SKILL ACTIVITY NO: 3

Date: 11/07/2021
Name: Aditi Rajesh Dalavi
Email_id: aditidalavi7337@gmail.com
Module Code: ML_13

Title: Analysis of auto data.

Skills/Competencies to be acquired:

1. Accepting values from users
2. Creating function for input validation of the data
3. Use of Control statement
4. To do Descriptive analysis.
5. Interpret the data. Find the frequency distribution of the data.
6. Find central tendency and measures of spread.Interpret it.
7. Find skewness and Kurtosis. Interpret it.
8. Inferential analysis.Interpret it.
9. Homoscedacity
10. Linear regression. Interpret it.

What is the purpose of this activity?

```
Implementation of the control statements
Creating functions to avoid repetition of the same logic
Creating user defined errors.Create function for input validation of the data.
Use of Control statement. To do Descriptive analysis. Find the frequency distribution of the data.
Find central tendency and measures of spread.Interpret it.
Find skewness and Kurtosis.Inferential analysis.Interpret it. Linear regression. Interpret it.
```

Steps performed in this activity.

```
Read the data.
Import the required libraries.
```

```
Analyise the data and explore the data. Plot the distributions of each exploration.
Find central tendency and measures of spread.Interpret it.
Find skewness and Kurtosis. Interpret it.
Inferential analysis.Interpret it.
linear regression
```

What resources / materials / equipment / tools did you use for this activity?

```
Python, matplotlib, sklearn,stats, scipy etc
```

What skills did you acquire?

```
Developing logic
Checking  all loopholes while executing the code.
```

Time taken to complete the activity?

```
2 days.
```

In [1]:

```
import time
import random
from math import *
import operator
import numpy as np
import pandas as pd
import statistics as stat

import matplotlib
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
%matplotlib inline

import seaborn as sys
sys.set(style='white',color_codes=True)
sys.set(font_scale=1.5)

from sklearn.linear_model import LinearRegression

from statsmodels.tools.eval_measures import rmse
```

```
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.metrics import r2_score

from statsmodels.stats.outliers_influence import variance_inflation_factor

import statsmodels.api as sa
import statsmodels.formula.api as smf
import statsmodels.stats.api as sms

import researchpy as rp
from scipy import stats
```

In [2]:

```
# read the dataset:
auto= pd.read_csv(r"C:\Users\aditi\Desktop\ML 13\ml pandas\New folder\datasets\Auto.csv")
```

In [3]:

```
# check 1st 5 rows:
auto.head()
```

Out[3]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

In [4]:

```
#check last 5 rows:
auto.tail()
```

Out[4]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
392	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
393	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
394	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
395	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
396	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

In [5]:

```
#check no of rows and columns.
auto.shape
```

Out[5]:

```
(397, 9)
```

There are 397 rows and 9 columns.

In [6]:

```
#check the data types and columns index wise non-null count.
auto.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 397 entries, 0 to 396
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           397 non-null    float64
 1   cylinders     397 non-null    int64  
 2   displacement  397 non-null    float64
 3   horsepower    397 non-null    object 
 4   weight        397 non-null    int64  
 5   acceleration  397 non-null    float64
 6   year          397 non-null    int64  
 7   origin        397 non-null    int64  
 8   name          397 non-null    object 
dtypes: float64(3), int64(4), object(2)
memory usage: 28.0+ KB
```

This data set has 3 float , 4 integer, and 2 object data types.

No null value present in the data.

In [7]:

```
### index of the columns:
auto.columns
```

Out[7]:
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'year', 'origin', 'name'],
      dtype='object')
```

8 columns are present

In [8]:
```
# check null value for confirmation:
auto.isnull().sum()
```

Out[8]:
```
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
year            0
origin          0
name            0
dtype: int64
```

no null value in the data.

In [9]:
```
# check unique values:
auto.nunique()
```

Out[9]:
```
mpg             129
cylinders         5
displacement     82
horsepower       94
weight          350
acceleration     95
year             13
origin            3
name            304
dtype: int64
```

Miles per gallon has 129 unique values & Cylinder has 5 unique values.

Displacement has 82 unique values & Horsepower has 94 unique values.

Weight has 350 unique values & Acceleration has 95 unique values.

Year has 13 unique values & Origin has 3 unique values.

Name has 304 unique values.

after seeing all values, grouping can be done with the help of origin, year, cylinders.

In [10]:
```
# value count of cylinder:
auto['cylinders'].value_counts()
```

Out[10]:
```
4    203
8    103
6     84
3      4
5      3
Name: cylinders, dtype: int64
```

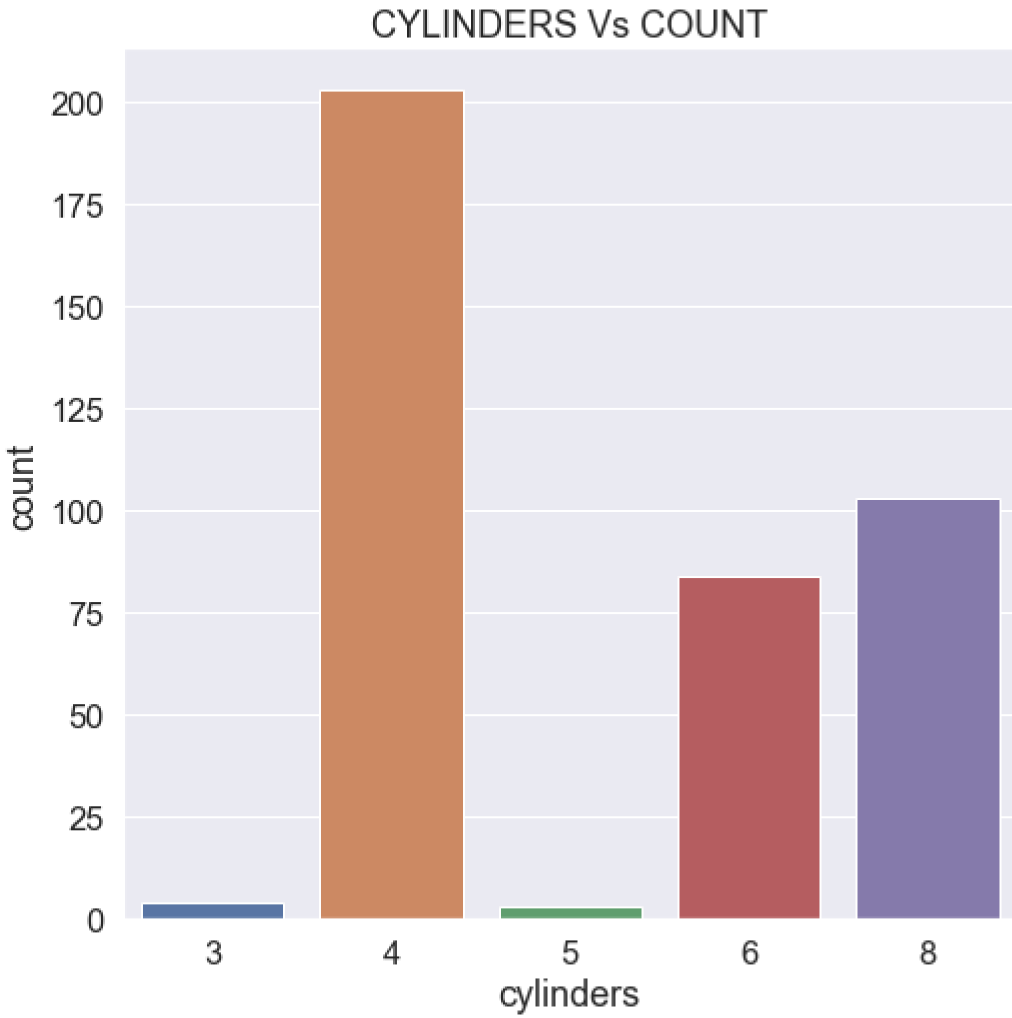
5 different types of cylinders are present in the given data.

data type is of integer.

In [11]:
```
# ploting countplot of cylinder vs count:
plt.figure(figsize=(8,8))

sys.countplot(auto['cylinders'])
plt.title('CYLINDERS Vs COUNT')
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[11]:
```
Text(0.5, 1.0, 'CYLINDERS Vs COUNT')
```



In this given data:

3 cylinder engine car , 4 cylinder engine car, 5 cylinder engine car, 6 cylinder engine car, 8 cylinder engine car are present.

maximum no of cars are of 4 cylinder engine and less number of cars are of 5 cylinder engine and 3 cylinder engine car.

In [12]:

```
# value count of year:
auto['year'].value_counts()
```

Out[12]:
```
73    40
78    36
76    34
75    30
82    30
70    29
79    29
80    29
81    29
71    28
72    28
77    28
74    27
Name: year, dtype: int64
```

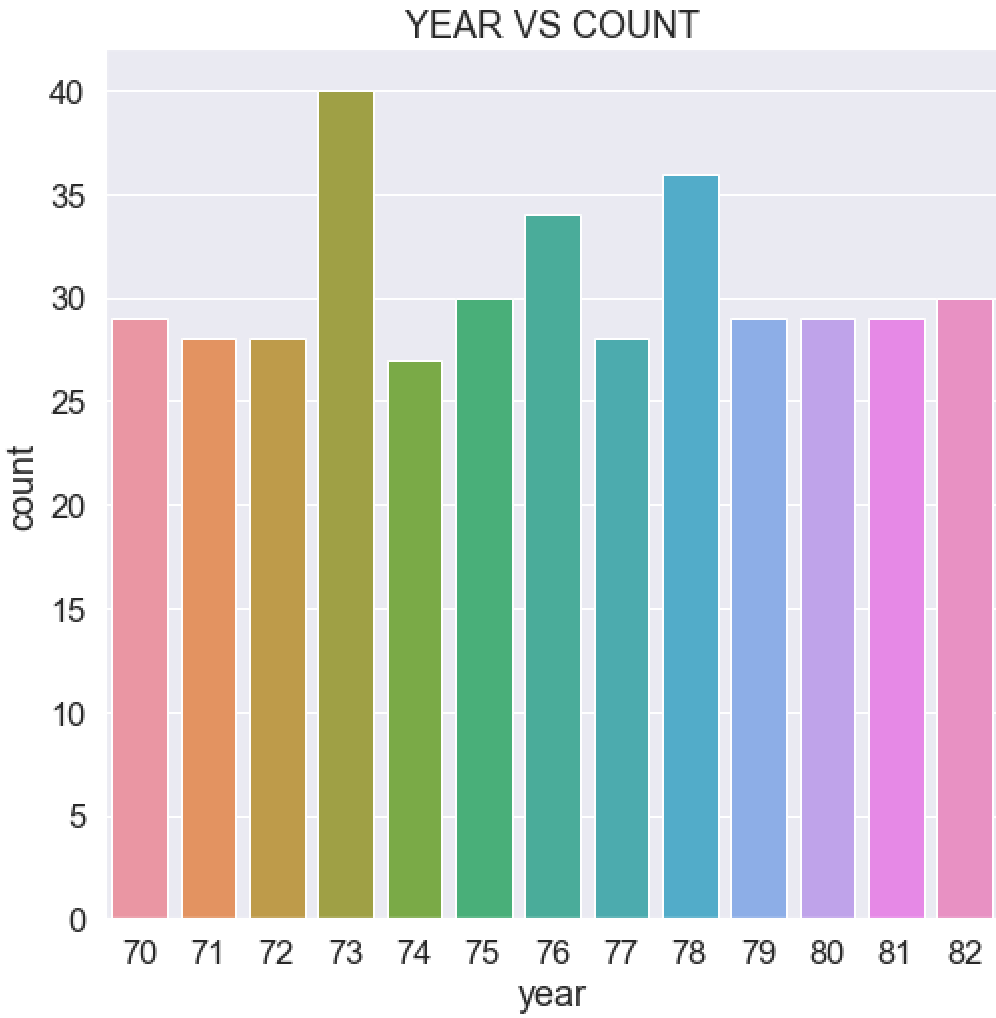
in given data, car models are from 1970 to 1982.

data type is of integer.

