In [1]:

```
#Importing packages and dataset
import numpy as np
import pandas as pd
import sklearn as sk
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
import statsmodels.api as sm

data = pd.read_csv('Advertising.csv', index_col = 0)
#Since, in the data the 0th index ('Unnamed_Column') represents index. Spec
ifying that in the dataframe so the he column is treated as an index instea
d of a seperate column
```

In [2]:

```
#Checking if the data is imported properly
data.head()
```

Out[2]:

	TV	Radio	Newspaper	Sales
1	230.1	37.8	69.2	22.1
2	44.5	39.3	45.1	10.4
3	17.2	45.9	69.3	9.3
4	151.5	41.3	58.5	18.5
5	180.8	10.8	58.4	12.9

In [3]:

```
#Checking dimensions of the data
data.shape
```

Out[3]:

```
(200, 4)
```

In [4]:

```
#Checking for Null Values
data.isnull().sum()
```

Out[4]:

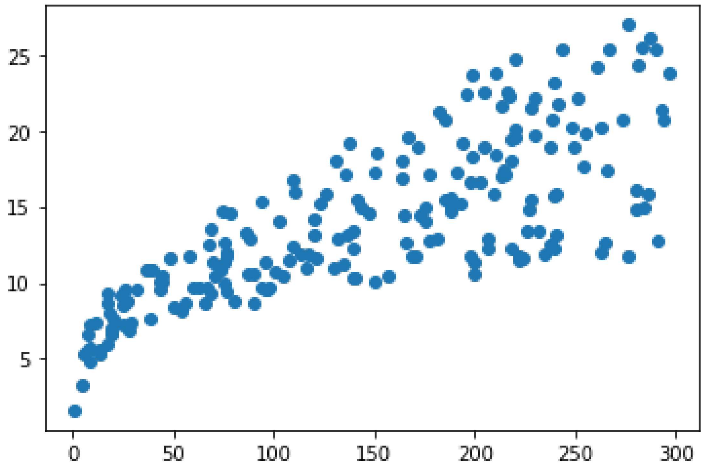
```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

In [5]:

```
#Plotting a catter-plot to understand the data better, presently doing a si
mple linear regression (1 predictor).
plt.scatter(data['TV'], data['Sales'])
```

Out[5]:

```
<matplotlib.collections.PathCollection at 0x1e16006eb48>
```

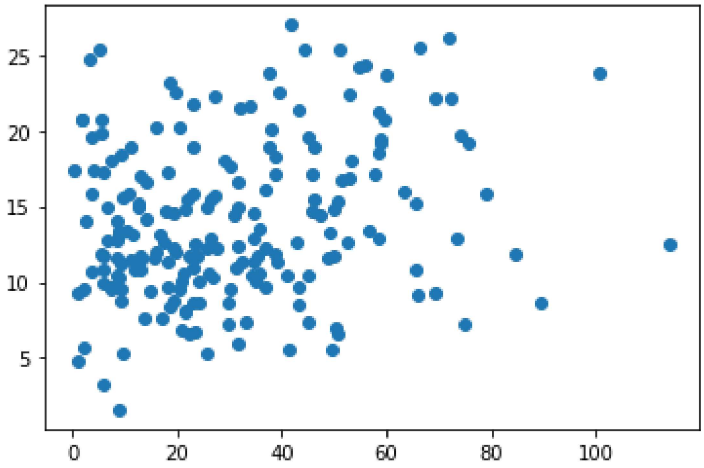


In [6]:

```
plt.scatter(data['Newspaper'], data['Sales'])
```

Out[6]:

```
<matplotlib.collections.PathCollection at 0x1e162ca0708>
```

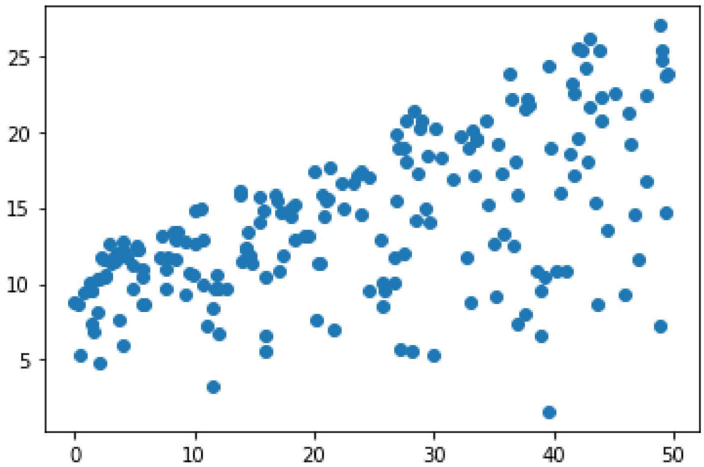


In [7]:

