Linear_MultipleLinear_polynomial(quadratic)_regression

February 12, 2024

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

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

[2]:
```python
# working on dataset to find out better platform for advertising to increase␣
↪sales
# reading dataset
df=pd.read_csv('advertising.csv')
df.head()
```

[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

[3]:
```python
df.shape
```

[3]: (200, 4)

[4]:
```python
df.info()
# datatypes are float of all column and non-null
```

```
<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
```

[5]:
```python
df.describe()
# checking skewness
```

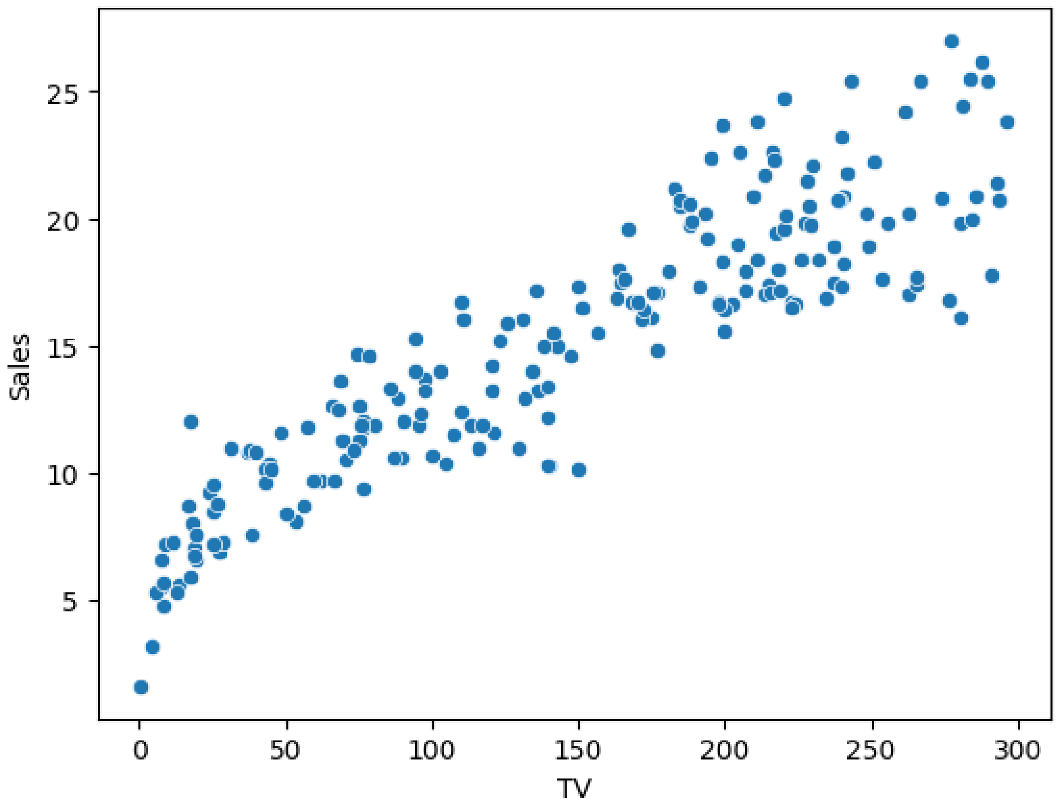
[5]:

	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

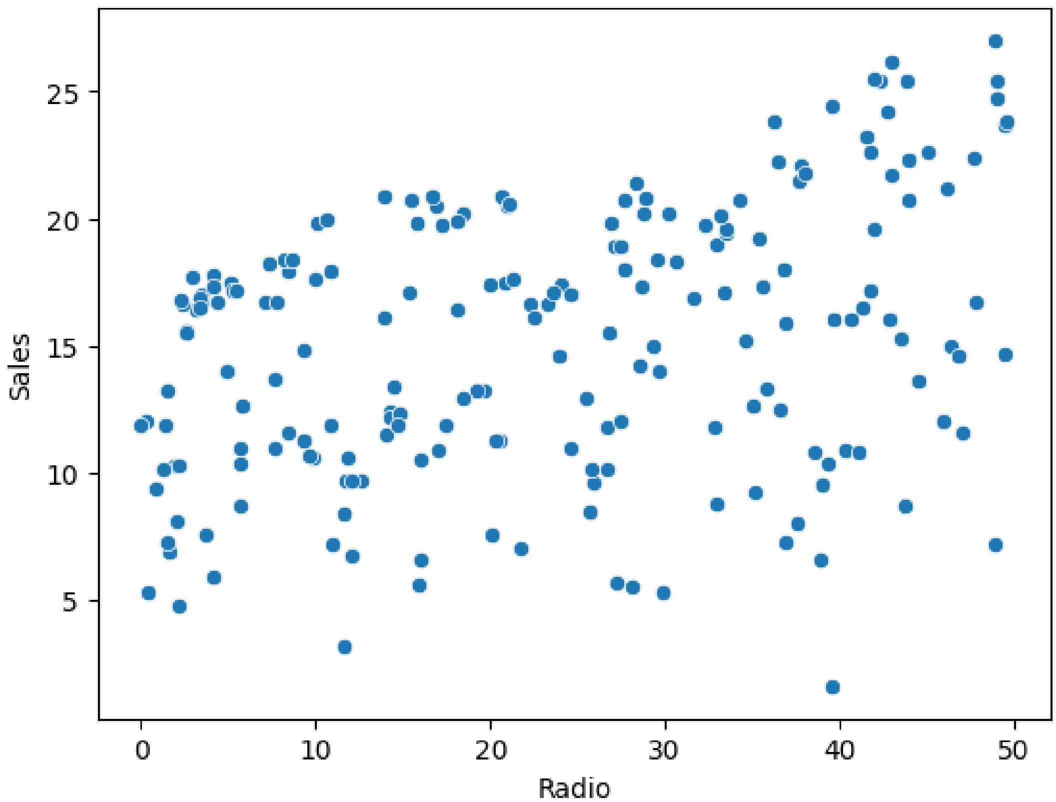
[6]:
```python
df.isnull().sum()
# no missing values
```

[6]:
```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

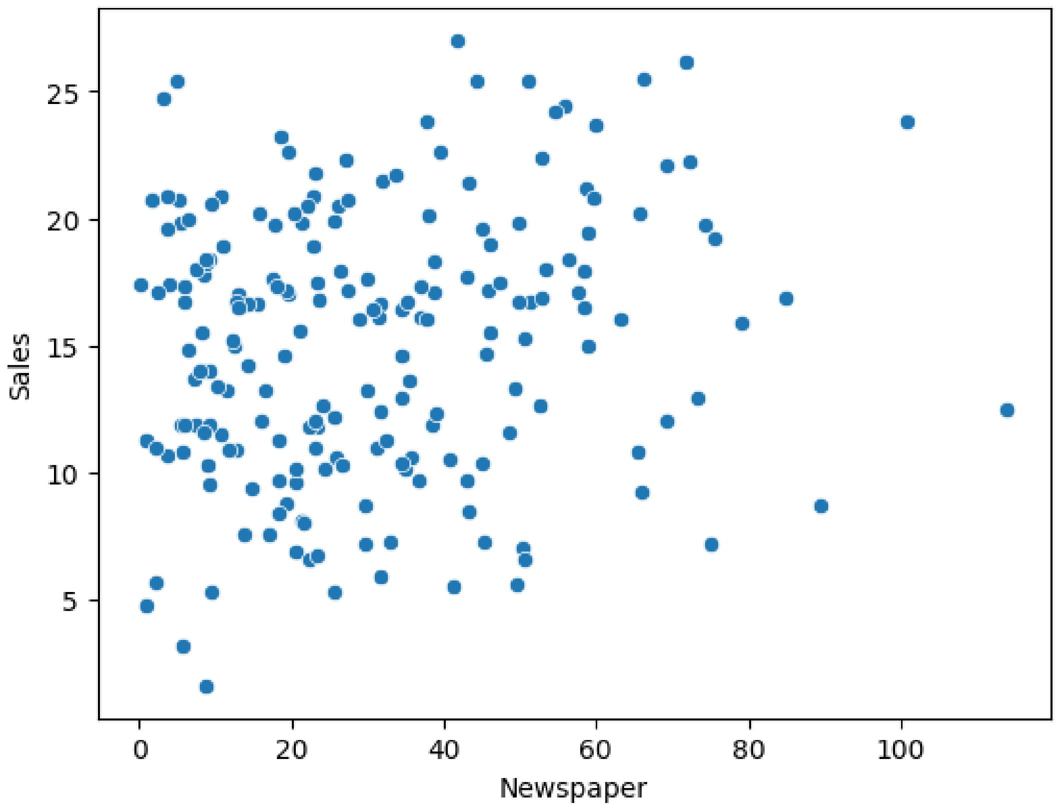
[7]:
```python
# visualize to check linear relationship
plt.figure()
sns.scatterplot(x='TV',y='Sales',data=df)
plt.show()
# we can observe there is linear relationship between TV(feature) and␣
↪Sales(Target), but correlation cannot be 1 due to distributed data.
```



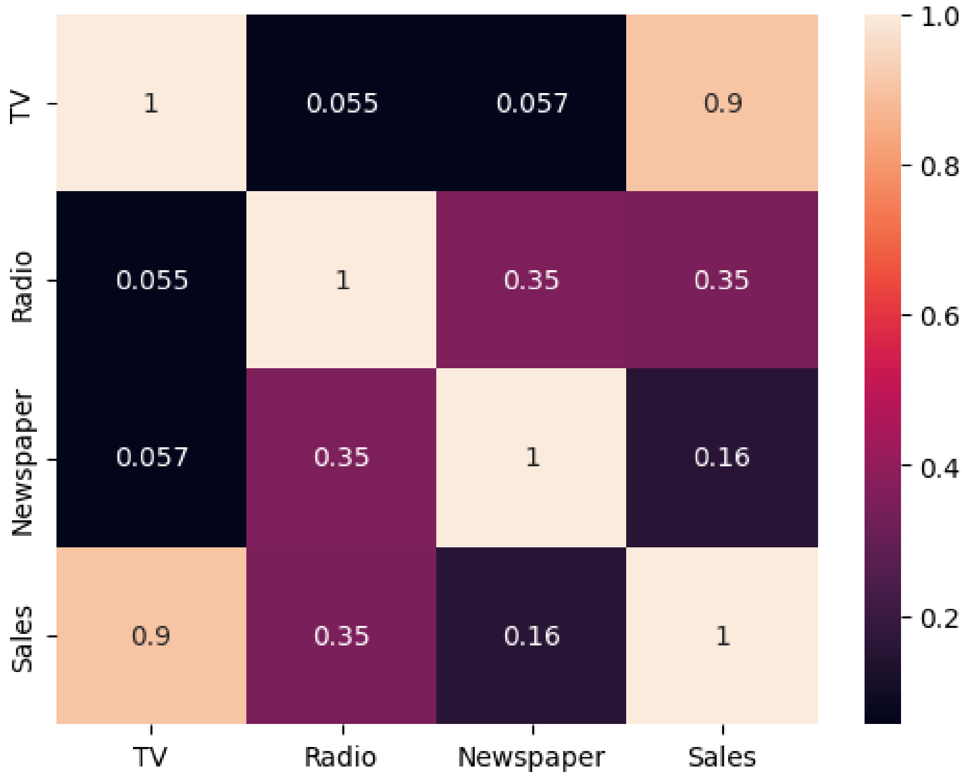
[8]:
```
plt.figure()
sns.scatterplot(x='Radio',y='Sales',data=df)
plt.show()
# we can observe there is linear relationship between Radio and Sales, but␣
 ↪correlation between data is poor due to distributed data.
```



[9]:
```
plt.figure()
sns.scatterplot(x='Newspaper',y='Sales',data=df)
plt.show()
# no linear relationship between Newspaper and Sales
```



[10]:
```
# to check correlation between data
plt.figure()
sns.heatmap(df.corr(),annot=True)
plt.show()
```



1 Linear Regression

Model for TV(Feature) and Sales(Target)

[11]:
```
# Selection of feature
X=df['TV']       #Feature
y=df['Sales']    #Target
```

[12]:
```
# splitting dataset
x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=1)
# splitting data with 30% test size and random_state Hyperparameter to control␣
↪the randomness in ML Model
```

[13]:
```
lr=LinearRegression()
```

[14]:
```
# print(y_train.ndim,y_train.shape)
# print(x_train.ndim,x_train.shape)
```

[15]:
```
# training model(fitting data)
# lr.fit(x_train,y_train)
lr.fit(np.array(x_train).reshape(-1,1),y_train)
```

```
# data reshape required as feature is single and fit requires 2D
# so x_train is reshaped
```

[15]: LinearRegression()

```
[16]: # Slope
lr.coef_
```

[16]: array([0.05566076])

```
[17]: # OLS:intercept
lr.intercept_  #this value will be same
```

[17]: 6.904032471762278

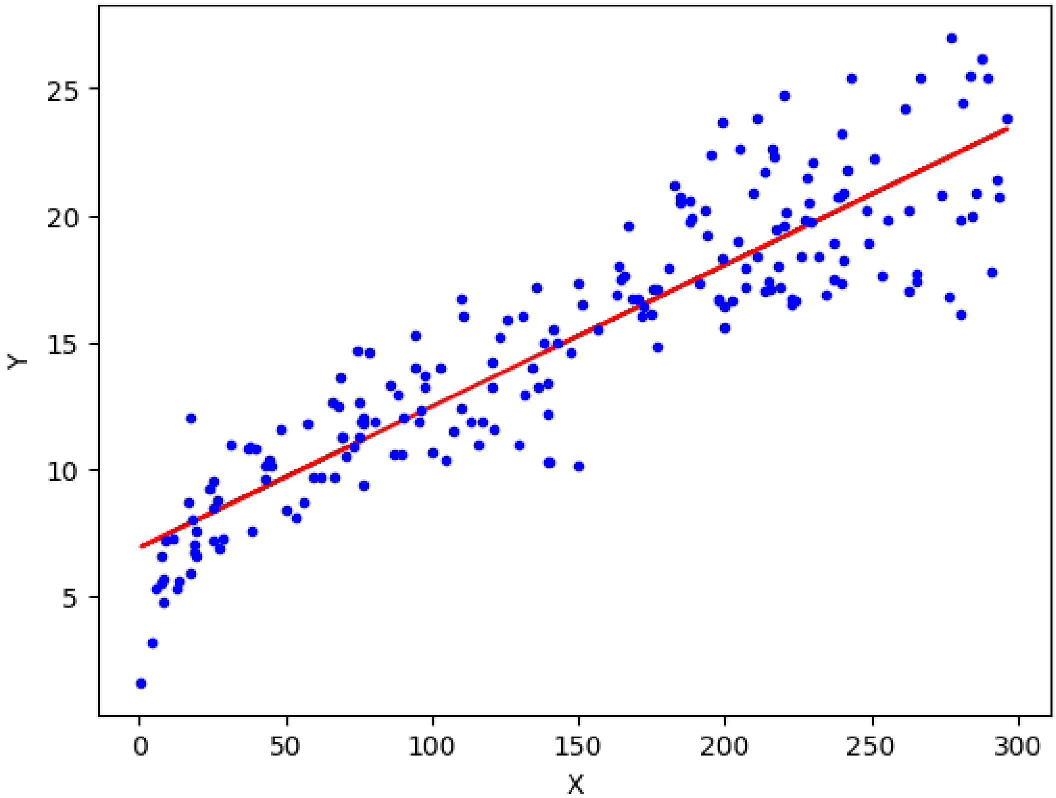
```
[18]: # Predict
y_pred=lr.predict(np.array(x_test).reshape(-1,1))
y_pred
```

```
[18]: array([18.63732145, 18.17533711, 12.23076755, 22.50017844, 21.03073428,
       22.68942504, 15.99343517, 16.96749854, 10.83368238, 18.89336096,
       16.06022809, 10.75575732, 18.85439842, 13.01558432, 19.4722329 ,
       13.90059046, 14.23455504, 23.08461646,  8.32894802, 18.63175537,
       12.49237314, 10.67783225,  8.30111764, 12.88199849, 13.18813269,
       17.39052034,  9.30301138, 20.75243046, 16.18824785, 20.26818182,
       20.25704967, 19.95648154, 15.23644879, 16.37749444, 20.73016616,
       17.19570767, 19.2829863 , 14.10653529, 18.97128603,  7.99498344,
        7.63318848, 11.9357655 ,  7.94488875, 18.26439433,  7.31035605,
       15.10286296, 11.25670419, 19.59468658, 18.31448902, 19.67817773,
       23.0289557 , 13.75587248,  7.98385129, 17.06768791, 21.68753129,
       16.12145493, 19.06590933,  8.29555156, 19.82289571,  9.29744531])
```

```
[19]: # Model evaluation
mse=mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
mae=mean_absolute_error(y_test,y_pred)
r2=r2_score(y_test,y_pred)*100
print('MSE:',mse)
print('RMSE',rmse)
print('MAE:',mae)
print("Accuracy: %.2f" %r2)
```

```
MSE: 5.143558863773587
RMSE 2.267941547697733
MAE: 1.86239036505223
Accuracy: 79.85
```

[20]:
```
X=np.array(X).reshape(-1,1)
plt.plot(x_train, lr.predict(np.array(x_train).reshape(-1,1)) , color="r")
plt.plot(X, y, "b.")
plt.xlabel("X")
plt.ylabel("Y")
plt.show()
```



Model for Radio(Feature) and Sales(Target)

[21]:
```
A=df['Radio']     #Feature
b=df['Sales']     #Target
x_train,x_test,y_train,y_test=train_test_split(A,b,test_size=0.3,random_state=1)
```

[22]:
```
lr=LinearRegression()
lr.fit(np.array(x_train).reshape(-1,1),y_train)
```

[22]: LinearRegression()

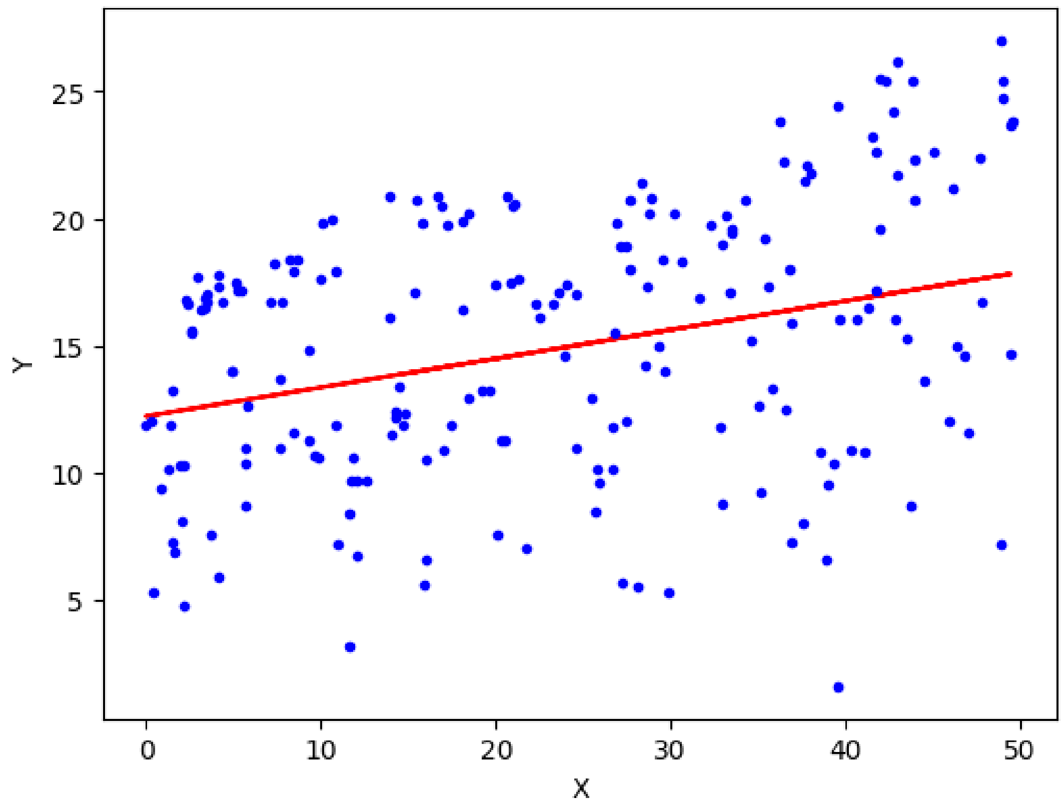
[23]:
```
y_pred=lr.predict(np.array(x_test).reshape(-1,1))
y_pred
```

[23]: array([17.83456599, 14.74545246, 12.38052673, 13.3649695 , 14.63229812,
        16.97459299, 15.79778784, 13.44417754, 14.03258011, 14.89255311,
        14.58703639, 14.54177465, 14.93781484, 17.63088817, 13.14997625,
        16.39750585, 14.30415053, 12.68604345, 16.63512997, 15.56016372,
        13.30839233, 16.36355955, 15.13017722, 13.80627143, 14.19099619,
        14.27020423, 15.24333157, 15.2885933 , 16.97459299, 14.11178815,
        16.91801582, 12.60683541, 16.25040521, 13.10471451, 15.63937176,
        14.59835182, 12.60683541, 12.8670904 , 17.18958624, 14.49651291,
        12.26737239, 12.25605695, 13.59127818, 15.94488848, 15.40174764,
        14.92649941, 17.51773383, 16.48802932, 17.32537145, 15.87699588,
        17.00853929, 16.13725086, 14.03258011, 17.44984122, 14.48519748,
        13.35365406, 12.83314409, 13.46680841, 13.19523799, 15.15280809])

[24]:
```
# Model evaluation
mse=mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
mae=mean_absolute_error(y_test,y_pred)
r2=r2_score(y_test,y_pred)*100
print('MSE:',mse)
print('RMSE',rmse)
print('MAE:',mae)
print("Accuracy: %.2f" %r2)
```

```
MSE: 22.079207158307437
RMSE 4.698851685072368
MAE: 4.129189952623039
Accuracy: 13.49
```

[25]:
```
A=np.array(A).reshape(-1,1)
plt.plot(x_train, lr.predict(np.array(x_train).reshape(-1,1)) , color="r")
plt.plot(A, b, "b.")
plt.xlabel("X")
plt.ylabel("Y")
plt.show()
```



Model for Newspaper(Feature) and Sales(Target)

[26]:
```
C=df['Newspaper']    #Feature
d=df['Sales']        #Target
x_train,x_test,y_train,y_test=train_test_split(C,d,test_size=0.3,random_state=1)
```

[27]:
```
lr=LinearRegression()
lr.fit(np.array(x_train).reshape(-1,1),y_train)
```

[27]:
```
LinearRegression()
```

[28]:
```
y_pred=lr.predict(np.array(x_test).reshape(-1,1))
y_pred
```

[28]:
```
array([15.1754091 , 14.91480786, 13.88094719, 14.4790484 , 14.84645344,
       16.39297229, 15.82477614, 16.05974447, 15.3078458 , 16.02556726,
       15.5898078 , 14.34661171, 13.73569404, 15.76069386, 15.97857359,
       16.94835199, 15.04297241, 13.92794086, 13.96211807, 13.96211807,
       13.71860543, 18.43506072, 15.41464959, 14.03047249, 15.21385847,
       14.65847877, 15.06433316, 14.54313068, 13.71860543, 14.54313068,
```

```
14.35515601, 17.18759248, 13.82113707, 15.06860532, 14.43205474,
14.50468131, 14.12445983, 14.90199141, 14.72683319, 14.29107374,
14.65847877, 14.55594713, 14.56449143, 15.52999768, 15.33347871,
14.38078892, 15.03870025, 14.93189647, 14.40214968, 16.73474441,
15.75214956, 14.09455477, 14.51749777, 16.07256093, 13.57762443,
14.31670665, 14.7353775 , 14.83363698, 13.93648516, 14.44059904])
```

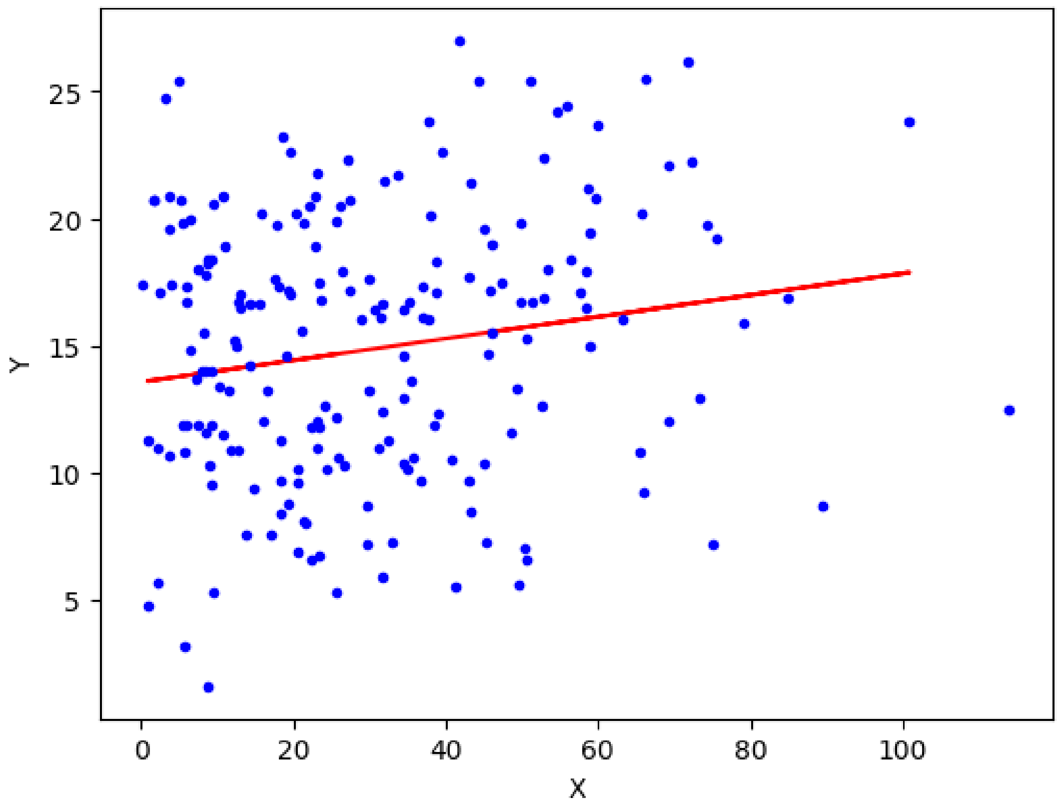
[29]:

```
# Model evaluation
mse=mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
mae=mean_absolute_error(y_test,y_pred)
r2=r2_score(y_test,y_pred)*100
print('MSE:',mse)
print('RMSE',rmse)
print('MAE:',mae)
print("Accuracy: %.2f" %r2)
```

```
MSE: 26.05927191114068
RMSE 5.104828293991942
MAE: 4.384239973311935
Accuracy: -2.10
```

[30]:

```
C=np.array(C).reshape(-1,1)
plt.plot(x_train, lr.predict(np.array(x_train).reshape(-1,1)) , color="r")
plt.plot(C, d, "b.")
plt.xlabel("X")
plt.ylabel("Y")
plt.show()
```




```
[31]: # r2----radio=0.13---->poor model
      # r2----newspaper=-0.02---->bad model
```

2 Multiple Linear Regression

```
[32]: # further increasing model efficiency by adding more feature
      # selection of feature: TV and Radio
      E=df[['TV','Radio']]     #Feature
      f=df['Sales']            #Target
      # splitting dataset
      x_train,x_test,y_train,y_test=train_test_split(E,f,test_size=0.3,random_state=1)
```

```
[33]: # model
      lr=LinearRegression()
      lr.fit(x_train,y_train)
```

```
[33]: LinearRegression()
```

```
[34]: lr.intercept_
```

[34]: 4.639008926907955

[35]:
```
lr.coef_
```

[35]:
```
array([0.05500479, 0.10164376])
```

[36]:
```
# predict
y_pred=lr.predict(x_test)
y_pred
```

[36]:
```
array([21.27554871, 18.04413436, 10.04526843, 21.07795257, 20.76423625,
       24.50740473, 16.83323361, 15.68162724, 10.14864711, 18.88583302,
       15.81165115, 10.52903732, 18.88798717, 15.53710632, 17.89256894,
       15.30376549, 13.7533847 , 21.04564029, 10.01123808, 19.22700869,
       11.13726975, 12.08849512,  8.6318737 , 11.9695358 , 12.61765092,
       16.84166307,  9.72360365, 21.0787461 , 18.08284546, 19.54310936,
       22.0528736 , 17.88322056, 16.49174353, 14.79364521, 21.37183984,
       16.9439132 , 17.21766262, 12.33599795, 21.02620801,  7.76014232,
        5.40022916,  9.64193492,  6.89748794, 19.20956586,  7.89673349,
       15.17050006, 13.69731125, 21.01207034, 20.49912402, 20.54570123,
       24.87342707, 14.9269724 ,  7.33240195, 19.3788249 , 21.28115586,
       14.76423945, 17.20643146,  7.13220997, 18.27975661,  9.63678816])
```

[37]:
```
# model evaluation
mse=mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
mae=mean_absolute_error(y_test,y_pred)
r2=r2_score(y_test,y_pred)*100
print('MSE:',mse)
print('RMSE',rmse)
print('MAE:',mae)
print("Accuracy: %.2f" %r2)
```

```
MSE: 2.364506943376236
RMSE 1.5376953350310443
MAE: 1.191975327783676
Accuracy: 90.74
```

[38]:
```
# efficiency of the model increased from previous model
```

3 Polynomial Regression

Since the data is distributed and doesn't have direct linear relationship, so the model evluation is not close to reality. We will use polynomial regression to increase efficiency and overcome problems

[39]:
```
from sklearn.preprocessing import PolynomialFeatures
```

[40]:
```
pf=PolynomialFeatures(2)  #object of polynomial features
# degree of x is 2 for quadratic model
```

[41]:
```
E=df[['TV','Radio']]     #Feature
f=df['Sales']            #Target
```

[42]:
```
x_train,x_test,y_train,y_test=train_test_split(E,f,test_size=0.3,random_state=1)
```

[43]:
```
# converting training and testing features to quadratic one
x_train_poly=pf.fit_transform(x_train)
x_test_poly=pf.transform(x_test)
# fit_transform-->training dataset
# transform-->testing dataset
```

[44]:
```
# sales=TV theta1+radio theta2+TV**2 theta3+radio**2 theta4+theta0
```

[45]:
```
# model building and trainig
lr=LinearRegression()
lr.fit(x_train_poly,y_train)
```

[45]:
```
LinearRegression()
```

[46]:
```
y_pred=lr.predict(x_test_poly)
y_pred
```

[46]:
```
array([23.18306453, 18.02290837, 11.27416586, 18.80860338, 19.7204984 ,
       24.57861205, 17.43409852, 15.8642468 , 10.32012397, 18.72173229,
       16.13732386, 10.50317618, 18.7508934 , 16.58482932, 17.22594704,
       15.97563608, 14.19043105, 18.25536219,  8.73183753, 19.40993222,
       11.83004901, 11.88396684,  7.56550199, 12.48461746, 13.04703178,
       16.91560902,  9.04897141, 20.48297234, 19.28447138, 18.64911677,
       22.82980906, 17.01974243, 17.25476878, 15.18192322, 21.00013673,
       17.10169   , 16.68424752, 13.18647729, 22.28216875,  6.8208962 ,
        6.05278055, 10.96099479,  6.48754869, 19.66440667,  6.24928586,
       15.59073835, 14.04887872, 21.57316158, 21.9418769 , 20.65432499,
       24.84536124, 15.49199453,  6.64540349, 20.9612716 , 19.86173448,
       15.15313651, 16.739875  ,  6.93552657, 17.4544774 ,  8.9819961 ])
```

[47]:
```
# Model evaluation
mse=mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
mae=mean_absolute_error(y_test,y_pred)
r2=r2_score(y_test,y_pred)*100
print('MSE:',mse)
print('RMSE',rmse)
print('MAE:',mae)
print("Accuracy: %.2f" %r2)
```

```
MSE: 1.4561026730448037
RMSE 1.2066907942985243
MAE: 0.9476471686239127
Accuracy: 94.29
```

[48]:
```
# efficiency increased from previous models along with reduction in errors␣
↪using polynomial regression
```