In [13]:
```
# plotting countplot of year vs count:
plt.figure(figsize=(8,8))
plt.title('YEAR VS COUNT')
sys.countplot(auto['year'])
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as
a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments witho
ut an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[13]:
```
<AxesSubplot:title={'center':'YEAR VS COUNT'}, xlabel='year', ylabel='count'>
```



In this given data,

car models are from 1970 to 1982.

maximum number of cars are from 1973 and minimum number of cars are from 1974.

1975 and 1982 model cars are of same count.

1970, 1979, 1980, 1981 model cars are of same count.

1971,1972,1977 model cars are of same count.

In [14]:
```
# value count of origin:
origin=auto['origin'].value_counts()
origin
```

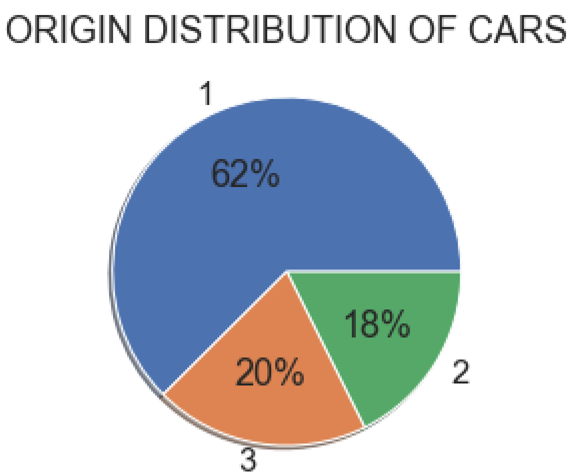
Out[14]:
```
1    248
3     79
2     70
Name: origin, dtype: int64
```

3 origins are present in te given data.

data type is of integer.

In [15]:
```
# plotting pie diagram of origin:
label= [1,3,2]
color=['green','red','yellow']
plt.pie(origin,
       startangle=0,
       labels=label,
       shadow=True,
       autopct='%1.0f%%')
plt.title('ORIGIN DISTRIBUTION OF CARS')
```

Out[15]:
```
Text(0.5, 1.0, 'ORIGIN DISTRIBUTION OF CARS')
```



In this data,

3 origins are there.

origin 1 has maximum number of cars.

origin 2 and origin 3 has almost same number of cars

ACCELERATION:

In [16]:

```
# displaying acceleration from given data:
acceleration = auto['acceleration'].astype(int)
acceleration
```

Out[16]:

```
0      12
1      11
2      11
3      12
4      10
       ..
392    15
393    24
394    11
395    18
396    19
Name: acceleration, Length: 397, dtype: int32
```

In [17]:

```
# displaying index of acceleration:
acc = (acceleration.index).astype(int)
acc
```

Out[17]:

```
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,
            ...
            387, 388, 389, 390, 391, 392, 393, 394, 395, 396],
           dtype='int64', length=397)
```

In [18]:

```
#describing acceration:
auto['acceleration'].describe()
```

Out[18]:

```
count    397.000000
mean      15.555668
std        2.749995
min        8.000000
25%       13.800000
```

```
50%        15.500000
75%        17.100000
max        24.800000
Name: acceleration, dtype: float64
```

Acceleration:

maximum acceleration in given data is 24.80 units.

minimum acceleration in given data is 8 units.

From mean 15.55, acceleration is deviated by 2.74.

Quantiles of acceleration:

In [19]:

```
# quantile of 25% of accleration:
qa1 = auto['acceleration'].quantile(0.25)
qa1
```

Out[19]: 13.8

Quantile of 25% of acceleration is 13.775

In [20]:

```
# quantile of 50% of acceleration:
qa2 = auto['acceleration'].quantile(0.50)
qa2
```

Out[20]: 15.5

Quantile of 50% of acceleration is 15.5

In [21]:

```
# quantile of 75% of acceleration:
qa3 = auto['acceleration'].quantile(0.75)
qa3
```

Out[21]: 17.1

Quantile of 75% of acceleration is 17.025

In [22]:
```
#inter-quantile region of acceleration:
IQR_A= qa3-qa1
IQR_A
```

Out[22]: 3.3000000000000007

Inter-Quantile of acceleration is 3.24.

In [23]:
```
# lower bound of acceleration:
lb_a = qa1-(1.5*IQR_A)
lb_a
```

Out[23]: 8.85

lower bound of acceleration is 8.90

In [24]:
```
# upper bound of acceleration:
ub_a = qa3+(1.5*IQR_A)
ub_a
```

Out[24]: 22.050000000000004

upper bound of acceleration is 21.89

In [25]:
```
# calculating skewness of acceleration before removing outliers:
auto['acceleration'].skew()
```

Out[25]: 0.2808175010382629

Skewness is fairly symmetrical.It is positive, hence right side tail is longer.

In [26]:
```
# calculating kurtosis of acceleration before removing outliers:
auto['acceleration'].kurt()
```

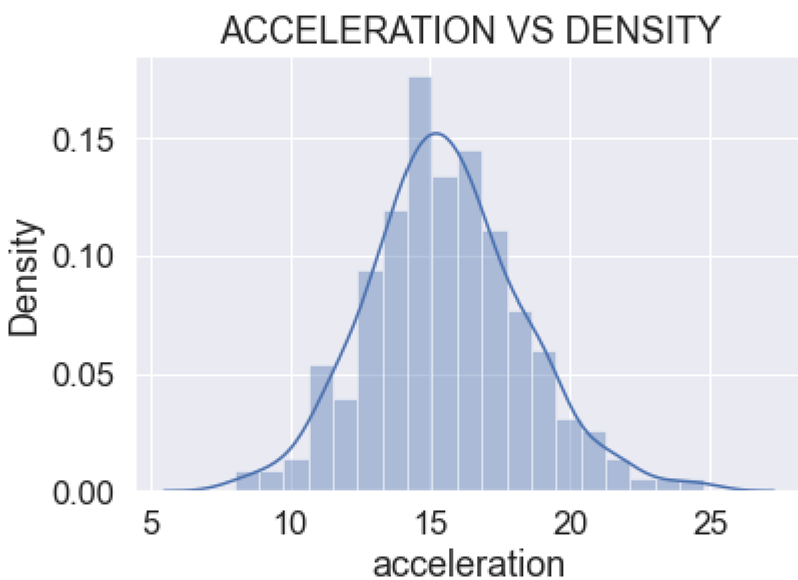
Out[26]: 0.4455252633429918

Kurtosis is approximately zero, hence its slightly pointy to normal distriburtion. there is lack of outliers too.

In [27]:
```
# plotting distplot of acceleration before removing outlier:
sys.distplot(auto['acceleration'])
plt.title('ACCELERATION VS DENSITY')
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[27]:
```
Text(0.5, 1.0, 'ACCELERATION VS DENSITY')
```



Right side tail is a bit longer, and it is normally distributed.

In [28]:
```
# checking outliers:
var_a= acceleration [(acceleration<lb_a)| (acceleration>ub_a)].index

var_a
```

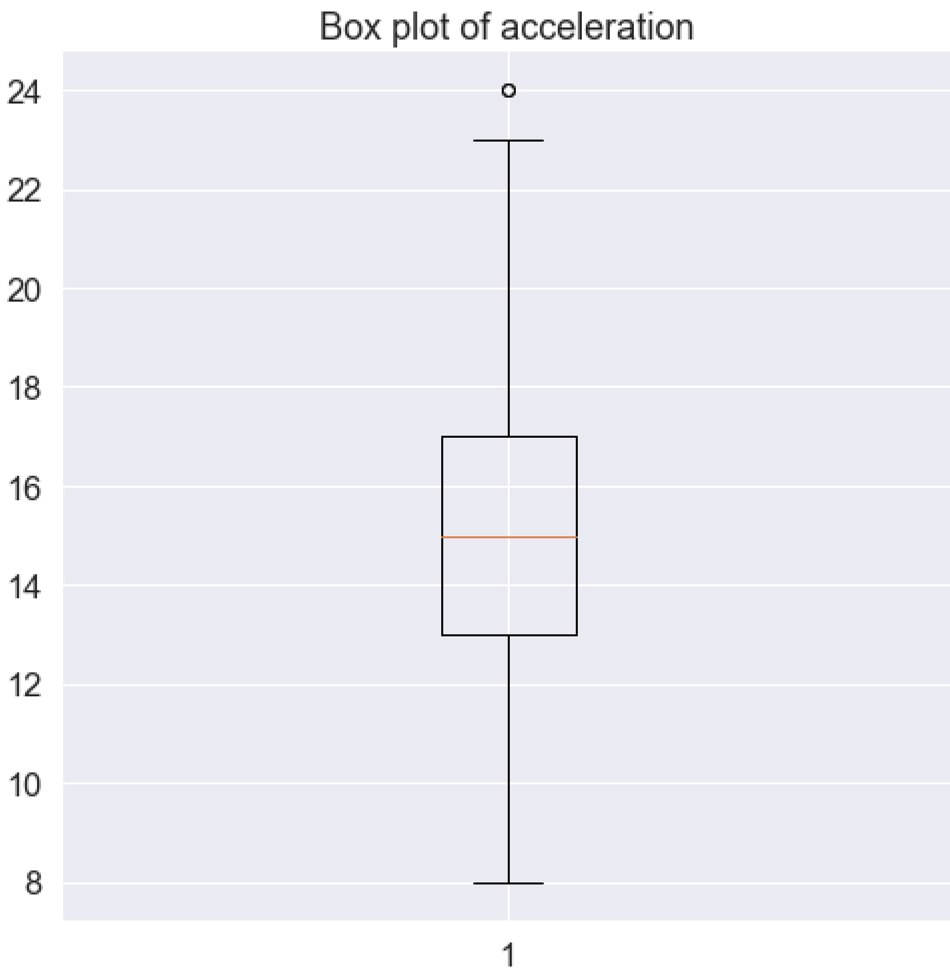
Out[28]:
```
Int64Index([7, 9, 11, 59, 299, 326, 393], dtype='int64')
```

outliers are present.

In [29]:
```
# plotting boxplot of acceleration to check the location of outliers:
plt.figure(figsize=(8,8))
```

```
plt.boxplot(acceleration);
plt.title('Box plot of acceleration')
```

Out[29]: Text(0.5, 1.0, 'Box plot of acceleration')



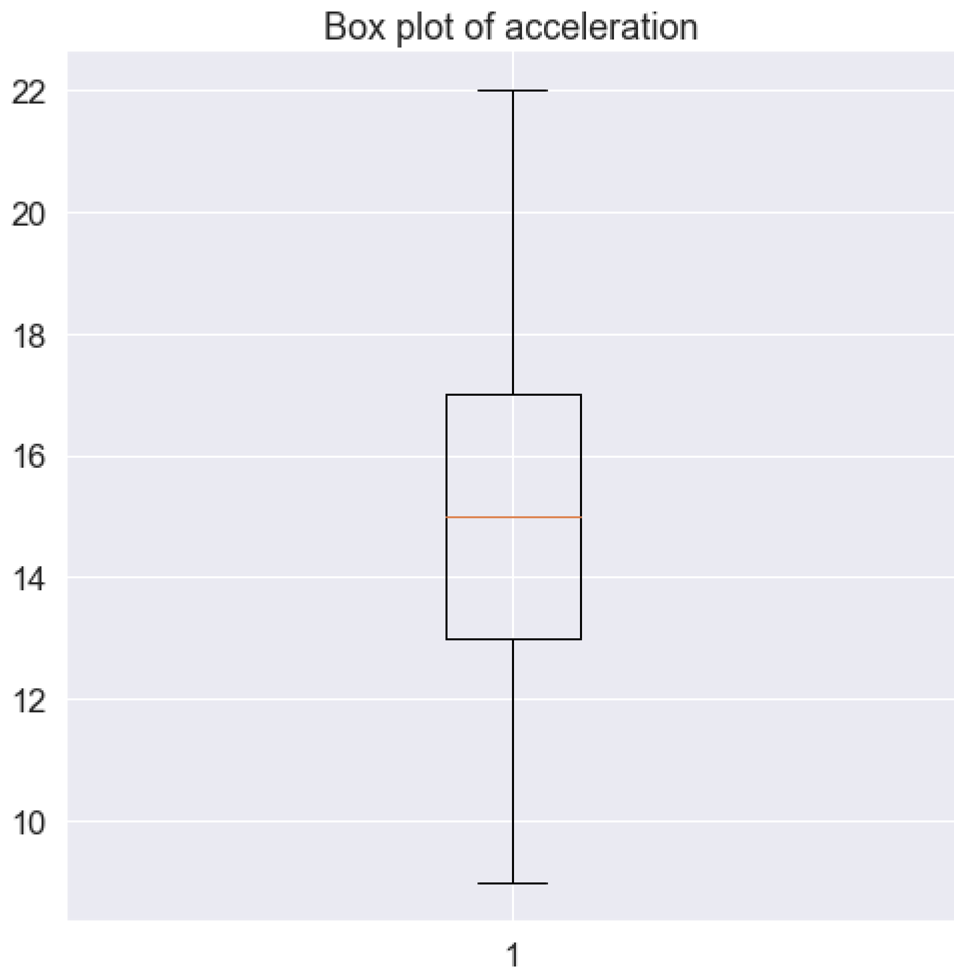
Outliers are present near minimum of acceleration.

In [30]:
```
# removing outliers from acceleration:
acceleration.drop(index= var_a, inplace=True)
```

In [31]:
```
# checking wheather outliers are removed or not:
plt.figure(figsize=(8,8))
```

```
plt.boxplot(acceleration);
plt.title('Box plot of acceleration')
```

Out[31]: Text(0.5, 1.0, 'Box plot of acceleration')



outlier is removed.

In [32]:
```
# calculating skewness of acceleration after removing outliers:
acceleration.skew()
```

Out[32]: 0.23526334303807253

skewness is positive and fairly skewed. it is approximately 0 hence it is symmetric.

In [33]:

```
# calculating kurtosis of acceleration after removing outliers:
acceleration.kurt()
```

Out[33]: -0.18937830823374346

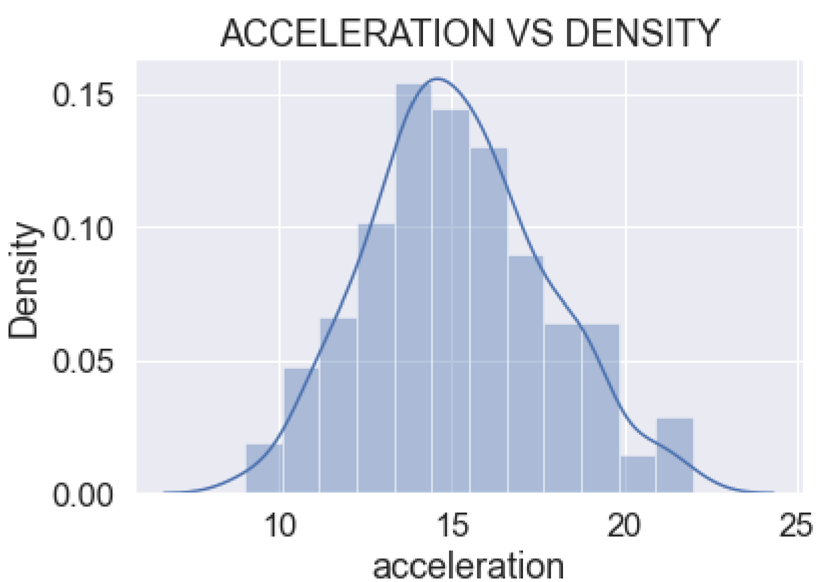
kurtosis is negative and approximately zero. hence it is slighly flat and it is normal distribution.