```
plt.scatter(data['Radio'], data['Sales'])
```

Out[7]:

```
<matplotlib.collections.PathCollection at 0x1e162d191c8>
```

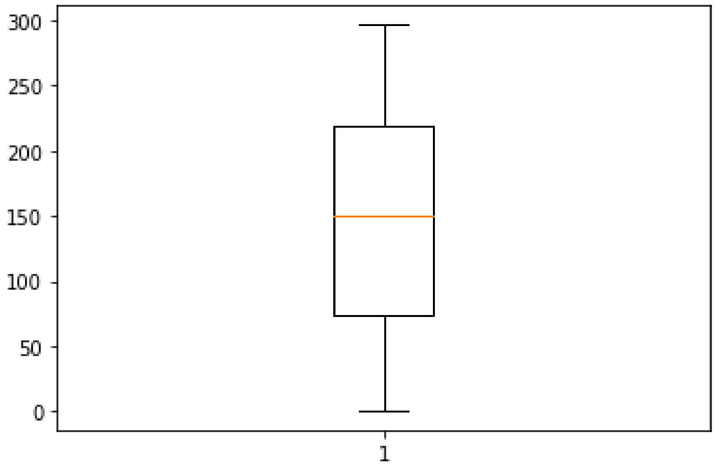


In [8]:

```
plt.boxplot(data['TV'])
```

Out[8]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1e162db2ac8>,
  <matplotlib.lines.Line2D at 0x1e162db2bc8>],
 'caps': [<matplotlib.lines.Line2D at 0x1e162db7a88>,
  <matplotlib.lines.Line2D at 0x1e162db7b88>],
 'boxes': [<matplotlib.lines.Line2D at 0x1e162dabf08>],
 'medians': [<matplotlib.lines.Line2D at 0x1e162dbca08>],
 'fliers': [<matplotlib.lines.Line2D at 0x1e162dbcb08>],
 'means': []}
```

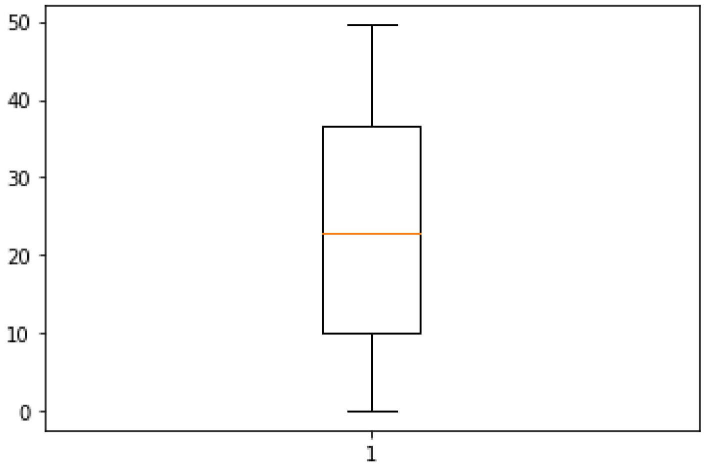


In [9]:

```
plt.boxplot(data['Radio'])
```

Out[9]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1e162e20448>,
  <matplotlib.lines.Line2D at 0x1e162e20c08>],
 'caps': [<matplotlib.lines.Line2D at 0x1e162e20d08>,
  <matplotlib.lines.Line2D at 0x1e162e23b88>],
 'boxes': [<matplotlib.lines.Line2D at 0x1e162e1d988>],
 'medians': [<matplotlib.lines.Line2D at 0x1e162e23c88>],
 'fliers': [<matplotlib.lines.Line2D at 0x1e162e28b08>],
 'means': []}
```

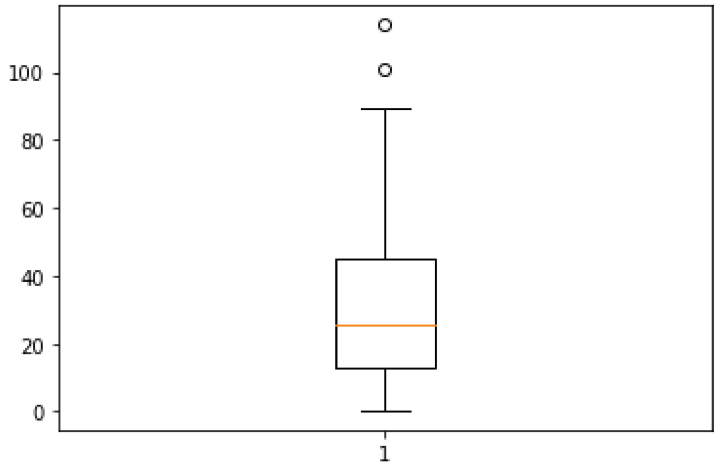


In [10]:

```
plt.boxplot(data['Newspaper'])
```

Out[10]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1e162e8b848>,
  <matplotlib.lines.Line2D at 0x1e162e8bfc8>],
 'caps': [<matplotlib.lines.Line2D at 0x1e162e8bf88>,
  <matplotlib.lines.Line2D at 0x1e162e90f88>],
 'boxes': [<matplotlib.lines.Line2D at 0x1e162e87dc8>],
 'medians': [<matplotlib.lines.Line2D at 0x1e162e90f08>],
 'fliers': [<matplotlib.lines.Line2D at 0x1e162e95f08>],
 'means': []}
```

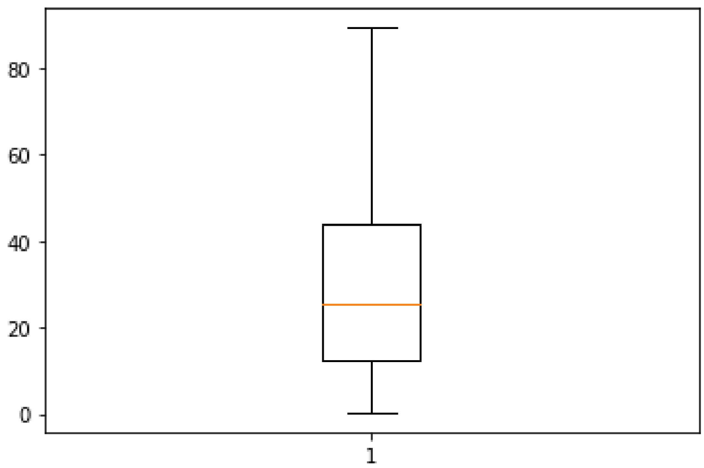


In [11]:

```
#Outliers present in data, since there're only 2 records removing them wo
n't make much of a difference
drop_index = data[data['Newspaper'] > 100].index
data.drop(drop_index, inplace = True)
plt.boxplot(data['Newspaper'])
```

Out[11]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1e162ef8f88>,
  <matplotlib.lines.Line2D at 0x1e162ef8f08>],
 'caps': [<matplotlib.lines.Line2D at 0x1e162efaf48>,
  <matplotlib.lines.Line2D at 0x1e162efaec8>],
 'boxes': [<matplotlib.lines.Line2D at 0x1e162ef85c8>],
 'medians': [<matplotlib.lines.Line2D at 0x1e162efeec8>],
 'fliers': [<matplotlib.lines.Line2D at 0x1e162efefc8>],
 'means': []}
```



In [12]:

```
#Since the Last column specifies the Y (dependent) variable, seperating out
the independent and dependent variable.
X = data.iloc[:, :-1]
y = data['Sales']
```

In [13]:

```
#Splitting data into training and testing
X_Train, X_Test, y_Train, y_Test = train_test_split(X, y, shuffle = True)
```

In [14]:

```
#Having a look at the splitted data
X_Train.head()
```

Out[14]:

	TV	Radio	Newspaper
78	120.5	28.5	14.2
6	8.7	48.9	75.0
154	171.3	39.7	37.7
44	206.9	8.4	26.4
112	241.7	38.0	23.2

In [15]:

```
X_Test.head()
```

Out[15]:

	TV	Radio	Newspaper
114	209.6	20.6	10.7
86	193.2	18.4	65.7
9	8.6	2.1	1.0
143	220.5	33.2	37.9
174	168.4	7.1	12.8

In [16]:

```
y_Train.head()
```

Out[16]:

```
78     14.2
6       7.2
154    19.0
44     12.9
112    21.8
Name: Sales, dtype: float64
```

In [17]:

```
y_Test.head()
```

Out[17]:

```
114    15.9
86     15.2
9       4.8
143    20.1
174    11.7
Name: Sales, dtype: float64
```

In [18]:

```
#Building Simple Linear Model using sklearn
model = LinearRegression().fit(X_Train.iloc[:,0].values.reshape(-1, 1), y_T
rain)
```

In [19]:

```
#Looking at the co-efficients
print("Simple Linear Regression Coefficients (for TV advertising):")
print(f'Sales = {model.intercept_} + {model.coef_[0]} (TV)')
```

```
Simple Linear Regression Coefficients (for TV advertising):
Sales = 7.056405958127174 + 0.045709579255157236 (TV)
```

So according to the model, when there is no TV marketing done then the sales value must ideally be 7.2350 and for every $1000 spent in TV Marketing there is an increase of 0.046 in Sales

NOTE: Sales is in thousands

In [20]:

```
#Predicting values
Pred = model.predict(X_Test.iloc[:, 0].values.reshape(-1, 1))
```

In [21]:

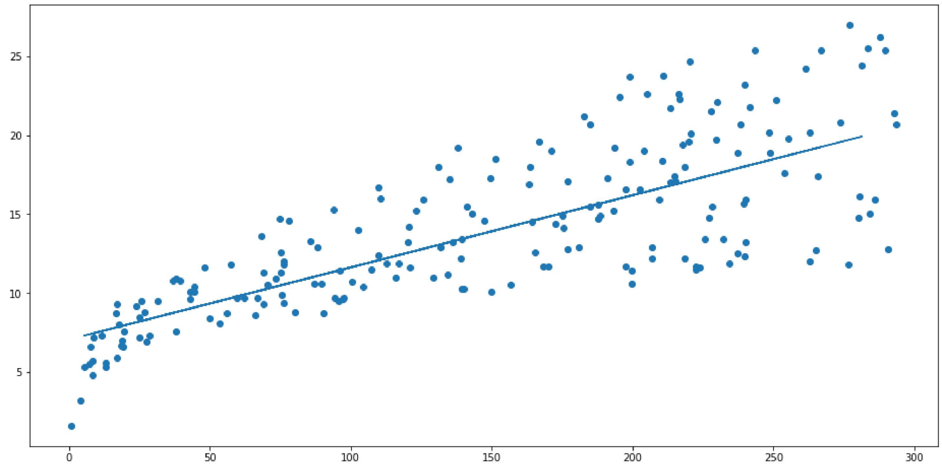
```
#Plotting the regression Line
plt.figure(figsize = (16, 8))

plt.scatter(X['TV'], y)

plt.plot(X_Test.iloc[:, 0], Pred, alpha=2)
```

Out[21]:

```
[<matplotlib.lines.Line2D at 0x1e1630c5fc8>]
```



In [22]:

```
#Displaying Metrics
data.iloc[:, 0].shape
est = sm.OLS(data['Sales'], sm.add_constant(data['TV']))
est = est.fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================
================
Dep. Variable:                  Sales   R-squared:
0.607
Model:                            OLS   Adj. R-squared:
0.605
Method:                 Least Squares   F-statistic:
302.8
Date:                Wed, 18 Sep 2019   Prob (F-statistic):
1.29e-41
Time:                        20:17:38   Log-Likelihood:
-514.27
No. Observations:                 198   AIC:
1033.
Df Residuals:                     196   BIC:
1039.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================
================
                 coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------
----------------
const          7.0306      0.462     15.219      0.000
6.120       7.942
TV             0.0474      0.003     17.400      0.000
0.042       0.053
==============================================================
================
Omnibus:                        0.404   Durbin-Watson:
1.872
Prob(Omnibus):                  0.817   Jarque-Bera (JB):
0.551
Skew:                          -0.062   Prob(JB):
0.759
Kurtosis:                       2.774   Cond. No.
338.
==============================================================
================

Warnings:
[1] Standard Errors assume that the covariance matrix of the e
rrors is correctly specified.
```

```
C:\Users\sragh\Anaconda3\lib\site-packages\numpy\core\fromnume
ric.py:2495: FutureWarning: Method .ptp is deprecated and will
be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

In [23]:

```
#9 Some more inights
print ('MAE:', metrics.mean_absolute_error(Pred, y_Test))
print ('RMSE:', np.sqrt(metrics.mean_squared_error(Pred, y_Test)))
print ('R-Squared:', metrics.r2_score(Pred, y_Test))
```

```
MAE: 2.476044181507283
RMSE: 3.148965788833073
R-Squared: 0.33820559387695215
```

As seen above, the accuracy is ~60% - 70% which is quite low.

Why Multiple Linear Regression?

Simple linear regression is a useful approach for predicting a response on the basis of a single predictor variable. However, in practice we often have more than one predictor. For example, in the Advertising data, we have examined the relationship between sales and TV advertising. We also have data for the amount of money spent advertising on the radio and in newspapers, and we may want to know whether either of these two media is associated with sales.

One option is to run three separate simple linear regressions, each of which uses a different advertising medium as a predictor. For instance, we can fit a simple linear regression to predict sales on the basis of the amount spent on radio advertisements.

However, the approach of fitting a separate simple linear regression model for each predictor is not entirely satisfactory. First of all, it is unclear how to make a single prediction of sales given levels of the three advertising media budgets, since each of the budgets is associated with a separate regression equation. Second, each of the three regression equations ignores the other two media in forming estimates for the regression coefficients. Instead of fitting a separate simple linear regression model for each predictor, a better approach is to extend the simple linear regression model so that it can directly accommodate multiple predictors. We can do this by giving each predictor a separate slope coefficient in a single model.

In [24]:

```
model_mlr = LinearRegression().fit(X_Train, y_Train)
```

In [25]:

```
Pred2 = model_mlr.predict(X_Test)
```

In [26]:

```
print("The linear model is: Sales = {:.5} + {:.5} (TV) + {:.5} (Radio) +
{:.5} (Newspaper)".format(model_mlr.intercept_, model_mlr.coef_[0], model_m
lr.coef_[1], model_mlr.coef_[2]))
```

```
The linear model is: Sales = 2.9646 + 0.044628 (TV) + 0.18982
(Radio) + 0.0010576 (Newspaper)
```

In [27]:

```
model_mlr.score(X_Train, y_Train)
```

Out[27]:

```
0.8830878394545426
```

In [28]:

```
# Print out the statistics
X = data[['TV', 'Radio', 'Newspaper']]
y = data['Sales']

X2 = sm.add_constant(X)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
```

```
                            OLS Regression Results
==============================================================
================
Dep. Variable:                  Sales   R-squared:
0.895
Model:                            OLS   Adj. R-squared:
0.894
Method:                 Least Squares   F-statistic:
553.5
Date:                Wed, 18 Sep 2019   Prob (F-statistic):
8.35e-95
Time:                        20:17:38   Log-Likelihood:
-383.24
No. Observations:                 198   AIC:
774.5
Df Residuals:                     194   BIC:
787.6
Df Model:                           3
Covariance Type:            nonrobust
==============================================================
================
                 coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------
----------------
const          2.9523      0.318      9.280      0.000
2.325       3.580
TV             0.0457      0.001     32.293      0.000
0.043       0.048
Radio          0.1886      0.009     21.772      0.000
0.171       0.206
Newspaper     -0.0012      0.006     -0.187      0.852      -
0.014       0.011
==============================================================
================
Omnibus:                       59.593   Durbin-Watson:
2.041
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
147.654
Skew:                          -1.324   Prob(JB):
8.66e-33
Kurtosis:                       6.299   Cond. No.
457.
==============================================================
================

Warnings:
[1] Standard Errors assume that the covariance matrix of the e
rrors is correctly specified.
```

```
C:\Users\sragh\Anaconda3\lib\site-packages\numpy\core\fromnume
ric.py:2495: FutureWarning: Method .ptp is deprecated and will
be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```