Sale Predictions

In [1]:
```
#importing necessary modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# reading dataset
df=pd.read_csv('advertising.csv')
```

In [3]:
```
#Getting insight of dataset
print(df.head())
```

```
      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
```

In [4]:
```
print(df.dtypes)
```

```
TV           float64
Radio        float64
Newspaper    float64
Sales        float64
dtype: object
```

In [5]:
```
df.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
```

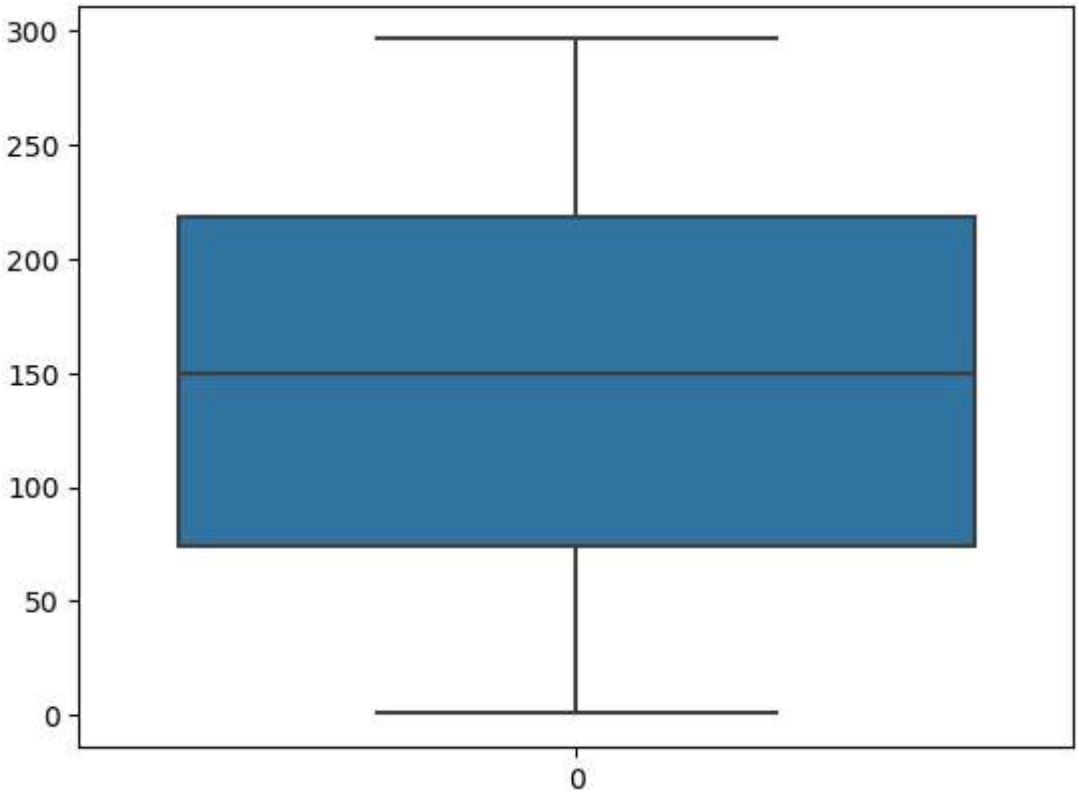
By using info we got the idea that all four columns have floar as a datatype which is apt as per our requirement and also there are no null values Hence no data cleaning

In [6]:
```
1 df.describe()
```

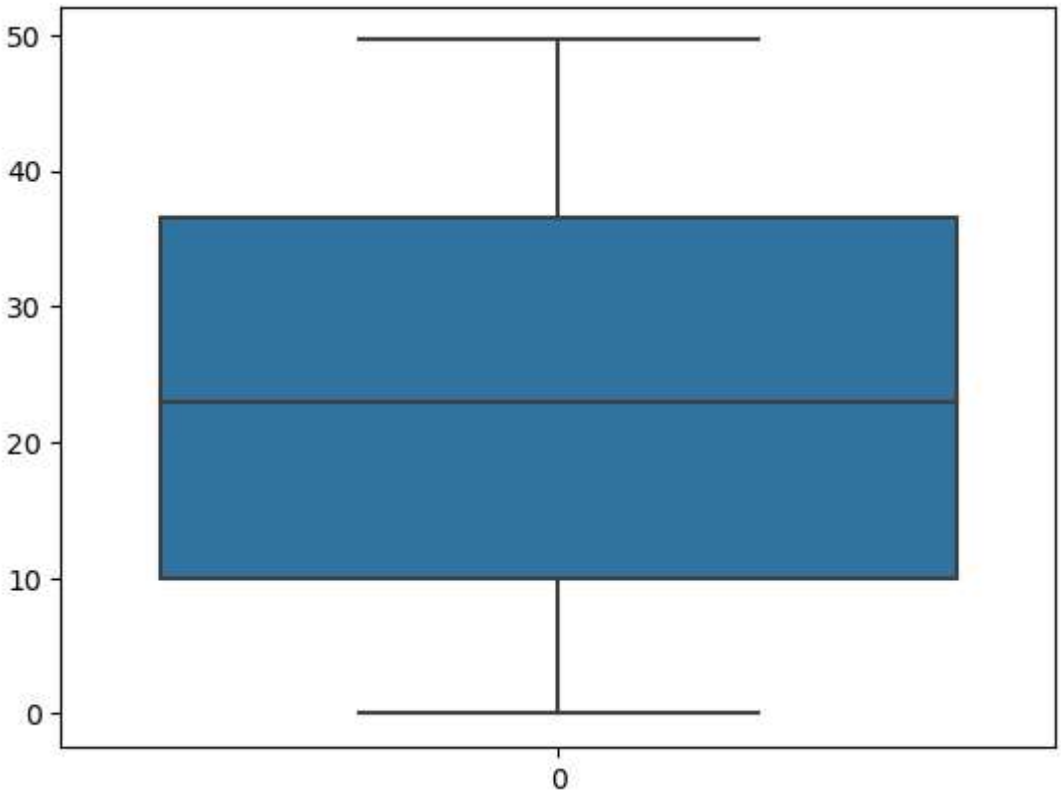
Out[6]:

	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

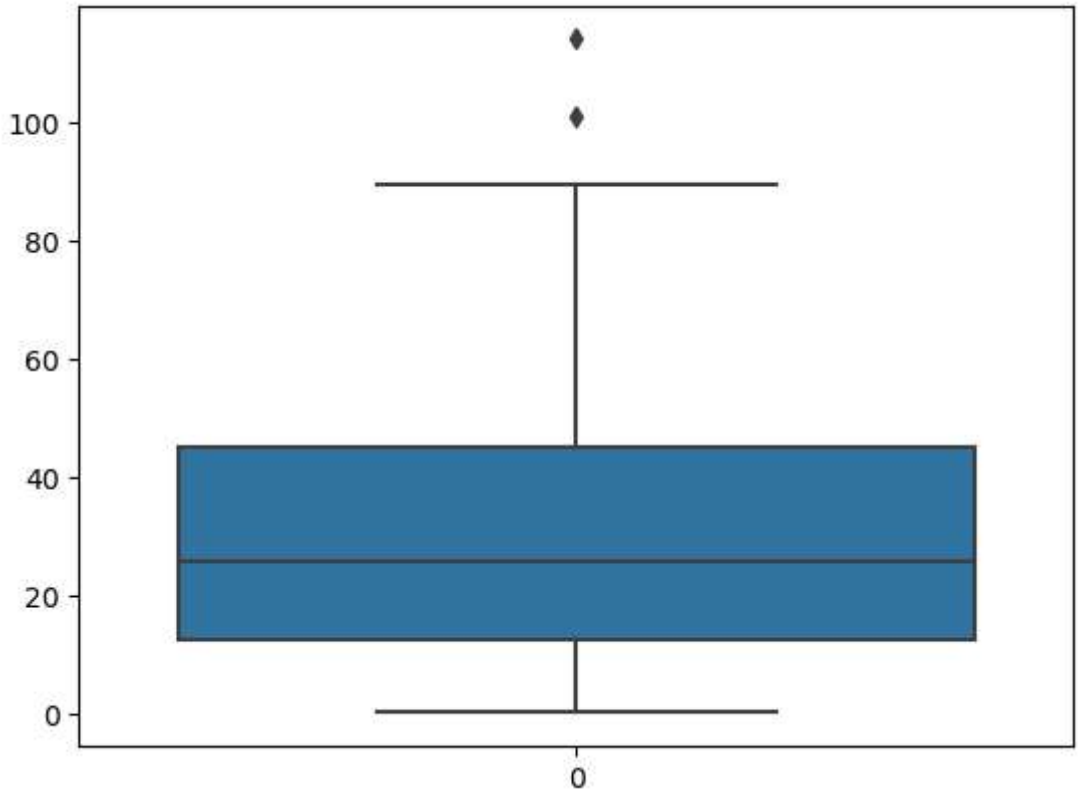
In [7]:
```
1 # Checking for outlier
2 sns.boxplot(df['TV'])
3 plt.show()
```



In [8]:
```
1 sns.boxplot(df['Radio'])
2 plt.show()
```

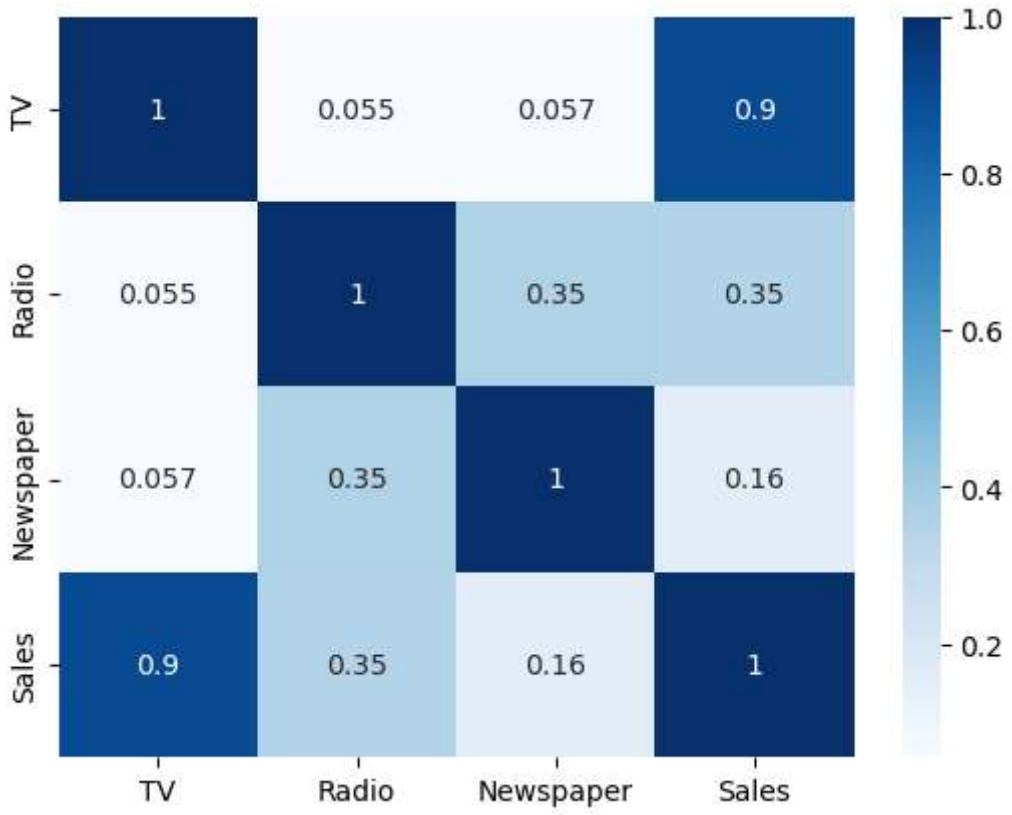


In [9]:
```
1 sns.boxplot(df['Newspaper'])
2 plt.show()
```



No considerable outliers noticed

In [10]:
```
# Checking correlation between variables
corr=df.corr()
sns.heatmap(corr,cmap='Blues',annot=True)
plt.show()
```



Correlation value lies between -1 to 1. Closer the value to one indicated strong relationship between variables. Here strong relation is observed between Sales and TV as value is 0.9 which is very close to 1. The value 0.9 indicated strong positive correlation.

In [11]:
```
# Building Model
X=df['TV']
y=df['Sales']
```

In [12]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_st
```

In [13]:
```
import statsmodels.api as sm
#to add intercept
X_train_sm=sm.add_constant(X_train)
```

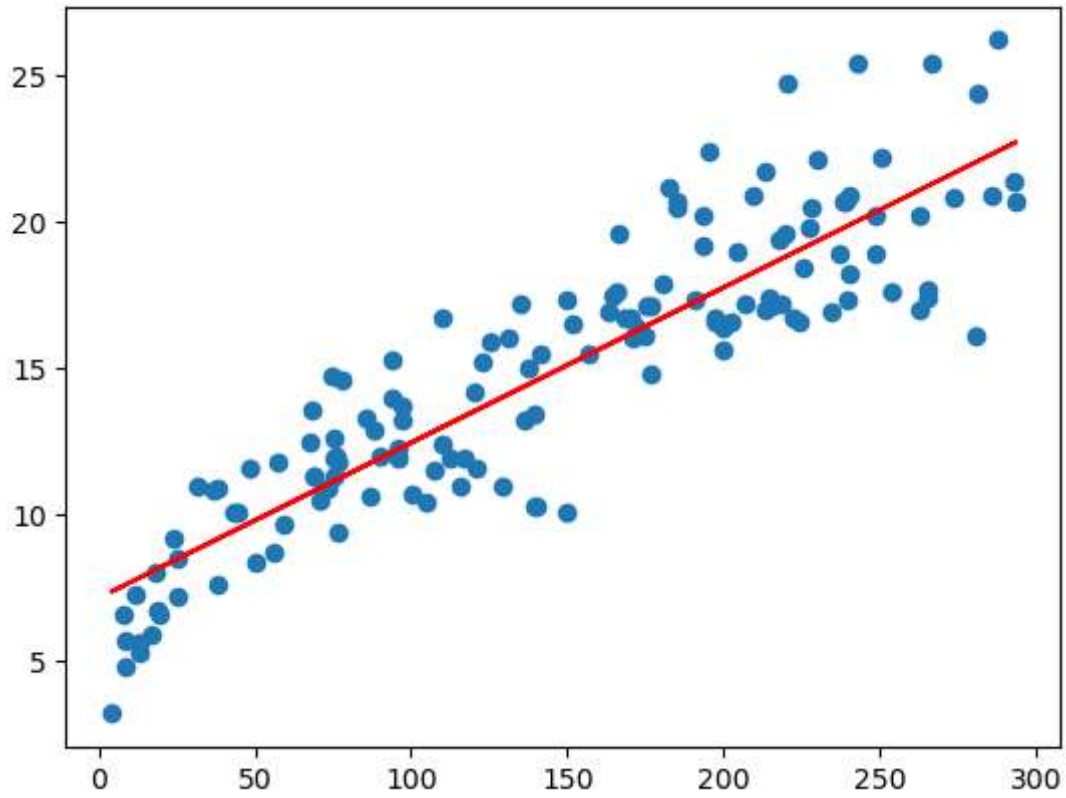
In [14]:
```
lr=sm.OLS(y_train,X_train_sm).fit()
```

In [15]:
```
print(lr.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.796
Model:                            OLS   Adj. R-squared:                  0.795
Method:                 Least Squares   F-statistic:                     540.0
Date:                Fri, 17 Nov 2023   Prob (F-statistic):           1.51e-49
Time:                        14:34:13   Log-Likelihood:                -307.76
No. Observations:                 140   AIC:                             619.5
Df Residuals:                     138   BIC:                             625.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.1506      0.382     18.699      0.000       6.394       7.907
TV             0.0534      0.002     23.237      0.000       0.049       0.058
==============================================================================
Omnibus:                        0.125   Durbin-Watson:                   2.155
Prob(Omnibus):                  0.939   Jarque-Bera (JB):                0.112
Skew:                           0.064   Prob(JB):                        0.945
Kurtosis:                       2.947   Cond. No.                         343.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The above summary tells us about key statistics like R-squared which are required for Linear Regression

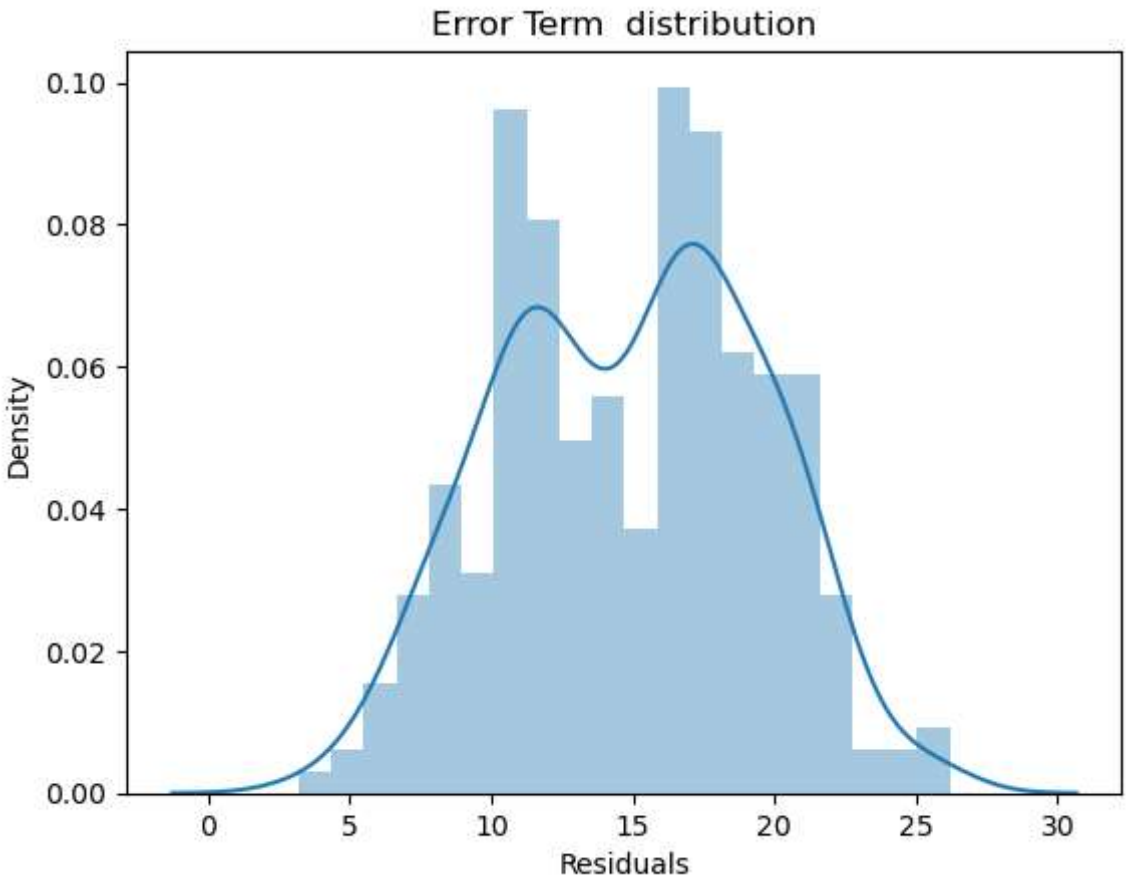
In [16]:
```
plt.scatter(X_train,y_train)
plt.plot(X_train,7.150+0.053*X_train,'r')
plt.show()
```



In [17]:
```
y_train_pred=lr.predict(X_train_sm)
residuals=(y_train,y_train_pred)
```

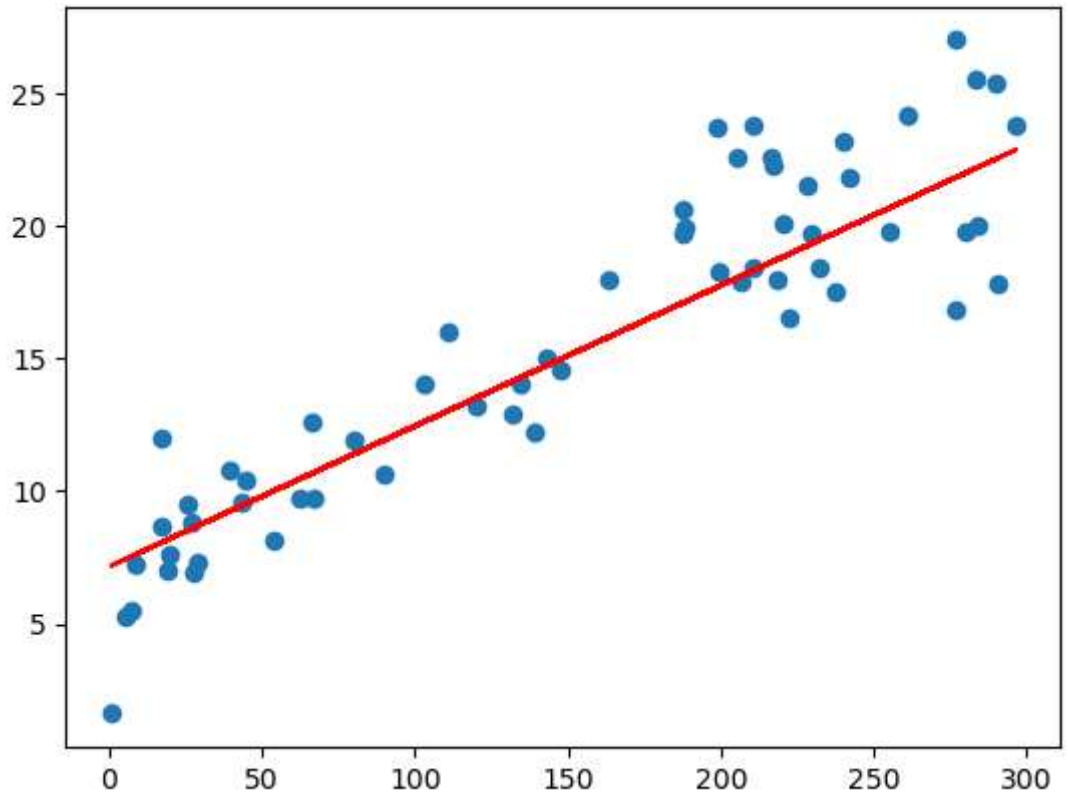
In [18]:
```
sns.distplot(residuals,bins=20)
plt.title('Error Term  distribution')
plt.xlabel('Residuals')
plt.show()
```

```
C:\Users\msi1\AppData\Local\Temp\ipykernel_10084\3097676044.py:1: UserWarnin
g:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://gis
t.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  sns.distplot(residuals,bins=20)
```



In [19]:
```
# Now we will predict using X_test
X_test_sm=sm.add_constant(X_test)
y_pred=lr.predict(X_test_sm)
```

In [20]:
```
plt.scatter(X_test,y_test)
plt.plot(X_test,7.150+0.053*X_test,'r')
plt.show()
```



In [21]:
```
from sklearn.metrics import mean_squared_error,r2_score
print(round(np.sqrt(mean_squared_error(y_test, y_pred)),2))
```

```
2.54
```

In [22]:
```
r_squared_value = r2_score(y_test, y_pred)
print(round(r_squared_value,2))
```

```
0.83
```

In [ ]:
```

```

In [ ]:
```

```