In [34]:

```
# plotting distplot of acceleration:
sys.distplot(acceleration)
plt.title('ACCELERATION VS DENSITY')
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[34]: Text(0.5, 1.0, 'ACCELERATION VS DENSITY')



peak is slightly flat and it is normal distribution.

HORSEPOWER:

In [35]:
```
#displaying horsepower from given data:
horsepower= auto['horsepower']
horsepower
```

Out[35]:
```
0      130
1      165
2      150
3      150
4      140
      ...
392     86
393     52
394     84
395     79
396     82
Name: horsepower, Length: 397, dtype: object
```

data type of horsepower is object, string maybe present in this data type.

In [36]:
```
#displaying the index of horsepower:
index_h = auto['horsepower'].index
index_h
```

Out[36]:
```
RangeIndex(start=0, stop=397, step=1)
```

the length of horsepower is of 392.

In [37]:
```
# checking the string in the dataframe of horsepower:
auto['horsepower'].unique()
```

Out[37]:
```
array(['130', '165', '150', '140', '198', '220', '215', '225', '190',
       '170', '160', '95', '97', '85', '88', '46', '87', '90', '113',
       '200', '210', '193', '?', '100', '105', '175', '153', '180', '110',
       '72', '86', '70', '76', '65', '69', '60', '80', '54', '208', '155',
       '112', '92', '145', '137', '158', '167', '94', '107', '230', '49',
       '75', '91', '122', '67', '83', '78', '52', '61', '93', '148',
       '129', '96', '71', '98', '115', '53', '81', '79', '120', '152',
       '102', '108', '68', '58', '149', '89', '63', '48', '66', '139',
       '103', '125', '133', '138', '135', '142', '77', '62', '132', '84',
       '64', '74', '116', '82'], dtype=object)
```

Horsepower contains '?' .

This need to be convert into numeric.

In [38]:
```
#converting the string in data into numeric form:
auto= auto[auto.horsepower != '?']
auto['horsepower']=pd.to_numeric(auto['horsepower'])
```

In [39]:
```
# Checking the conversion:
auto['horsepower'].unique()
```

Out[39]:
```
array([130, 165, 150, 140, 198, 220, 215, 225, 190, 170, 160,  95,  97,
        85,  88,  46,  87,  90, 113, 200, 210, 193, 100, 105, 175, 153,
       180, 110,  72,  86,  70,  76,  65,  69,  60,  80,  54, 208, 155,
       112,  92, 145, 137, 158, 167,  94, 107, 230,  49,  75,  91, 122,
        67,  83,  78,  52,  61,  93, 148, 129,  96,  71,  98, 115,  53,
        81,  79, 120, 152, 102, 108,  68,  58, 149,  89,  63,  48,  66,
       139, 103, 125, 133, 138, 135, 142,  77,  62, 132,  84,  64,  74,
       116,  82], dtype=int64)
```

Horsepower is converted into integer data type. Hence has no string value in it

In [40]:
```
hp=auto['horsepower']
hp
```

Out[40]:
```
0      130
1      165
2      150
3      150
4      140
      ...
392     86
393     52
394     84
395     79
396     82
Name: horsepower, Length: 392, dtype: int64
```

In [41]:
```
# as the dtype is changed into int hence describing it:
auto['horsepower'].describe().astype(int)
```

Out[41]:
```
count    392
mean     104
std       38
min       46
25%       75
```

```
50%       93
75%      126
max      230
Name: horsepower, dtype: int32
```

HORSEPOWER:

the mean of horsepower is 104.

maximum horsepower in given data is 230 units.

minimum horsepower in given data is 46 units.

From mean, horsepower is deviated by 38.

Quantiles of Horsepower:

In [42]:

```
# quantile of 25% of horsepower:
qh1 = auto['horsepower'].quantile(0.25)
qh1
```

Out[42]:

```
75.0
```

Quantile of 25% of horsepower is 75

In [43]:

```
# quantile of 50% of horsepower:
qh2 = auto['horsepower'].quantile(0.50)
qh2
```

Out[43]:

```
93.5
```

Quantile of 50% of horsepower is 93.5

In [44]:

```
# quantile of 75% of horsepower:
qh3 = auto['horsepower'].quantile(0.75)
qh3
```

Out[44]:

```
126.0
```

Quantile of 75% of horsepower is 126

In [45]:
```
#inter-quantile region of horsepower:
IQR_H= qh3-qh1
IQR_H
```

Out[45]: 51.0

inter-quantile region of horsepower is 51

In [46]:
```
# lower bound of horsepower:
lb_h = qh1-(1.5*IQR_H)
lb_h
```

Out[46]: -1.5

the lower bound of horsepower is -1.5

In [47]:
```
# upper bound of horsepower:
ub_h = qh3+(1.5*IQR_H)
ub_h
```

Out[47]: 202.5

the upper bound of howerpower is 202.5

In [48]:
```
# calculating skewness of horsepower before removing outliers:
hp.skew()
```

Out[48]: 1.0873262824048697

Horsepower is highly skewed and positive. hence right side tail is longer than left side.

In [49]:
```
# calculating skewness of horsepower before removing outliers:
hp.kurt()
```

Out[49]: 0.696946999742821

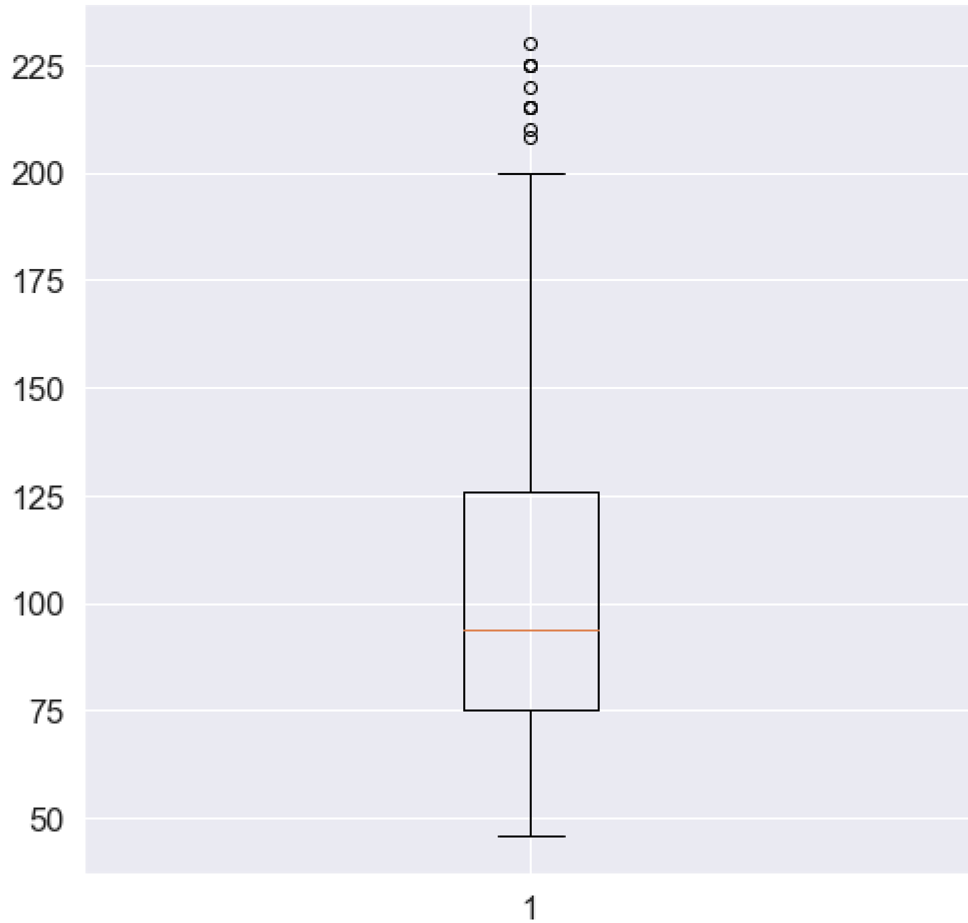
Kurtosis is positve, hence the peak is pointy. The distribution is leptokurtic in nature.

In [50]:
```
# checking the outliers.
var_h= hp [(hp < lb_h) | (hp > ub_h)].index

var_h
```

Out[50]:
```
Int64Index([6, 7, 8, 13, 25, 27, 67, 94, 95, 116], dtype='int64')
```

10 outliers are present in horsepower.

In [51]:
```
# plotting boxplot to check where outliers are:
plt.figure(figsize=(8,8))
plt.boxplot(hp);
```



Outliers are present above minimum horsepower. hence need to remove outliers.

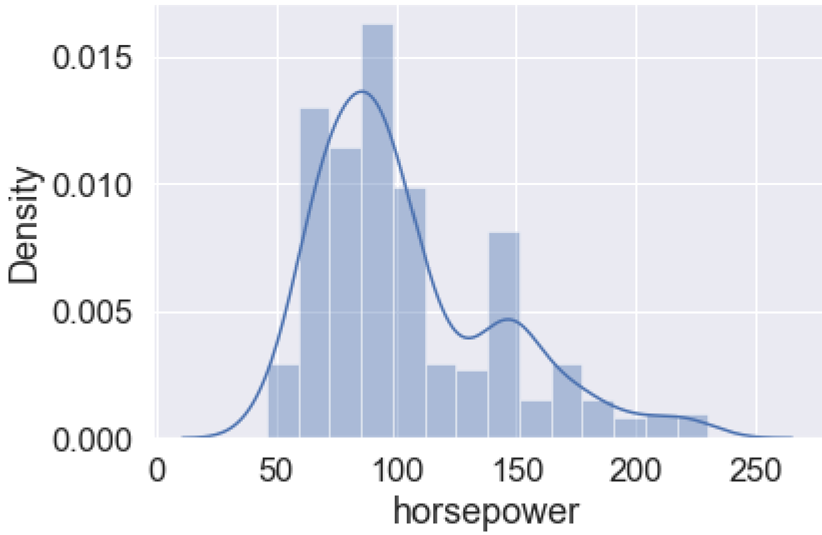
In [52]:

```
# distplot before outliers:
sys.distplot(auto['horsepower'])
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[52]:

```
<AxesSubplot:xlabel='horsepower', ylabel='Density'>
```



The peak is pointy. The distribution is leptokurtic in nature. Right side tail is longer than left side

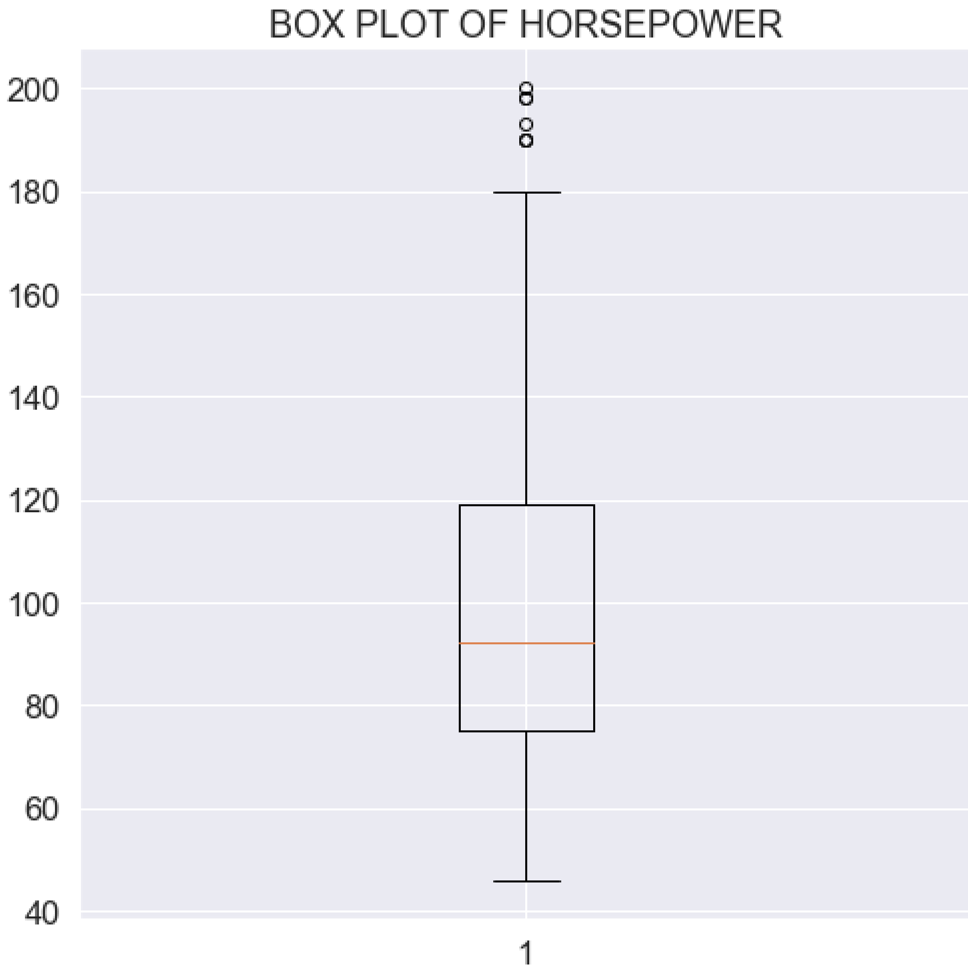
In [53]:

```
# removing outliers:
hp.drop(index=hp[(hp<lb_h)|(hp>ub_h)].index, inplace=True)
```

In [54]:

```
# checking wheather outliers are removed or not:
plt.figure(figsize=(8,8))
plt.boxplot(hp);
plt.title('BOX PLOT OF HORSEPOWER')
```

Out[54]: `Text(0.5, 1.0, 'BOX PLOT OF HORSEPOWER')`



outliers are still present.

In [55]:
```
#calculating skewness of horsepower after removing outliers:
hp.skew()
```

Out[55]: 0.8612205021180016

Horsepower is moderately skewed and positive. hence right side tail is longer than left side.

In [56]:
```
# Calculating Kurtosis of horsepower after removing outliers:
hp.kurt()
```

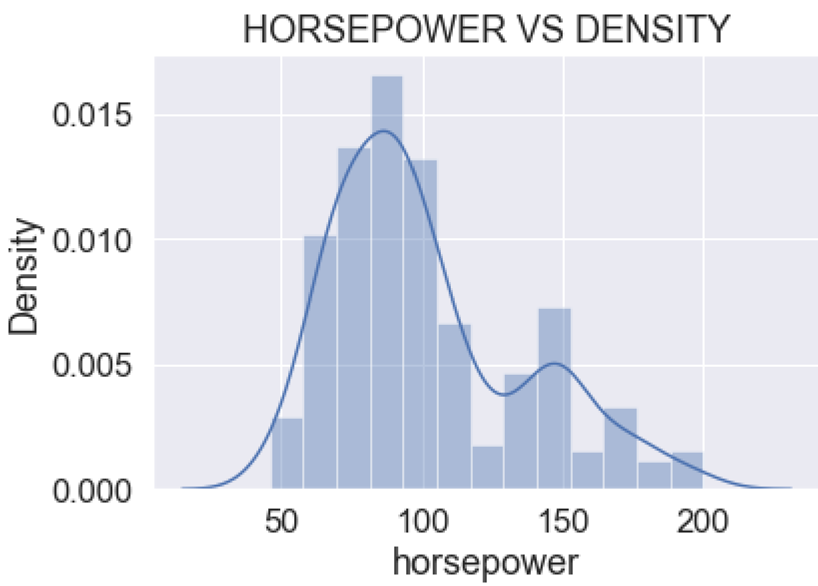
Out[56]: -0.029394876722813

kurtosis is negative and approximately zero. hence it is slighly flat and it is leptokurtic distribution.

In [57]:
```
# plotting distplot of horsepower:
plt.title('HORSEPOWER VS DENSITY')
sys.distplot(hp)
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[57]: <AxesSubplot:title={'center':'HORSEPOWER VS DENSITY'}, xlabel='horsepower', ylabel='Density'>



The peak is flat. The distribution is leptokurtic in nature. Right side tail is longer than left side

DISPLACEMENT

In [58]:
```
#displaying displacement from given data:
displacement = auto['displacement']
displacement
```

Out[58]:
```
0      307.0
1      350.0
2      318.0
3      304.0
4      302.0
       ...
392    140.0
393     97.0
394    135.0
395    120.0
396    119.0
Name: displacement, Length: 392, dtype: float64
```

In [59]:
```
# displaying index of displacement:
index_d = auto['displacement'].index
index_d
```

Out[59]:
```
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,
            ...
            387, 388, 389, 390, 391, 392, 393, 394, 395, 396],
           dtype='int64', length=392)
```

In [60]:
```
# describing displacement of car:
displacement.describe().astype(int)
```

Out[60]:
```
count    392
mean     194
std      104
min       68
25%      105
50%      151
75%      275
max      455
Name: displacement, dtype: int32
```

Displacement:

Minimum displacement by any car is 68 units.

Maximum displacement by any car is 455 units.

Mean of displacement by any car is 193.

From mean, displacement is deviated by 104.

Quantiles of displacement:

In [61]:
```
# quantile of 25% of displacement:
qd1= displacement.quantile(0.25)
qd1
```

Out[61]: 105.0

Quantile of 25% of displacement is 105

In [62]:
```
# quantile of 50% of displacement:
qd2= displacement.quantile(.50)
qd2
```

Out[62]: 151.0

Quantile of 50% of displacement is 151

In [63]:
```
# quantile of 75% of displacement:
qd3= displacement.quantile(0.75)
qd3
```

Out[63]: 275.75

Quantile of 75% of displacement is 275.75

In [64]:
```
# inter-quantile region of displacement:
IQR_D = qd3-qd1
IQR_D
```

Out[64]: 170.75

inter-quantile region of displacement is 124.75

In [65]:
```
#lower bound of displacement:
lb_d = qd1-(1.5*IQR_D)
lb_d
```

Out[65]: -151.125

lower bound of displacement is -36.125

In [66]:

```
#upper bound of displacement:
ub_d = qd3 + (1.5*IQR_D)
ub_d
```

Out[66]: 531.875

upper bound of displacement is 462.875

In [67]:

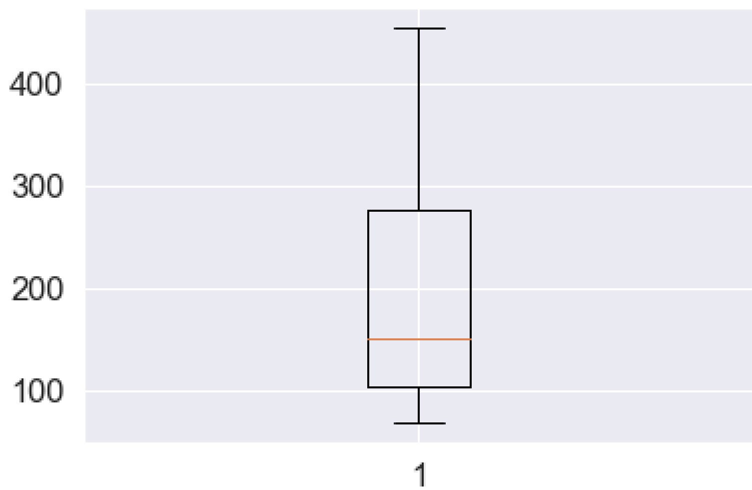
```
# checking outliers:
var_d = displacement[(displacement < lb_d) | (displacement > ub_d)].index

var_d
```

Out[67]: Int64Index([], dtype='int64')

empty brackets indicates no outliers

In [68]:

```
# boxplot of displacement with no outliers:
plt.boxplot(displacement);
```



No outliers present in displacement.

In [69]:
```
# calculating skewness of displacement:
displacement.skew()
```

Out[69]:
```
0.7016690996581041
```

displacement is moderately skewed.positive skewness indicates tail at right side is a bit longer. hence it is assymetrical distribution.

In [70]:
```
# calculating kurtosis of displacement:
displacement.kurt()
```

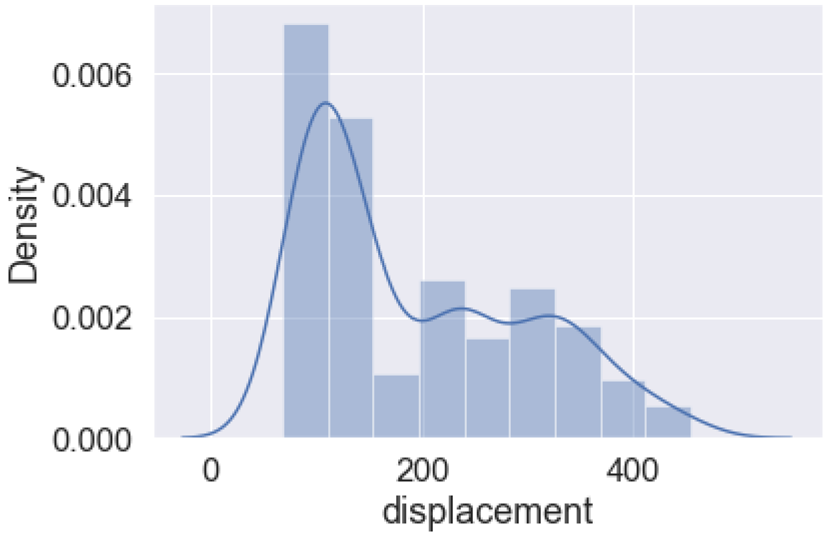
Out[70]:
```
-0.778316930213621
```

displacement is platykurtic in nature and negative kurtosis indicates peak is flat.

In [71]:
```
# plotting distplot of displacement:
sys.distplot(displacement)
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[71]:
```
<AxesSubplot:xlabel='displacement', ylabel='Density'>
```



distribution is platykurtic (assymetric) distribution. right side tail is longer as the skewness is positive.

MILES PER GALLON(MPG)

In [72]:
```
#displaying miles per gallon from given data:
mpg = auto['mpg']
mpg
```

Out[72]:
```
0      18.0
1      15.0
2      18.0
3      16.0
4      17.0
       ...
392    27.0
393    44.0
394    32.0
395    28.0
396    31.0
Name: mpg, Length: 392, dtype: float64
```

In [73]:
```
# displaying index of miles per gallon:
index_d = auto['mpg'].index
index_d
```

Out[73]:
```
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,
            ...
            387, 388, 389, 390, 391, 392, 393, 394, 395, 396],
           dtype='int64', length=392)
```

In [74]:
```
#describing miles per gallon of car:
auto['mpg'].describe().astype(int)
```

Out[74]:
```
count    392
mean      23
std        7
min        9
25%       17
50%       22
75%       29
max       46
Name: mpg, dtype: int32
```

Miles per gallon:

Maximum miles per gallon covered by any car is 46 units.

Minimum miles per gallon covered by any car is 9 units

Mean of miles per gallon is 23.

From mean position, miles per gallon is deviated by 7.

Quantiles of miles per gallon:

In [75]:
```
# quantile of 25% of miles per gallon:
qm1 = mpg.quantile(0.25)
qm1
```

Out[75]:
```
17.0
```

Quantile of 25% of mpg is 17

In [76]:
```
# quantile of 50% of miles per gallon:
qm2 = mpg.quantile(0.50)
qm2
```

Out[76]: 22.75

Quantile of 50% of miles per gallon is 22.75

In [77]:
```
# quantile of 25% of miles per gallon:
qm3 = mpg.quantile(0.75)
qm3
```

Out[77]: 29.0

Quantile of 75% of miles per gallon is 29.

In [78]:
```
# inter-quantile region of miles per gallon:
IQR_M = qm3-qm1
IQR_M
```

Out[78]: 12.0

Inter-quantile region of miles per gallon is 12.

In [79]:
```
# lower bound of miles per gallon:
lb_m = qm1-(1.5*IQR_M)
lb_m
```

Out[79]: -1.0

Lower bound of miles per gallon is -1

In [80]:
```
# upper bound of miles per gallon:
ub_m = qm3+(1.5*IQR_M)
ub_m
```

Out[80]: 47.0

Upper bound of miles per gallon is 47

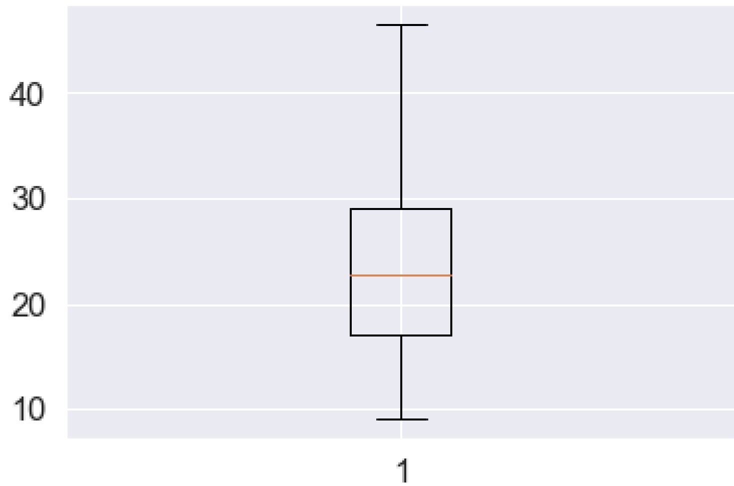
In [81]:
```
# checking outliers:
var_m = mpg[(mpg < lb_m) | (mpg > ub_m)].index
```

```
var_m
```

Out[81]: `Int64Index([], dtype='int64')`

Empty brackets indicated no outliers.

In [82]:
```
plt.boxplot(mpg);
```



no outliers in miles per gallon.

In [83]:
```
# calculating skewness of miles per gallon:
mpg.skew()
```

Out[83]: `0.45709232306041025`

mpg is fairly skewed. Positive skewness indicates tail at right side is a bit longer. hence it is assymetrical distribution.

In [84]:
```
# calculating kurtosis of miles per gallon:
mpg.kurt()
```

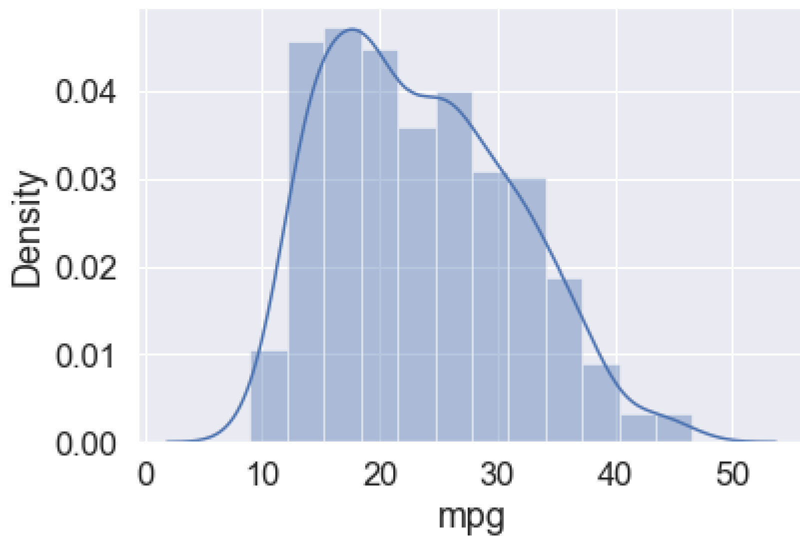
Out[84]: `-0.5159934946351457`

mpg is platykurtic in nature and negative kurtosis indicates peak is flat.

In [85]:
```
# plotting distplot of miles per gallon:
sys.distplot(mpg)
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[85]: `<AxesSubplot:xlabel='mpg', ylabel='Density'>`



Distribution is platykurtic (assymetric) in nature. Right side tail is longer as the skewness is positive.

WEIGHT:

In [86]:
```
#displaying weight from given data:
weight = auto['weight']
weight
```

Out[86]:
```
0      3504
1      3693
2      3436
3      3433
4      3449
       ...
```

```
392    2790
393    2130
394    2295
395    2625
396    2720
Name: weight, Length: 392, dtype: int64
```

In [87]:

```
# displaying index of weight from given data:
index_w = auto['weight']
index_w
```

Out[87]:

```
0      3504
1      3693
2      3436
3      3433
4      3449
       ...
392    2790
393    2130
394    2295
395    2625
396    2720
Name: weight, Length: 392, dtype: int64
```

In [88]:

```
# describing weight:
auto['weight'].describe().astype(int)
```

Out[88]:

```
count     392
mean     2977
std       849
min      1613
25%      2225
50%      2803
75%      3614
max      5140
Name: weight, dtype: int32
```

Weight:

Minimum weight of any car is 1613 units.

Maximum weight of any car is 5140 units.

Mean of all car weight is 2970.

From mean, car weight is deviated by 847.

Quantiles of weight:

In [89]:
```
# quantile of 25% of weight:
qw1 = weight.quantile(0.25)
qw1
```

Out[89]: 2225.25

quantile of 25% of weight is 2225.25

In [90]:
```
# quantile of 50% of weight:
qw2 = weight.quantile(0.50)
qw2
```

Out[90]: 2803.5

quantile of 50% of weight is 2803.5

In [91]:
```
# quantile of 75% of weight:
qw3 = weight.quantile(0.75)
qw3
```

Out[91]: 3614.75

quantile of 75% of weight is 3614.75

In [92]:
```
# Inter-quantile region of weight:
IQR_W = qw3-qw1
IQR_W
```

Out[92]: 1389.5

Inter-quantile of weight is 1389.5

In [93]:
```
# Lower bound of weight:
lb_w = qw1 - (1.5*IQR_W)
```

```
lb_w
```

Out[93]: 141.0

Lower bound of weight is 141

In [94]:

```
# Upper bound of weight:
ub_w = qw3 + (1.5*IQR_W)
ub_w
```

Out[94]: 5699.0

Upper bound of weight is 5699

In [95]:

```
# checking outliers:
var_w = weight[(weight < lb_w) | (weight > ub_w)].index
var_w
```

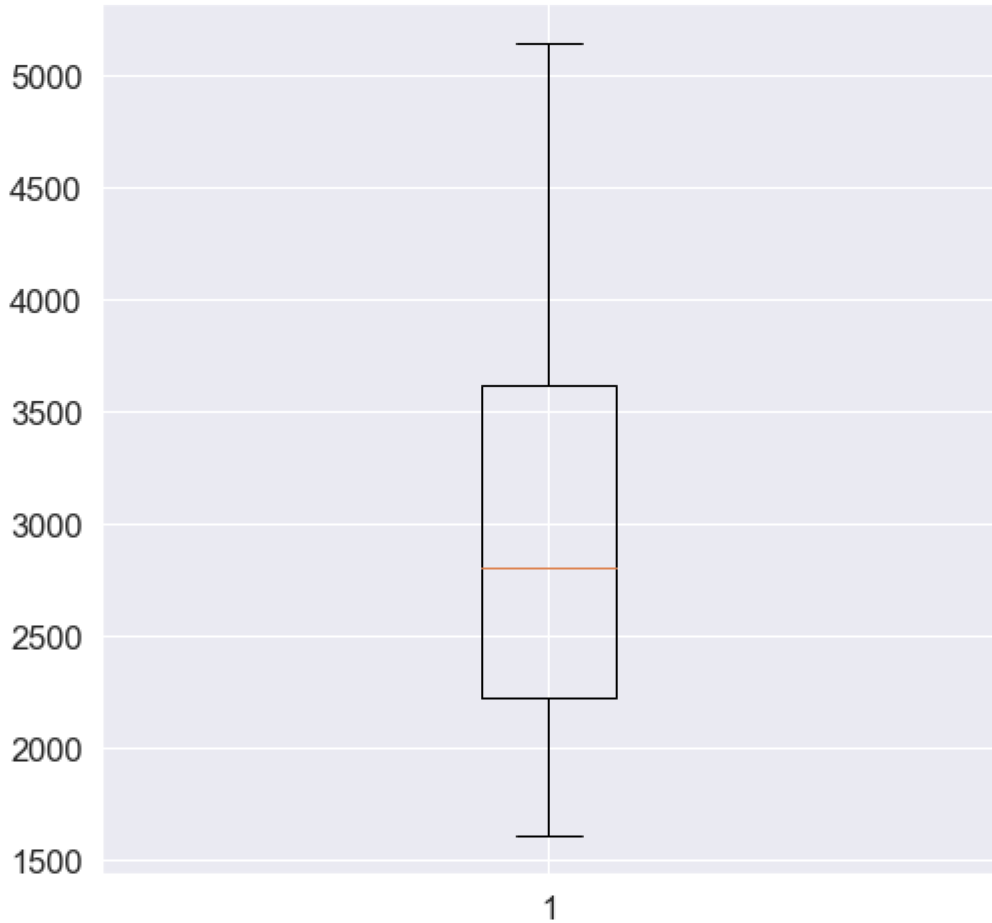
Out[95]: Int64Index([], dtype='int64')

In [96]:

```
#### No outliers are present in the data.
```

In [97]:

```
plt.figure(figsize= (8,8))
plt.boxplot(weight);
```



no outliers are present

In [98]:
```
# skewness of weight:
weight.skew()
```

Out[98]: 0.5195856740558396

Weight is moderately skewed. Positive skewness indicates tail at right side is a bit longer. Hence it is assymetrical distribution.

In [99]:
```
# kurtosis of weight:
weight.kurt()
```

Out[99]: -0.809259388327968

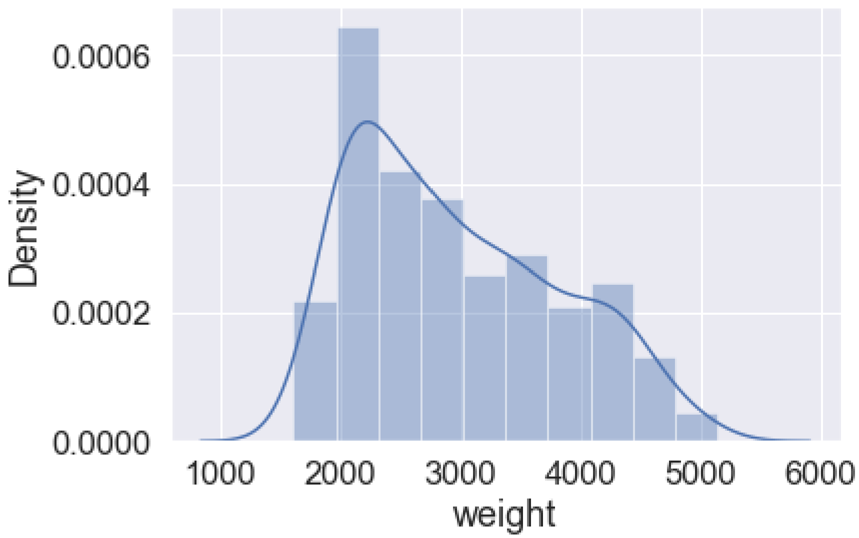
Weight is platykurtic and negative kurtosis indicates peak is flat.

In [100…

```
# plotting distplot of weight:
sys.distplot(weight)
```

```
C:\Users\aditi\anaconda_7june\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[100… <AxesSubplot:xlabel='weight', ylabel='Density'>



Distribution is platykurtic (assymetric) in nature. Right side tail is longer as the skewness is positive.

LINEAR REGRESSION:

In [101…

```
# summarizing the data with rp.summary:
rp.summary_cont(auto[['mpg','cylinders', 'displacement', 'horsepower',
                     'weight', 'acceleration', 'year', 'origin']])
```

Out[101…

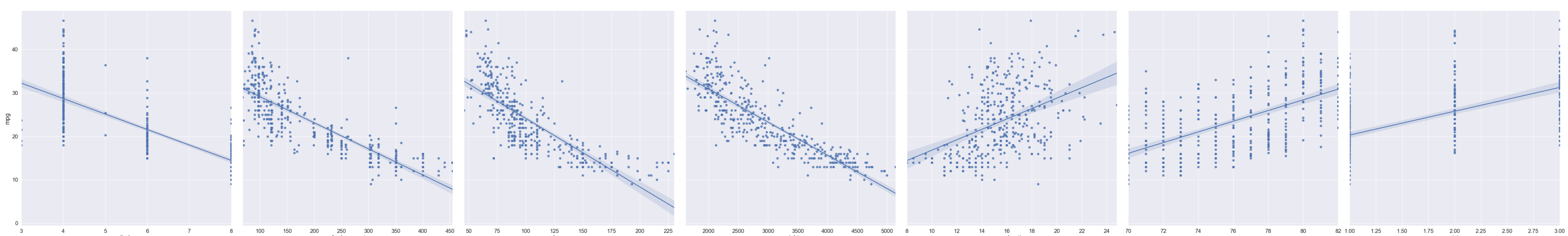
Variable	N	Mean	SD	SE	95% Conf.	Interval

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	mpg	392.0	23.4459	7.8050	0.3942	22.6709	24.2210
1	cylinders	392.0	5.4719	1.7058	0.0862	5.3026	5.6413
2	displacement	392.0	194.4120	104.6440	5.2853	184.0208	204.8032
3	horsepower	392.0	104.4694	38.4912	1.9441	100.6472	108.2916
4	weight	392.0	2977.5842	849.4026	42.9013	2893.2381	3061.9303
5	acceleration	392.0	15.5413	2.7589	0.1393	15.2674	15.8153
6	year	392.0	75.9796	3.6837	0.1861	75.6138	76.3454
7	origin	392.0	1.5765	0.8055	0.0407	1.4965	1.6565

In [102…

```
# Visualising the relationship between features and responses
sys.set(style='white', color_codes=True)
sys.set(font_scale=1.5)

sys.pairplot(auto,
             x_vars=['cylinders', 'displacement', 'horsepower',
                     'weight', 'acceleration', 'year', 'origin'],
             y_vars='mpg',
             height= 10,
             aspect=0.95,
             kind='reg')
```

Out[102… <seaborn.axisgrid.PairGrid at 0x1ac537f6b50>



In [103…

```
#List of feature names for feature column:
feature_cols=['cylinders', 'displacement', 'horsepower',
              'weight', 'acceleration', 'year', 'origin']
print(type(feature_cols))
```

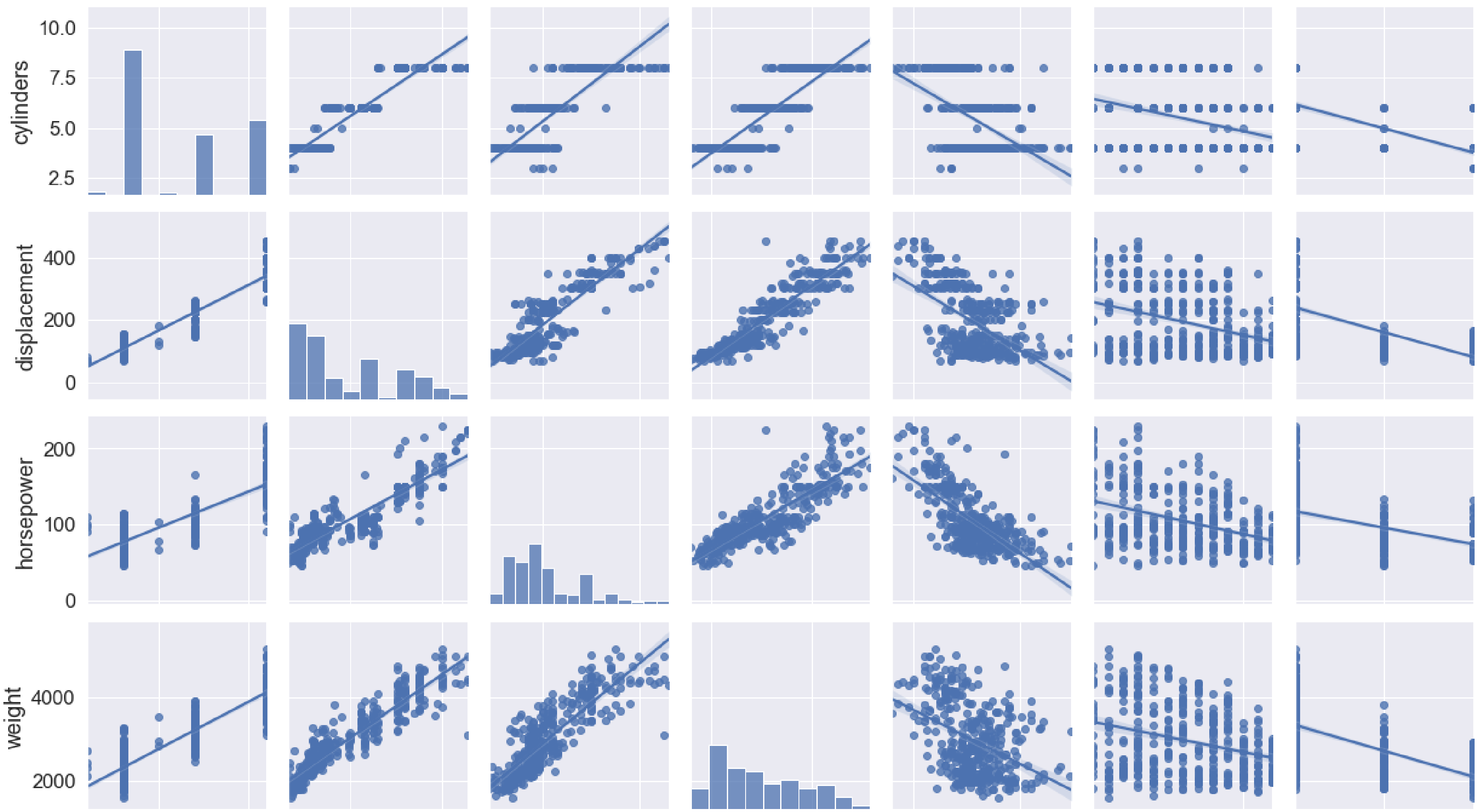
```
#subset of auto dataframe:
X= auto[feature_cols]

#selecting a series for dataframe:
y= auto['mpg']
print(type(y))
```

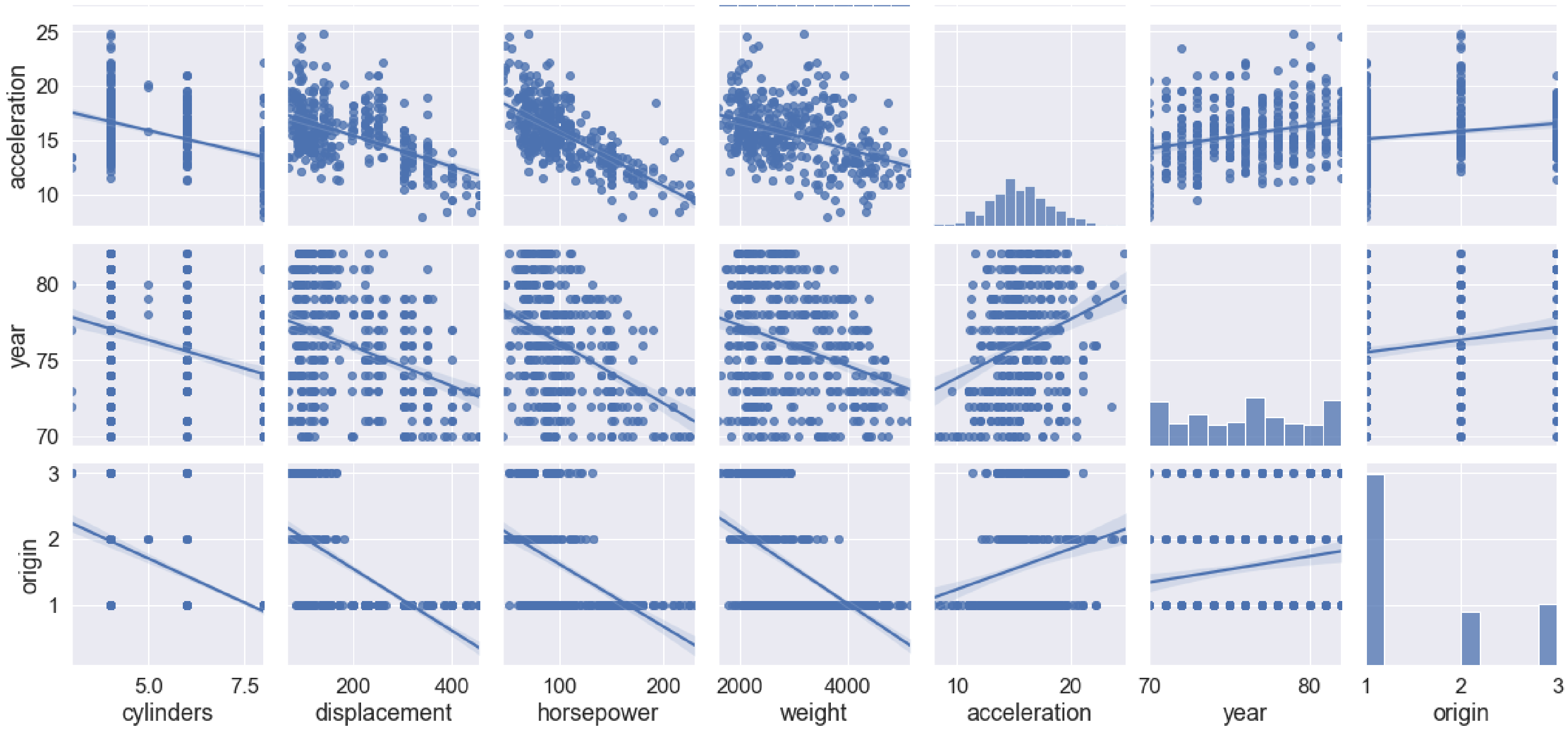
```
<class 'list'>
<class 'pandas.core.series.Series'>
```

In [104…

```
# plotting pairplot of X of regression kind:
sys.pairplot(X,kind='reg')
```

Out[104… <seaborn.axisgrid.PairGrid at 0x1ac59be0fa0>





In [105…

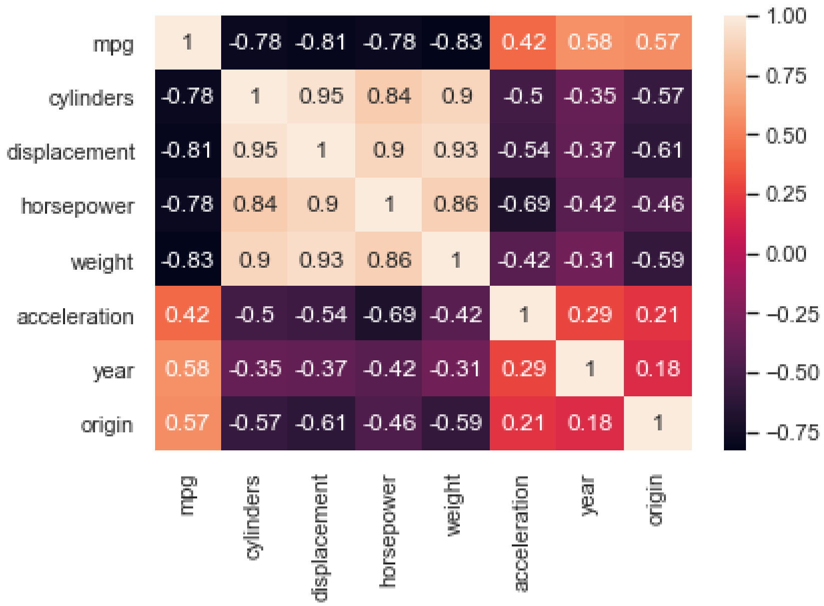
```
# Corelation between X and y:
auto.corr()
```

Out[105…

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
mpg	1.000000	-0.777618	-0.805127	-0.778427	-0.832244	0.423329	0.580541	0.565209
cylinders	-0.777618	1.000000	0.950823	0.842983	0.897527	-0.504683	-0.345647	-0.568932
displacement	-0.805127	0.950823	1.000000	0.897257	0.932994	-0.543800	-0.369855	-0.614535
horsepower	-0.778427	0.842983	0.897257	1.000000	0.864538	-0.689196	-0.416361	-0.455171
weight	-0.832244	0.897527	0.932994	0.864538	1.000000	-0.416839	-0.309120	-0.585005
acceleration	0.423329	-0.504683	-0.543800	-0.689196	-0.416839	1.000000	0.290316	0.212746
year	0.580541	-0.345647	-0.369855	-0.416361	-0.309120	0.290316	1.000000	0.181528
origin	0.565209	-0.568932	-0.614535	-0.455171	-0.585005	0.212746	0.181528	1.000000

In [106…

```
# plotting correlation between X and y with the help of heatmap:
sys.set(font_scale=1)
sys.heatmap(auto.corr(), annot = True)

plt.show()
```



In [107…

```
# Creating a model of data:
model = smf.ols("mpg ~ cylinders + displacement + horsepower + weight + acceleration + year + origin ", data= auto).fit()
```

In [108…

```
#print the coefficients:
model.params
```

Out[108…

```
Intercept      -17.218435
cylinders       -0.493376
displacement     0.019896
horsepower      -0.016951
weight          -0.006474
acceleration     0.080576
year             0.750773
origin           1.426140
dtype: float64
```

In [109…

```
# Creating the summary of the model:
model.summary()
```

Out[109…

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.821
Model:	OLS	**Adj. R-squared:**	0.818
Method:	Least Squares	**F-statistic:**	252.4
Date:	Sun, 11 Jul 2021	**Prob (F-statistic):**	2.04e-139
Time:	21:05:07	**Log-Likelihood:**	-1023.5
No. Observations:	392	**AIC:**	2063.
Df Residuals:	384	**BIC:**	2095.
Df Model:	7		
Covariance Type:	nonrobust		

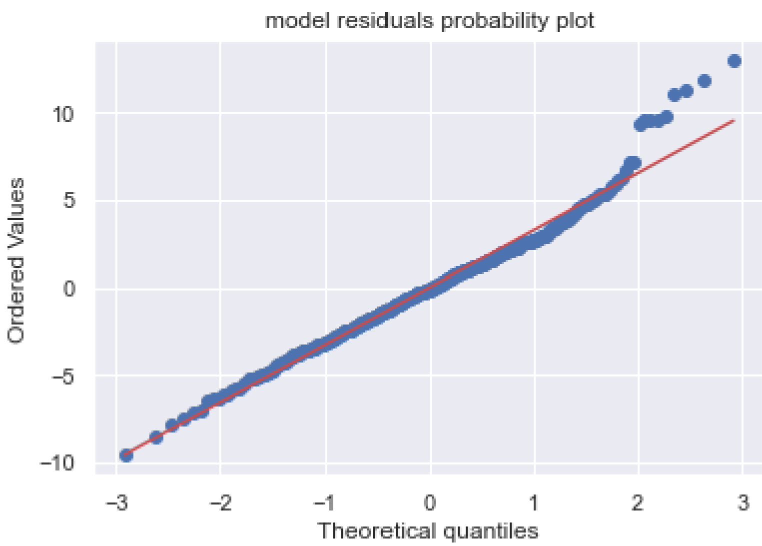
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-17.2184	4.644	-3.707	0.000	-26.350	-8.087
cylinders	-0.4934	0.323	-1.526	0.128	-1.129	0.142
displacement	0.0199	0.008	2.647	0.008	0.005	0.035
horsepower	-0.0170	0.014	-1.230	0.220	-0.044	0.010
weight	-0.0065	0.001	-9.929	0.000	-0.008	-0.005
acceleration	0.0806	0.099	0.815	0.415	-0.114	0.275
year	0.7508	0.051	14.729	0.000	0.651	0.851
origin	1.4261	0.278	5.127	0.000	0.879	1.973

Omnibus:	31.906	**Durbin-Watson:**	1.309
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	53.100
Skew:	0.529	**Prob(JB):**	2.95e-12
Kurtosis:	4.460	**Cond. No.**	8.59e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.59e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [110…

```
# Diagnosing Normality of the model
stats.probplot(model.resid, plot= plt)
plt.title("model residuals probability plot");
```



The residuals which will be represented as dots (in blue) fall on the red line. This plot indicates that the model's residuals are normally distributed.

In [111…

```
# Kolmogorov-Smirnov test (for normality)
stats.kstest(model.resid, 'norm')
```

Out[111…

```
KstestResult(statistic=0.26378409799336416, pvalue=1.4607824270648814e-24)
```

The test is significant which indicates that the model's residuals are normally distributed.

ACCEPT the NULL HYPOTHESIS (that the residuals are NOT normally distributed)

Diagnosing Homoscedasticity

In [112…

```
# Bruesch-Pagan test:
name = ['Lagrange multiplier statistic',
       'p-value',
       'f-value',
       'f p-value']

test = sms.het_breuschpagan(model.resid, model.model.exog)
test

pd.DataFrame(name, test)
```

Out[112…

	0
29.476202	Lagrange multiplier statistic
0.000118	p-value
4.460342	f-value
0.000087	f p-value

Since our p-value is less than 0.05, this indicates that heteroscedasticity is present, and we reject the null hypothesis of homoscedasticity.

In [113…

```
# splitting X abd y into training and testing sets:
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=100,test_size=0.3)
```

In [114…

```
# default split is 75% for training and 25% for testing
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(274, 7)
(274,)
(118, 7)
(118,)
```

y_train and y_test needs to be reshaped

In [115…

```
# reshaping y_train values:
y_train.values.reshape(274,1)
```

Out[115…

```
array([[24. ],
       [27.5],
       [27. ],
       [21.5],
       [20.2],
       [25. ],
       [28. ],
       [26. ],
       [10. ],
       [27.2],
       [19. ],
       [14. ],
       [14. ],
       [32.8],
       [36. ],
       [15. ],
       [18.5],
       [27. ],
       [19. ],
       [27. ],
       [17. ],
       [18.1],
       [16.5],
       [12. ],
       [32. ],
       [28. ],
       [13. ],
       [26. ],
       [36. ],
       [18. ],
       [31. ],
       [17. ],
       [14. ],
       [25.5],
       [19. ],
       [23. ],
       [44.6],
       [20. ],
       [11. ],
       [29. ],
       [26.5],
       [13. ],
       [15. ],
       [26.8],
       [32.7],
```

```
       [15. ],
       [16. ],
       [23.9],
       [14. ],
       [16. ],
       [13. ],
       [31. ],
       [27.9],
       [16. ],
       [20. ],
       [34.3],
       [27. ],
       [22.4],
       [29. ],
       [37.3],
       [32.2],
       [21. ],
       [19. ],
       [23. ],
       [22. ],
       [31. ],
       [34.5],
       [23. ],
       [23.7],
       [43.4],
       [20.2],
       [39.1],
       [14. ],
       [19.9],
       [18. ],
       [23.2],
       [21. ],
       [14. ],
       [22. ],
       [13. ],
       [36. ],
       [27. ],
       [36. ],
       [19.1],
       [30. ],
       [17.5],
       [35.1],
       [37. ],
       [13. ],
       [24.2],
       [15.5],
       [33.5],
       [37. ],
       [33. ],
```

```
       [14. ],
       [21.1],
       [26. ],
       [25. ],
       [38. ],
       [24.3],
       [26. ],
       [14. ],
       [31.9],
       [21. ],
       [34. ],
       [24.5],
       [10. ],
       [24. ],
       [23. ],
       [29. ],
       [16.2],
       [43.1],
       [16. ],
       [28. ],
       [34.1],
       [16. ],
       [21.5],
       [32.4],
       [29.8],
       [14. ],
       [20.5],
       [20.5],
       [33.5],
       [33.5],
       [24. ],
       [46.6],
       [25. ],
       [26. ],
       [33. ],
       [32.4],
       [16.9],
       [44. ],
       [31.6],
       [16.5],
       [ 9. ],
       [37.7],
       [15.5],
       [21. ],
       [23. ],
       [26. ],
       [25. ],
       [40.8],
       [21. ],
```

```
       [39. ],
       [17. ],
       [28. ],
       [25. ],
       [24.5],
       [13. ],
       [31.8],
       [25. ],
       [31. ],
       [18. ],
       [14. ],
       [26. ],
       [17.5],
       [30. ],
       [14. ],
       [17.5],
       [17. ],
       [13. ],
       [22. ],
       [15. ],
       [18. ],
       [12. ],
       [23.5],
       [36.1],
       [26. ],
       [18.2],
       [15. ],
       [20. ],
       [16. ],
       [29. ],
       [20. ],
       [29. ],
       [18.1],
       [29.5],
       [15. ],
       [25.1],
       [33. ],
       [37.2],
       [32. ],
       [19.2],
       [20.6],
       [11. ],
       [19.2],
       [22. ],
       [19. ],
       [30. ],
       [15. ],
       [13. ],
       [25. ],
```

```
       [38. ],
       [12. ],
       [31.5],
       [14. ],
       [17.7],
       [18. ],
       [34.2],
       [28. ],
       [23. ],
       [20.2],
       [30. ],
       [19. ],
       [13. ],
       [36.4],
       [19. ],
       [16. ],
       [17.5],
       [26.6],
       [18. ],
       [29.9],
       [12. ],
       [22. ],
       [21. ],
       [28. ],
       [18. ],
       [14. ],
       [13. ],
       [17. ],
       [32. ],
       [22.5],
       [21.6],
       [18. ],
       [27.4],
       [20. ],
       [28.4],
       [30.5],
       [26.4],
       [17. ],
       [25. ],
       [15. ],
       [12. ],
       [18. ],
       [25.8],
       [20.5],
       [26. ],
       [23.8],
       [31.3],
       [29. ],
       [28. ],
```

```
       [13. ],
       [32. ],
       [13. ],
       [17. ],
       [23. ],
       [13. ],
       [39.4],
       [26. ],
       [34. ],
       [15. ],
       [13. ],
       [13. ],
       [14. ],
       [23. ],
       [29.8],
       [27. ],
       [15.5],
       [32. ],
       [28. ],
       [21.5],
       [18.5],
       [24. ],
       [18.5],
       [11. ],
       [35. ],
       [28.1],
       [33.7],
       [22. ],
       [37. ],
       [26.6],
       [44.3],
       [22.3],
       [14. ]])
```

Data is reshaped.

In [116…

```
# Checking shape of y_test values:
y_test.shape
```

Out[116… (118,)

y_test need to be reshaped.

In [117…

```
# reshaping y_test values:
y_test.values.reshape(118,1)
```

Out[117…
```
array([[20. ],
       [26. ],
       [31.5],
       [20.2],
       [30. ],
       [14. ],
       [36. ],
       [16. ],
       [27. ],
       [19. ],
       [19. ],
       [25.4],
       [20.8],
       [22. ],
       [29. ],
       [30.9],
       [14. ],
       [32. ],
       [18.6],
       [25.5],
       [13. ],
       [22. ],
       [16. ],
       [24. ],
       [18. ],
       [31. ],
       [29.5],
       [15.5],
       [26. ],
       [20. ],
       [34.4],
       [17.6],
       [15. ],
       [15. ],
       [36.1],
       [13. ],
       [24. ],
       [18. ],
       [18. ],
       [13. ],
       [24. ],
       [18. ],
       [15. ],
       [16. ],
       [16. ],
       [29. ],
       [19.4],
       [18. ],
       [27. ],
```

```
       [20. ],
       [17.6],
       [27. ],
       [28. ],
       [14. ],
       [20.3],
       [25.4],
       [23.9],
       [31. ],
       [24. ],
       [15. ],
       [12. ],
       [38. ],
       [27.2],
       [34.7],
       [13. ],
       [36. ],
       [14.5],
       [35.7],
       [18. ],
       [19. ],
       [30. ],
       [20.6],
       [19.4],
       [15. ],
       [26. ],
       [16.5],
       [15.5],
       [11. ],
       [30.5],
       [30. ],
       [33.8],
       [32.9],
       [38. ],
       [28.8],
       [38.1],
       [14. ],
       [15. ],
       [17.5],
       [19.8],
       [24. ],
       [16. ],
       [25. ],
       [19. ],
       [23. ],
       [41.5],
       [32.1],
       [21. ],
       [13. ],
```

```
       [32.3],
       [28. ],
       [24. ],
       [18. ],
       [25. ],
       [34.1],
       [22. ],
       [18. ],
       [19.2],
       [19. ],
       [31. ],
       [20. ],
       [27.2],
       [26. ],
       [15. ],
       [35. ],
       [22. ],
       [16. ],
       [24. ],
       [30.7]])
```

y_test is reshaped.

In [118…

```
# 1st 10 rows of X_train:
X_train.head(10)
```

Out[118…

	cylinders	displacement	horsepower	weight	acceleration	year	origin
171	4	134.0	96	2702	13.5	75	3
267	4	134.0	95	2560	14.2	78	3
391	4	151.0	90	2950	17.3	82	1
243	3	80.0	110	2720	13.5	77	3
251	8	302.0	139	3570	12.8	78	1
180	4	121.0	115	2671	13.5	75	2
367	4	112.0	88	2605	19.6	82	1
19	4	97.0	46	1835	20.5	70	2
26	8	307.0	200	4376	15.0	70	1
299	4	141.0	71	3190	24.8	79	2

In [119…
```
# 1st 10 rows of y_train:
y_train.head(10)
```

Out[119…
```
171    24.0
267    27.5
391    27.0
243    21.5
251    20.2
180    25.0
367    28.0
19     26.0
26     10.0
299    27.2
Name: mpg, dtype: float64
```

In [120…
```
# checking X_train columns:
X_train.columns
```

Out[120…
```
Index(['cylinders', 'displacement', 'horsepower', 'weight', 'acceleration',
       'year', 'origin'],
      dtype='object')
```

In [121…
```
#creating classifier linear regression:
linreg1 = LinearRegression()
```

In [122…
```
# using fit method to train the model:
linreg1 = linreg1.fit(X_train, y_train)
linreg1
```

Out[122…
```
LinearRegression()
```

In [123…
```
linreg1.predict(X_test)
```

Out[123…
```
array([20.71583956, 28.15422546, 30.94236911, 24.79623704, 27.0195287 ,
       11.99277183, 34.31707133, 18.57939432, 28.032728  , 21.85178276,
       20.24216229, 28.31130945, 24.2700595 , 26.2972445 , 30.43612975,
       27.9878452 , 10.11329081, 31.36088971, 20.88046345, 24.51879206,
        6.40131585, 21.22564443, 16.41105372, 27.48729351, 19.87677811,
       27.9990026 , 30.28872047, 19.48048342, 26.00784953, 20.56426275,
       31.81154683, 20.63606955, 22.13183306, 13.94996691, 34.43855241,
       18.05635537, 22.00411339, 27.07143949, 18.15401022, 11.3440506 ,
       26.22245875, 21.75855781, 18.84953637, 14.0291218 , 20.24400567,
```

```
        29.75551618, 24.09570087, 21.60056492, 28.03802481, 23.29286845,
        24.54904669, 25.36407664, 27.57806154, 13.28160084, 25.34943283,
        24.43586886, 24.26261061, 30.4343015 , 23.45211012, 10.45164862,
         9.71803165, 35.85818933, 30.44382055, 30.74583588, 13.0300035 ,
        30.24183413, 15.66778395, 30.39128912, 20.21285747, 18.25331486,
        25.7991004 , 22.93943109, 19.84833992, 17.64437028, 30.67485182,
        17.65280996, 17.33475223,  7.58006785, 29.03096623, 29.39410278,
        33.87819413, 30.54269341, 32.02601848, 25.50830325, 35.17446406,
        10.11549721, 23.64501603, 17.57581813, 25.76666946, 22.3486505 ,
        15.0340029 , 21.11755487, 22.61815256, 24.18829167, 31.45298107,
        30.31620983, 24.00439896, 13.46063314, 35.09411205, 26.10076323,
        26.36463918, 17.78585789, 25.56128972, 35.12735996, 23.42222927,
        19.48082282, 21.35026348, 21.00686151, 28.71160284, 23.65298965,
        29.18163988, 22.53641781, 15.46283456, 29.44442918, 19.34015461,
        16.53448143, 27.0446265 , 26.90205402])
```

In [124…

```python
# displaying coefficients of linreg1:
linreg1.coef_
```

Out[124…

```
array([-0.3744712 ,  0.02517938, -0.03258995, -0.00642647,  0.16511297,
        0.73482302,  1.61863657])
```

In [125…

```python
#checking the shape of linreg1 cofficients:
linreg1.coef_.shape
```

Out[125…

```
(7,)
```

In [126…

```python
# transposing linreg1 coefficients:
np.transpose(linreg1.coef_).shape
```

Out[126…

```
(7,)
```

transposed linreg1

In [127…

```python
# concating X_train columns and linreg1 transposed coefficients:
coefficients = pd.concat([pd.DataFrame(X_train.columns),pd.DataFrame(np.transpose(linreg1.coef_))], axis = 1)
coefficients
```

Out[127…

	0	0
0	cylinders	-0.374471

	0	0
1	displacement	0.025179
2	horsepower	-0.032590
3	weight	-0.006426
4	acceleration	0.165113
5	year	0.734823
6	origin	1.618637

concated X_train columns and linreg1 transposed coefficients

In [128…

```
# intercept of linreg1:
linreg1.intercept_
```

Out[128…

```
-17.711803529587975
```

hence, intercepted linreg1

In [129…

```
# To predict the values of y on the test set we use linreg1.predict( )
y_pred = linreg1.predict(X_test)
y_pred
```

Out[129…

```
array([20.71583956, 28.15422546, 30.94236911, 24.79623704, 27.0195287 ,
       11.99277183, 34.31707133, 18.57939432, 28.032728  , 21.85178276,
       20.24216229, 28.31130945, 24.2700595 , 26.2972445 , 30.43612975,
       27.9878452 , 10.11329081, 31.36088971, 20.88046345, 24.51879206,
        6.40131585, 21.22564443, 16.41105372, 27.48729351, 19.87677811,
       27.9990026 , 30.28872047, 19.48048342, 26.00784953, 20.56426275,
       31.81154683, 20.63606955, 22.13183306, 13.94996691, 34.43855241,
       18.05635537, 22.00411339, 27.07143949, 18.15401022, 11.3440506 ,
       26.22245875, 21.75855781, 18.84953637, 14.0291218 , 20.24400567,
       29.75551618, 24.09570087, 21.60056492, 28.03802481, 23.29286845,
       24.54904669, 25.36407664, 27.57806154, 13.28160084, 25.34943283,
       24.43586886, 24.26261061, 30.4343015 , 23.45211012, 10.45164862,
        9.71803165, 35.85818933, 30.44382055, 30.74583588, 13.0300035 ,
       30.24183413, 15.66778395, 30.39128912, 20.21285747, 18.25331486,
       25.7991004 , 22.93943109, 19.84833992, 17.64437028, 30.67485182,
       17.65280996, 17.33475223,  7.58006785, 29.03096623, 29.39410278,
       33.87819413, 30.54269341, 32.02601848, 25.50830325, 35.17446406,
```

```
       10.11549721, 23.64501603, 17.57581813, 25.76666946, 22.3486505 ,
       15.0340029 , 21.11755487, 22.61815256, 24.18829167, 31.45298107,
       30.31620983, 24.00439896, 13.46063314, 35.09411205, 26.10076323,
       26.36463918, 17.78585789, 25.56128972, 35.12735996, 23.42222927,
       19.48082282, 21.35026348, 21.00686151, 28.71160284, 23.65298965,
       29.18163988, 22.53641781, 15.46283456, 29.44442918, 19.34015461,
       16.53448143, 27.0446265 , 26.90205402])
```

Hence predicted values of y.

In [130…

```
# Errors are the difference between observed and predicted values.
y_error = y_test - y_pred
y_error
```

Out[130…

```
125   -0.715840
142   -2.154225
278    0.557631
254   -4.596237
328    2.980471
         ...
335    5.555571
15     2.659845
34    -0.534481
173   -3.044626
360    3.797946
Name: mpg, Length: 118, dtype: float64
```

Hence, errors has been calculated

In [131…

```
# print the p-values for the model coefficients
model.pvalues
```

Out[131…

```
Intercept       2.401841e-04
cylinders       1.277965e-01
displacement    8.444649e-03
horsepower      2.196328e-01
weight          7.874953e-21
acceleration    4.154780e-01
year            3.055983e-39
origin          4.665681e-07
dtype: float64
```

p-values of model coefficients aren't giving the clear view of hypothesis testing, hence create the for loop.

In [132…

```
# for loop for checking the p-values condition (hypothesis testing):
```

```
for i in model.pvalues:
    print(i)
    if i < 0.05:
        print("TRUE reject null")
    else:
        print("False accept null")
```

```
0.00024018409897104526
TRUE reject null
0.1277964675577367
False accept null
0.00844464948162475
TRUE reject null
0.2196328232263538
False accept null
7.874953333196628e-21
TRUE reject null
0.415478017837248
False accept null
3.055982581074993e-39
TRUE reject null
4.665680973942778e-07
TRUE reject null
```

some of the columns has been rejected and some has been accepted.

In [133…

```
# maximum of p values in given model:
max(model.pvalues)
```

Out[133…

```
0.415478017837248
```

This is the maximum of p value of accepting the null value.

In [134…

```
# Inserting intercept into feature column:
feature_cols_added_intercept = []
feature_cols_added_intercept = feature_cols.copy()
feature_cols_added_intercept.insert(0, 'Intercept')
feature_cols_added_intercept
```

Out[134…

```
['Intercept',
 'cylinders',
 'displacement',
 'horsepower',
 'weight',
```

```
 'acceleration',
 'year',
 'origin']
```

Hence, inserted intercept in the featured column

In [135…

```
# ziping feature column and p values of model:
list(zip(feature_cols_added_intercept, model.pvalues))
```

Out[135…

```
[('Intercept', 0.00024018409897104526),
 ('cylinders', 0.1277964675577367),
 ('displacement', 0.00844464948162475),
 ('horsepower', 0.2196328232263538),
 ('weight', 7.874953333196628e-21),
 ('acceleration', 0.415478017837248),
 ('year', 3.055982581074993e-39),
 ('origin', 4.665680973942778e-07)]
```

here the clear overview can be seen for the p-value condition. but manually we cant say, hence again creating for loop.

In [136…

```
# 'for loop' for checking the p-values condition (hypothesis testing):
for each in list(zip(feature_cols_added_intercept, model.pvalues)):
    if each[1] <=0.05:
        print('REJECT the NULL hypothesis: the col {} has strong relationship with response variable'.format({each[0]}))
    else:
        print('ACCEPT THE NULL HYPOTHESIS: the col {} has no relationship with response variable'.format({each[0]}))
```

```
REJECT the NULL hypothesis: the col {'Intercept'} has strong relationship with response variable
ACCEPT THE NULL HYPOTHESIS: the col {'cylinders'} has no relationship with response variable
REJECT the NULL hypothesis: the col {'displacement'} has strong relationship with response variable
ACCEPT THE NULL HYPOTHESIS: the col {'horsepower'} has no relationship with response variable
REJECT the NULL hypothesis: the col {'weight'} has strong relationship with response variable
ACCEPT THE NULL HYPOTHESIS: the col {'acceleration'} has no relationship with response variable
REJECT the NULL hypothesis: the col {'year'} has strong relationship with response variable
REJECT the NULL hypothesis: the col {'origin'} has strong relationship with response variable
```

Columns that rejected null hypothesis: Intercept, displacement, weight, year, origin.

```
hence these columns has strong relationship with response variable.
```

Columns that accepted null hypothesis: cylinders, horsepower, acceleration.

```
hence these columns has no relationship with response variable.
```

In [137…

```
# print the R-squared value for the model
model.rsquared
```

Out[137…

```
0.8214780764810599
```

Model evaluation metrics for regression

In [138…

```
# y-intercept of linreg1:
print('y-intercept : ', linreg1.intercept_)
```

```
y-intercept :  -17.711803529587975
```

Hence the y-intercept of linreg1 is -17.711

In [139…

```
# beta coefficients of linreg1:
print('beta coefficients : ', linreg1.coef_)
```

```
beta coefficients :  [-0.3744712   0.02517938 -0.03258995 -0.00642647  0.16511297  0.73482302
  1.61863657]
```

Hence, beta coefficients of linreg1 are above.

In [140…

```
# Mean Abslute Error of linreg1:
print('Mean Abs Error MAE : ', metrics.mean_absolute_error(y_test, y_pred))
```

```
Mean Abs Error MAE :  2.577105635399067
```

Hence, Mean Absolute Error is 2.577

In [141…

```
# Mean Square Error:
print('Mean Sq  Error MSE : ', metrics.mean_squared_error(y_test, y_pred))
```

```
Mean Sq  Error MSE :  10.513396137620628
```

Hence, Mean Square Error is 10.5133

In [142…

```
# Root Mean Square Error:
print('Root Mean Sq Error RMSE : ', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Root Mean Sq Error RMSE :  3.2424367592322643
```

Root Mean Square Error is 3.2424

In [143…

```
# R2 value:
print('r2 value : ', metrics.r2_score(y_test, y_pred))
```

```
r2 value :  0.7997486706042077
```

R2 value is 0.7997

In [144…

```
# statsmodel with rejected null hypothesis columns:
model_1= smf.ols(formula="mpg ~ displacement + weight + year + origin ", data=auto).fit()

# print the R-squared value for the model_1:
print(model_1.rsquared, model.rsquared_adj)

# statsmodel with original model:
model_2 = smf.ols(formula="mpg ~ cylinders + displacement + horsepower + weight + acceleration + year + origin ",
              data=auto).fit()
# print the R-squared value for the model_1:
print(model_2.rsquared, model.rsquared_adj)

# print the R-squared value for the model
print("cylinders:",model_2.rsquared, model_2.rsquared_adj)
print("acceleration:",model_2.rsquared, model_2.rsquared_adj)
print('horsepower:',model_2.rsquared, model_2.rsquared_adj)
```

```
0.8180977417246627 0.8182237705835792
0.8214780764810599 0.8182237705835792
cylinders: 0.8214780764810599 0.8182237705835792
acceleration: 0.8214780764810599 0.8182237705835792
horsepower: 0.8214780764810599 0.8182237705835792
```

R-squared will always increase as you add more features to the model, even if they are unrelated to the response. Selecting the model with the highest R-squared is not a reliable approach for choosing the best linear model.

Adjusted R-square is constant throughout the model.

In [145…

```
# Running linear regression using statsmodels:
X_train = sa.add_constant(X_train)
X_test  = sa.add_constant(X_test)
```

In [146…

```
# shape of X_train, y_train:
X_train.shape, y_train.shape
```

Out[146…

```
((274, 8), (274,))
```

In [147…

```
type(auto.columns)
```

Out[147…

```
pandas.core.indexes.base.Index
```

In [148…

```
# defining linreg2 with the help of smf.ols:
linreg2 = smf.ols(formula = "mpg ~ cylinders + displacement + horsepower + weight + acceleration + year + origin " , data
linreg2
```

Out[148…

```
<statsmodels.regression.linear_model.OLS at 0x1ac5e5954f0>
```

In [149…

```
# head of X_train:
X_train.head()
```

Out[149…

	const	cylinders	displacement	horsepower	weight	acceleration	year	origin
171	1.0	4	134.0	96	2702	13.5	75	3
267	1.0	4	134.0	95	2560	14.2	78	3
391	1.0	4	151.0	90	2950	17.3	82	1
243	1.0	3	80.0	110	2720	13.5	77	3
251	1.0	8	302.0	139	3570	12.8	78	1

In [150…

```
# displaying y_train:
y_train
```

Out[150…

```
171    24.0
267    27.5
391    27.0
243    21.5
251    20.2
       ...
347    37.0
```

```
364    26.6
325    44.3
282    22.3
8      14.0
Name: mpg, Length: 274, dtype: float64
```

In [151…

```
# Linear regression can be run by using sa.OLS:
linreg2 = sa.OLS(y_train, X_train).fit()
linreg2
```

Out[151…

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1ac5e5a5b80>
```

In [152…

```
# summary of linreg2:
linreg2.summary()
```

Out[152…

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.825
Model:	OLS	**Adj. R-squared:**	0.821
Method:	Least Squares	**F-statistic:**	179.3
Date:	Sun, 11 Jul 2021	**Prob (F-statistic):**	7.34e-97
Time:	21:05:29	**Log-Likelihood:**	-720.17
No. Observations:	274	**AIC:**	1456.
Df Residuals:	266	**BIC:**	1485.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-17.7118	5.612	-3.156	0.002	-28.762	-6.662
cylinders	-0.3745	0.399	-0.940	0.348	-1.159	0.410
displacement	0.0252	0.009	2.777	0.006	0.007	0.043
horsepower	-0.0326	0.017	-1.957	0.051	-0.065	0.000
weight	-0.0064	0.001	-8.251	0.000	-0.008	-0.005

acceleration	0.1651	0.118	1.405	0.161	-0.066	0.396
year	0.7348	0.063	11.728	0.000	0.611	0.858
origin	1.6186	0.332	4.878	0.000	0.965	2.272

Omnibus:	25.091	**Durbin-Watson:**	2.320
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	35.308
Skew:	0.617	**Prob(JB):**	2.15e-08
Kurtosis:	4.253	**Cond. No.**	8.51e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.51e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [153…

```
X_train.columns
```

Out[153…

```
Index(['const', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'year', 'origin'],
      dtype='object')
```

Detecting and Removing Multicollinearity

In [154…

```
# selecting the range:
[i for i in range(X_train.shape[1])]
```

Out[154…

```
[0, 1, 2, 3, 4, 5, 6, 7]
```

In [155…

```
# variance inflation factor for a integer in range:
variance_inflation_factor(X_train.values, 2)
```

Out[155…

```
22.056346462464866
```

In [156…
```
# variance inflation factor for a range:
[variance_inflation_factor(X_train.values, i) for i in range(X_train.shape[1])]
```

Out[156…
```
[745.8335860111331,
 11.398263158609154,
 22.056346462464866,
 10.196381179538657,
 10.847080747359017,
 2.555021893358731,
 1.252210420117701,
 1.7510734532392658]
```

In [157…
```
# defining vif:
vif = [variance_inflation_factor(X_train.values, i) for i in range(X_train.shape[1])]
```

In [158…
```
vif[1:]
```

Out[158…
```
[11.398263158609154,
 22.056346462464866,
 10.196381179538657,
 10.847080747359017,
 2.555021893358731,
 1.252210420117701,
 1.7510734532392658]
```

In [159…
```
# Returns indices of the max element of the array in a particular axis:
np.argmax(vif[1:])
```

Out[159…
```
1
```

In [160…
```
# checking the length of vif:
len(vif)
```

Out[160…
```
8
```

the length of variance inflation factor is 8.

In [161…
```
#creating a dataframe to remove collinear variables:
a= pd.DataFrame()
a
```

Out[161... —

Created data frame to remove collinear variable:

In [162...

```
#creating a function to remove the collinear variables
def calculate_vif(x):
    thresh = 10
    output = pd.DataFrame()
    k = x.shape[1]
    dropped_columns = []
    vif=[variance_inflation_factor(x.values, j) for j in range(x.shape[1])]

    for i in range(1,k):
        print("==> Iteration no.", i)
        print(vif)

        # RETURN INDICES OF MAX ELEMENT OF THE ARRAY IN A PARTICULAR AXIS.
        a = np.argmax(vif)

        print('Max VIF is for variable no.:',a)

        if vif[a] <= thresh :
            break
        if i==1:
            output = x.drop(x.columns[a], axis = 1)
            vif = [variance_inflation_factor(output.values, j) for j in range(output.shape[1])]
        elif i > 1:
            output = output.drop(output.columns[a], axis = 1)
            vif = [variance_inflation_factor(output.values, j) for j in range(output.shape[1])]

        dropped_columns.append(X_train.columns[a])

        print(dropped_columns)
    return(output, dropped_columns)
```

In [163...

```
# performing iterations:
train_out, dropped_columns = calculate_vif(X_train)
```

```
==> Iteration no. 1
[745.8335860111331, 11.398263158609154, 22.056346462464866, 10.196381179538657, 10.847080747359017, 2.555021893358731, 1.
252210420117701, 1.7510734532392658]
Max VIF is for variable no.: 0
['const']
```

```
==> Iteration no. 2
[117.63621630131608, 94.80757926006876, 69.3923623431544, 134.07055468183543, 68.63843802948894, 119.09427433801984, 8.29
2449395143672]
Max VIF is for variable no.: 3
['const', 'horsepower']
==> Iteration no. 3
[116.18756743925765, 81.54041762375337, 55.56504394548114, 55.801258886256, 119.08901712579028, 8.17835144565855]
Max VIF is for variable no.: 4
['const', 'horsepower', 'weight']
==> Iteration no. 4
[106.79907199586206, 75.97828896049653, 44.78149642953716, 16.708775726981646, 7.465060346550492]
Max VIF is for variable no.: 0
['const', 'horsepower', 'weight', 'const']
==> Iteration no. 5
[32.38684919137678, 43.84409196048599, 9.780649036709525, 7.109920475726767]
Max VIF is for variable no.: 1
['const', 'horsepower', 'weight', 'const', 'cylinders']
==> Iteration no. 6
[3.312455320645012, 9.677484953330532, 5.578096908903526]
Max VIF is for variable no.: 1
```

Max VIF is for variable no is 4

6 iterations are performed.

In [164…

```
# Displaying the dropped columns:
dropped_columns
```

Out[164…

```
['const', 'horsepower', 'weight', 'const', 'cylinders']
```

the dropped columns are const, horsepower, weight, cylinders.

In [165…

```
X_test.drop(dropped_columns, axis = 1, inplace = True)
```

Dropping the columns permanently.

In [166…

```
# displaying the train_out data:
train_out.head()
```

Out[166…

	displacement	acceleration	origin
171	134.0	13.5	3

	displacement	acceleration	origin
267	134.0	14.2	3
391	151.0	17.3	1
243	80.0	13.5	3
251	302.0	12.8	1

train out data has displacement, acceleration, and origin columns.

In [167…

```
# adding constant to train_out data:
train_out = sa.add_constant(train_out)

X_test    = sa.add_constant(X_test)
```

added constant to train out data.

In [168…

```
# displaying the train_out data:
train_out
```

Out[168…

	const	displacement	acceleration	origin
171	1.0	134.0	13.5	3
267	1.0	134.0	14.2	3
391	1.0	151.0	17.3	1
243	1.0	80.0	13.5	3
251	1.0	302.0	12.8	1
...	...	...	...	...
347	1.0	85.0	19.4	3
364	1.0	350.0	19.0	1
325	1.0	90.0	21.7	2
282	1.0	140.0	17.3	1
8	1.0	455.0	10.0	1

274 rows × 4 columns

In [169…

```
# using fit method on trained model:
linreg3 = sa.OLS(y_train, train_out).fit()
```

In [170…

```
# view the summary of trained model:
linreg3.summary()
```

Out[170…

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.661
Model:	OLS	**Adj. R-squared:**	0.658
Method:	Least Squares	**F-statistic:**	175.8
Date:	Sun, 11 Jul 2021	**Prob (F-statistic):**	3.50e-63
Time:	21:05:35	**Log-Likelihood:**	-810.74
No. Observations:	274	**AIC:**	1629.
Df Residuals:	270	**BIC:**	1644.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	28.5323	2.848	10.019	0.000	22.925	34.139
displacement	-0.0509	0.004	-12.380	0.000	-0.059	-0.043
acceleration	0.1645	0.127	1.299	0.195	-0.085	0.414
origin	1.5060	0.449	3.356	0.001	0.623	2.389

Omnibus:	26.594	**Durbin-Watson:**	2.255
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	40.168
Skew:	0.617	**Prob(JB):**	1.89e-09
Kurtosis:	4.412	**Cond. No.**	2.24e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.24e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

Checking normality of residuals

In [171…

```
# Perform a Shapiro-Wilk Test:

stats.shapiro(linreg3.resid)
```

Out[171…

```
ShapiroResult(statistic=0.9700528979301453, pvalue=1.7096039300668053e-05)
```

test statistic is 0.970052 and the corresponding p-value is 1.70960 .

p- value is greater than 0.05. hence reject alternate hypothesis.

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: