 23.8 18.4  8.1 24.2
 14.  16.  11.  13.4 22.3 18.3 12.4  8.8  8.7  6.9 14.2  5.3 17.3 13.6
 21.7 12.9 16.7  7.3 19.4 22.2 11.5 16.9 17.2 19.7 21.8 12.2  9.4 15.9
```

```
  6.6 15.5  7.  15.2 24.7  1.6 17.7  5.7 19.6 10.8 11.6  9.5 20.8  9.6
 10.9 19.2 20.1 12.3 10.3 18.2 20.6  3.2 15.3 13.3 19.9  8.  20.   8.4
  7.6 27.  16.8 17.6 26.2  6.7  5.9 14.8 25.5]
```

In [6]:
```
# to check the information of the dataset:
adv.info()
```

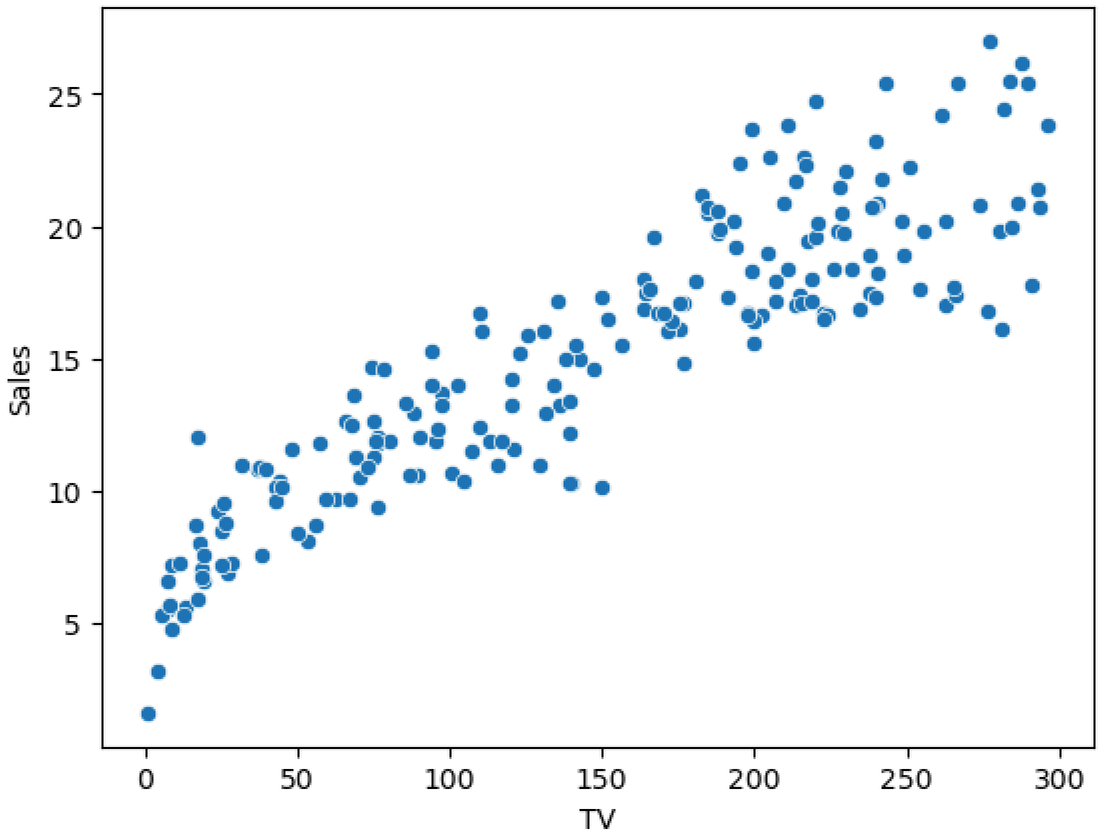
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   TV         200 non-null    float64
 1   Radio      200 non-null    float64
 2   Newspaper  200 non-null    float64
 3   Sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
```

In [7]:
```
# to check the statistical value of all columns:
adv.describe()
```

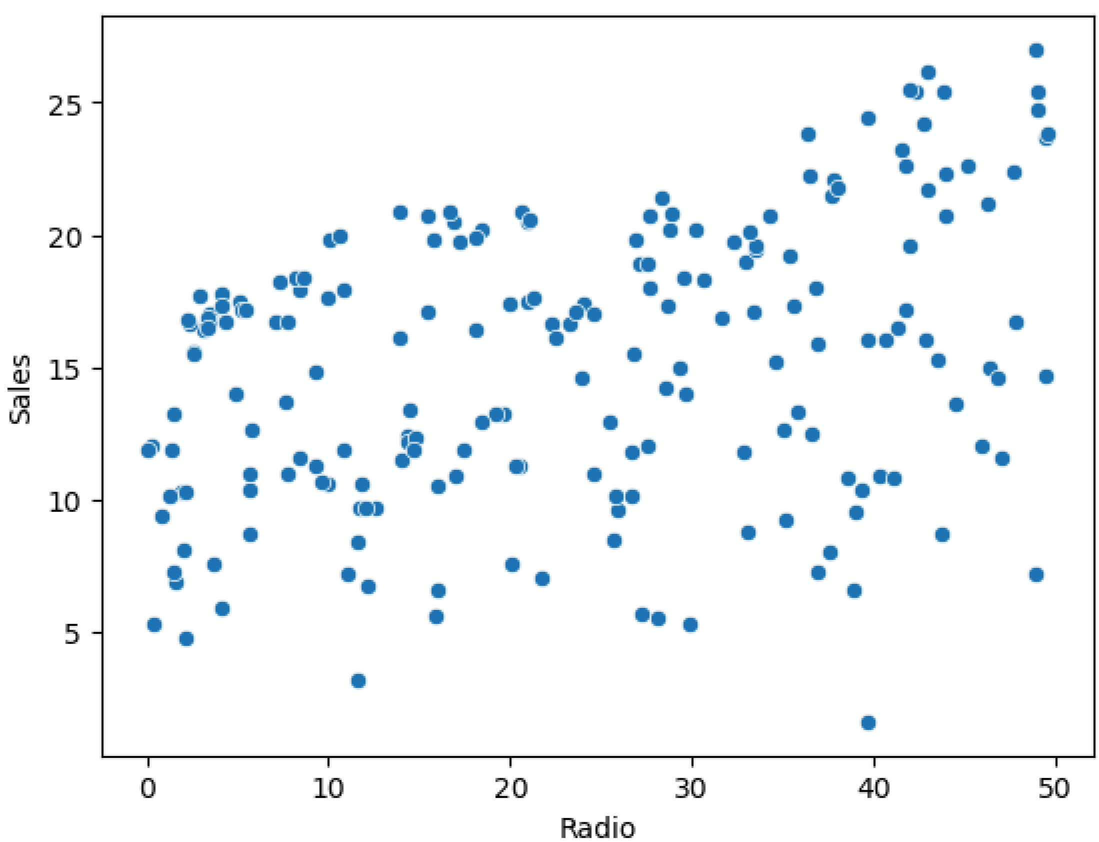
Out[7]:

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

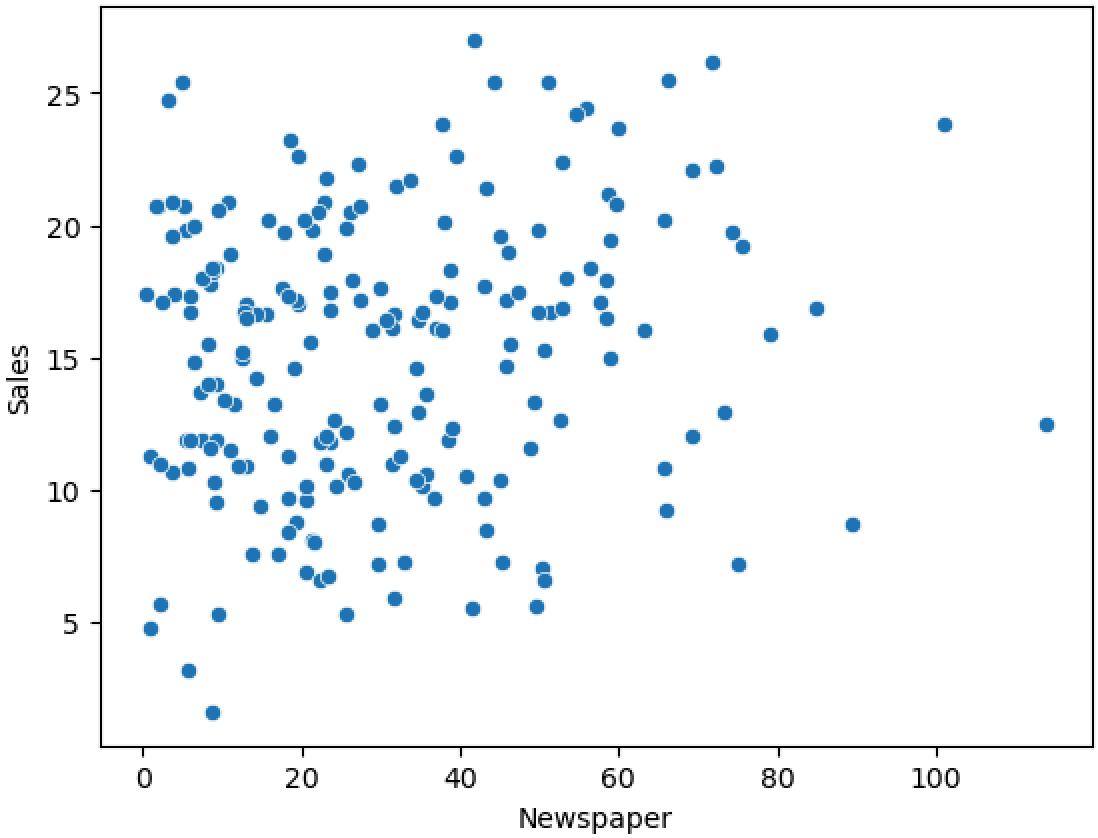
In [8]:
```
# Data Visualization:
sns.scatterplot(x=adv.TV, y=adv.Sales)
plt.show()
```



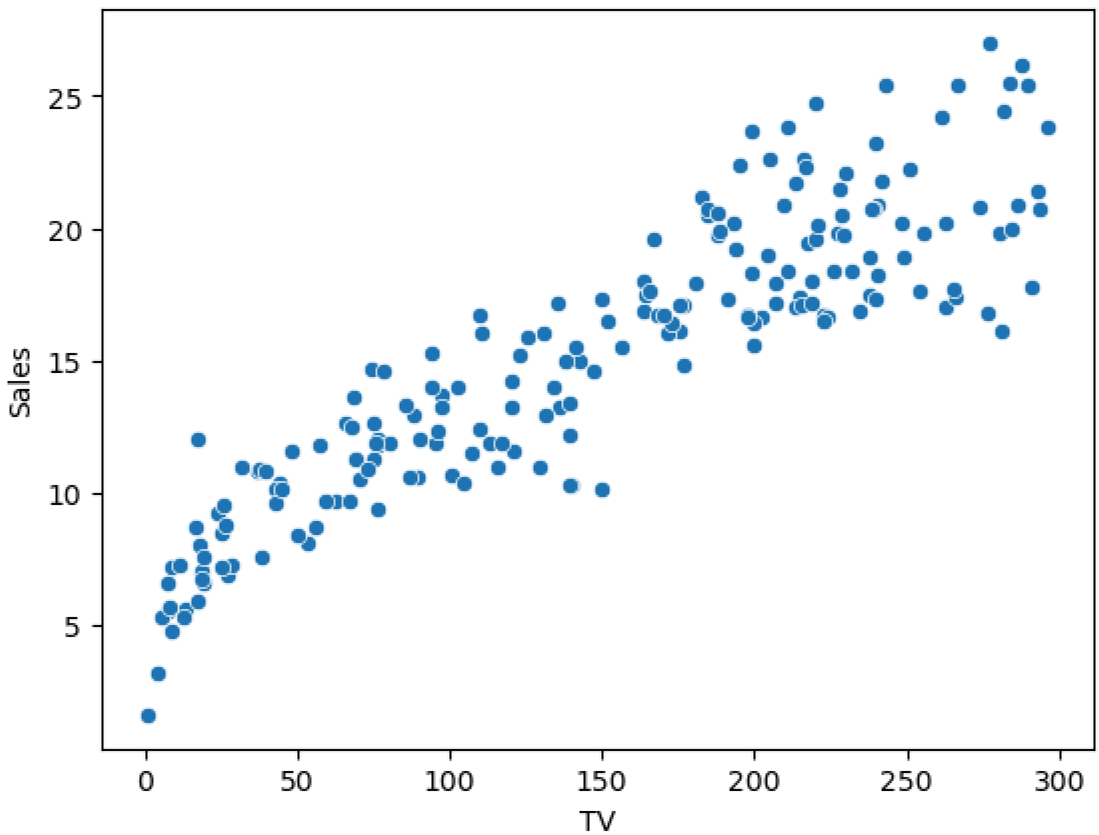
In [9]:
```
sns.scatterplot(x=adv.Radio, y=adv.Sales)
plt.show()
```

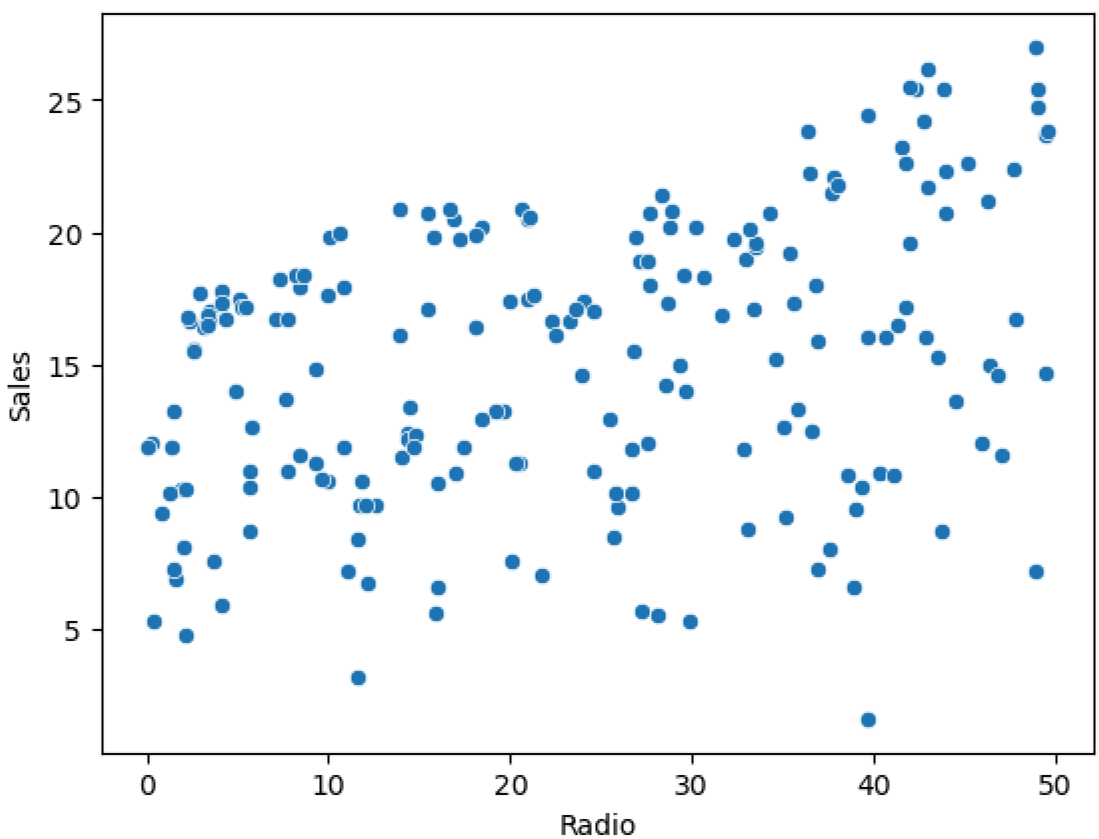


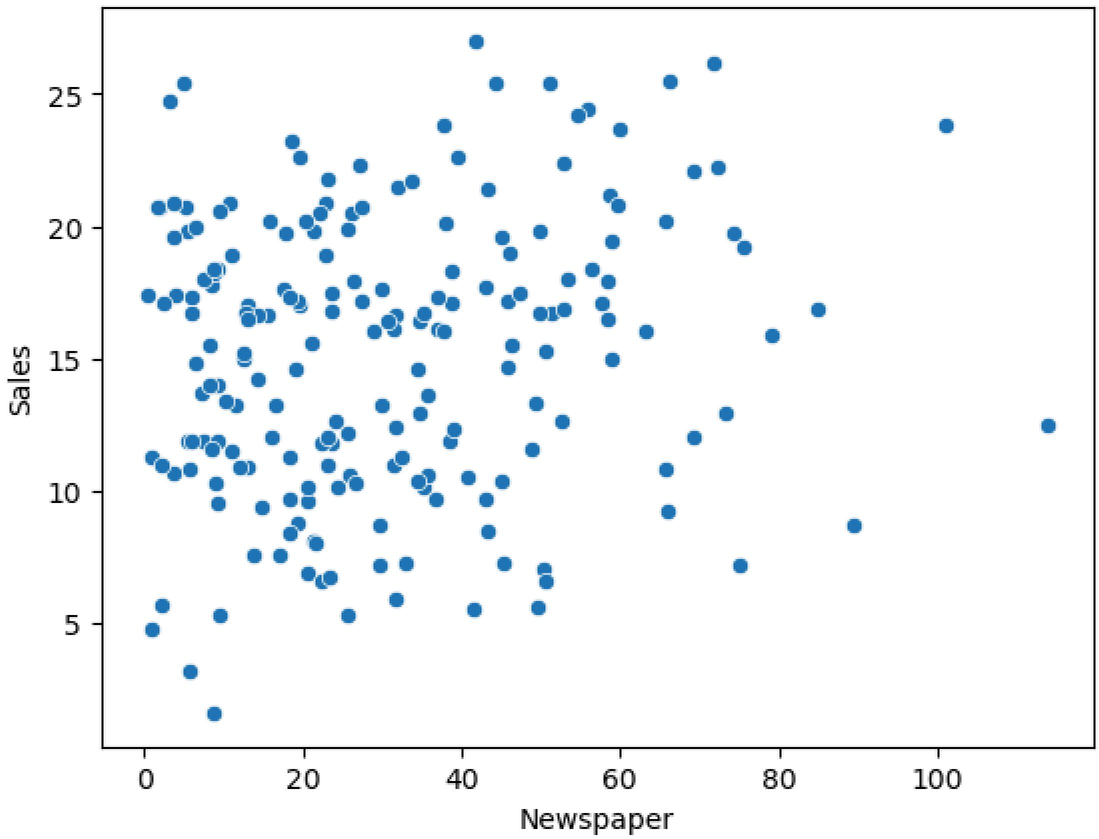
In [10]:
```
sns.scatterplot(x=adv.Newspaper, y=adv.Sales)
plt.show()
```



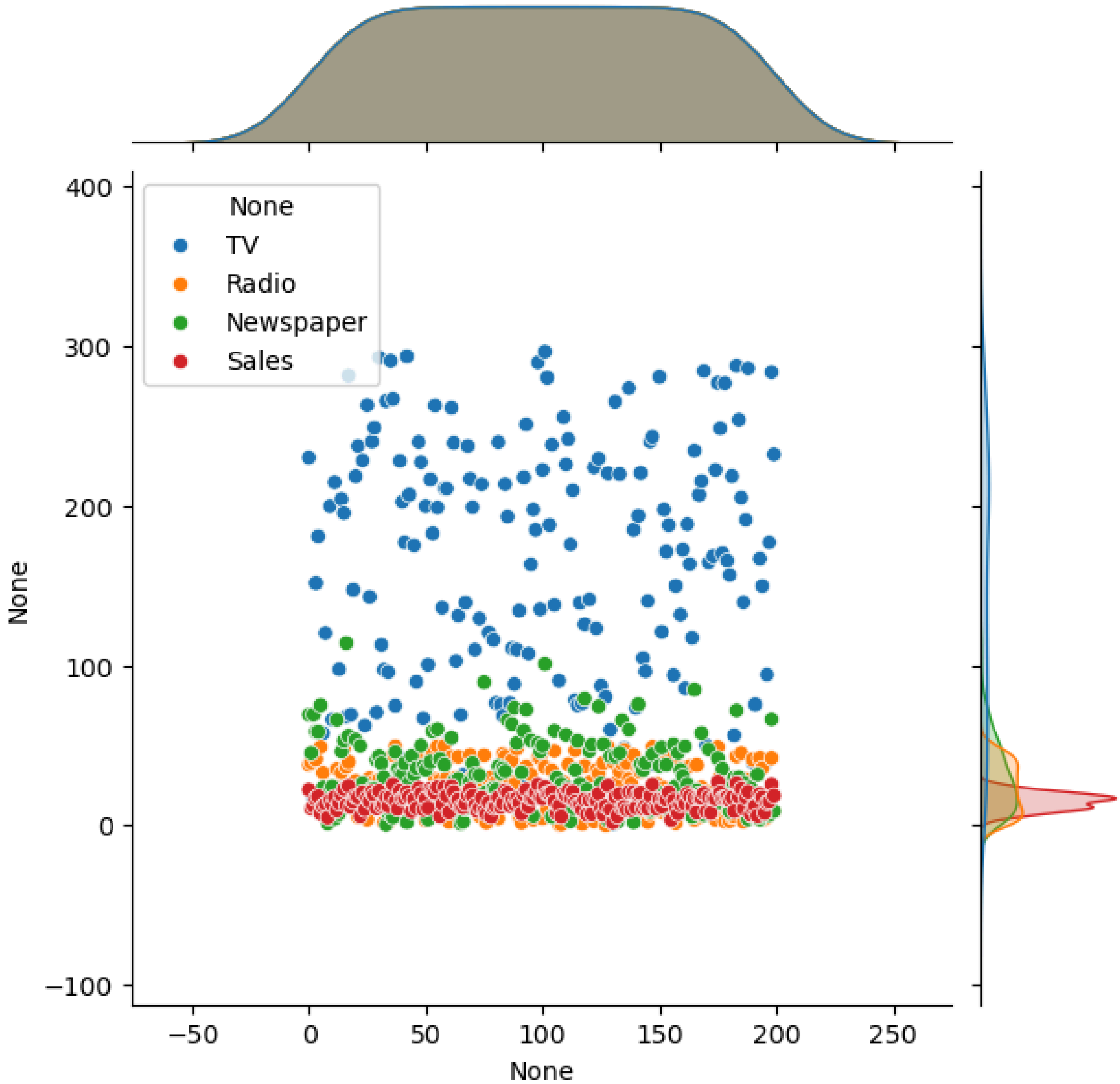
In [11]:
```
# Plotting the scatterplot for all the continuous columns at a time.
for i in ['TV','Radio','Newspaper']:
    sns.scatterplot(x=adv[i], y=adv.Sales)
    plt.show()
```


Sales
TV
0 50 100 150 200 250 300
5 10 15 20 25

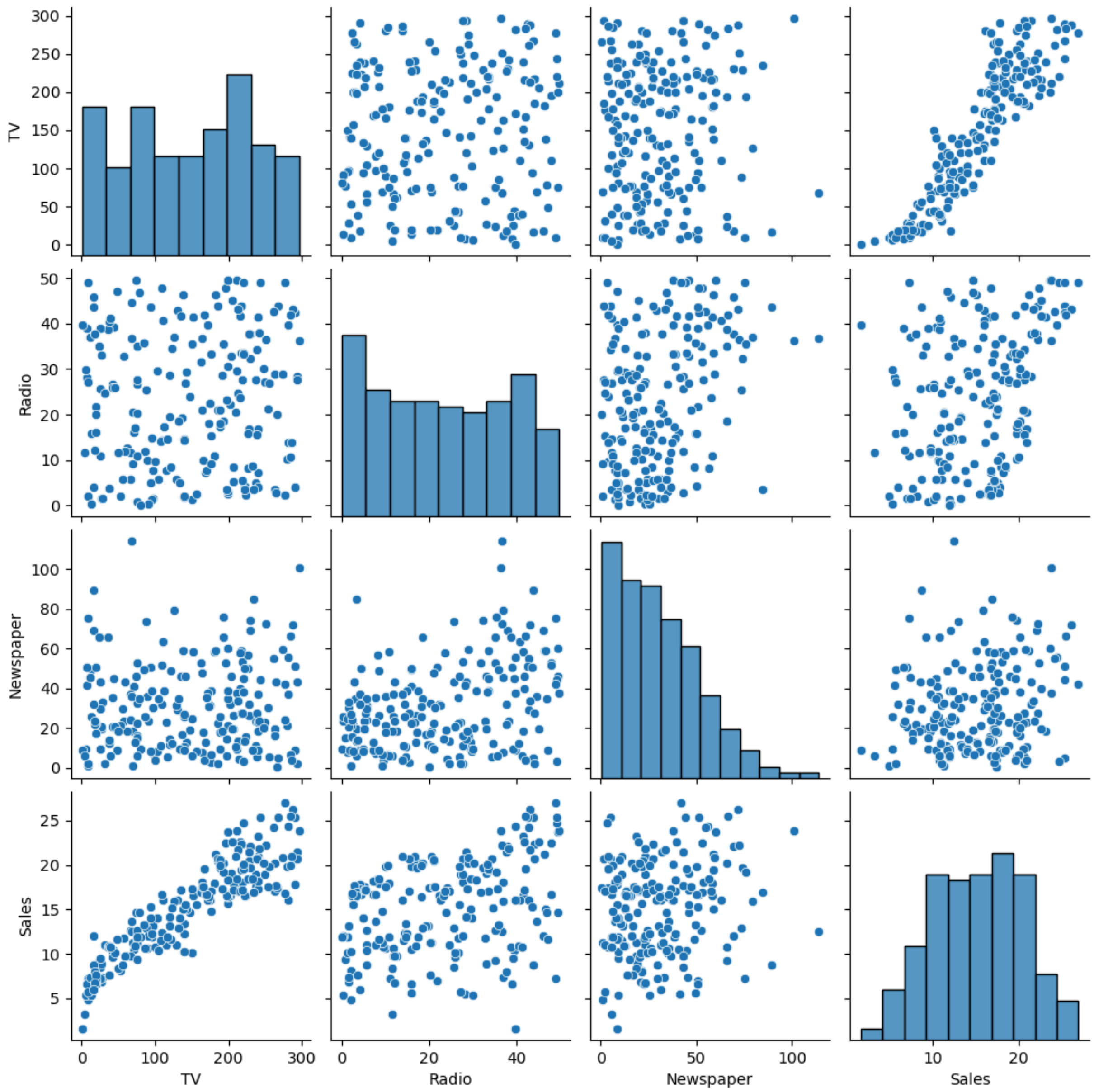

Sales
Radio
0 10 20 30 40 50
5 10 15 20 25



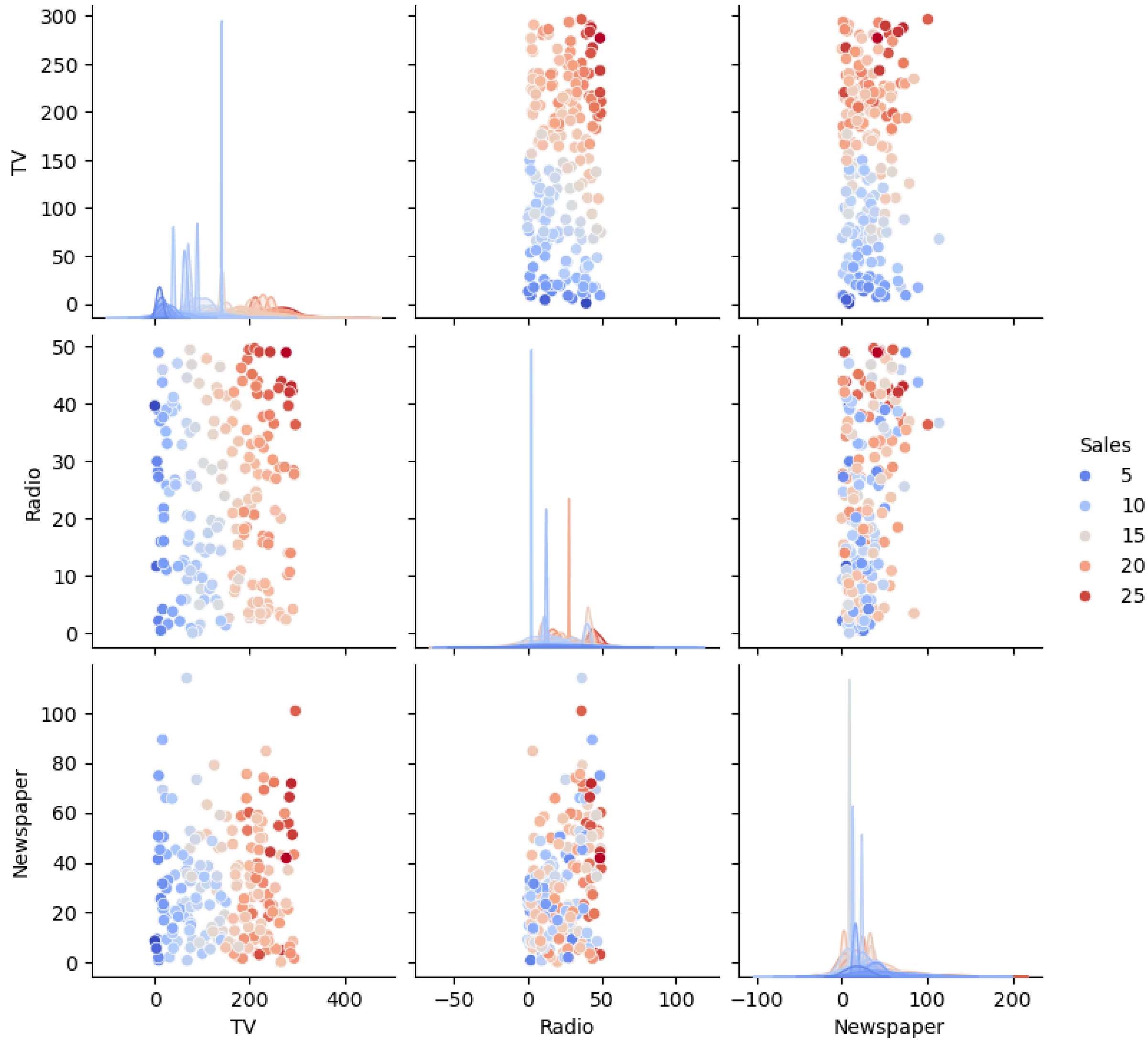
In [12]:
```
sns.jointplot(data=adv)
plt.show()
```



In [13]:
```
sns.pairplot(adv)
plt.show()
```



In [14]:
```
sns.pairplot(adv,hue='Sales',palette='coolwarm')
plt.show()
```

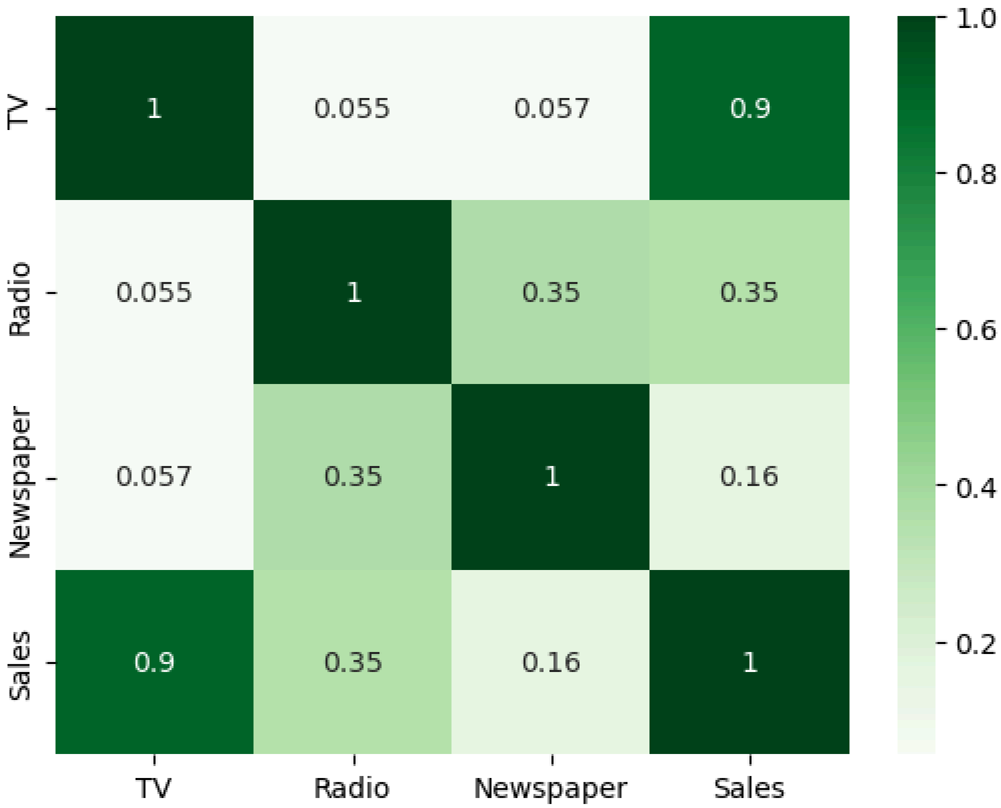


In [15]:
```
# Correlation: finds the statistical relationship between 2 varibales.
c = adv.corr()
c
```

Out[15]:

	TV	Radio	Newspaper	Sales
TV	1.000000	0.054809	0.056648	0.901208
Radio	0.054809	1.000000	0.354104	0.349631
Newspaper	0.056648	0.354104	1.000000	0.157960
Sales	0.901208	0.349631	0.157960	1.000000

In [16]:
```
# plotting the correlation using heatmap:
sns.heatmap(c,annot=True,cmap='Greens')
plt.show()
```



In [17]:

```
# Encoding:- As the dataset doesnot contain any string columns therefore this step
```

In [18]:

```
# Creation of ip/op:- separating the input columns from output columns
adv
```

Out[18]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9
...	...	...	...	...
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	18.4

200 rows × 4 columns

In [19]:
```
# ip will store all the input columns except the target one.
ip = adv.drop('Sales',axis=1)
ip.head()
```

Out[19]:

	TV	Radio	Newspaper
0	230.1	37.8	69.2
1	44.5	39.3	45.1
2	17.2	45.9	69.3
3	151.5	41.3	58.5
4	180.8	10.8	58.4

In [20]:
```
op = adv.Sales
op.head()
```

Out[20]:
```
0    22.1
1    10.4
2    12.0
3    16.5
4    17.9
Name: Sales, dtype: float64
```

In [21]:
```
# Train Test Split: splitting of the 100% datas into training and testing datas.
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(ip,op,test_size=0.15,random_state = 5)
```

In [22]:
```
xtrain.head()
```

Out[22]:

	TV	Radio	Newspaper
25	262.9	3.5	19.5
156	93.9	43.5	50.5
42	293.6	27.7	1.8
141	193.7	35.4	75.6
50	199.8	3.1	34.6

In [23]:
```
xtest.head()
```

Out[23]:

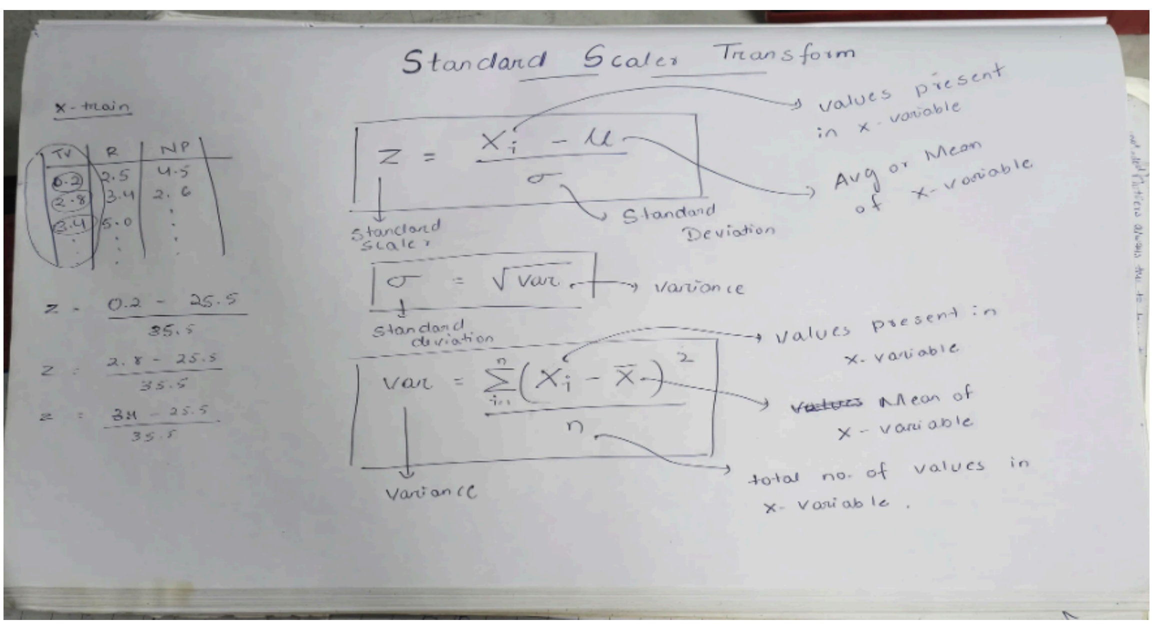
	TV	Radio	Newspaper
119	19.4	16.0	22.3
77	120.5	28.5	14.2
148	38.0	40.3	11.9
149	44.7	25.8	20.6
154	187.8	21.1	9.5

In [24]:
```
ytrain.head()
```

Out[24]:
```
25      17.0
156     15.3
42      20.7
141     19.2
50      16.4
Name: Sales, dtype: float64
```

In [25]:
```
ytest.head()
```

Out[25]:
```
119      6.6
77      14.2
148     10.9
149     10.1
154     20.6
Name: Sales, dtype: float64
```



In [26]:
```
# Stadardizing the datas using Standard Scaler Transform:
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

In [27]:
```
xtrain = sc.fit_transform(xtrain)
xtest = sc.fit_transform(xtest)
```

In [28]:
```
xtrain
```

```
Out[28]: array([[ 1.38344542, -1.32993638, -0.50913682],
                [-0.58787665,  1.38145277,  0.92126676],
                [ 1.74154949,  0.31045406, -1.32585112],
                [ 0.57625319,  0.83239647,  2.07943224],
                [ 0.64740742, -1.35705027,  0.18760815],
                [-0.51205657, -0.91644953, -1.24279543],
                [-1.23759641, -1.31637943, -0.77214651],
                [-0.05946902, -0.59786131, -0.22767031],
                [ 0.88886521,  0.68327007,  0.33987692],
                [-0.95647888, -0.71309535, -0.56450728],
                [-0.14695372, -0.31994392,  0.18760815],
                [ 1.10816021, -0.51651963, -0.14922882],
                [-1.47438835,  0.98152287, -0.41223851],
                [ 0.35929112, -0.04202653,  0.04456779],
                [ 0.9798493 , -0.42162101, -0.19998508],
                [-1.16410925,  1.09675691,  0.67209968],
                [ 0.51443066, -0.34027934, -0.22767031],
                [ 0.96701821, -0.49618421,  0.89358153],
                [ 0.32896308, -0.34027934,  0.00765415],
                [-1.59220108,  1.06964302,  0.92588096],
                [-0.24726952,  0.77816869, -0.83674538],
                [-0.62870284, -1.54684751, -0.33841123],
                [ 0.73022627, -0.99779121, -0.19075667],
                [ 0.62174524,  0.01220125, -0.75368969],
                [-0.7710113 ,  1.60514238,  0.18299395],
                [-0.63686808, -0.89611411,  0.23836441],
                [-1.45455848, -0.20470988, -0.62449194],
                [ 1.58524348, -0.88255717, -0.42146692],
                [ 1.36478202,  1.32722499,  1.11506337],
                [-0.80717165,  0.80528258,  1.02277927],
                [-1.0999538 , -0.78088007, -0.55989307],
                [-1.02763311, -1.18080997, -0.0384879 ],
                [ 0.77455186,  0.43246657, -0.97978574],
                [ 0.70806348,  1.48990834, -0.50452261],
                [-1.40556704,  0.81206105,  1.63185434],
                [ 0.80604635,  0.1003214 , -0.80444594],
                [-0.0349733 ,  0.2494478 ,  0.72285594],
                [ 1.21430832,  0.47991588, -0.47222318],
                [ 0.03501447,  0.05287209, -0.52759364],
                [-0.0944629 , -0.26571614, -0.64294877],
                [-1.31574941,  0.1003214 , -1.3073943 ],
                [-1.18160619,  0.18844155, -0.46299477],
                [-0.48522792,  0.43924504, -1.02131358],
                [-1.38457071,  1.07642149, -0.97978574],
                [ 1.77421044,  0.89340272,  3.24682612],
                [-0.40240907,  1.6729271 ,  0.96279461],
                [ 0.59608306,  1.66614863,  1.03200768],
                [ 0.30213444, -1.03846204,  0.21529338],
                [-0.91215329, -1.1740315 , -0.29226918],
                [ 0.62174524, -1.32993638, -1.13666871],
                [ 1.02417489, -0.98423426, -1.00747097],
                [ 0.28113811, -1.08591135, -0.81828856],
                [ 1.43010393,  1.40178819, -1.17819656],
                [ 0.22164851,  0.5748145 ,  1.03200768],
                [ 0.42577949, -0.83510786,  1.28578896],
                [ 1.69605744,  1.3001111 ,  0.95356619],
```

```
[-0.3919109 ,  1.18487706,  1.50727081],
[-0.88532465,  1.4492375 ,  0.2337502 ],
[ 0.82937561,  0.03253667,  1.24887532],
[-0.8025058 , -0.83510786, -1.1320545 ],
[ 1.11399252, -1.28926554,  0.29373487],
[ 1.13615531,  1.00863676, -0.33841123],
[-1.48255359, -1.28926554,  0.049182  ],
[ 1.54441728, -1.41127805, -0.3153402 ],
[-0.54588399, -1.05201899, -1.07668404],
[ 1.59107579, -0.6249752 ,  0.29834907],
[-1.67501994,  1.11709233, -1.00747097],
[-1.37057316,  0.66971312, -0.51836523],
[-0.90282159, -0.7741016 ,  0.28912066],
[ 0.86436949,  0.31045406,  1.05507871],
[ 1.70772207, -1.28926554, -1.01669938],
[ 0.63924218,  0.50702977,  0.37679056],
[-0.33008838, -1.04524052, -0.34302543],
[ 0.85620425,  0.70360548,  1.31347419],
[ 0.47360447, -0.14370362, -0.39378169],
[-0.65319856,  0.16132765,  1.97791972],
[-0.85966247, -0.48262727,  0.47368887],
[-0.04663793, -1.43839194, -0.99362835],
[-1.0591276 , -1.43161347, -0.42146692],
[-0.74768205, -1.56718293, -0.98439994],
[ 0.84570609,  1.40856666, -0.15384303],
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```

```
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[-1.58520231,  0.27656169, -1.3120085 ],
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[ 0.77571832,  1.79493962,  0.33064851],
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[ 0.38145391,  0.69682701,  0.37679056],
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[ 1.5094234 ,  0.39179573,  1.34577363],
[-1.46389018, -0.09625431,  0.91665255],
[ 1.11749191, -1.07235441, -1.00747097],
[-0.66602965, -0.76732313, -0.21382769],
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[ 1.73338425,  0.35112489,  0.58442979],
[ 1.54675021,  1.74749031,  0.51983092],
[-0.87832587, -0.93678495, -1.36737896],
[-1.39040303,  0.1748846 ,  0.58904399],
[ 1.11749191, -0.43517796, -0.35225384],
[-0.79200763,  0.24266933, -0.37993908],
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[-0.46306513, -1.18080997,  0.17837974],
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[-1.54670904,  0.93407356,  0.67671389],
[ 0.36628989, -0.52329811, -1.29816589],
[-1.63536021, -0.78088007, -1.14589712],
[-1.22243239,  1.21876942, -1.14128291],
[-1.58286938, -1.424835  , -1.36276476],
[-0.17378237, -1.18080997,  0.03533938],
[-0.561048  , -0.56396894,  0.38601897],
[-0.21694149,  0.93407356,  2.24554362],
```

```
        [-1.46505664, -0.74698771, -0.32918282],
        [-0.10612753,  1.25944026,  0.70901333]])
```

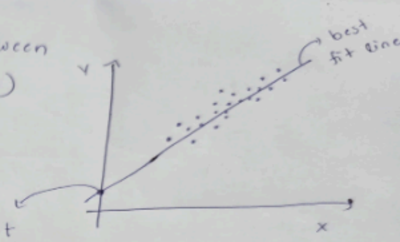
In [29]:
```
xtest
```

Out[29]:
```
array([[-1.71612085, -0.53499267, -0.38003424],
       [-0.50447354,  0.29265688, -0.74795583],
       [-1.49320651,  1.07395805, -0.8524274 ],
       [-1.41290941,  0.11388458, -0.45725235],
       [ 0.30209288, -0.19731165, -0.9614412 ],
       [-0.49848121, -1.03820359,  0.81911762],
       [ 0.73593692, -1.43547537, -0.68436445],
       [-1.25950599,  0.57736832, -0.32552734],
       [ 1.03315605,  0.19996013, -0.35278079],
       [-0.63270921, -0.64755301,  0.0469365 ],
       [ 1.47898473, -0.67403779, -1.22489124],
       [-0.80169266, -1.50168734, -1.05682828],
       [ 0.89653113, -1.25670307, -0.32552734],
       [ 0.47826712, -0.1178573 ,  0.04239426],
       [ 0.43512241,  1.67648692,  1.33239096],
       [ 0.90611884,  0.67668627, -1.15221536],
       [-0.13294963,  1.14017002,  1.26425733],
       [ 0.78387549,  0.90180695,  0.06056323],
       [-1.03299625, -1.54141452, -0.72070238],
       [-1.50638962,  0.96139771,  1.58675651],
       [-0.07182796, -1.42223298, -1.01594811],
       [-0.23601755,  0.34562645, -0.82063171],
       [ 1.19974257,  0.31252047, -0.67073772],
       [ 0.86177567, -1.36926341,  2.45886695],
       [ 0.23977274,  1.46460864,  1.27334182],
       [ 1.0583238 ,  0.82235259,  1.89108672],
       [ 0.7167615 , -1.36926341, -0.7979205 ],
       [ 1.42385538,  1.02760968,  1.1416168 ],
       [-1.86113502,  0.26617209,  0.48753396],
       [ 0.61009818,  1.25273035,  0.14232358]])
```

Linear Regression

(It finds the linear relationship between dependent and independent variables)

Here, we use the formula of Straight line equation



slope of the line

$$\boxed{y = mx + c}$$

y → dependent variable (op)

x → independent variable (ip)

c → y-intercept (the point at which the straight line intersects the y-axis)

$$\boxed{m = \frac{y_2 - y_1}{x_2 - x_1}}$$

m → Slope of the line

$$\boxed{y = m_1 . x_1 + m_2 . x_2 + \dots + m_n . x_n}$$

Multiple Linear Regression

In [30]:
```python
# Ml Algorithm:
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

In [31]:
```python
lr.fit(xtrain,ytrain)
```

Out[31]:
```
▾ LinearRegression
LinearRegression()
```

In [32]:
```python
# Prediction using testing datas:
pred = lr.predict(xtest)
pred
```

Out[32]:
```
array([ 6.0977766 , 13.03920365,  9.6222318 ,  8.51971231, 16.04781597,
       11.04273374, 16.16537643,  9.95863291, 20.09777389, 11.00159697,
       20.80805065,  8.86112365, 17.20223308, 17.01916139, 19.62867087,
       20.2229928 , 16.13869179, 20.02913473,  7.72565543,  9.44477367,
       12.3993731 , 14.37531347, 21.04380067, 16.93216054, 18.38514281,
       21.23382504, 16.17554387, 23.24373732,  6.68168273, 19.76196046])
```

To find the accuracy of the model we need to find the MSE (Mwean Squared Error) and r2Score.

In [33]:
```python
# to find the MSE:
from sklearn.metrics import mean_squared_error
error = mean_squared_error(pred,ytest)
error
```

Out[33]:
```
3.1048626876695975
```

In [34]:
```python
# r2Score:- finds the accuracy of the model.
from sklearn.metrics import r2_score
acc = r2_score(pred,ytest)
acc
```

Out[34]:
```
0.8737580848329649
```

To plot the Best fit line:

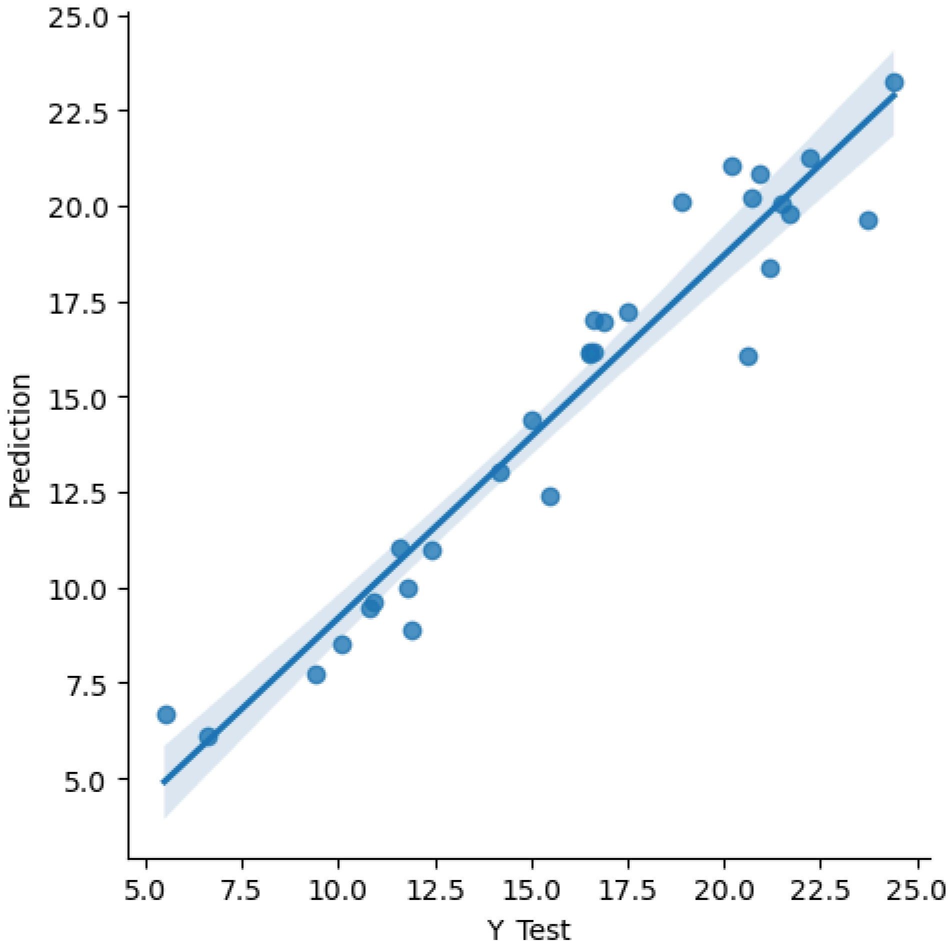
```
lmplot: stands for linear model plot
```

In [35]:
```python
df = pd.DataFrame({'Y_Test':list(ytest),
                   'Prediction':list(pred)})
df
```

Out[35]:

	Y_Test	Prediction
0	6.6	6.097777
1	14.2	13.039204
2	10.9	9.622232
3	10.1	8.519712
4	20.6	16.047816
5	11.6	11.042734
6	16.6	16.165376
7	11.8	9.958633
8	18.9	20.097774
9	12.4	11.001597
10	20.9	20.808051
11	11.9	8.861124
12	17.5	17.202233
13	16.6	17.019161
14	23.7	19.628671
15	20.7	20.222993
16	16.5	16.138692
17	21.5	20.029135
18	9.4	7.725655
19	10.8	9.444774
20	15.5	12.399373
21	15.0	14.375313
22	20.2	21.043801
23	16.9	16.932161
24	21.2	18.385143
25	22.2	21.233825
26	16.5	16.175544
27	24.4	23.243737
28	5.5	6.681683
29	21.7	19.761960

In [36]:
```
# to plot the best fit line:
sns.lmplot(x='Y_Test',y='Prediction',data=df)
plt.show()
```



Classification Model:-

```
The nature of the output column/dependent column should be
categorical.
Eg: (0/1), (True/False), (Male/Female) etc.
```

In [37]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [38]:
```
# Data Reading:-
main = pd.read_csv(r"C:\Users\lab25\Downloads\maintenance_data (1).csv")
main
```

Out[38]:

	lifetime	broken	pressureInd	moistureInd	temperatureInd	team	provider
0	56	0	92.178854	104.230204	96.517159	TeamA	Provider4
1	81	1	72.075938	103.065701	87.271062	TeamC	Provider4
2	60	0	96.272254	77.801376	112.196170	TeamA	Provider1
3	86	1	94.406461	108.493608	72.025374	TeamC	Provider2
4	34	0	97.752899	99.413492	103.756271	TeamB	Provider1
...	...	...	...	...	...	...	...
995	88	1	88.589759	112.167556	99.861456	TeamB	Provider4
996	88	1	116.727075	110.871332	95.075631	TeamA	Provider4
997	22	0	104.026778	88.212873	83.221220	TeamB	Provider1
998	78	0	104.911649	104.257296	83.421491	TeamA	Provider4
999	63	0	116.901354	99.998694	47.641493	TeamB	Provider1

1000 rows × 7 columns

In [39]:
```
# Data Cleaning:
main.isnull().sum()
```

Out[39]:
```
lifetime          0
broken            0
pressureInd       0
moistureInd       0
temperatureInd    0
team              0
provider          0
dtype: int64
```

In [40]:
```
main.dtypes
```

Out[40]:
```
lifetime            int64
broken              int64
pressureInd       float64
moistureInd       float64
temperatureInd    float64
team               object
provider           object
dtype: object
```

In [41]:
```
for i in main.columns:
    print(i,':','\n',main[i].unique(),'\n')
```

```
lifetime :
 [56 81 60 86 34 30 68 65 23 38 29 82 80 48 92 88 74 61 35 26 63 79 53 73
 13 36 31 25 58 19 84 12 15 43  1 20 16  3 18  7 47 39 57  4 24 28 49 76
 52  8 40 46  5 41 93 77 62 85 55 33 17 45  9 72 50 42 44 54 64 27 22 59
 66 83 14 51 71 21 78  6 69 89  2 67 87 11 10 32 37 90]

broken :
 [0 1]

pressureInd :
 [ 92.17885406  72.07593772  96.27225443  94.40646126  97.75289859
  87.67880097  94.61417404  96.48330289 105.486158    99.17823531
  97.81784409  67.81225145  86.36611059  76.14465414 103.1072633
  88.41407945  84.35504868  79.66925455  86.22910861  84.17942039
 100.0059233  115.6075596   97.69718903 101.4156229  118.9786971
 102.1127749  129.1243378  109.0330362  107.2980695  127.2639544
 138.1911205   72.55408417  95.21464918  91.24713174  81.55537698
  69.13459519 132.8574784   54.73533145  84.89864628  94.15228726
  84.34406647  95.75352436 123.9284399  101.5053508  120.9455502
  83.06857115 113.3491219   75.64669299 113.4358321   81.77978353
  68.85065142 150.665421    72.42312878  97.13286233 113.965257
  57.46321326 144.3445174   80.69223153  93.91332598  73.32115289
  83.95831157  56.17177135 105.9000372  115.698401   119.7459957
 105.8937636   87.39284133  82.88180029 122.287991    85.07220883
 119.204381   107.7859931   90.67123432  66.63788383 107.8373588
 113.2726053   85.33137798  82.52821911  90.63682861 112.60533
  78.66593081  70.10171881  99.12691885 129.8155876  129.3586686
  86.43068027 127.6432644   95.24539906  83.49423659  96.21961865
  79.1113931  106.8671887  111.2558114   96.12034618  86.10751429
 108.4133588  100.2518501  117.9043996  121.6736792   60.23306632
  94.23091985  74.48747426  92.453609   112.047415   125.0326918
  96.00878453 109.6711377  154.9245853  105.7582145   93.35727589
  99.96158153  95.92226826 111.7239334   97.9282765  128.7277348
 133.1077066  126.7058619  150.6956895   80.01967528  74.57754143
 140.9858744   35.76360199  91.60822135 103.7075508  111.8094367
 124.8601041  112.7364301  102.194994   128.3172975   94.01171684
  91.39931729 102.7097196   77.4666105  143.8647421   93.91140451
 122.8634385  120.0742901   65.11291145  75.99730079  90.59983598
  85.97976393 111.6690617   86.99664346  93.62245547 143.8612427
  64.28565742  97.53345121  77.83610485  95.78219396  80.16096302
 114.6298749   82.67022466 101.1211088   85.4702501  129.5853061
 113.0908777  113.4148533   84.11160975  84.24156074  96.84048235
 112.7450016   92.35071864  73.14513861 121.1085311   82.61100175
 125.8449723   99.43119894  96.06869558  89.14378006  82.39429705
 122.5191039  114.6734454  104.1060598  104.1285145   86.49978354
 102.5436645  114.7006664   89.62264913 101.1584808   51.69950796
  81.50310722 134.9526042   89.32006408  80.94962803  81.82940534
 107.4348672  116.6937881   85.44405211  80.00815226 110.6439173
  90.84614958  99.49925475  78.77184657  71.10556819  70.35776433
  93.24543008  88.68783476  65.55163161 129.4538603  119.2571561
 122.5029001   89.3451342  105.1548812   96.43645598  98.14785492
  92.10080195  87.09276089 102.3336394   91.63775968 104.6585302
 116.8149535   87.96763611  96.14067129  53.45018161  90.38576175
  67.89336141 111.5160364  121.3890098  147.4138919  109.7446432
  79.82891144 104.6414108   79.9061587  121.6248825  110.7350681
 101.7492024   71.81758969 108.1568179  105.0382945   90.48431219
```

```
  96.57340584  93.48628393  79.0391301  124.7428685  110.0800055
 109.7472599   72.25553465  94.39762265  99.1729528  123.5105012
 102.185641    87.22145536  95.8067128  123.0263818   88.10845571
  88.67721939 110.6072377   38.78754767  89.33143548  75.81598114
  85.226111    83.58406008 108.7205931   96.61713227 108.7769039
 101.3580689  129.0020995   97.10854231 116.6944294  115.1857482
  89.40512082  88.77023945 114.142562    79.25673701 103.7368214
  96.10586879 119.514682    88.15204937  76.76859083 116.3087415
  81.94855191 114.3549146   48.59034661  99.52789867  81.37314584
  72.29605807 105.7066065   85.29060065  95.72174212  81.92521008
 127.2580478   89.75231566  90.944893    79.63958383 130.1991676
 112.5857118   86.02485068  98.94246341 107.9141561  100.5258397
 100.1524759   74.66116758 101.9277194  122.3290021   72.34009193
  84.52197479 108.0678329  102.8312375   77.30203512  92.27626092
  93.21014475  81.95766678 118.0336224  104.1600552   90.20638283
 101.3526393   84.41393902  90.44987724 113.0237965   79.53109778
 104.3627063  112.0633881  108.8375233  118.101249   127.3713508
  73.20541659  89.6800915  173.2825408   83.57488346 133.0639889
 113.2849762  103.8908585  116.246305    93.69823433 124.6300872
 114.5831739   86.90220321  71.48203946  95.3103348  111.6225804
 105.9714478   96.46384171  99.00365273 146.48261    109.8195707
  94.03852545  97.30113122  86.41755545 132.093877   114.2781179
  70.04576881 122.9730061   88.99176552 104.7316543   67.46314505
  86.65688722 130.6205854  136.3466953  117.6863649   86.81929694
  77.4245435  136.5477996   75.46380429  91.11156321 126.4345257
  93.31462565  76.06914566 106.8312633  104.7029198   64.97934021
  90.99176758  76.23814115 112.2521075  105.5142856  138.9968485
  80.7822454   58.28240383 126.2074958  111.737241    57.43642184
  84.13029987  89.42263505  88.40910573 100.777048   132.8250743
  93.80107698 116.0347608   79.21047345  63.47598728 105.4103217
 123.7075284  108.4494949   85.78027201 129.7160319   65.7483249
  83.3672664  111.9591844  133.8946635   95.31746825 100.3562126
 104.6556904  107.3121062  129.4026635   88.04750683 129.540845
  92.1617229   81.05687592  96.68465852  77.00011108 127.821078
 105.6359631   86.3692016  109.1177255   96.97853587 120.1842062
 108.5361485   79.39533761  96.65174149  83.85966038  85.57802723
 129.8158207   93.67574478  94.01292355  98.56889316  85.54546864
  97.52706923 102.1167092  118.5137949   88.37081726 110.4460737
 112.4511083   85.56228351  36.95721852 123.3028407   86.67802992
  71.49098287  69.53731478 100.2848608  103.1069062   99.16949664
  89.03305936  96.00625928 104.4622671  144.8317169   95.11565143
  66.93302741  71.22337836 103.4524605  118.4184127   57.19314091
 102.6766575  133.7792866   99.21774611 116.814456   120.2859938
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```

team :

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 ['TeamA' 'TeamC' 'TeamB']

provider :
 ['Provider4' 'Provider1' 'Provider2' 'Provider3']
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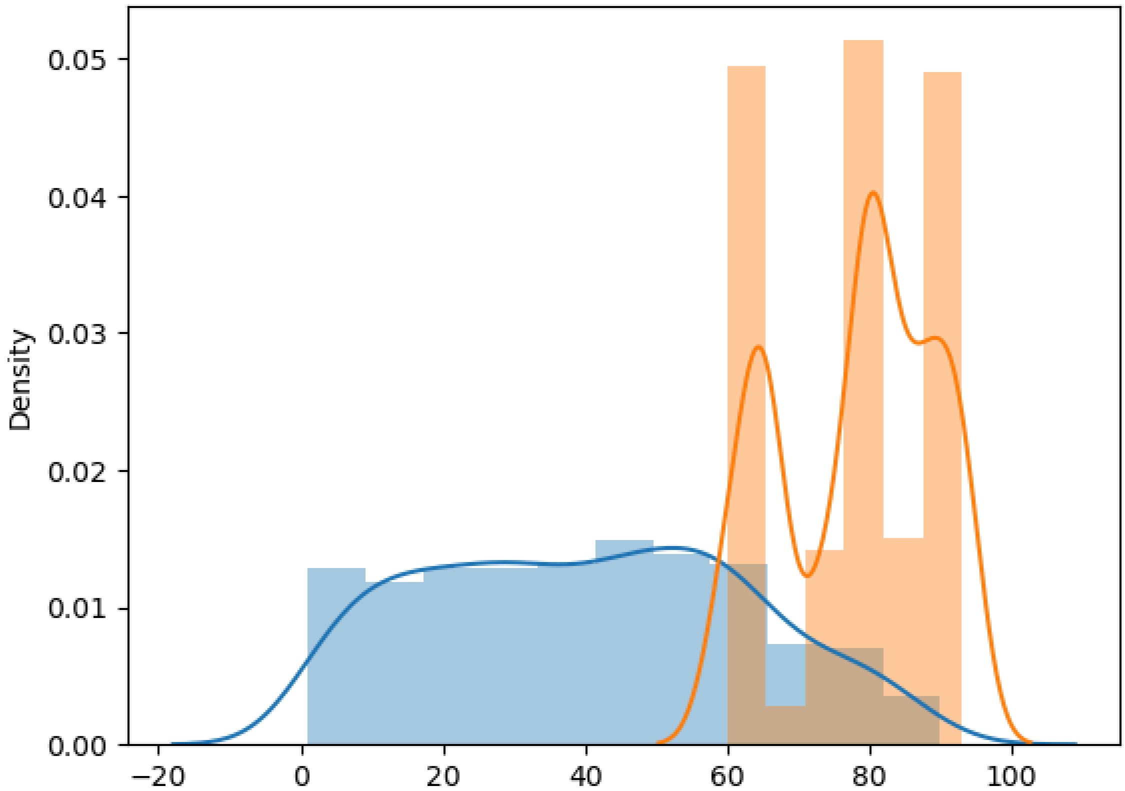
In [42]:
```python
main.describe(include='all')
```

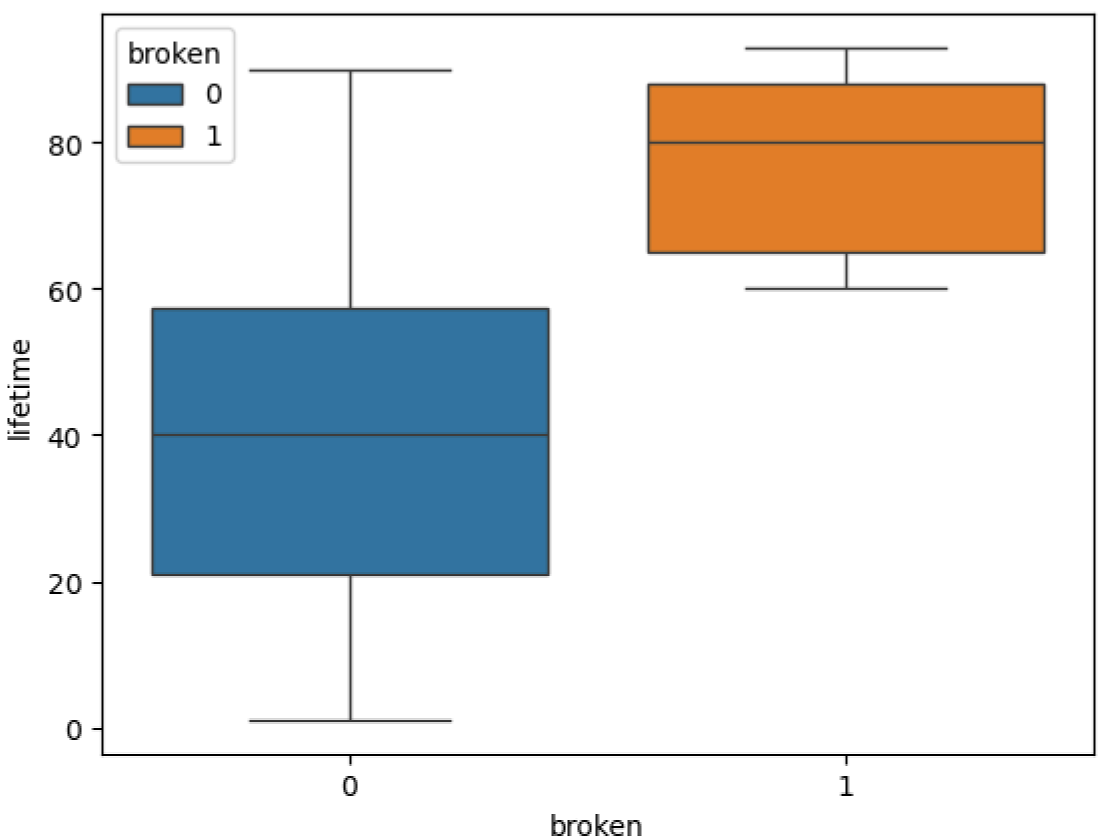
Out[42]:

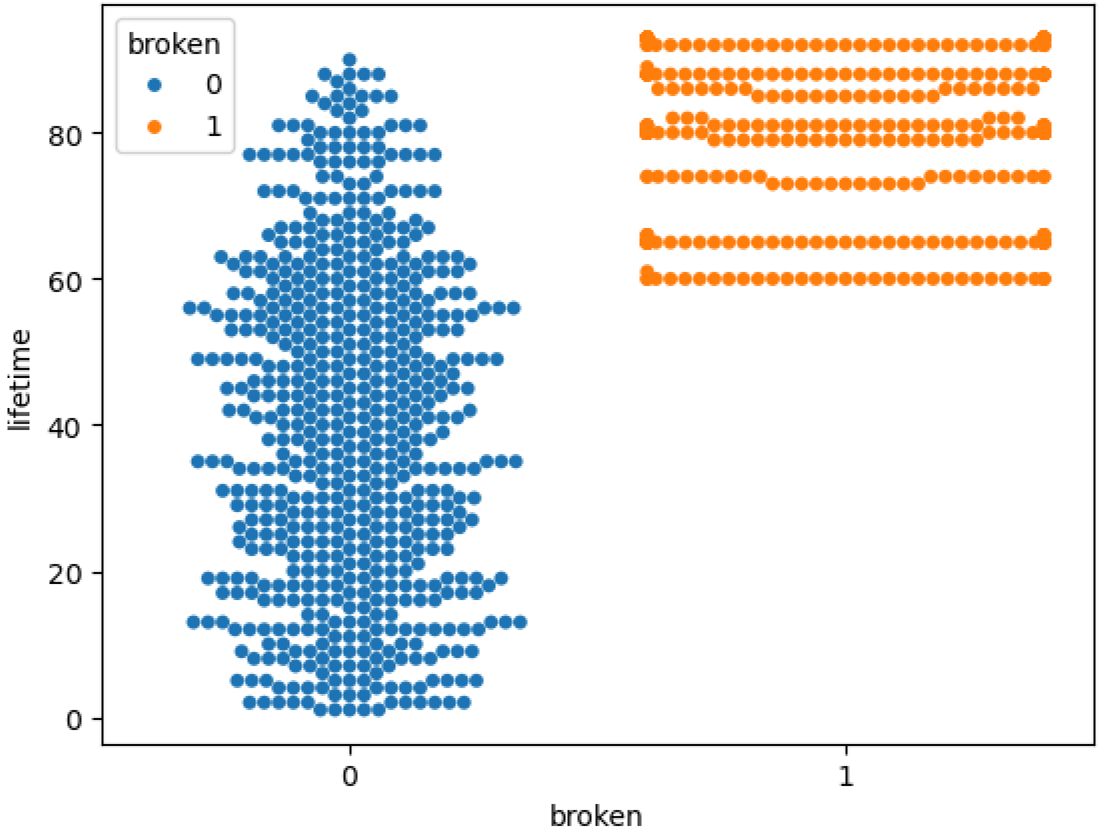
	lifetime	broken	pressureInd	moistureInd	temperatureInd	team	prov
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000	1
unique	NaN	NaN	NaN	NaN	NaN	3	
top	NaN	NaN	NaN	NaN	NaN	TeamB	Provi
freq	NaN	NaN	NaN	NaN	NaN	356	
mean	55.195000	0.397000	98.599338	99.376723	100.628541	NaN	I
std	26.472737	0.489521	19.964052	9.988726	19.633060	NaN	I
min	1.000000	0.000000	33.481917	58.547301	42.279598	NaN	I
25%	34.000000	0.000000	85.558076	92.771764	87.676913	NaN	I
50%	60.000000	0.000000	97.216997	99.433959	100.592277	NaN	I
75%	80.000000	1.000000	112.253190	106.120762	113.662885	NaN	I
max	93.000000	1.000000	173.282541	128.595038	172.544140	NaN	I

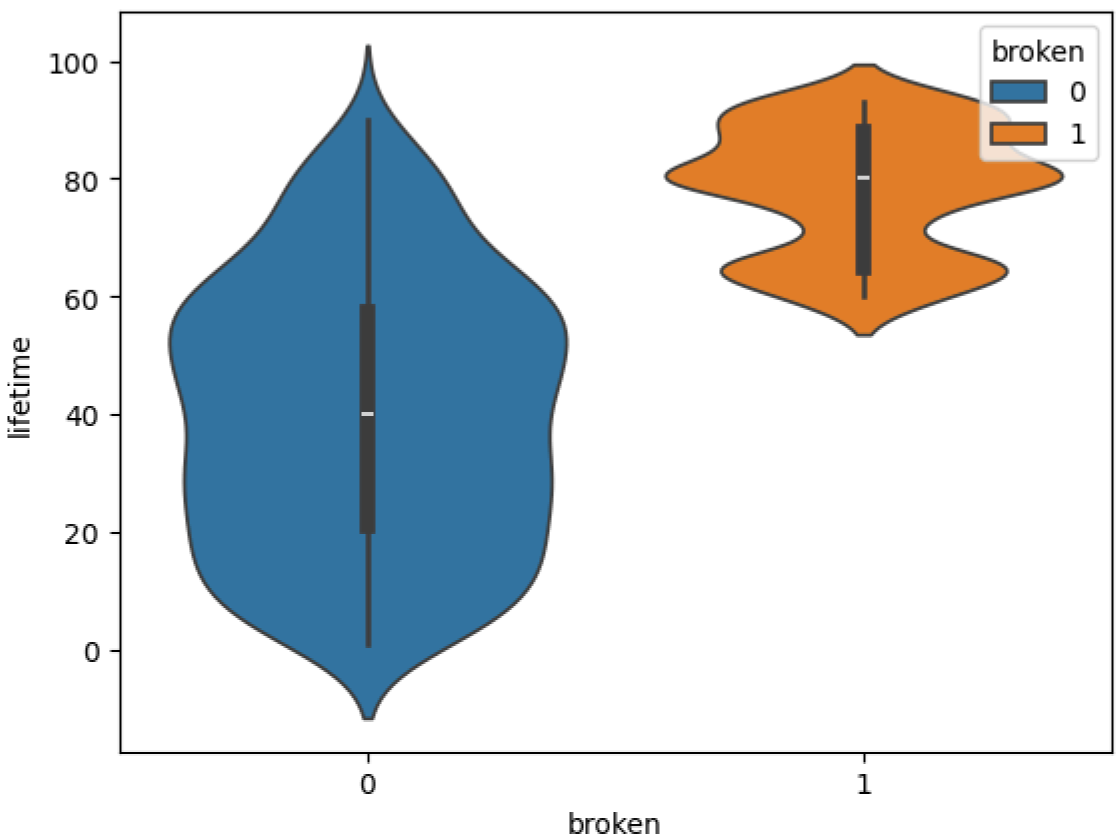
In [43]:
```python
#Data Visualization or EDA
import warnings
warnings.filterwarnings('ignore')
```

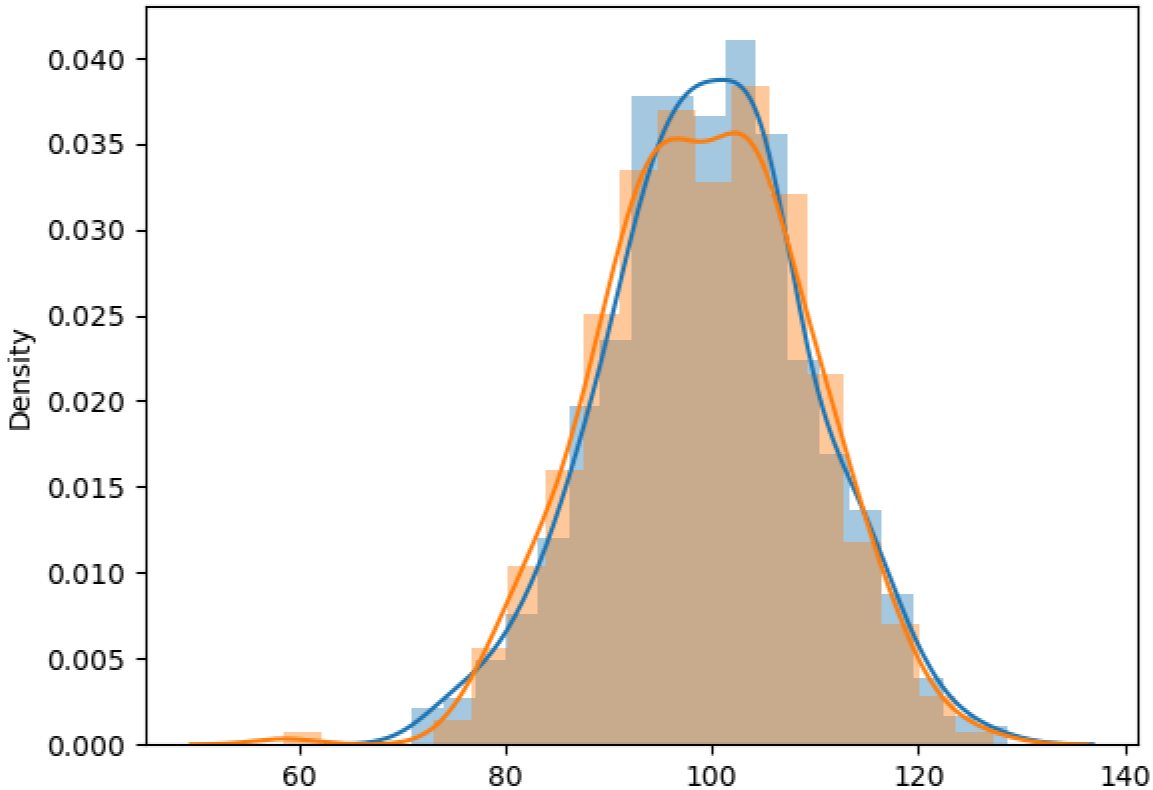
In [44]:
```python
for i in ['lifetime','moistureInd','pressureInd','temperatureInd']:
    #distplot
    sns.distplot(x=main[i][main.broken==0])
    sns.distplot(x=main[i][main.broken==1])
    plt.show()

    #boxplot
    sns.boxplot(x=main.broken,y=main[i],hue=main.broken)
    plt.show()

    #swarmplot
    sns.swarmplot(x=main.broken,y=main[i],hue=main.broken)
    plt.show()

    #violinplot
    sns.violinplot(x=main.broken,y=main[i],hue=main.broken)
    plt.show()
```


Density
0.05
0.04
0.03
0.02
0.01
0.00
−20
0
20
40
60
80
100

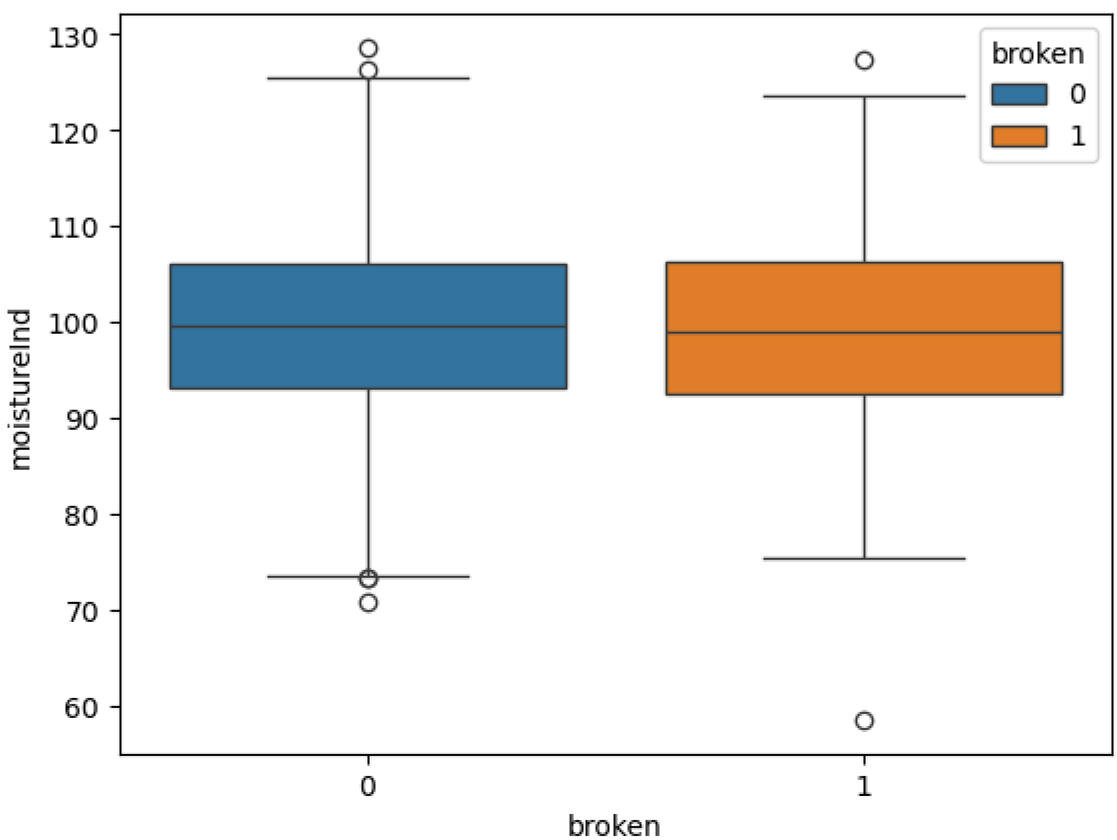

broken
0
1
lifetime
80
60
40
20
0
0
1
broken


broken
0
1
lifetime
0
20
40
60
80
0
1
broken

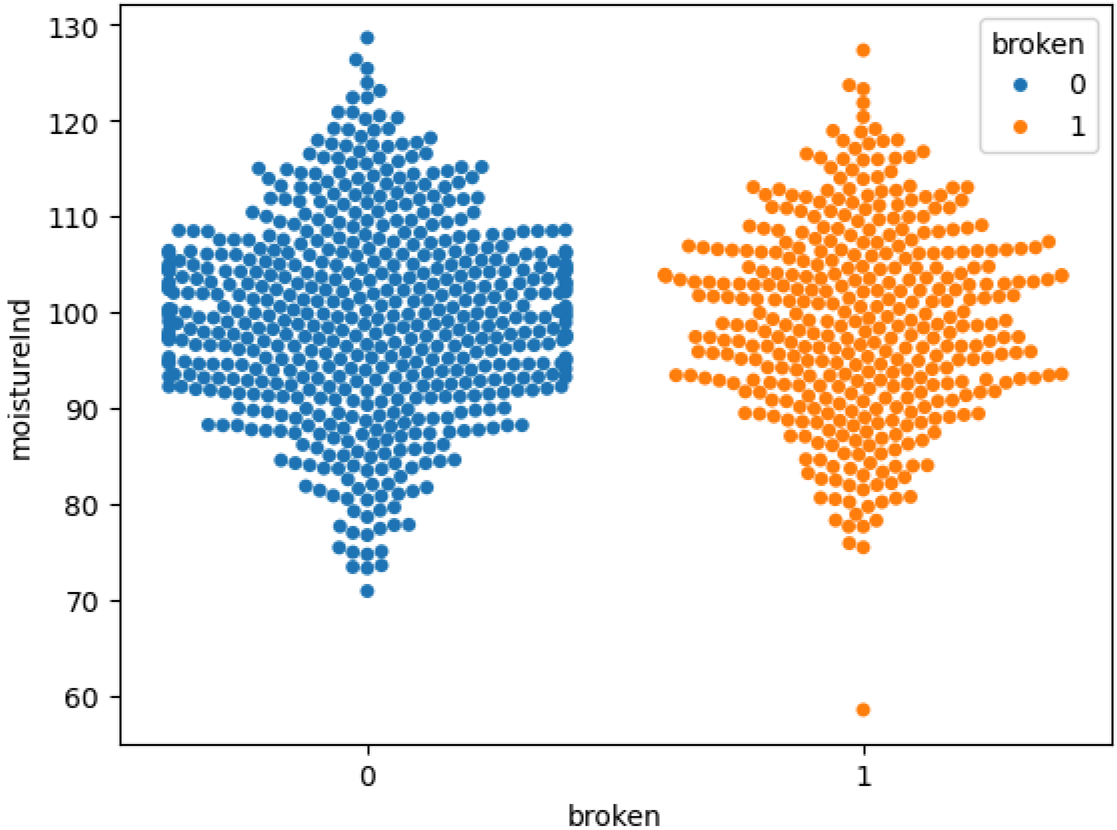

broken
0
1
lifetime
0
20
40
60
80
100
0
1
broken

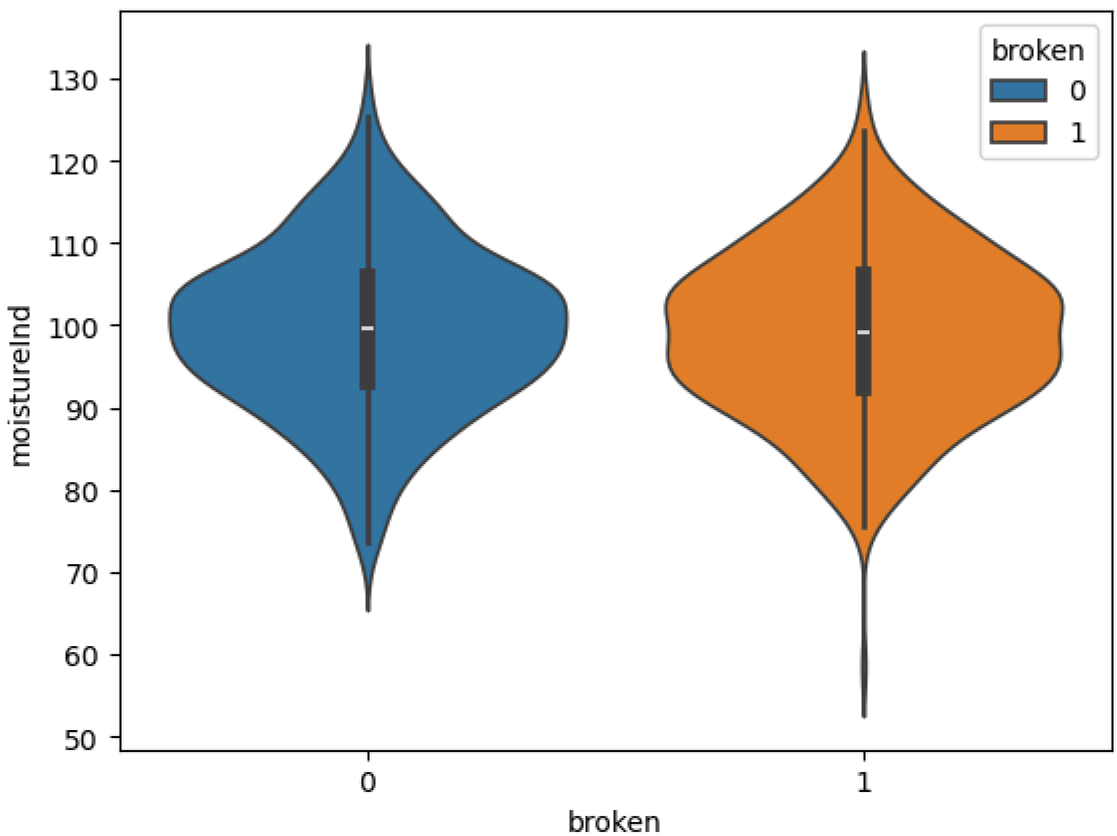


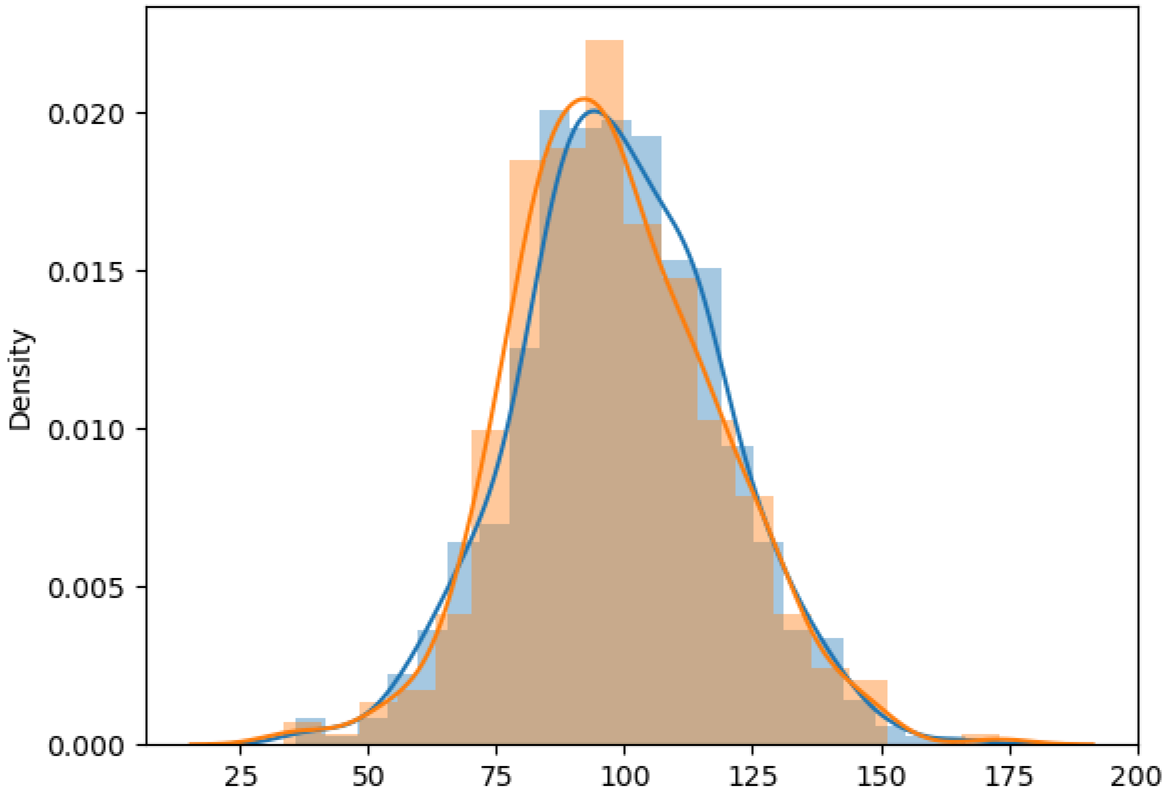
Density
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
60
80
100
120
140

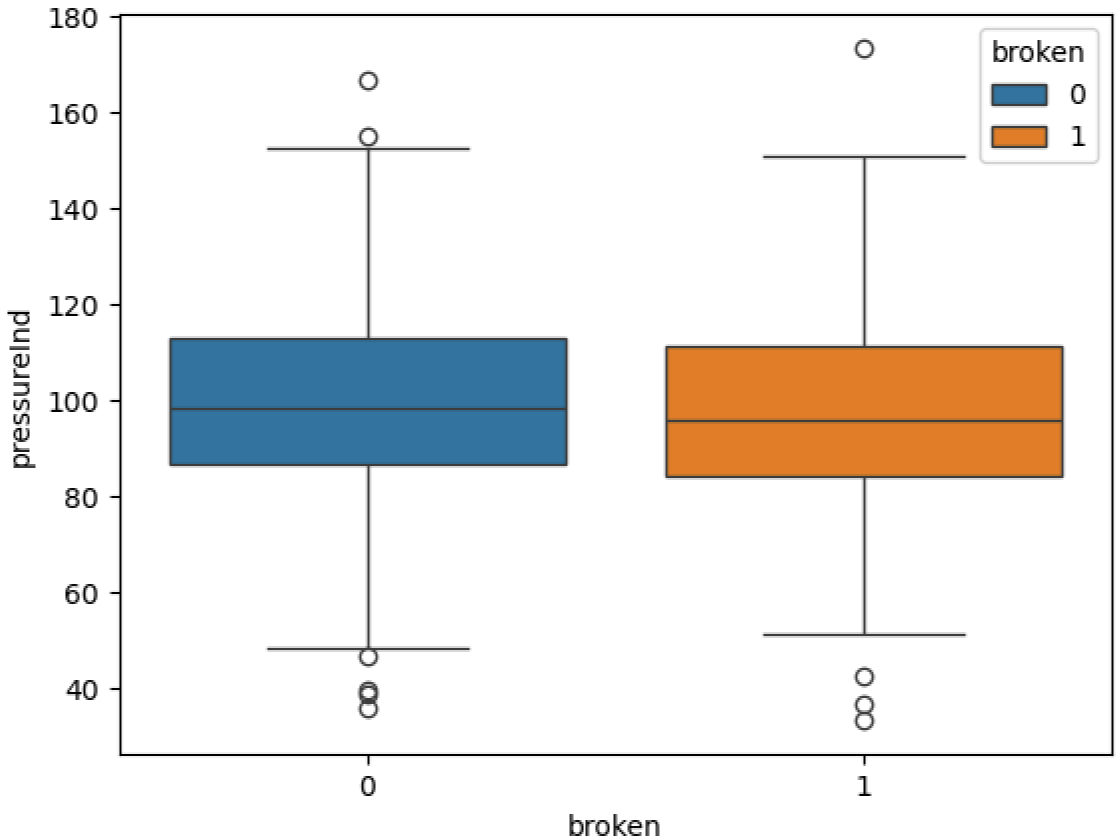


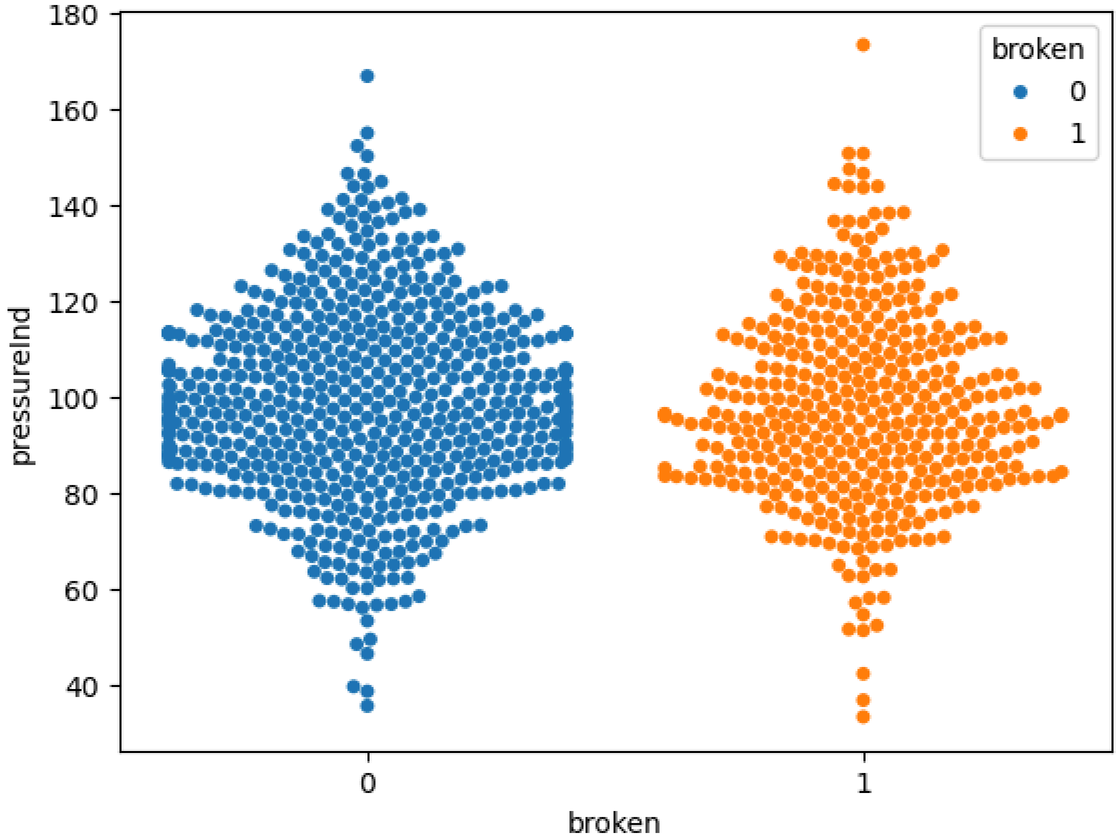
broken
0
1
moistureInd
130
120
110
100
90
80
70
60
0
1
broken

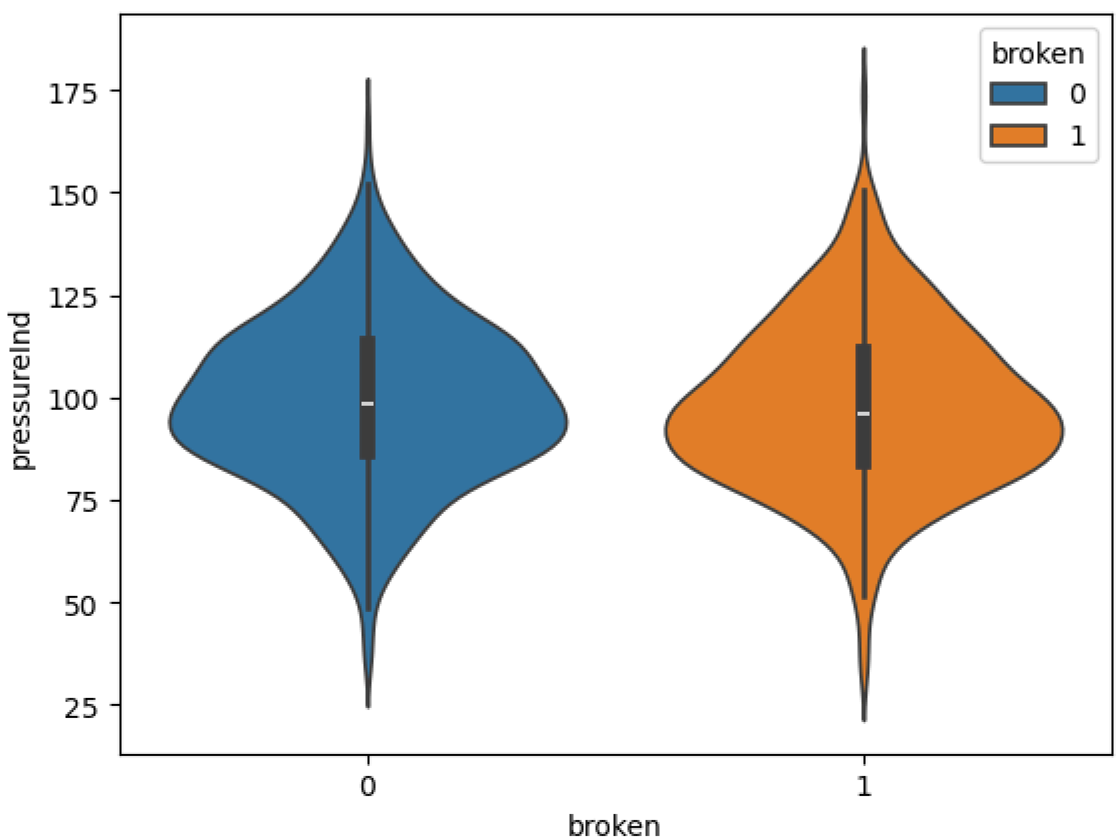

broken
0
1
moistureInd
130
120
110
100
90
80
70
60
0
1
broken

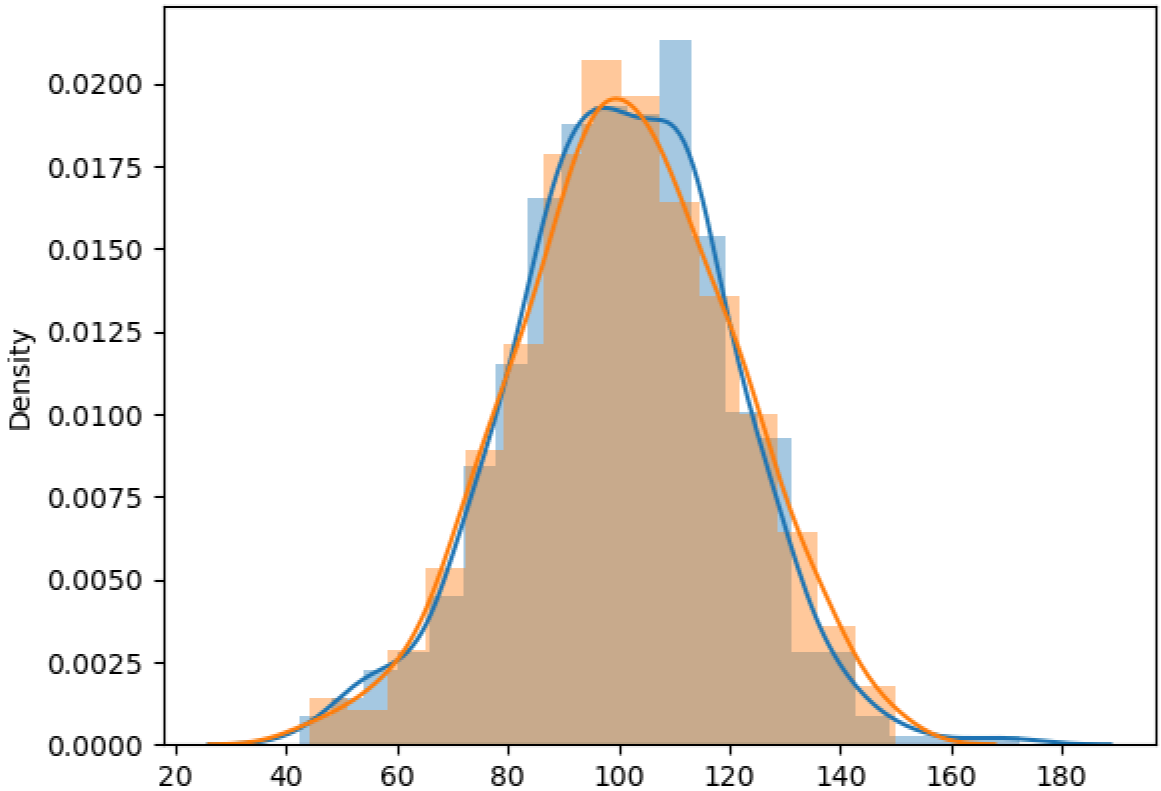

broken
0
1
moistureInd
130
120
110
100
90
80
70
60
50
0
1
broken

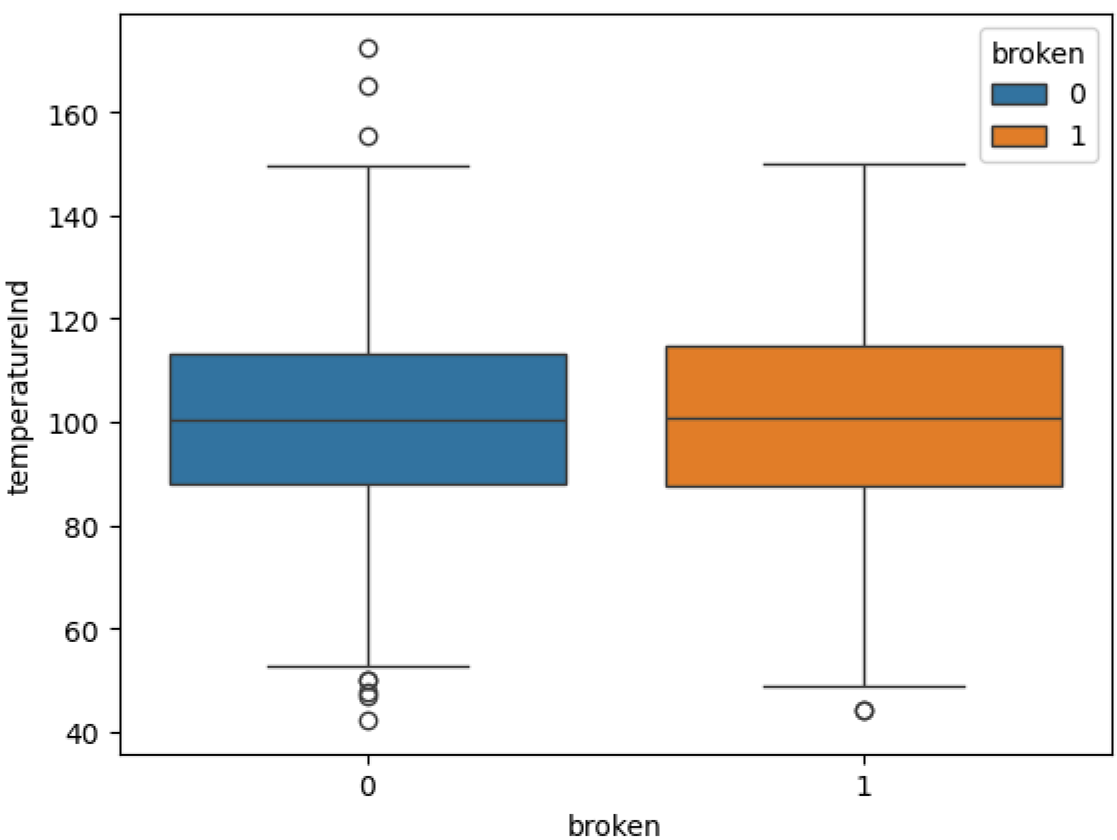

Density
0.000
0.005
0.010
0.015
0.020
25
50
75
100
125
150
175
200

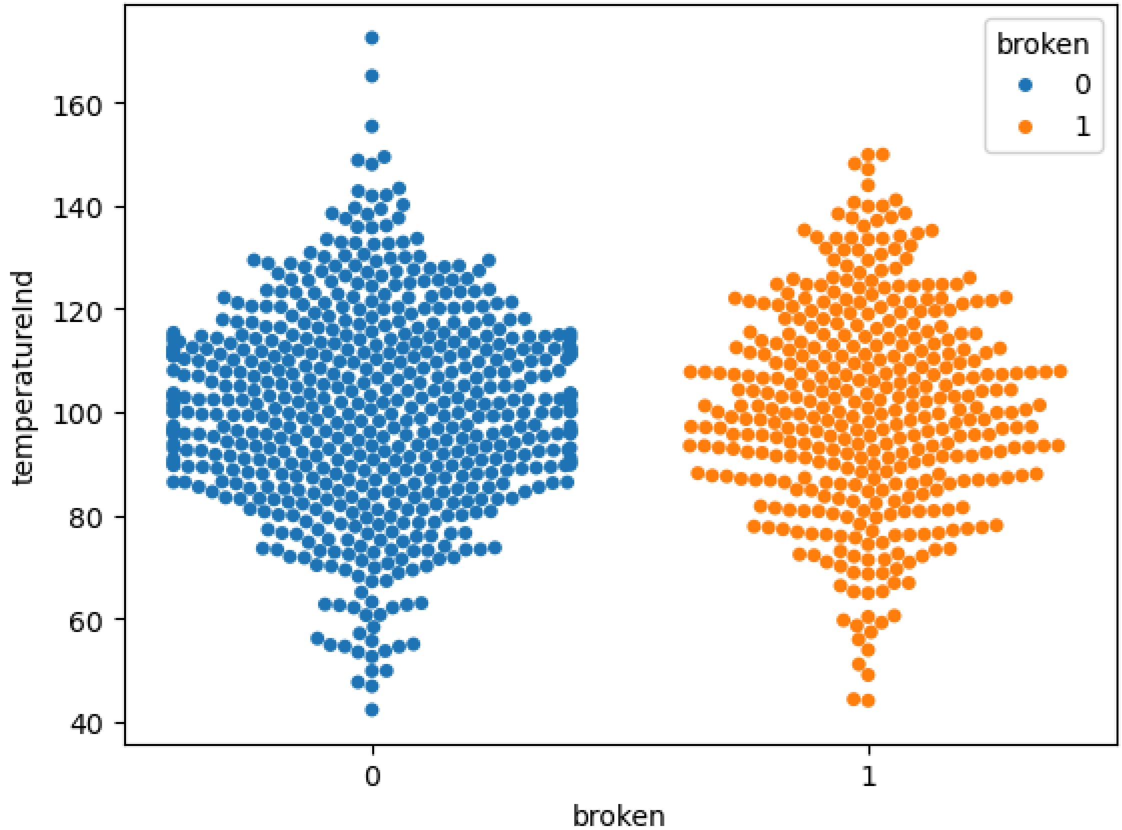

pressureInd
broken
0
1
40
60
80
100
120
140
160
180

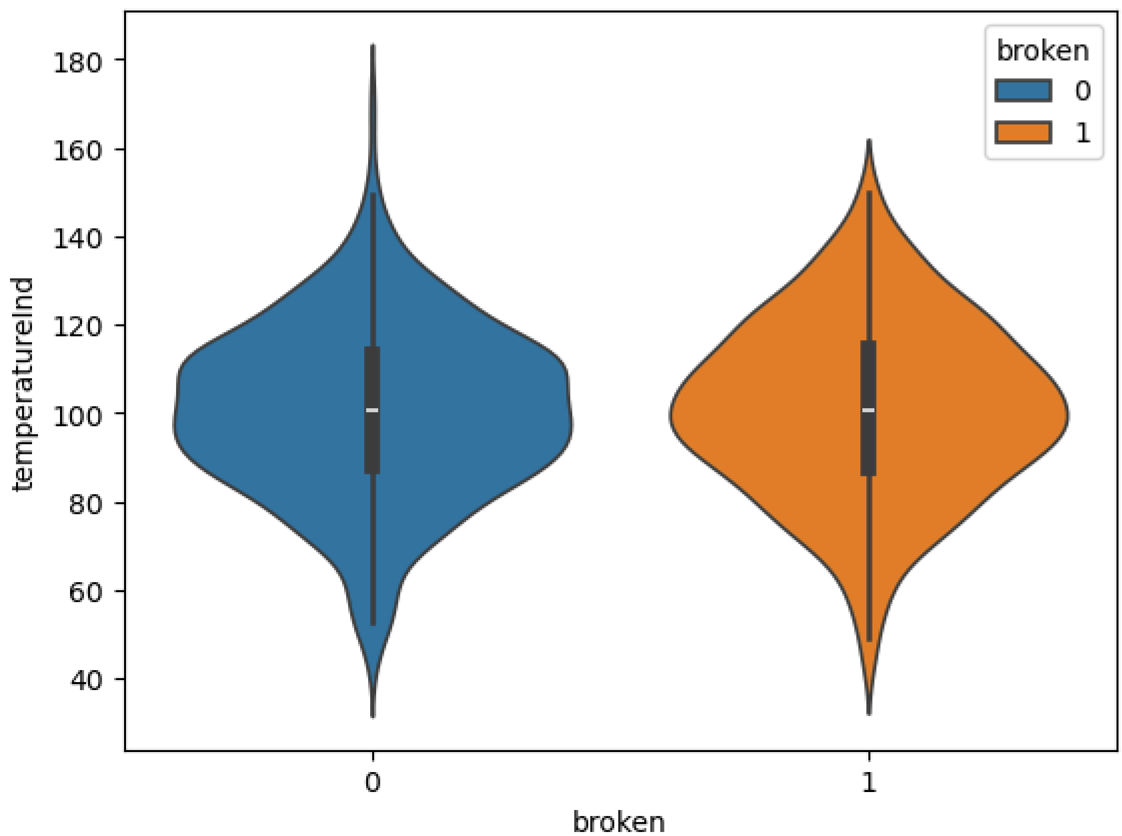

broken
0
1
pressureInd
broken
0
1
180
160
140
120
100
80
60
40


broken
0
1
pressureInd
broken
0
1
175
150
125
100
75
50
25

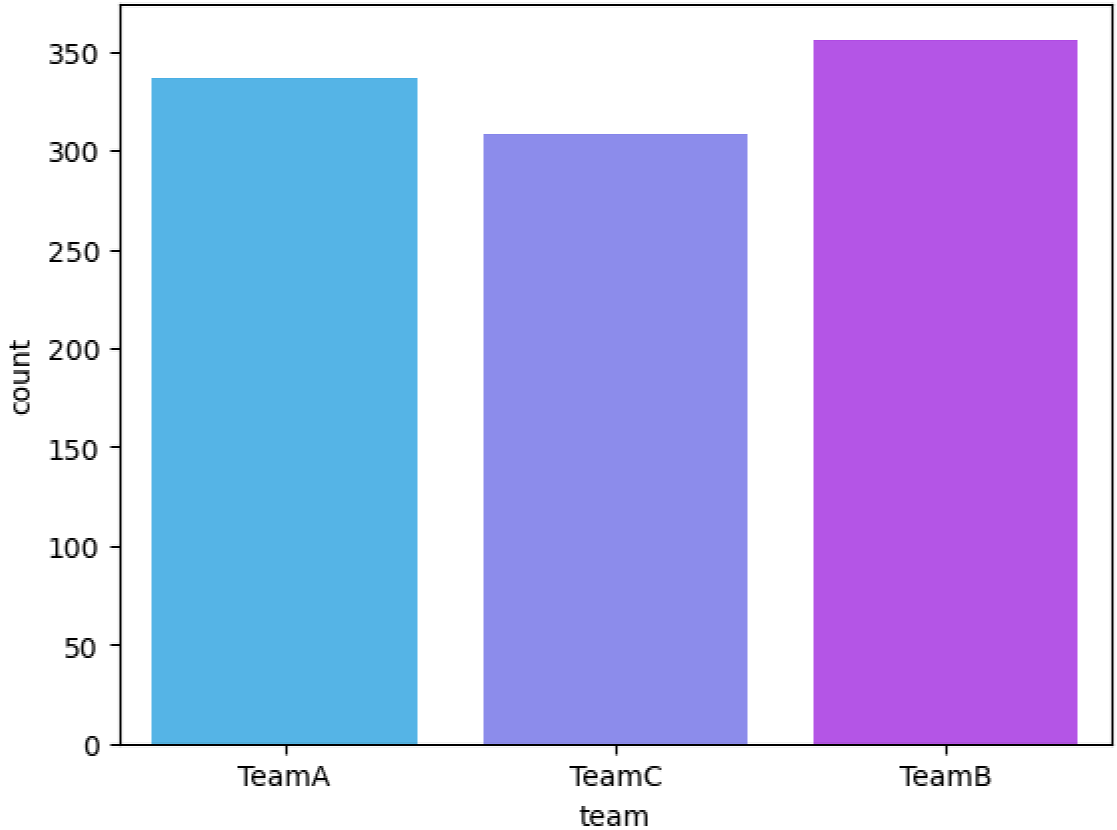

0.0200
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
Density
20
40
60
80
100
120
140
160
180


broken
0
1
160
140
120
100
80
60
40
temperatureInd
0
1
broken

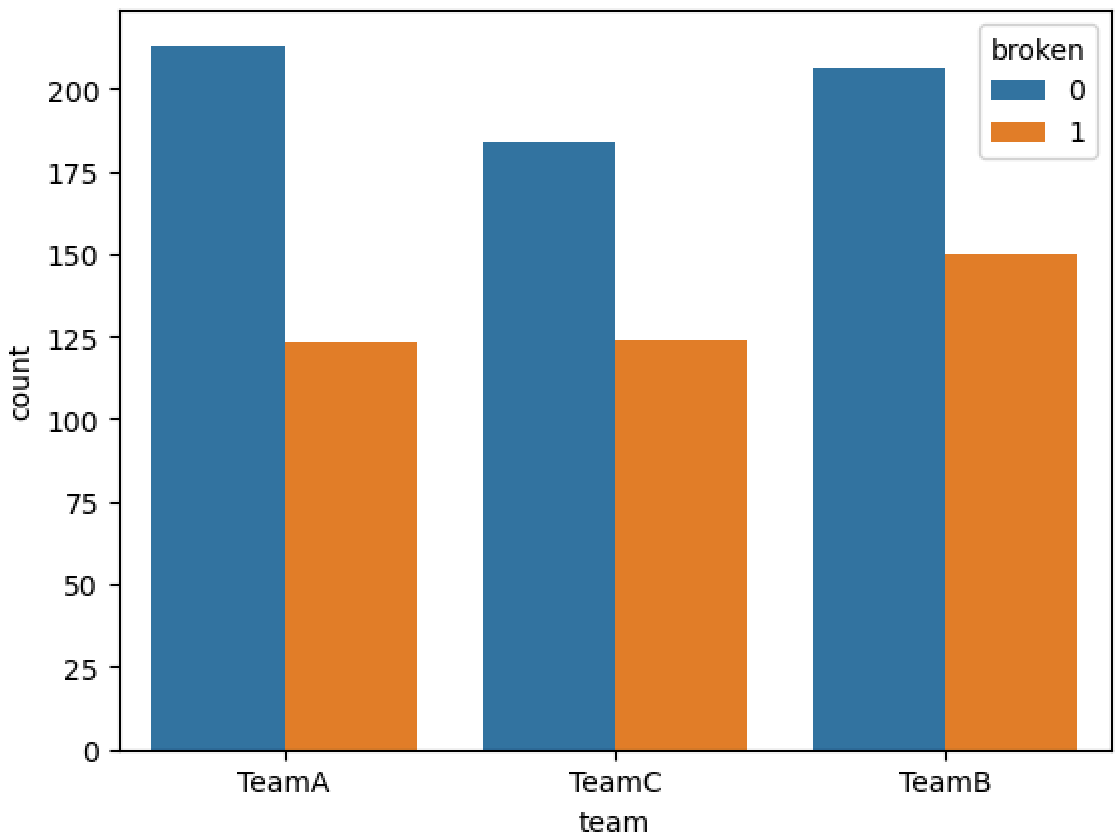




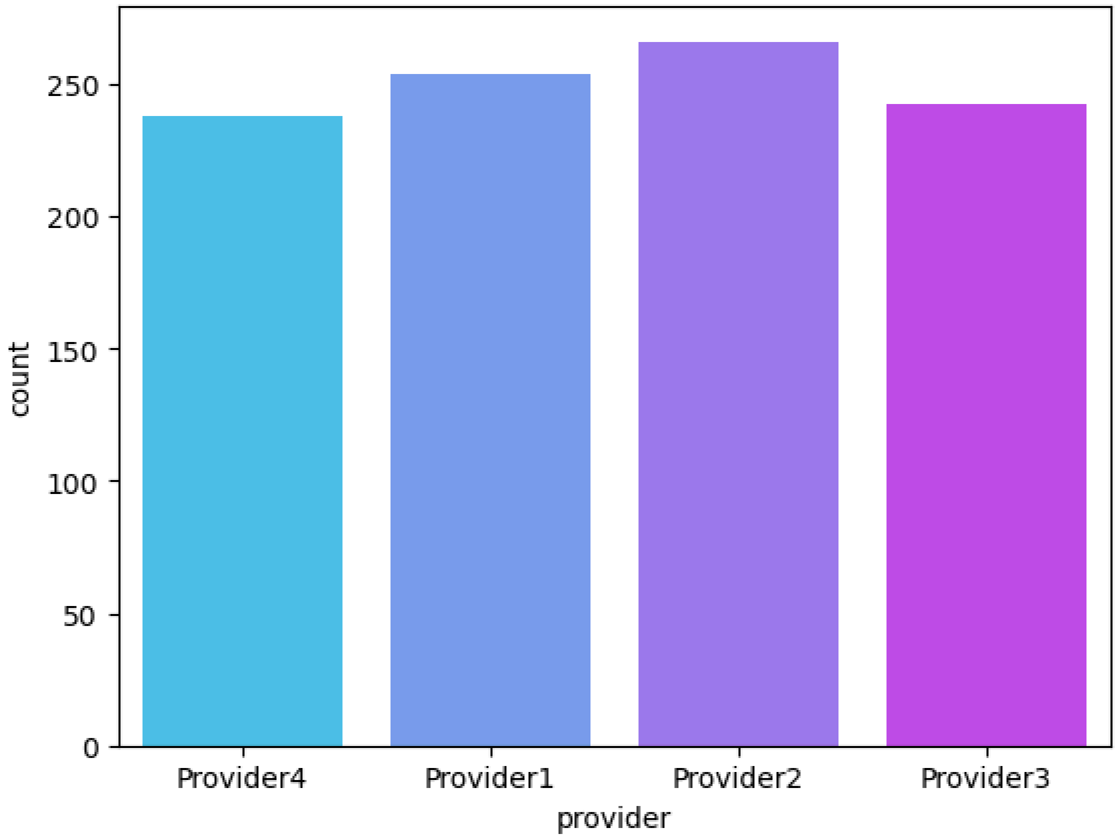
In [45]:
```
sns.countplot(x=main.team,palette='cool')
plt.show()
```



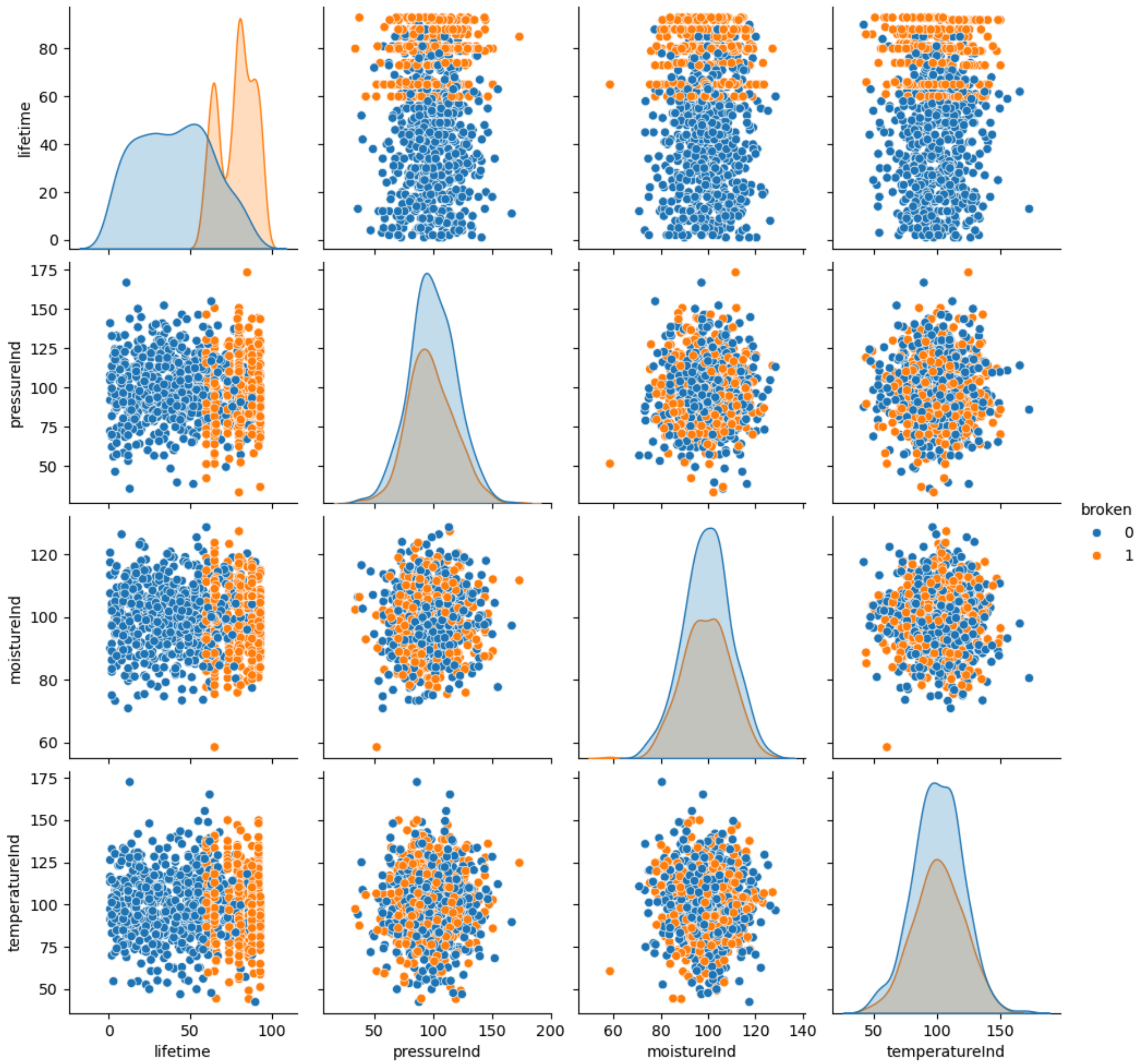
In [46]:
```
sns.countplot(x=main.team,hue=main.broken)
plt.show()
```



In [47]:
```
sns.countplot(x=main.provider,palette='cool')
plt.show()
```



In [48]:
```
sns.pairplot(main,hue='broken')
plt.show()
```



In [49]:
```
# Encoding:
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [50]:
```
# changing the team's column:
main.team = le.fit_transform(main.team)
```

In [51]:
```
main.team.unique()
```

Out[51]:
```
array([0, 2, 1])
```

In [52]:
```
le.inverse_transform([0, 2, 1])
```

Out[52]:
```
array(['TeamA', 'TeamC', 'TeamB'], dtype=object)
```

In [53]:
```
main.provider = le.fit_transform(main.provider)
main.provider.unique()
```

Out[53]:
```
array([3, 0, 1, 2])
```

In [54]:
```
le.inverse_transform([3, 0, 1, 2])
```

Out[54]:
```
array(['Provider4', 'Provider1', 'Provider2', 'Provider3'], dtype=object)
```

In [55]:
```
main
```

Out[55]:

	lifetime	broken	pressureInd	moistureInd	temperatureInd	team	provider
0	56	0	92.178854	104.230204	96.517159	0	3
1	81	1	72.075938	103.065701	87.271062	2	3
2	60	0	96.272254	77.801376	112.196170	0	0
3	86	1	94.406461	108.493608	72.025374	2	1
4	34	0	97.752899	99.413492	103.756271	1	0
...	...	...	...	...	...	...	...
995	88	1	88.589759	112.167556	99.861456	1	3
996	88	1	116.727075	110.871332	95.075631	0	3
997	22	0	104.026778	88.212873	83.221220	1	0
998	78	0	104.911649	104.257296	83.421491	0	3
999	63	0	116.901354	99.998694	47.641493	1	0

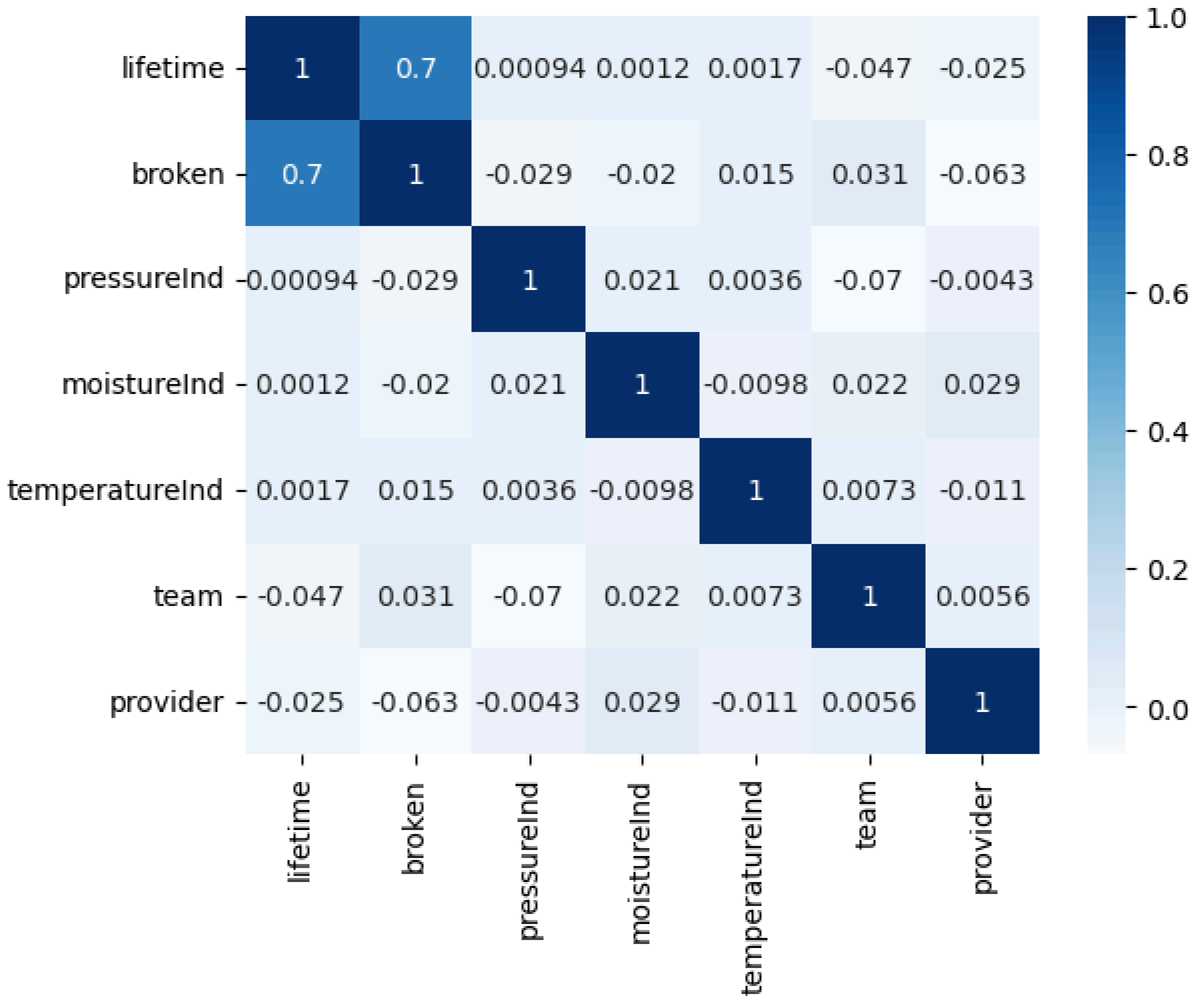
1000 rows × 7 columns

In [56]:
```
# finding the correlation
cr = main.corr()
cr
```

Out[56]:

	lifetime	broken	pressureInd	moistureInd	temperatureInd	team
lifetime	1.000000	0.702656	0.000943	0.001196	0.001744	-0.046537
broken	0.702656	1.000000	-0.028942	-0.019520	0.015364	0.030876
pressureInd	0.000943	-0.028942	1.000000	0.020543	0.003641	-0.069528
moistureInd	0.001196	-0.019520	0.020543	1.000000	-0.009842	0.022420
temperatureInd	0.001744	0.015364	0.003641	-0.009842	1.000000	0.007310
team	-0.046537	0.030876	-0.069528	0.022420	0.007310	1.000000
provider	-0.025172	-0.062972	-0.004337	0.028906	-0.010822	0.005606

In [57]:
```
sns.heatmap(cr,annot=True,cmap='Blues')
plt.show()
```



In [58]:
```
# Creation of ip/op:-
ip = main.drop('broken',axis=1)
```

In [59]:
```
ip.head()
```

Out[59]:

	lifetime	pressureInd	moistureInd	temperatureInd	team	provider
0	56	92.178854	104.230204	96.517159	0	3
1	81	72.075938	103.065701	87.271062	2	3
2	60	96.272254	77.801376	112.196170	0	0
3	86	94.406461	108.493608	72.025374	2	1
4	34	97.752899	99.413492	103.756271	1	0

In [60]:
```
op = main.broken
op.head()
```

Out[60]:
```
0    0
1    1
2    0
3    1
4    0
Name: broken, dtype: int64
```

In [61]:
```
# Train Test Split:
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(ip,op,train_size=0.8)
```

In [62]:
```
xtrain.head()
```

Out[62]:

	lifetime	pressureInd	moistureInd	temperatureInd	team	provider
755	58	111.645399	87.898850	79.455241	2	3
677	80	136.581015	92.822475	87.678519	1	0
368	33	111.737241	96.470432	85.473700	1	1
492	55	146.333342	98.237506	103.209237	1	0
333	45	146.482610	98.848252	106.979033	2	3

In [63]:
```
xtest.head()
```

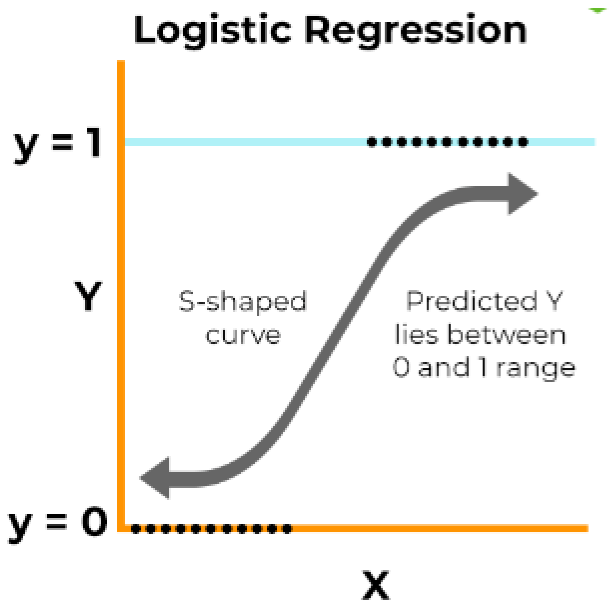
Out[63]:

	lifetime	pressureInd	moistureInd	temperatureInd	team	provider
285	65	112.585712	101.614264	80.835685	1	2
671	31	114.023531	111.605584	108.894301	0	3
24	26	118.978697	105.298916	115.247085	0	1
562	85	109.626240	99.704141	112.418278	2	1
932	9	90.785683	94.055371	84.737974	2	0

In [64]:
```
# Standardizing the data:-
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

In [65]:
```
xtrain = sc.fit_transform(xtrain)
xtest = sc.fit_transform(xtest)
```

Logistic Regression :- uses a logistic function called a sigmoid function for predictions. The sigmoid function refers to an S-shaped curve that converts any real value to a range between 0 and 1.



Uses Sigmoid Function Formula:-

$$f(x) = \frac{1}{1 + e^{-x}}$$

In [66]:
```
# Applying ML Algorithm:-
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

In [67]:
```
lr.fit(xtrain,ytrain)
```

Out[67]:
```
▾ LogisticRegression
LogisticRegression()
```

In [68]:
```
# Prediction:-
ypred = lr.predict(xtest)
ypred
```

Out[68]:
```
array([0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0,
       0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 1], dtype=int64)
```

Accuracy:-

In a classification model accuracy is found out by using Confusion Matrix

Accuracy:- (TN + TP)/All values

Recall:- (TP)/(FN+TP)

In [69]:
```python
from sklearn.metrics import recall_score,accuracy_score
acc = accuracy_score(ypred,ytest)
rec = recall_score(ypred,ytest)
```

In [70]:
```python
print(f"Accuracy:",acc)
print(f"Recall:",rec)
```

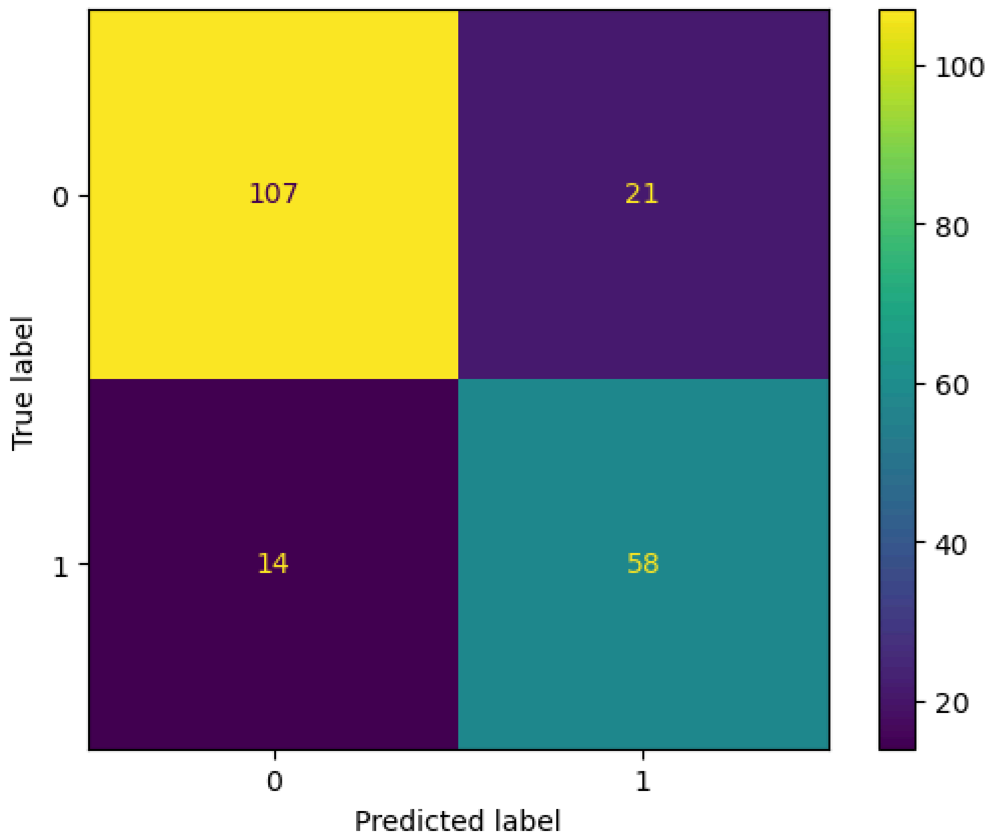
```
Accuracy: 0.825
Recall: 0.8055555555555556
```

In [71]:
```python
# Confusion matrix:-
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix
cm = confusion_matrix(ypred,ytest)
```

In [72]:
```python
cm
```

Out[72]:
```
array([[107,  21],
       [ 14,  58]], dtype=int64)
```

In [73]:
```python
cmd = ConfusionMatrixDisplay(cm)
cmd.plot()
plt.show()
```



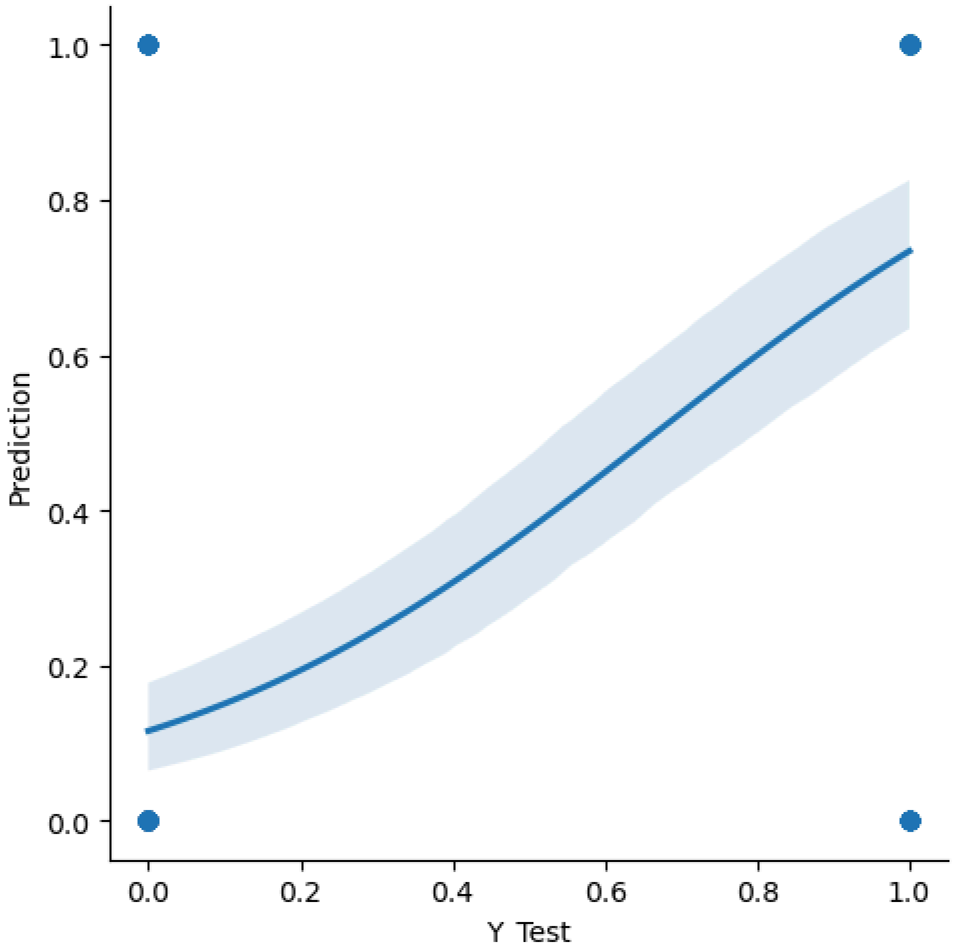
In [74]:
```
df1 = pd.DataFrame({'Y_Test':list(ytest),
                    'Prediction':list(ypred)})
df1
```

Out[74]:

	Y_Test	Prediction
0	1	0
1	0	0
2	0	0
3	0	1
4	0	0
...	...	...
195	0	0
196	1	1
197	0	0
198	0	0
199	1	1

200 rows × 2 columns

In [75]:
```
# to plot the best fit line:
sns.lmplot(x='Y_Test',y='Prediction',data=df1,logistic=True)
plt.show()
```



KNN:- (K-Nearest Neighbor):- based on the principle of proximity, where data points are classified or predicted based on the majority vote of their nearest neighbors.

In [76]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
```

In [77]:
```
knn.fit(xtrain,ytrain)
```

Out[77]:
```
▾ KNeighborsClassifier

KNeighborsClassifier()
```

In [78]:
```
pred1 = knn.predict(xtest)
```

In [79]:
```
from sklearn.metrics import recall_score,accuracy_score
acc = accuracy_score(pred1,ytest)
rec = recall_score(pred1,ytest)
print(f"Accuracy:",acc)
print(f"Recall:",rec)
```

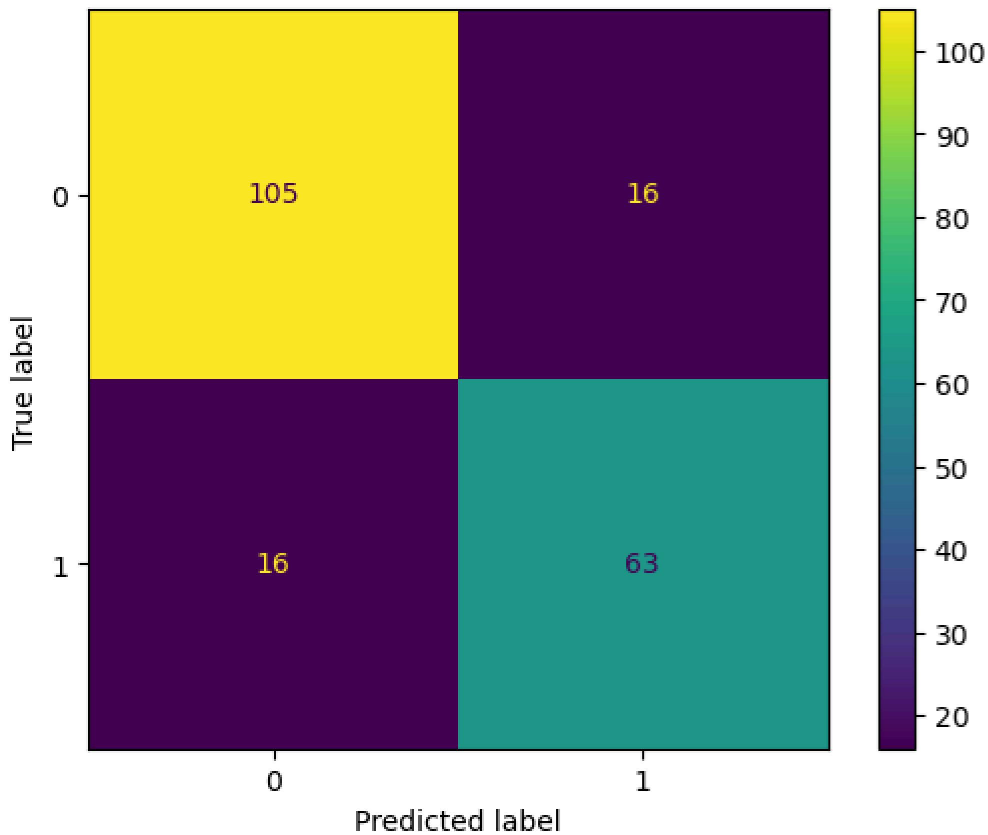
```
Accuracy: 0.84
Recall: 0.7974683544303798
```

In [80]:
```
# Confusion matrix:-
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix
cm1 = confusion_matrix(pred1,ytest)
```

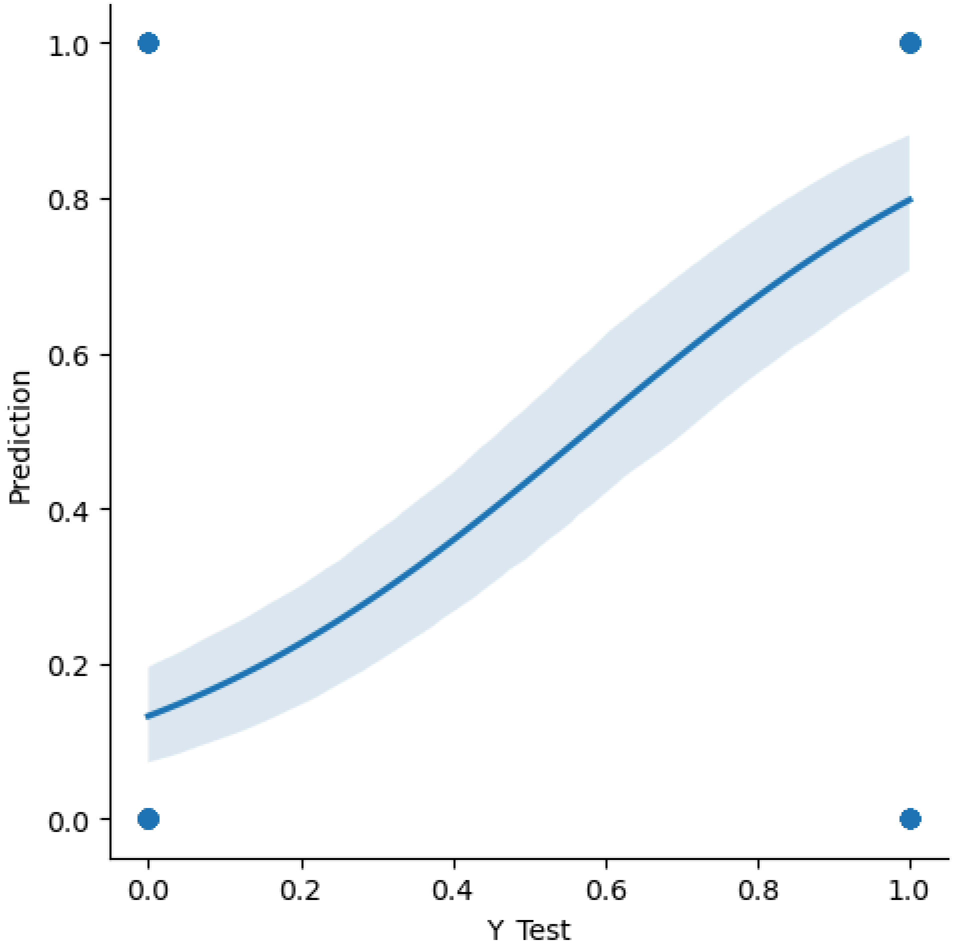
In [81]:
```
cm1
```

Out[81]:
```
array([[105,  16],
       [ 16,  63]], dtype=int64)
```

In [82]:
```
cmd = ConfusionMatrixDisplay(cm1)
cmd.plot()
plt.show()
```



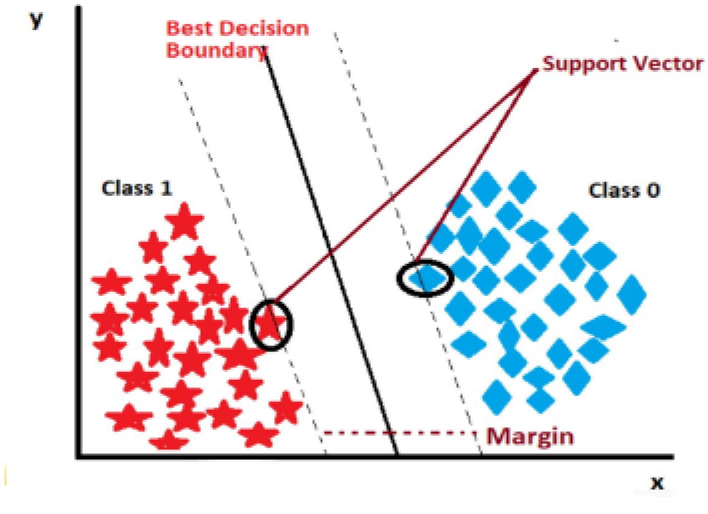
In [83]:
```
df2 = pd.DataFrame({'Y_Test':list(ytest),
                    'Prediction':list(pred1)})
sns.lmplot(x='Y_Test',y='Prediction',data=df2,logistic=True)
plt.show()
```



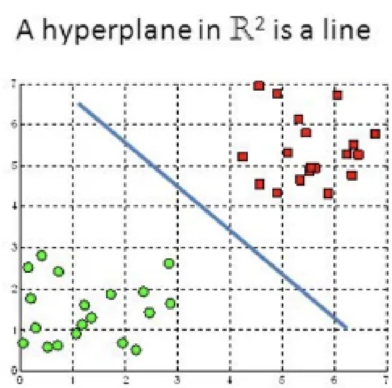
SVM:- Support Vector Machine:-

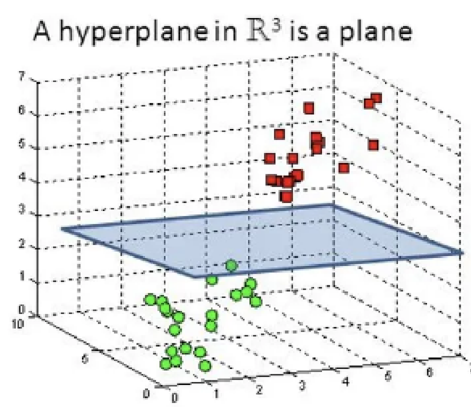
SVC :- Support Vector Classifier :- to find the best fit hyperplane/line thats separates the categories in the best way.

```
 A Hyperplane is a decision boundary that helps classifying data
points.
```



Categorizing the data





Kernel Function:-
1. linear -> 1D to 2D
2. Poly -> 2D to 3D
3. Sigmoid -> 2D to 3D
4. rbf (Radial Basis Function) -> 1D - 2D - 3D

gamma -> coefficient of the kernel function.

C :- Regularization Parameter (this restrict our model to be overfitted.)
Range of C:-
i. (0.01 - 1) - Small (noisy data, wants to avoid underfitting)

ii. (1 - 10) - Medium (good training starting point)
iii. (10 - 1000) - High (Data is clean, helps to minimize overfitting)

In [84]:
```
from sklearn.svm import SVC
sv = SVC(kernel = 'rbf', gamma = 0.01, C = 1000 )
sv.fit(xtrain,ytrain)
```

Out[84]:
```
SVC
SVC(C=1000, gamma=0.01)
```

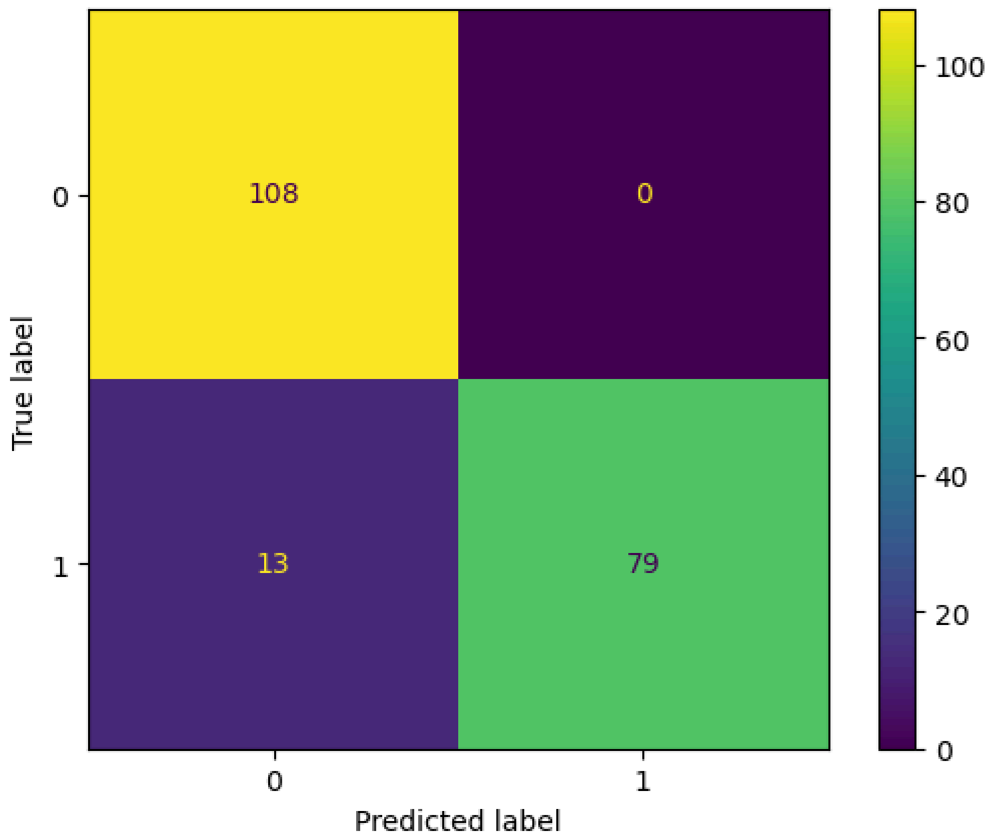
In [85]:
```
pred2 = sv.predict(xtest)
pred2
```

Out[85]:
```
array([1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0,
       1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 1], dtype=int64)
```

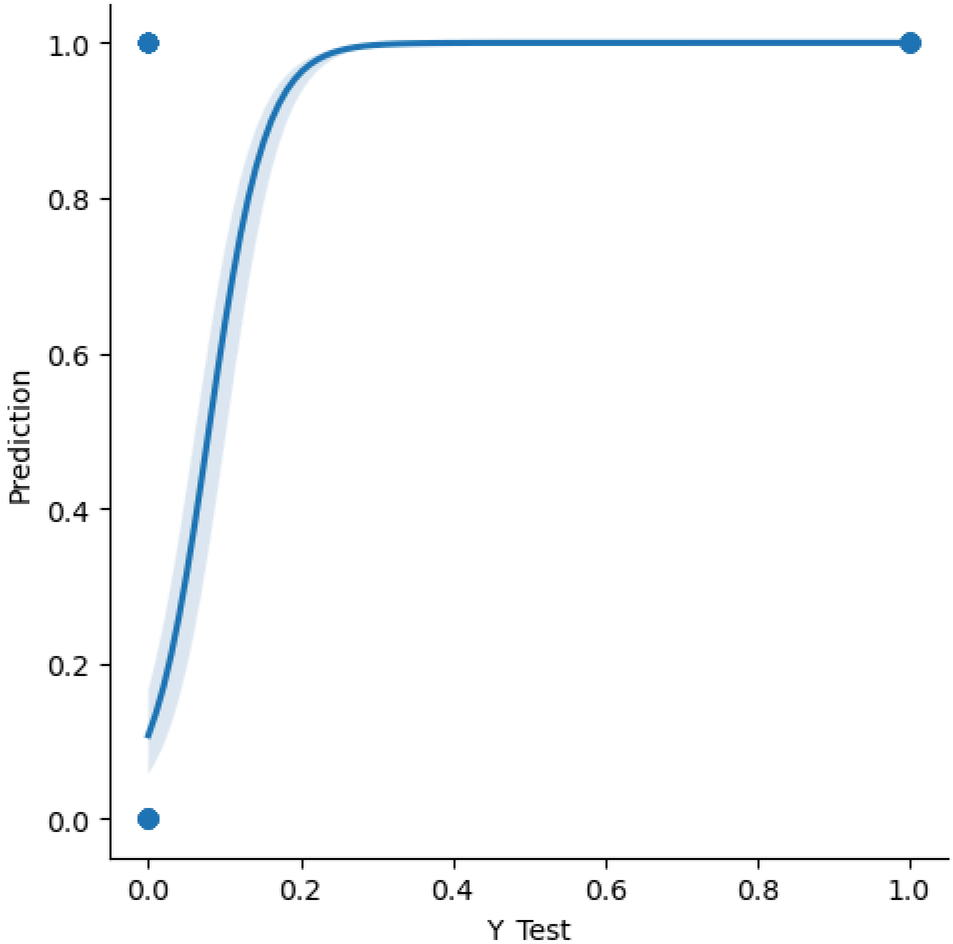
In [86]:
```
from sklearn.metrics import accuracy_score, recall_score
acc = accuracy_score(pred2,ytest)
rec = recall_score(pred2,ytest)
print(acc)
print(rec)
```

```
0.935
0.8586956521739131
```

In [87]:
```
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix
cm = confusion_matrix(pred2,ytest)
cm2 = ConfusionMatrixDisplay(cm)
cm2.plot()
plt.show()
```

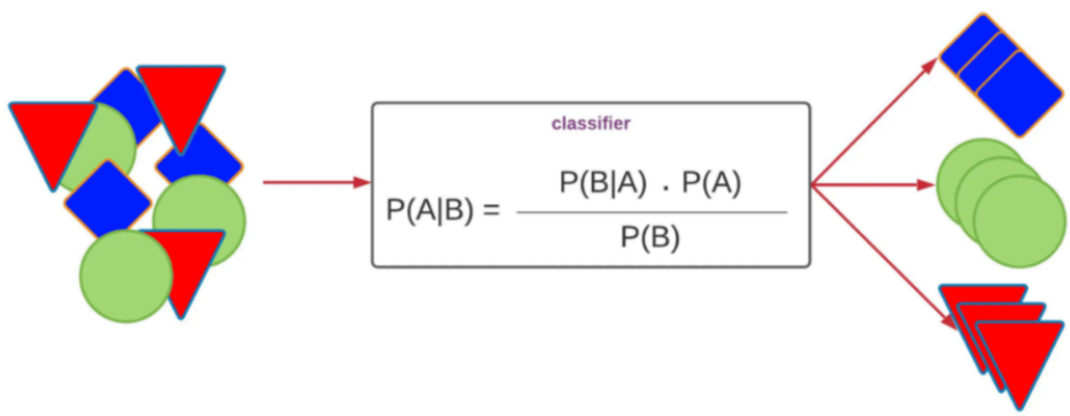


In [88]:
```
df3 = pd.DataFrame({'Y_Test':list(ytest),
                    'Prediction':list(pred2)})
sns.lmplot(x='Y_Test',y='Prediction',data=df3,logistic=True)
plt.show()
```



Naive Bayes:- it works on conditional probability.

```
Naive Bayes uses Bayes Theorem to predict the category of a new
data point.
```



```
There are 3 kind of Bayes Theorem:-
1. Gaussian NB :- data is numerical as well as categorical.
2. Multinomial NB :- only for text datas.
3. Bernoulli NB :- only for categorical datas.
```

In [89]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(xtrain,ytrain)
```

Out[89]:
```
▾ GaussianNB
GaussianNB()
```

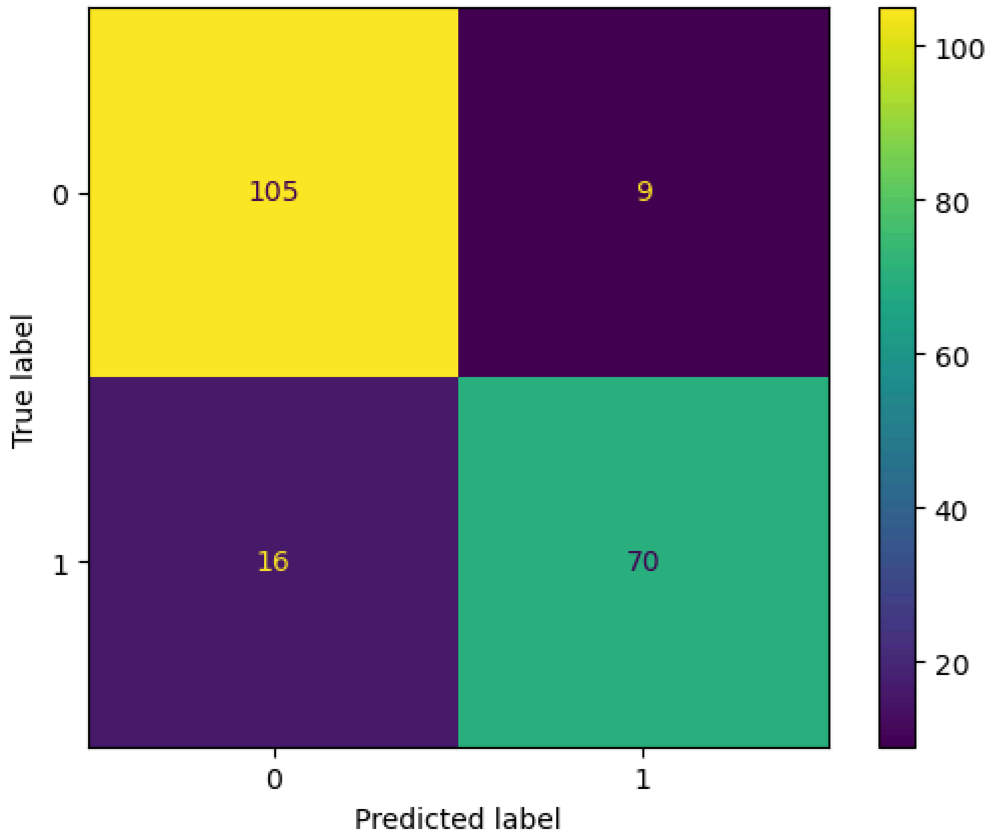
In [90]:
```
pred4 = gnb.predict(xtest)
pred4
```

Out[90]:
```
array([1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 1], dtype=int64)
```

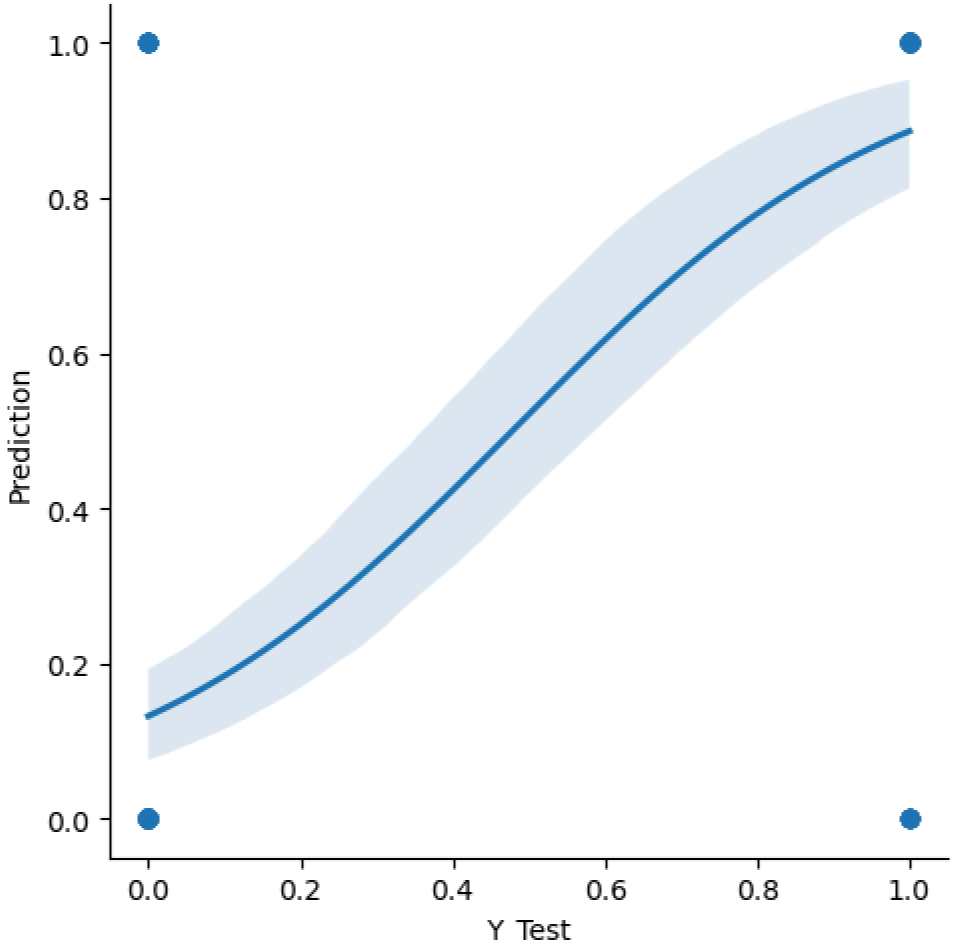
In [91]:
```
from sklearn.metrics import accuracy_score, recall_score
acc = accuracy_score(pred4,ytest)
rec = recall_score(pred4,ytest)
print(acc)
print(rec)
```

```
0.875
0.813953488372093
```

In [92]:
```
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix
cmm = confusion_matrix(pred4,ytest)
cm_2 = ConfusionMatrixDisplay(cmm)
cm_2.plot()
plt.show()
```



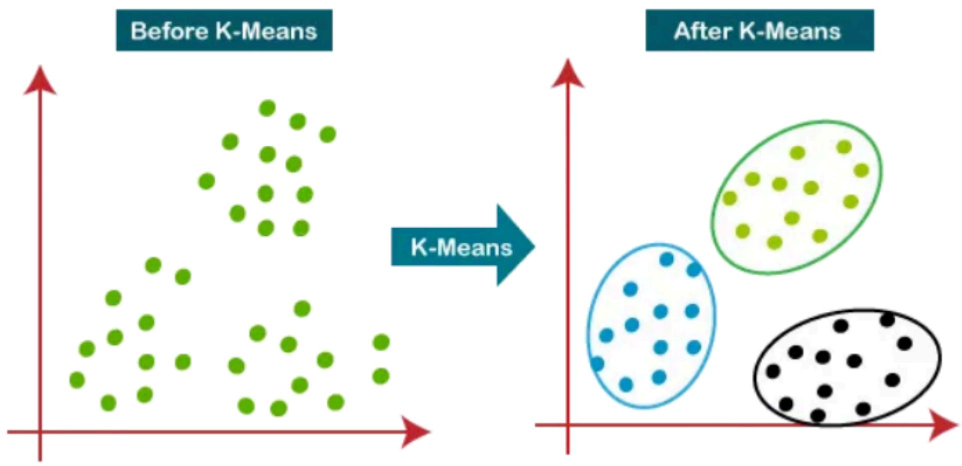
In [93]:
```
df4 = pd.DataFrame({'Y_Test':list(ytest),
                    'Prediction':list(pred4)})
sns.lmplot(x='Y_Test',y='Prediction',data=df4,logistic=True)
plt.show()
```



Unsupervised Learning:-

Machines tries to group the datas based on similar patterns or features.

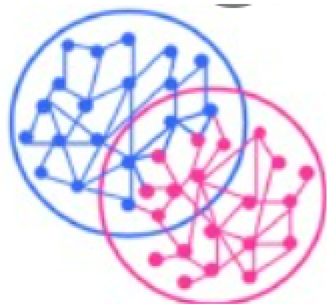
- It refers to the algorithm that learns patterns from unlabelled data.



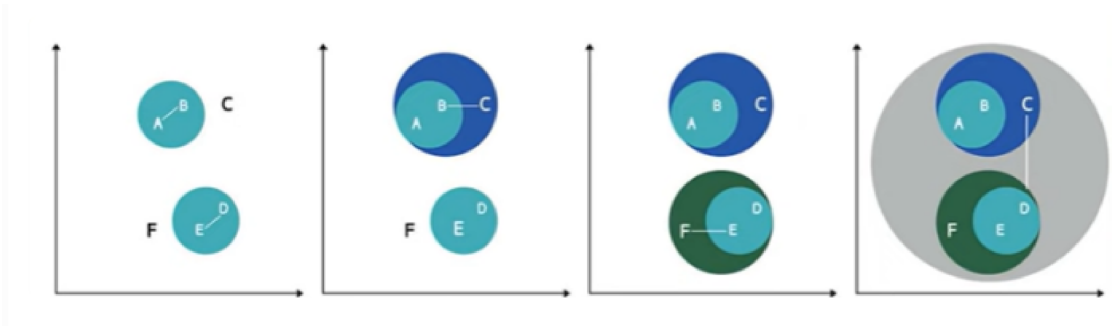
Types of Unsupervised Machine Learning:-
1. Exclusive Unsupervised ML
2. Overlapping Unsupervised ML
3. Hierarchical Unsupervised ML

Exclusive Clustering

Overlapping Clustering



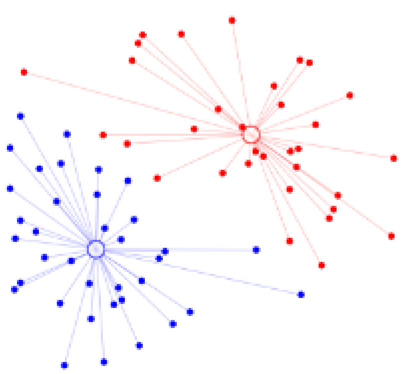
Hierarchical Clustering



K-Means Clustering:- it belongs to exclusive unsupervised machine learning algorithm.

Clustering :- means grouping up of the datas.

1st Iteration :- Centroids were chosen complete randomly.



2nd Iteration :- Again centroids will be reassigned based on mean data points (means are found out by considering all the data points of the particular cluster)

```
The process will be repeated till all the data points have been
clearly clustered.
```

In [94]:
```
# importing the libraries:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [95]:
```
iris = pd.read_csv(r"C:\Users\lab25\Downloads\iris (1)\iris.data",header=None)
iris
```

Out[95]:

	0	1	2	3	4
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

In [96]:
```
iris.columns = ['SL','SW','PL','PW','Flower']
iris.head()
```

Out[96]:

	SL	SW	PL	PW	Flower
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [97]:
```
# Data Cleaning:-
iris.dtypes
```

Out[97]:
```
SL        float64
SW        float64
PL        float64
PW        float64
Flower     object
dtype: object
```

In [98]:
```
iris.isnull().sum()
```

Out[98]:
```
SL        0
SW        0
PL        0
PW        0
Flower    0
dtype: int64
```

In [99]:
```
for i in iris.columns:
    print(f"{i}:\n{iris[i].unique()}\n")
```

```
SL:
[5.1 4.9 4.7 4.6 5.  5.4 4.4 4.8 4.3 5.8 5.7 5.2 5.5 4.5 5.3 7.  6.4 6.9
 6.5 6.3 6.6 5.9 6.  6.1 5.6 6.7 6.2 6.8 7.1 7.6 7.3 7.2 7.7 7.4 7.9]

SW:
[3.5 3.  3.2 3.1 3.6 3.9 3.4 2.9 3.7 4.  4.4 3.8 3.3 4.1 4.2 2.3 2.8 2.4
 2.7 2.  2.2 2.5 2.6]

PL:
[1.4 1.3 1.5 1.7 1.6 1.1 1.2 1.  1.9 4.7 4.5 4.9 4.  4.6 3.3 3.9 3.5 4.2
 3.6 4.4 4.1 4.8 4.3 5.  3.8 3.7 5.1 3.  6.  5.9 5.6 5.8 6.6 6.3 6.1 5.3
 5.5 6.7 6.9 5.7 6.4 5.4 5.2]

PW:
[0.2 0.4 0.3 0.1 0.5 0.6 1.4 1.5 1.3 1.6 1.  1.1 1.8 1.2 1.7 2.5 1.9 2.1
 2.2 2.  2.4 2.3]

Flower:
['Iris-setosa' 'Iris-versicolor' 'Iris-virginica']
```

In [100…
```
# We need to drop the op column 'flower'.
ip = iris.drop('Flower',axis=1)
ip.head()
```

Out[100…

	SL	SW	PL	PW
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

In [101…

```
# To Apply the K-Means Clustering Algorithm:-
from sklearn.cluster import KMeans
km = KMeans(n_clusters=3)
km.fit(ip)
```

Out[101…

```
▾ KMeans
KMeans(n_clusters=3)
```

In [102…

```
# prediction:
km_pred = km.predict(ip)
km_pred
```

Out[102…

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 2, 2, 2, 2, 0, 2, 2, 2,
       2, 2, 2, 0, 0, 2, 2, 2, 2, 0, 2, 0, 2, 0, 2, 2, 0, 0, 2, 2, 2, 2,
       2, 0, 2, 2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 0])
```

In [103…

```
centroids = km.cluster_centers_
centroids
```

Out[103…

```
array([[5.9016129 , 2.7483871 , 4.39354839, 1.43387097],
       [5.006     , 3.418     , 1.464     , 0.244     ],
       [6.85      , 3.07368421, 5.74210526, 2.07105263]])
```

In [104…

```
iris['Prediction'] = km_pred
iris
```

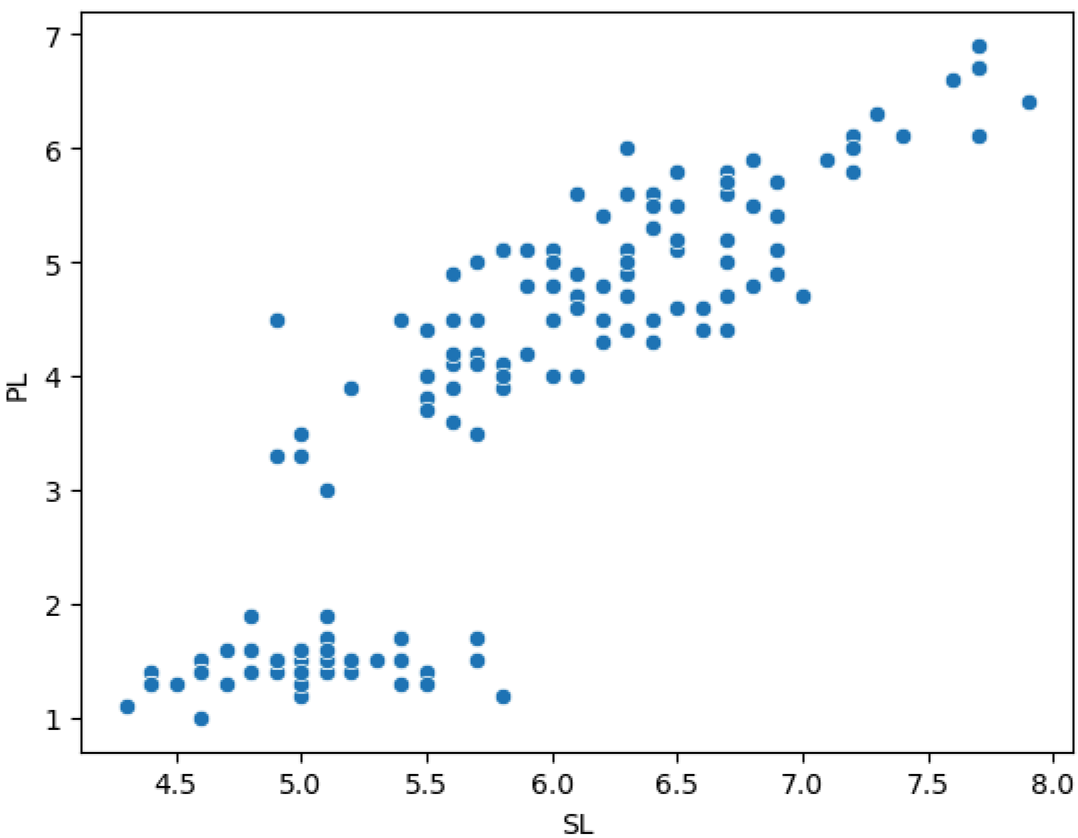
Out[104…

	SL	SW	PL	PW	Flower	Prediction
0	5.1	3.5	1.4	0.2	Iris-setosa	1
1	4.9	3.0	1.4	0.2	Iris-setosa	1
2	4.7	3.2	1.3	0.2	Iris-setosa	1
3	4.6	3.1	1.5	0.2	Iris-setosa	1
4	5.0	3.6	1.4	0.2	Iris-setosa	1
...	...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica	2
146	6.3	2.5	5.0	1.9	Iris-virginica	0
147	6.5	3.0	5.2	2.0	Iris-virginica	2
148	6.2	3.4	5.4	2.3	Iris-virginica	2
149	5.9	3.0	5.1	1.8	Iris-virginica	0

150 rows × 6 columns

In [105…

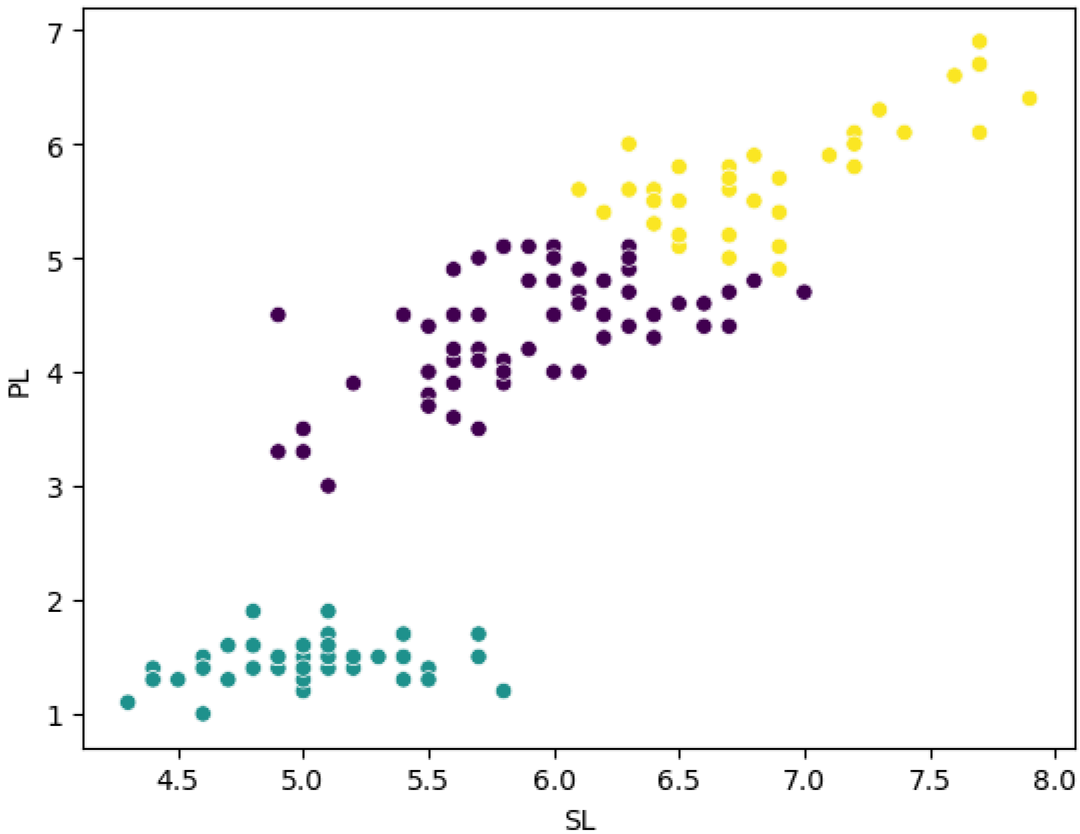
```
sns.scatterplot(x=iris.SL,y=iris.PL)
plt.show()
```



In [106…

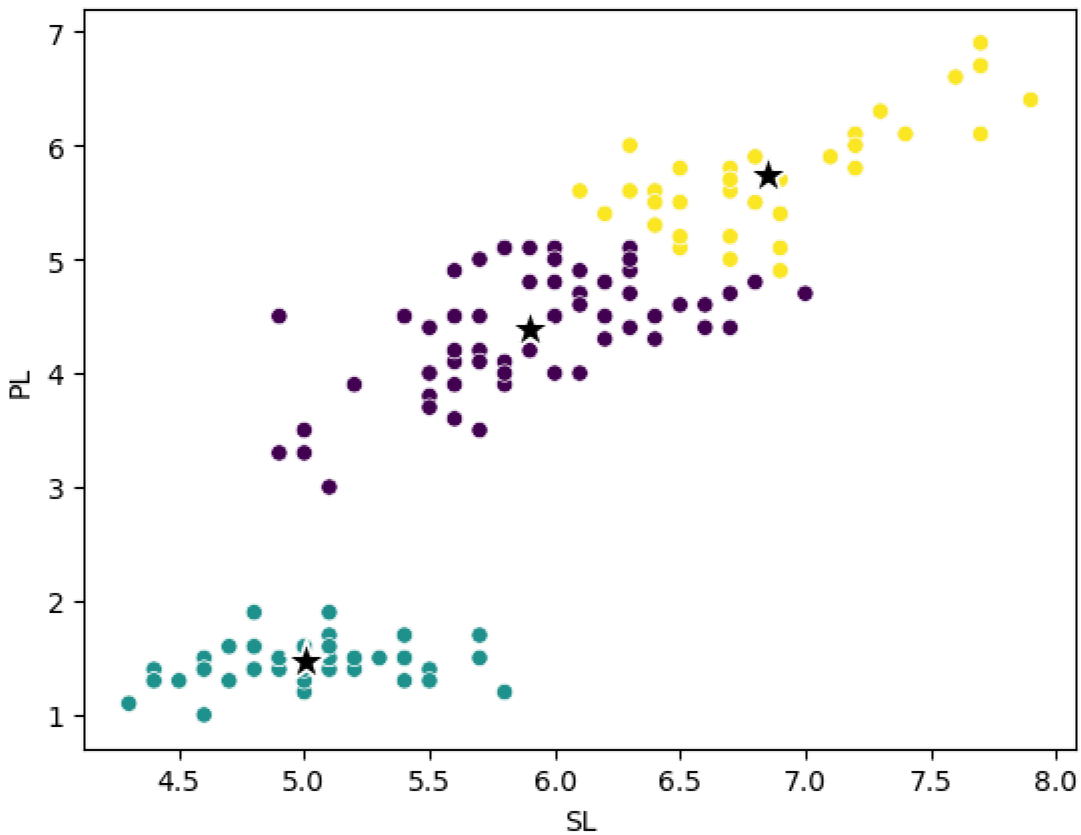
```
sns.scatterplot(x=iris.SL,y=iris.PL,
                c = km_pred)
```

```
plt.show()
```



In [107…

```
# Plotting along the centroid values:-
sns.scatterplot(x=iris.SL,y=iris.PL,
                c = km_pred)
sns.scatterplot(x=centroids[:,0],y=centroids[:,2],
               s=250,marker='*',color='k')
plt.show()
```



In [ ]: