18BCE101

DM prac 3

AIM:

Implement suitable method (using concept of Quartile) in C/C++/Java/Python for detection of outliers present in the following data set : also take steps of remove these identified outliers from the given data set. Name Value

A 45

B 37

C 59

D 150

E 47

F 39

G 5

H 43

I 52

J 100

Numeric Outlier

This is the simplest, nonparametric outlier detection method in a one dimensional feature space. Here outliers are calculated by means of the IQR (InterQuartile Range). The first and the third quartile (Q1, Q3) are calculated. An outlier is then a data point xi that lies outside the interquartile range. That is:

Using the interquartile multiplier value k=1.5, the range limits are the typical upper and lower whiskers of a box plot.

xi > Q3 + k x IQR

xi<Q1-k x IQR

In [1]:
```
#importing required libraries

from matplotlib import pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

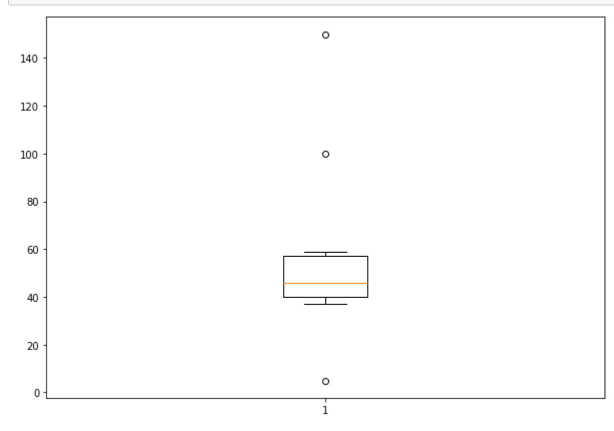
```
C:\Users\labdh\Anaconda3\lib\site-packages\statsmodels\tools\_testing.py:19: FutureWarning: p
andas.util.testing is deprecated. Use the functions in the public API at pandas.testing inste
ad.
  import pandas.util.testing as tm
```

Working on sample data

In [2]:
```
data = [45, 37, 59, 150, 47, 39, 5, 43, 52, 100]
data.sort()
print(data)

q1, q3= np.percentile(data,[25,75])
iqr = q3 - q1
lower_bound = q1 -(1.5 * iqr)
upper_bound = q3 +(1.5 * iqr)

print()
print("Lower bound",lower_bound)
print("First Quartile",q1)
print("Third Quartile",q3)
print("Upper bound",upper_bound)
print("Inter quartile range",iqr)
```

```
[5, 37, 39, 43, 45, 47, 52, 59, 100, 150]

Lower bound 14.125
First Quartile 40.0
Third Quartile 57.25
Upper bound 83.125
Inter quartile range 17.25
```

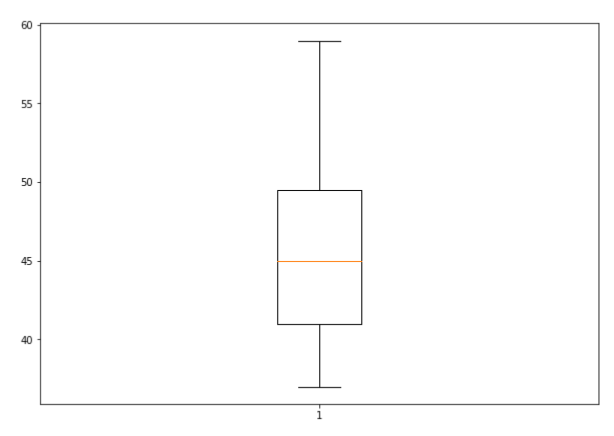
In [3]:
```
fig = plt.figure(figsize =(10, 7))
plt.boxplot(data)
plt.show()
```



Thus we observe that points - (5, 100, 150) are the outliers

In [4]:
```
#removing outliers

data_clean = []

for i in data:
    if i >= lower_bound and i <= upper_bound:
        data_clean.append(i)
print(data_clean)

fig = plt.figure(figsize =(10, 7))
plt.boxplot(data_clean)
plt.show()
```

```
[37, 39, 43, 45, 47, 52, 59]
```



Real world example

mtcars data produced by analysis performed for the Motor Trend, a magazine about the automobile industry. By looking at a data set of a collection of cars, we are interested in exploring the relationship between a set of variables and miles per gallon (MPG) as outcome.

In [5]:
```
#defining the function for outlier removal

def outlier_treatment(datacolumn):
    sorted(datacolumn)
    Q1,Q3 = np.percentile(datacolumn , [25,75])
    IQR = Q3 - Q1
    lower_range = Q1 - (1.5 * IQR)
    upper_range = Q3 + (1.5 * IQR)
    return lower_range,upper_range
```

In [6]:
```
#loading the dataset

df = pd.read_csv('mtcars.csv')
print(df.shape)
df.head()
```

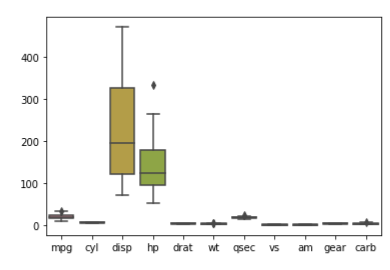
```
(32, 12)
```

Out[6]:

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
1	Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
2	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
4	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2

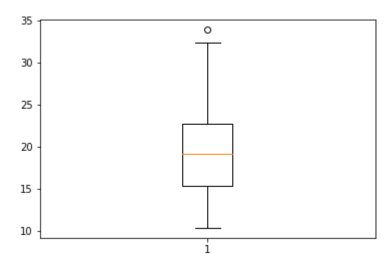
In [7]:
```
#plotting the boxplot of the columns

sns.boxplot(data = df)
```

Out[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b03af68448>
```



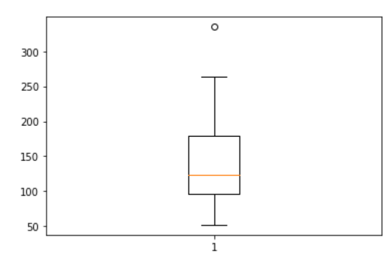
In [8]:
```
plt.boxplot(df.mpg)
```

Out[8]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x2b03b173348>,
  <matplotlib.lines.Line2D at 0x2b03b173b08>],
 'caps': [<matplotlib.lines.Line2D at 0x2b03b173c48>,
  <matplotlib.lines.Line2D at 0x2b03b177a88>],
 'boxes': [<matplotlib.lines.Line2D at 0x2b03b170988>],
 'medians': [<matplotlib.lines.Line2D at 0x2b03b177bc8>],
 'fliers': [<matplotlib.lines.Line2D at 0x2b03b17ba08>],
 'means': []}
```



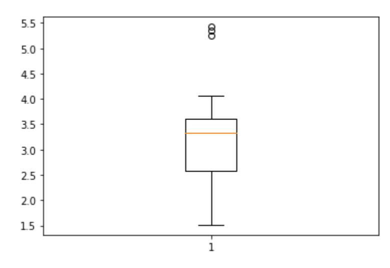
In [9]:
```
plt.boxplot(df.hp)
```

Out[9]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x2b03aeaca48>,
  <matplotlib.lines.Line2D at 0x2b03aeac448>],
 'caps': [<matplotlib.lines.Line2D at 0x2b03aea9908>,
  <matplotlib.lines.Line2D at 0x2b03ae58288>],
 'boxes': [<matplotlib.lines.Line2D at 0x2b03ae9f208>],
 'medians': [<matplotlib.lines.Line2D at 0x2b03ae58508>],
 'fliers': [<matplotlib.lines.Line2D at 0x2b03aedb2c8>],
 'means': []}
```



In [10]:
```
plt.boxplot(df.wt)
```

Out[10]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x2b03b1d3f48>,
  <matplotlib.lines.Line2D at 0x2b03b1d7988>],
 'caps': [<matplotlib.lines.Line2D at 0x2b03b1d7ac8>,
  <matplotlib.lines.Line2D at 0x2b03b1d7b48>],
 'boxes': [<matplotlib.lines.Line2D at 0x2b03b1d3848>],
 'medians': [<matplotlib.lines.Line2D at 0x2b03b1dcf48>],
 'fliers': [<matplotlib.lines.Line2D at 0x2b03b1dcfc8>],
 'means': []}
```



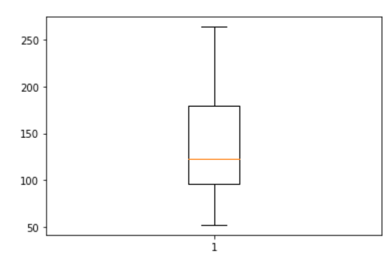
In [12]:
```
# select columns
df = df[['mpg','cyl','disp','hp','wt']]

# create a predictors and predictant variables
X = df.drop('mpg',axis=1)
y = df.mpg

# 80% train split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# using linear regression object call fit
reg = LinearRegression().fit(X_train, y_train)

# adjusted-rsquared value
reg.score(X_test, y_test)
```

Out[12]:
```
0.5831506764829771
```

In [13]:
```
#outlier treatment of hp

lowerbound, upperbound = outlier_treatment(df.hp)

print("Lowerbound = ",lowerbound)
print("\nUpperbound",upperbound)

df = df[df['hp']< upperbound]

plt.boxplot(df.hp)
```

```
Lowerbound =  -28.75

Upperbound 305.25
```

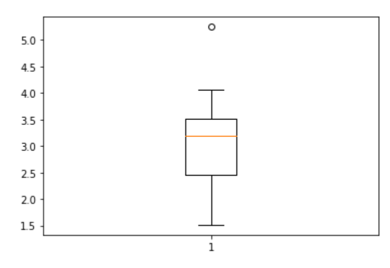
Out[13]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x2b03b24cfc8>,
  <matplotlib.lines.Line2D at 0x2b03b24cd08>],
 'caps': [<matplotlib.lines.Line2D at 0x2b03b255ac8>,
  <matplotlib.lines.Line2D at 0x2b03b259988>],
 'boxes': [<matplotlib.lines.Line2D at 0x2b03b24cac8>],
 'medians': [<matplotlib.lines.Line2D at 0x2b03b259ac8>],
 'fliers': [<matplotlib.lines.Line2D at 0x2b03b25da88>],
 'means': []}
```



In [14]:
```
#outlier treatment of wt

lowerbound, upperbound = outlier_treatment(df.wt)

print("Lowerbound = ",lowerbound)
print("\nUpperbound",upperbound)

df = df[df['wt']< upperbound]

plt.boxplot(df.wt)
```

```
Lowerbound =  0.8812500000000001

Upperbound 5.311249999999999
```

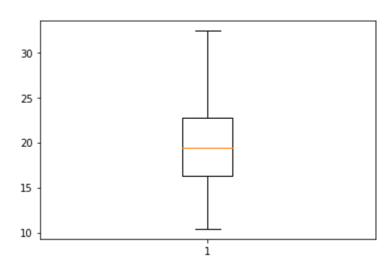
Out[14]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x2b03b2b7e08>,
  <matplotlib.lines.Line2D at 0x2b03b2b7f48>],
 'caps': [<matplotlib.lines.Line2D at 0x2b03b2badc8>,
  <matplotlib.lines.Line2D at 0x2b03b2baf08>],
 'boxes': [<matplotlib.lines.Line2D at 0x2b03b2b7388>],
 'medians': [<matplotlib.lines.Line2D at 0x2b03b2bed48>],
 'fliers': [<matplotlib.lines.Line2D at 0x2b03b2bee88>],
 'means': []}
```



In [15]:
```
#outlier treatment of mpg

lowerbound, upperbound = outlier_treatment(df.mpg)

print("Lowerbound = ",lowerbound)
print("\nUpperbound",upperbound)

df = df[df['mpg']< upperbound]

plt.boxplot(df.mpg)
```

```
Lowerbound =  6.799999999999995

Upperbound 32.400000000000006
```

Out[15]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x2b03b325608>,
  <matplotlib.lines.Line2D at 0x2b03b325dc8>],
 'caps': [<matplotlib.lines.Line2D at 0x2b03b325f08>,
  <matplotlib.lines.Line2D at 0x2b03b329d48>],
 'boxes': [<matplotlib.lines.Line2D at 0x2b03b321b48>],
 'medians': [<matplotlib.lines.Line2D at 0x2b03b329e88>],
 'fliers': [<matplotlib.lines.Line2D at 0x2b03b32ecc8>],
 'means': []}
```



In [21]:
```
#post outlier treatment

reg = LinearRegression().fit(X_train, y_train)

# adjusted-rsquared value
reg.score(X_test, y_test)
```

Out[21]:
```
0.7424468023730224
```

Conclusion

Thus we conclude that after performing outlier detection and removing using IQR, we are improving the performance. The higher the adjusted R^2 better the regression equation as it implies that the independent variable is chosen to determine the dependent variable can explain the variation in the dependent variable.

In [ ]: