Linear Regression

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

In [2]:
```
# Importing Dataset
df = pd.read_csv(r'C:\Users\Zainab\Dropbox\PC\Documents\Sem_2\Machine_Learning\data
```

In [3]:
```
# To check no. of rows and cols
df.shape
```

Out[3]:
```
(398, 9)
```

In [4]:
```
# To check top 5 rows

df.head()
```

Out[4]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car 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 [5]:
```
# To check bottom 5 rows

df.tail()
```

Out[5]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
393	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
394	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
395	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
396	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
397	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

In [6]:

```
# To check Dtype

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64  
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object 
 4   weight        398 non-null    int64  
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64  
 7   origin        398 non-null    int64  
 8   car name      398 non-null    object 
dtypes: float64(3), int64(4), object(2)
memory usage: 28.1+ KB
```

In [7]:

```
# To Describe Data

df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
mpg	398.0	23.514573	7.815984	9.0	17.500	23.0	29.000	46.6
cylinders	398.0	5.454774	1.701004	3.0	4.000	4.0	8.000	8.0
displacement	398.0	193.425879	104.269838	68.0	104.250	148.5	262.000	455.0
weight	398.0	2970.424623	846.841774	1613.0	2223.750	2803.5	3608.000	5140.0
acceleration	398.0	15.568090	2.757689	8.0	13.825	15.5	17.175	24.8
model year	398.0	76.010050	3.697627	70.0	73.000	76.0	79.000	82.0
origin	398.0	1.572864	0.802055	1.0	1.000	1.0	2.000	3.0

In [8]:

```
# To check null values and sum of them

df.isnull().sum()
```

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

In [9]:
```
# To check columns

df.columns.str.lower()
```

Out[9]:
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model year', 'origin', 'car name'],
      dtype='object')
```

In [10]:
```
a = df[['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model year', 'origin']]
a
```

Out[10]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	1
1	15.0	8	350.0	165	3693	11.5	70	1
2	18.0	8	318.0	150	3436	11.0	70	1
3	16.0	8	304.0	150	3433	12.0	70	1
4	17.0	8	302.0	140	3449	10.5	70	1
...	...	...	...	...	...	...	...	...
393	27.0	4	140.0	86	2790	15.6	82	1
394	44.0	4	97.0	52	2130	24.6	82	2
395	32.0	4	135.0	84	2295	11.6	82	1
396	28.0	4	120.0	79	2625	18.6	82	1
397	31.0	4	119.0	82	2720	19.4	82	1

398 rows × 8 columns

In [11]:
```
# For loop to check distinct values of each column

for i in a:
    print(i)
    print('       '*20)
    print(df[i].unique().tolist())
    print('       '*20)
    print('------'*20)
```

```
mpg

[18.0, 15.0, 16.0, 17.0, 14.0, 24.0, 22.0, 21.0, 27.0, 26.0, 25.0, 10.0, 11.0, 9.
0, 28.0, 19.0, 12.0, 13.0, 23.0, 30.0, 31.0, 35.0, 20.0, 29.0, 32.0, 33.0, 17.5, 1
5.5, 14.5, 22.5, 24.5, 18.5, 29.5, 26.5, 16.5, 31.5, 36.0, 25.5, 33.5, 20.5, 30.5,
21.5, 43.1, 36.1, 32.8, 39.4, 19.9, 19.4, 20.2, 19.2, 25.1, 20.6, 20.8, 18.6, 18.
1, 17.7, 27.5, 27.2, 30.9, 21.1, 23.2, 23.8, 23.9, 20.3, 21.6, 16.2, 19.8, 22.3, 1
7.6, 18.2, 16.9, 31.9, 34.1, 35.7, 27.4, 25.4, 34.2, 34.5, 31.8, 37.3, 28.4, 28.8,
26.8, 41.5, 38.1, 32.1, 37.2, 26.4, 24.3, 19.1, 34.3, 29.8, 31.3, 37.0, 32.2, 46.
6, 27.9, 40.8, 44.3, 43.4, 36.4, 44.6, 40.9, 33.8, 32.7, 23.7, 23.6, 32.4, 26.6, 2
5.8, 23.5, 39.1, 39.0, 35.1, 32.3, 37.7, 34.7, 34.4, 29.9, 33.7, 32.9, 31.6, 28.1,
30.7, 24.2, 22.4, 34.0, 38.0, 44.0]

----------------------------------------------------------------------------------
--------------------------------------
cylinders

[8, 4, 6, 3, 5]

----------------------------------------------------------------------------------
--------------------------------------
displacement

[307.0, 350.0, 318.0, 304.0, 302.0, 429.0, 454.0, 440.0, 455.0, 390.0, 383.0, 340.
0, 400.0, 113.0, 198.0, 199.0, 200.0, 97.0, 110.0, 107.0, 104.0, 121.0, 360.0, 14
0.0, 98.0, 232.0, 225.0, 250.0, 351.0, 258.0, 122.0, 116.0, 79.0, 88.0, 71.0, 72.
0, 91.0, 97.5, 70.0, 120.0, 96.0, 108.0, 155.0, 68.0, 114.0, 156.0, 76.0, 83.0, 9
0.0, 231.0, 262.0, 134.0, 119.0, 171.0, 115.0, 101.0, 305.0, 85.0, 130.0, 168.0, 1
11.0, 260.0, 151.0, 146.0, 80.0, 78.0, 105.0, 131.0, 163.0, 89.0, 267.0, 86.0, 18
3.0, 141.0, 173.0, 135.0, 81.0, 100.0, 145.0, 112.0, 181.0, 144.0]

----------------------------------------------------------------------------------
--------------------------------------
horsepower

['130', '165', '150', '140', '198', '220', '215', '225', '190', '170', '160', '9
5', '97', '85', '88', '46', '87', '90', '113', '200', '210', '193', '?', '100', '1
05', '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', '14
9', '89', '63', '48', '66', '139', '103', '125', '133', '138', '135', '142', '77',
'62', '132', '84', '64', '74', '116', '82']

----------------------------------------------------------------------------------
--------------------------------------
weight

[3504, 3693, 3436, 3433, 3449, 4341, 4354, 4312, 4425, 3850, 3563, 3609, 3761, 308
6, 2372, 2833, 2774, 2587, 2130, 1835, 2672, 2430, 2375, 2234, 2648, 4615, 4376, 4
382, 4732, 2264, 2228, 2046, 2634, 3439, 3329, 3302, 3288, 4209, 4464, 4154, 4096,
4955, 4746, 5140, 2962, 2408, 3282, 3139, 2220, 2123, 2074, 2065, 1773, 1613, 183
4, 1955, 2278, 2126, 2254, 2226, 4274, 4385, 4135, 4129, 3672, 4633, 4502, 4456, 4
422, 2330, 3892, 4098, 4294, 4077, 2933, 2511, 2979, 2189, 2395, 2288, 2506, 2164,
2100, 4100, 3988, 4042, 3777, 4952, 4363, 4237, 4735, 4951, 3821, 3121, 3278, 294
5, 3021, 2904, 1950, 4997, 4906, 4654, 4499, 2789, 2279, 2401, 2379, 2124, 2310, 2
472, 2265, 4082, 4278, 1867, 2158, 2582, 2868, 3399, 2660, 2807, 3664, 3102, 2875,
2901, 3336, 2451, 1836, 2542, 3781, 3632, 3613, 4141, 4699, 4457, 4638, 4257, 221
9, 1963, 2300, 1649, 2003, 2125, 2108, 2246, 2489, 2391, 2000, 3264, 3459, 3432, 3
158, 4668, 4440, 4498, 4657, 3907, 3897, 3730, 3785, 3039, 3221, 3169, 2171, 2639,
2914, 2592, 2702, 2223, 2545, 2984, 1937, 3211, 2694, 2957, 2671, 1795, 2464, 257
2, 2255, 2202, 4215, 4190, 3962, 3233, 3353, 3012, 3085, 2035, 3651, 3574, 3645, 3
193, 1825, 1990, 2155, 2565, 3150, 3940, 3270, 2930, 3820, 4380, 4055, 3870, 3755,
2045, 1945, 3880, 4060, 4140, 4295, 3520, 3425, 3630, 3525, 4220, 4165, 4325, 433
```

```
5, 1940, 2740, 2755, 2051, 2075, 1985, 2190, 2815, 2600, 2720, 1800, 2070, 3365, 3
735, 3570, 3535, 3155, 2965, 3430, 3210, 3380, 3070, 3620, 3410, 3445, 3205, 4080,
2560, 2230, 2515, 2745, 2855, 2405, 2830, 3140, 2795, 2135, 3245, 2990, 2890, 326
5, 3360, 3840, 3725, 3955, 3830, 4360, 4054, 3605, 1925, 1975, 1915, 2670, 3530, 3
900, 3190, 3420, 2200, 2150, 2020, 2595, 2700, 2556, 2144, 1968, 2120, 2019, 2678,
2870, 3003, 3381, 2188, 2711, 2434, 2110, 2800, 2085, 2335, 2950, 3250, 1850, 214
5, 1845, 2910, 2420, 2500, 2905, 2290, 2490, 2635, 2620, 2725, 2385, 1755, 1875, 1
760, 2050, 2215, 2380, 2320, 2210, 2350, 2615, 3230, 3160, 2900, 3415, 3060, 3465,
2605, 2640, 2575, 2525, 2735, 2865, 3035, 1980, 2025, 1970, 2160, 2205, 2245, 196
5, 1995, 3015, 2585, 2835, 2665, 2370, 2790, 2295, 2625]

---------------------------------------------------------------------------------
-------------------------------------
acceleration

[12.0, 11.5, 11.0, 10.5, 10.0, 9.0, 8.5, 8.0, 9.5, 15.0, 15.5, 16.0, 14.5, 20.5, 1
7.5, 12.5, 14.0, 13.5, 18.5, 19.0, 13.0, 19.5, 18.0, 17.0, 23.5, 16.5, 21.0, 16.9,
14.9, 17.7, 15.3, 13.9, 12.8, 15.4, 17.6, 22.2, 22.1, 14.2, 17.4, 16.2, 17.8, 12.
2, 16.4, 13.6, 15.7, 13.2, 21.9, 16.7, 12.1, 14.8, 18.6, 16.8, 13.7, 11.1, 11.4, 1
8.2, 15.8, 15.9, 14.1, 21.5, 14.4, 19.4, 19.2, 17.2, 18.7, 15.1, 13.4, 11.2, 14.7,
16.6, 17.3, 15.2, 14.3, 20.1, 24.8, 11.3, 12.9, 18.8, 18.1, 17.9, 21.7, 23.7, 19.
9, 21.8, 13.8, 12.6, 16.1, 20.7, 18.3, 20.4, 19.6, 17.1, 15.6, 24.6, 11.6]

---------------------------------------------------------------------------------
-------------------------------------
model year

[70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82]

---------------------------------------------------------------------------------
-------------------------------------
origin

[1, 3, 2]

---------------------------------------------------------------------------------
-------------------------------------
```

In [12]:

```python
# drop column car name

df = df.drop('car name',axis = 1)
```

In [13]:

```python
# check if changes occurred

df.head()
```

Out[13]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	1
1	15.0	8	350.0	165	3693	11.5	70	1
2	18.0	8	318.0	150	3436	11.0	70	1
3	16.0	8	304.0	150	3433	12.0	70	1
4	17.0	8	302.0	140	3449	10.5	70	1

In [14]:

```python
# replace origin values with asia, america and europe

df['origin'] = df['origin'].replace({1 : 'America',2:'europe',3: 'Asia'})
```

In [15]:

```python
df.head()
```

Out[15]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130	3504	12.0	70	America
1	15.0	8	350.0	165	3693	11.5	70	America
2	18.0	8	318.0	150	3436	11.0	70	America
3	16.0	8	304.0	150	3433	12.0	70	America
4	17.0	8	302.0	140	3449	10.5	70	America

In [16]:
```
#Referenced bucketting
```

In [17]:
```
# Create Dummy Variables
df = pd.get_dummies(df, columns = ['origin'])
df
```

Out[17]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin_America	ori
0	18.0	8	307.0	130	3504	12.0	70	1	
1	15.0	8	350.0	165	3693	11.5	70	1	
2	18.0	8	318.0	150	3436	11.0	70	1	
3	16.0	8	304.0	150	3433	12.0	70	1	
4	17.0	8	302.0	140	3449	10.5	70	1	
...	...	...	...	...	...	...	...	...	
393	27.0	4	140.0	86	2790	15.6	82	1	
394	44.0	4	97.0	52	2130	24.6	82	0	
395	32.0	4	135.0	84	2295	11.6	82	1	
396	28.0	4	120.0	79	2625	18.6	82	1	
397	31.0	4	119.0	82	2720	19.4	82	1	

398 rows × 10 columns

In [18]:
```
#drop any 1 column of origin bcz if a,b are 0 then c is 1
# a   b   c
# 1   0   0
# 0   1   0
# 0   0   1
```

In [19]:
```
df = df.drop('origin_Asia', axis = 1)
```

Dealing with missing values

In [20]:
```
df.isnull().sum()
```

Out[20]:
```
mpg               0
cylinders         0
displacement      0
horsepower        0
weight            0
acceleration      0
model year        0
origin_America    0
origin_europe     0
dtype: int64
```

In [21]:
```
df.dtypes
```

Out[21]:
```
mpg               float64
cylinders           int64
displacement      float64
horsepower         object
weight              int64
acceleration      float64
model year          int64
origin_America      uint8
origin_europe       uint8
dtype: object
```

In [22]:
```
# if the string is in digits

hp_digit = pd.DataFrame(df.horsepower.str.isdigit())
df[hp_digit['horsepower']==False]                          # will take only those rows
```

Out[22]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin_America	ori
32	25.0	4	98.0	?	2046	19.0	71	1	
126	21.0	6	200.0	?	2875	17.0	74	1	
330	40.9	4	85.0	?	1835	17.3	80	0	
336	23.6	4	140.0	?	2905	14.3	80	1	
354	34.5	4	100.0	?	2320	15.8	81	0	
374	23.0	4	151.0	?	3035	20.5	82	1	

In [23]:
```
#Replace missing values with NaN

df = df.replace('?', np.nan)
df[hp_digit['horsepower']==False]
```

Out[23]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin_America	ori
32	25.0	4	98.0	NaN	2046	19.0	71	1	
126	21.0	6	200.0	NaN	2875	17.0	74	1	
330	40.9	4	85.0	NaN	1835	17.3	80	0	
336	23.6	4	140.0	NaN	2905	14.3	80	1	
354	34.5	4	100.0	NaN	2320	15.8	81	0	
374	23.0	4	151.0	NaN	3035	20.5	82	1	

In [24]:

```
# Replace missing values with nan

#df['horsepower'] = df['horsepower'].replace('?', np.nan)
#df
```

In [25]:

```
df.median()
```

Out[25]:

```
mpg                 23.0
cylinders            4.0
displacement       148.5
horsepower          93.5
weight            2803.5
acceleration        15.5
model year          76.0
origin_America       1.0
origin_europe        0.0
dtype: float64
```

In [26]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   mpg             398 non-null    float64
 1   cylinders       398 non-null    int64  
 2   displacement    398 non-null    float64
 3   horsepower      392 non-null    object 
 4   weight          398 non-null    int64  
 5   acceleration    398 non-null    float64
 6   model year      398 non-null    int64  
 7   origin_America  398 non-null    uint8  
 8   origin_europe   398 non-null    uint8  
dtypes: float64(3), int64(3), object(1), uint8(2)
memory usage: 22.7+ KB
```

In [27]:

```
#replace missing values with median values
#df = df.fillna(df.median())

df = df.apply(lambda x:x.fillna(x.median()), axis=0)
df['horsepower'] = df['horsepower'].astype('float64') #converting hp columns to
```

In [28]:

```
#df = df.fillna(df.median())
```

In [29]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   mpg             398 non-null    float64
 1   cylinders       398 non-null    int64  
 2   displacement    398 non-null    float64
 3   horsepower      398 non-null    float64
 4   weight          398 non-null    int64  
 5   acceleration    398 non-null    float64
 6   model year      398 non-null    int64  
 7   origin_America  398 non-null    uint8  
 8   origin_europe   398 non-null    uint8  
dtypes: float64(4), int64(3), uint8(2)
memory usage: 22.7 KB
```

Bivariate Plots

In [30]:

```
# df.columns.tolist()
df.columns.str.lower().tolist()
```

Out[30]:

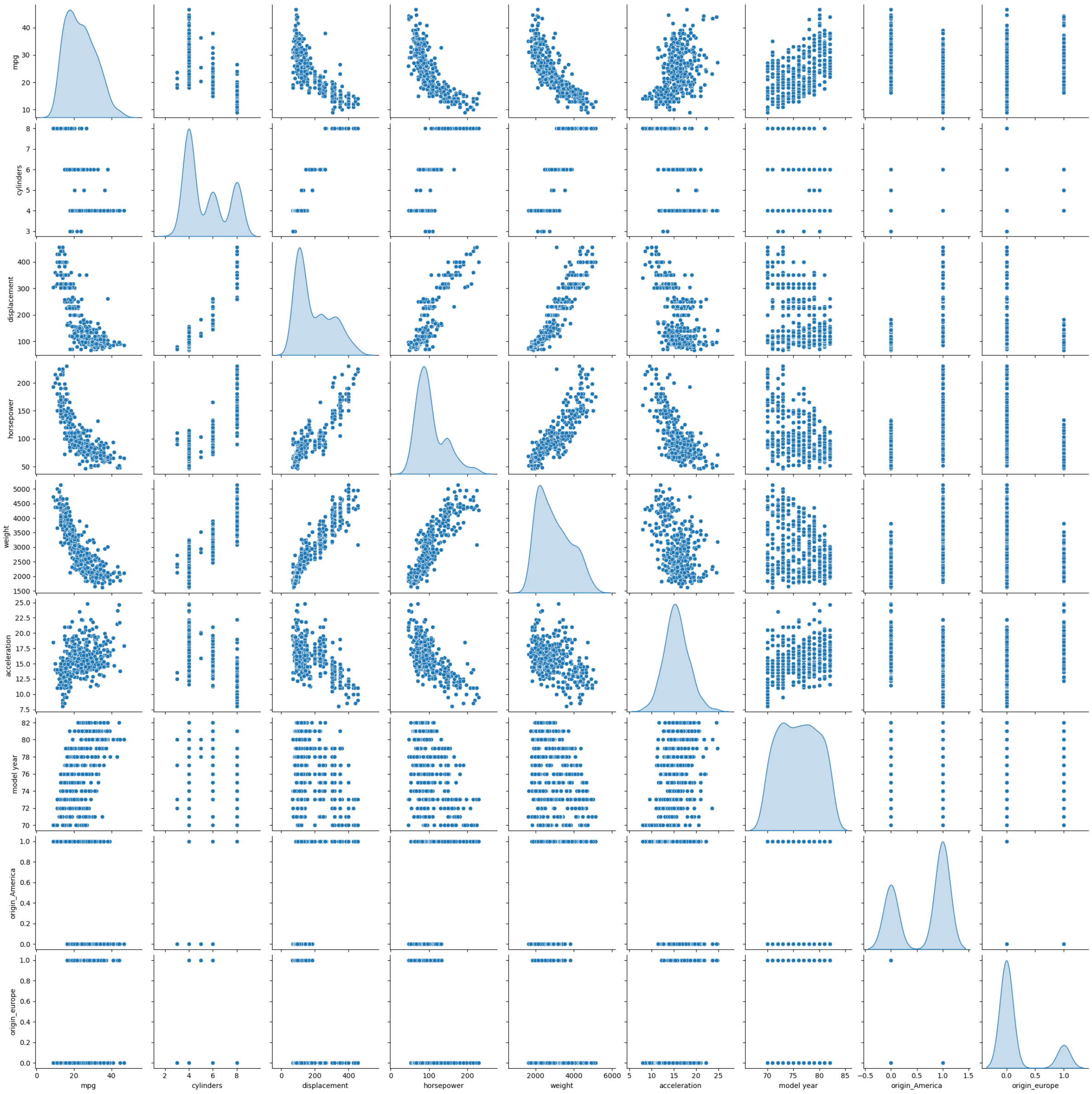
```
['mpg',
 'cylinders',
 'displacement',
 'horsepower',
 'weight',
 'acceleration',
 'model year',
 'origin_america',
 'origin_europe']
```

In [31]:

```
# pair plot
sns.pairplot(df,diag_kind ='kde')
```

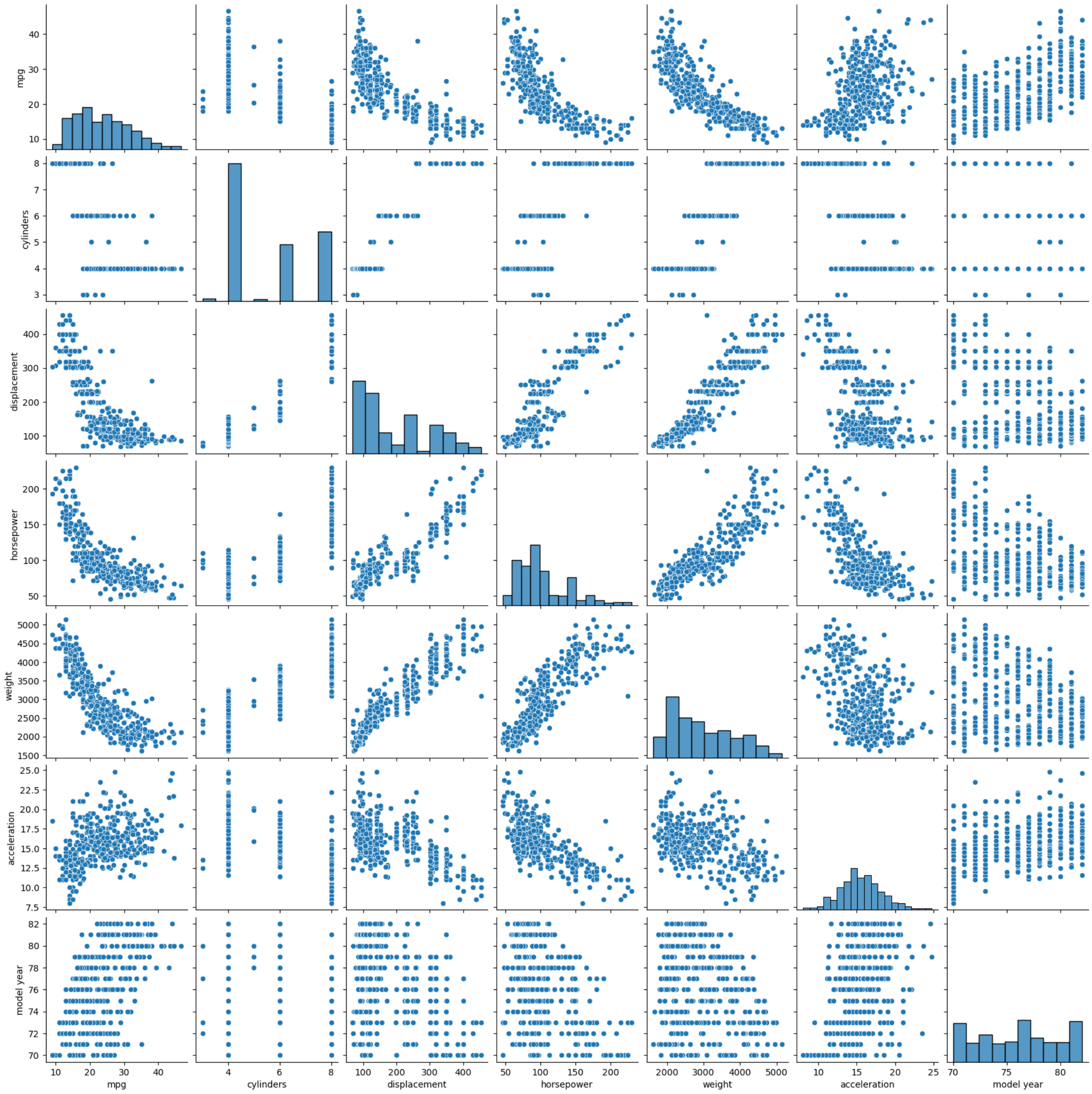
Out[31]:

```
<seaborn.axisgrid.PairGrid at 0x1dcbca44fa0>
```



In [32]:
```
df = df.iloc[:,0:7]
sns.pairplot(df,diag_kind ='auto')
```

Out[32]: <seaborn.axisgrid.PairGrid at 0x1dcc12a51f0>



Splitting Data

In [33]:
```
from sklearn.model_selection import train_test_split
```

In [34]:
```
# providing independent and dependent variables
# Building the linear model
# xs = independent, response, predictor , feature variables
x = df.drop('mpg', axis = 1)
# y is target, dependent variable
y = df['mpg']
```

In [35]:
```
#Split X and y into train and test set in 70:30 ratio
#random_state is mandatory, to give you the same output always

x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.30 , random_
```

METHOD 1 - USING SKLEARN

In [36]:
```
from sklearn.linear_model import LinearRegression
```

for idx, col_name in enumerate(X_train.columns): print('The coefficient for {} is {}'.format(col_name, regression*model.coef*[0][idx]))

intercept = regression*model.intercept*[0] print('The intercept for our model is {}'.format(intercept))

In [37]:
```
from sklearn.linear_model import LinearRegression

regression_model = LinearRegression()
regression_model.fit(x_train, y_train)

for idx, col_name in enumerate(x_train.columns):
    print('The coefficient for {} is {}'.format(col_name,regression_model.coef_[id

print('    '*20)

intercept = regression_model.intercept_
print('The intercept for our model is {}'.format(intercept))
print('    '*20)

print('R-square value for training data ',
      regression_model.score(x_train, y_train))
print('R-square value for testing data ',
      regression_model.score(x_test, y_test))
print('    '*20)

1 - (1 - regression_model.score(x_train, y_train)) * (x_train.shape[0] - 1) / (
    x_train.shape[0] - x_train.shape[1] - 1)
```

```
The coefficient for cylinders is -0.18095805032305984
The coefficient for displacement is 0.010983679987754718
The coefficient for horsepower is -0.00898274748809643
The coefficient for weight is -0.007188819033277062
The coefficient for acceleration is 0.029142901338762905
The coefficient for model year is 0.7883566858707725

The intercept for our model is -15.621707993406712

R-square value for training data  0.79968038605472
R-square value for testing data  0.8268047501149661
```

Out[37]:
```
0.7952452654507655
```

In [38]:
```
regression_model = LinearRegression()
regression_model.fit(x_train, y_train)
```

Out[38]:
```
LinearRegression()
```

In [39]:
```
for idx, col_name in enumerate(x_train.columns):
    print('The coefficient for {} is {}'.format(col_name, regression_model.coef_[i
```

```
The coefficient for cylinders is -0.18095805032305984
The coefficient for displacement is 0.010983679987754718
The coefficient for horsepower is -0.00898274748809643
The coefficient for weight is -0.007188819033277062
The coefficient for acceleration is 0.029142901338762905
The coefficient for model year is 0.7883566858707725
```

In [40]:
```
intercept = regression_model.intercept_
print('The intercept for our model is {}'.format(intercept))
```

```
The intercept for our model is -15.621707993406712
```

In [41]:
```
print('R-square value for training data: ',
      regression_model.score(x_train, y_train))
print('R-square value for testing data: ',
      regression_model.score(x_test, y_test))
```

```
R-square value for training data:  0.79968038605472
R-square value for testing data:  0.8268047501149661
```

In [42]:
```
n = x_train.shape[0] # number of observations
p = x_train.shape[1] # number of predictors
adj_r_squared = 1 - (1 - regression_model.score(x_train, y_train)) * (n - 1) / (n
print('Adjusted R-square value for training data: ', adj_r_squared)
```

```
Adjusted R-square value for training data:  0.7952452654507655
```

METHOD 2 - STATSMODELS

In [43]:
```
import statsmodels.api as sm
```

In [44]:
```
# Add a constant to the predictor variable x -- sm.add_constant(x_train, prepend =
model = sm.OLS(y_train, sm.add_constant(x_train,prepend=False))
```

In [45]:
```
# Fit the linear regression model
result = model.fit()
```

In [46]:
```
# Print the model summary
result.summary()
```

Out[46]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.800
Model:	OLS	**Adj. R-squared:**	0.795
Method:	Least Squares	**F-statistic:**	180.3
Date:	Sun, 26 Mar 2023	**Prob (F-statistic):**	1.46e-91
Time:	23:44:42	**Log-Likelihood:**	-744.60
No. Observations:	278	**AIC:**	1503.
Df Residuals:	271	**BIC:**	1529.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
cylinders	-0.1810	0.433	-0.418	0.677	-1.034	0.672
displacement	0.0110	0.010	1.145	0.253	-0.008	0.030
horsepower	-0.0090	0.017	-0.541	0.589	-0.042	0.024
weight	-0.0072	0.001	-8.326	0.000	-0.009	-0.005
acceleration	0.0291	0.122	0.239	0.811	-0.211	0.269
model year	0.7884	0.064	12.333	0.000	0.663	0.914
const	-15.6217	5.694	-2.743	0.006	-26.833	-4.411

Omnibus:	27.346	**Durbin-Watson:**	2.229
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	41.717
Skew:	0.622	**Prob(JB):**	8.73e-10
Kurtosis:	4.433	**Cond. No.**	8.19e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.19e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

https://datascience.oneoffcoder.com/estimating-standard-error-coefficients.html

Checking assumptions

Linearity:

- The relationship between the independent variables and the dependent variable should be linear
- This means that the change in the dependent variable should be proportional to the change in the independent variables.

- You can plot the independent variables against the dependent variable using scatterplots or partial regression plots. If the relationship appears to be non-linear, you may need to transform the independent variables or use non-linear regression.

Independence of errors:

- The errors or residuals (the differences between the predicted and actual values) should be independent of each other.
- This means that the errors for one observation should not be related to the errors for another observation.
- You can plot the residuals against the predicted values or against the independent variables.
- If there is a pattern in the residuals, such as a U-shape or a curve, this may indicate non-independence of errors.

Homoscedasticity:

- The variance of the errors should be constant across all levels of the independent variables.
- This means that the spread of the residuals should be similar across the range of the independent variables.
- You can plot the residuals against the predicted values or against the independent variables.
- If the variance of the residuals appears to increase or decrease with the predicted values, this may indicate heteroscedasticity.

Normality:

- The errors should be normally distributed around zero.
- This means that the distribution of the residuals should follow a normal distribution.
- You can plot a histogram of the residuals or use a normal probability plot.
- If the distribution appears to be skewed or have heavy tails, this may indicate non-normality.

No multicollinearity:

- There should be no perfect linear relationship between the independent variables.
- This means that each independent variable should provide unique and independent information to the model.
- You can use correlation matrices or variance inflation factors (VIFs) to check for multicollinearity.
- If the correlations between independent variables are high or if the VIFs are greater than 5 or 10, this may indicate multicollinearity.

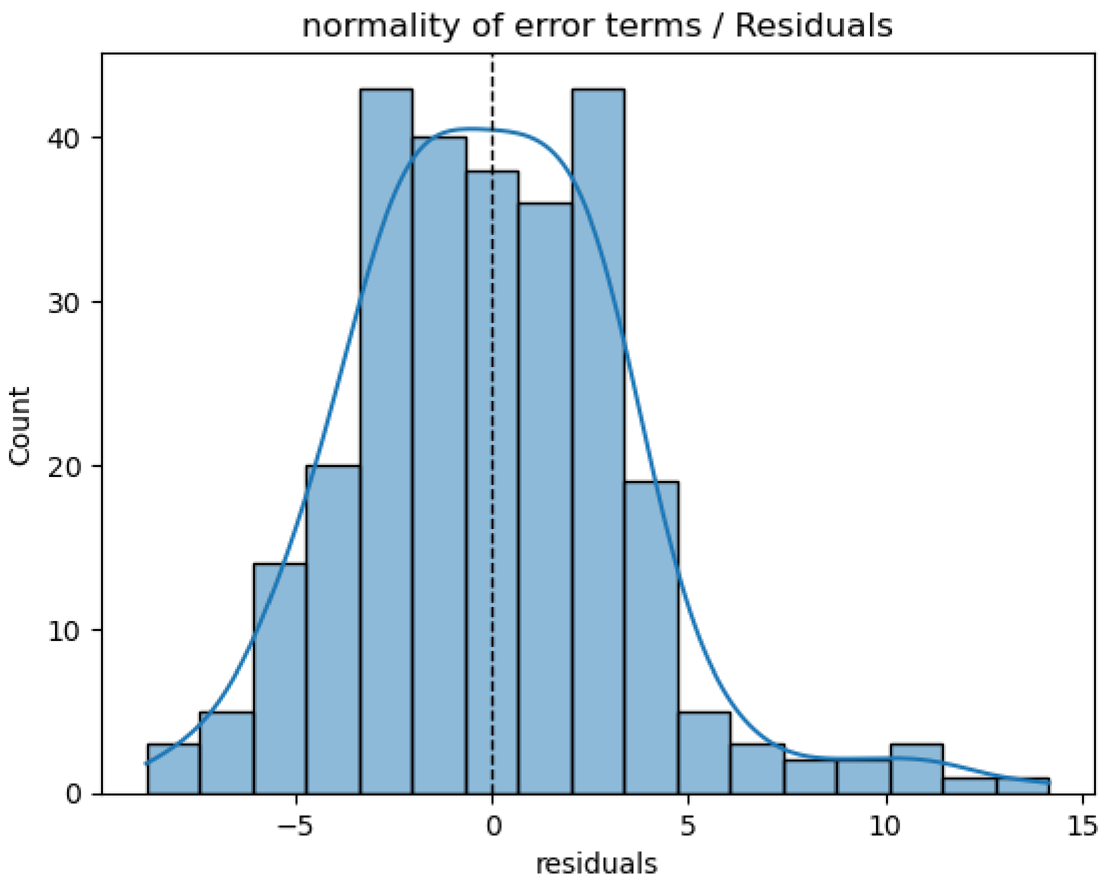
In [47]:
```
df = pd.concat([x_train,y_train], axis = 1)
df['y_pred'] = regression_model.predict(x_train)
df['residuals'] = df['mpg']-df['y_pred']
df.head()
```

Out[47]:

	cylinders	displacement	horsepower	weight	acceleration	model year	mpg	y_pred	residual
350	4	105.0	63.0	2215	14.9	81	34.7	32.611112	2.08888
59	4	97.0	54.0	2254	23.5	72	23.0	25.479167	-2.47916
120	4	121.0	112.0	2868	15.5	73	19.0	21.363441	-2.36344
12	8	400.0	150.0	3761	9.5	70	15.0	14.403729	0.59627
349	4	91.0	68.0	1985	16.0	81	34.1	34.097768	0.00223

Check Normality of error terms

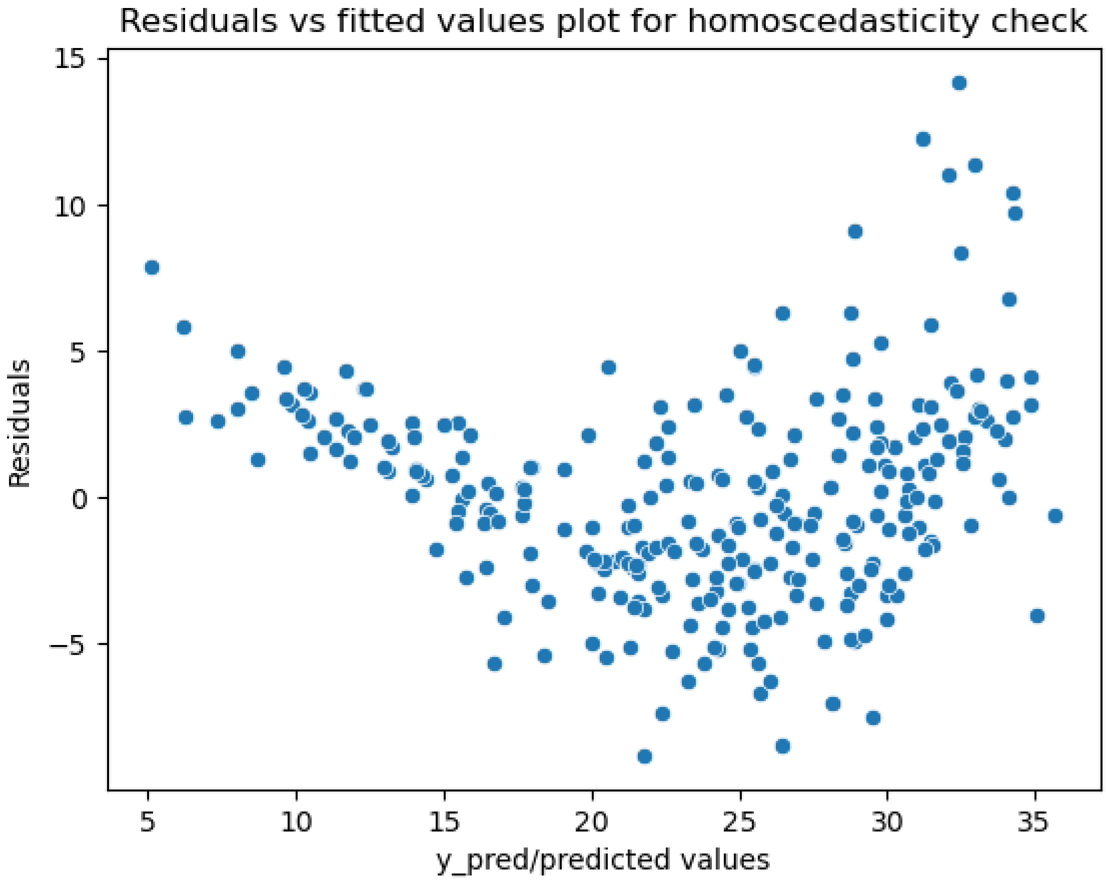
In [48]:
```
p = sns.histplot(df['residuals'],kde = True)
p = plt.title('normality of error terms / Residuals')
p = plt.axvline(df['residuals'].mean(),color = 'k', linestyle = 'dashed', linewidtl
```



Constant variance in error terms

In [49]:
```
p = sns.scatterplot(df['y_pred'], df['residuals'])
plt.xlabel('y_pred/predicted values')
plt.ylabel('Residuals')
p = plt.title('Residuals vs fitted values plot for homoscedasticity check')
```

```
C:\Users\Zainab\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarni
ng: Pass the following variables as keyword args: x, y. From version 0.12, the onl
y valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



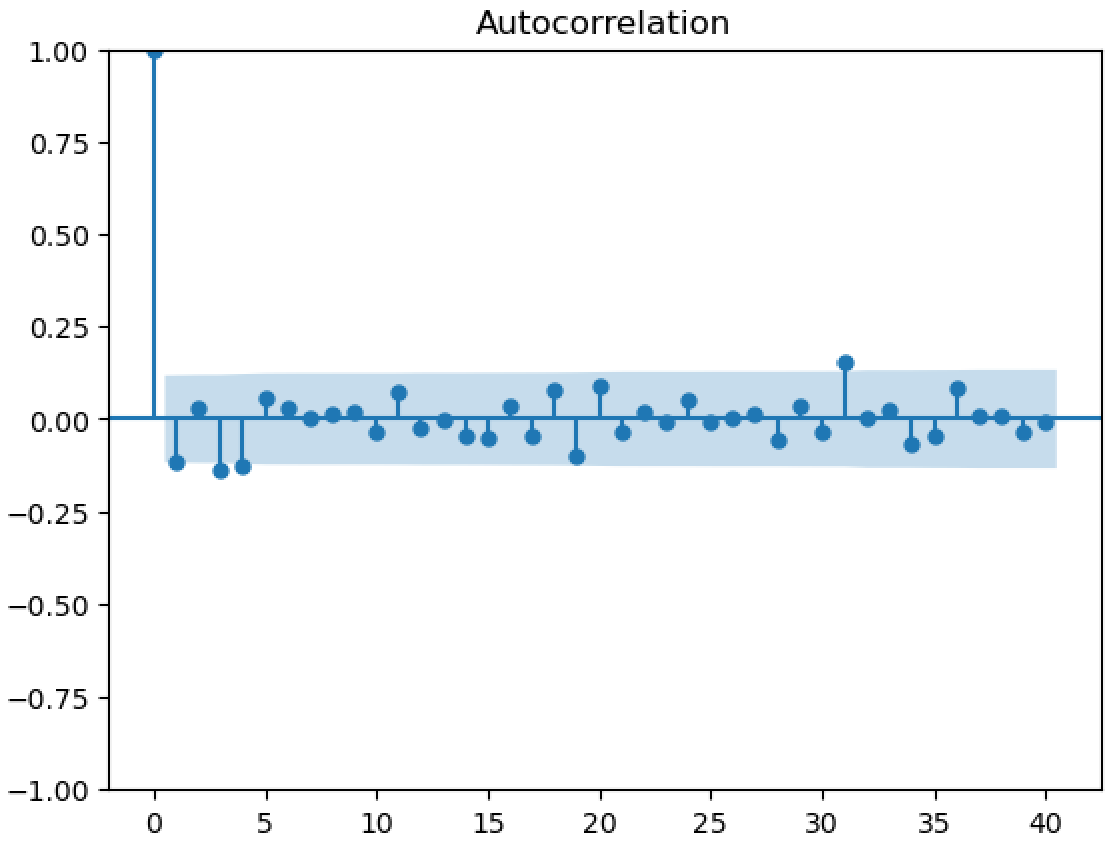
In [50]:
```
import statsmodels.stats.api as sms
from statsmodels.compat import lzip
name = ['F statistic', 'p-value']
test = sms.het_goldfeldquandt(df['residuals'], x_train)
lzip(name, test)
```

Out[50]:
```
[('F statistic', 0.8100294504172026), ('p-value', 0.8871421907493916)]
```

- **Null: Error terms are homoscedastic**
- **Alt: Error terms are heteroscedastic**
- **As p-value>0.05, we fail to reject null i.e. error terms have constant variance**

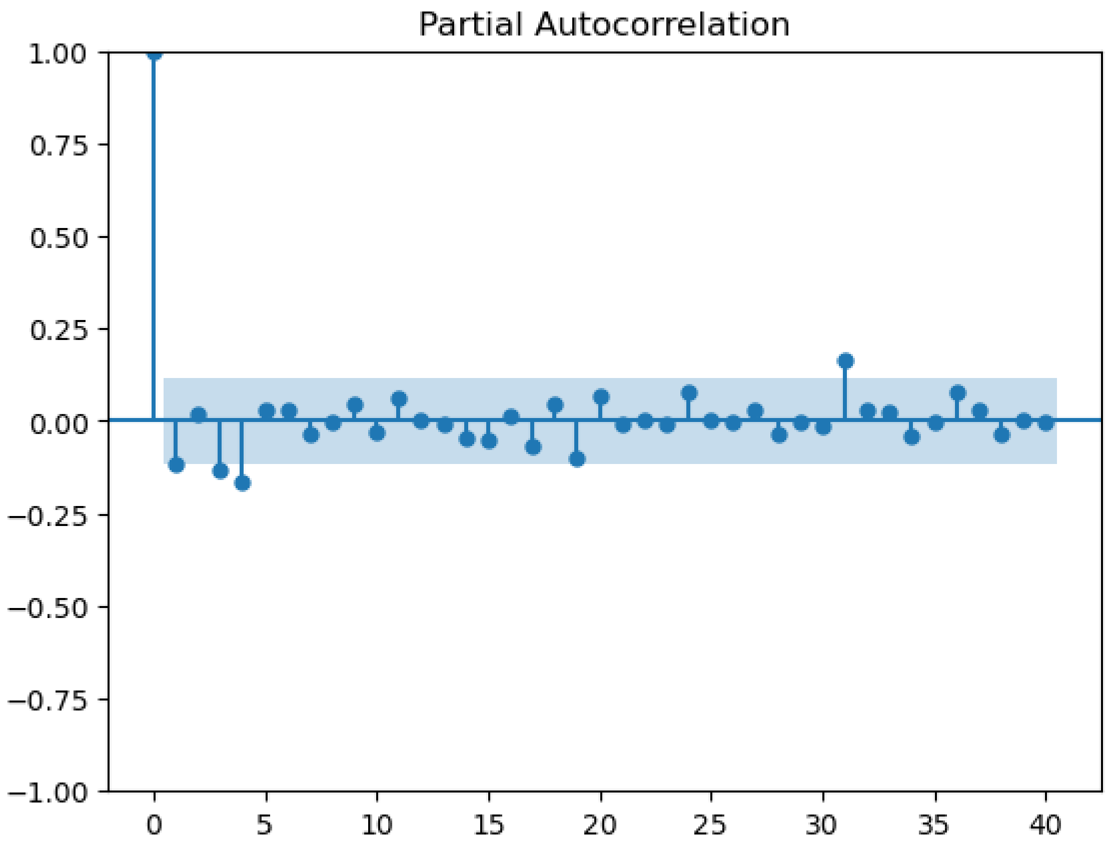
No Autocorrelation

In [51]:
```
import statsmodels.api as sm
sm.graphics.tsa.plot_acf(df['residuals'], lags=40)
plt.show()
```



In [52]:
```
sm.graphics.tsa.plot_pacf(df['residuals'], lags=40)
plt.show()
```

```
C:\Users\Zainab\anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1, 1] interval. After 0.13, the default will change tounadjusted Yule-Walker ('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```

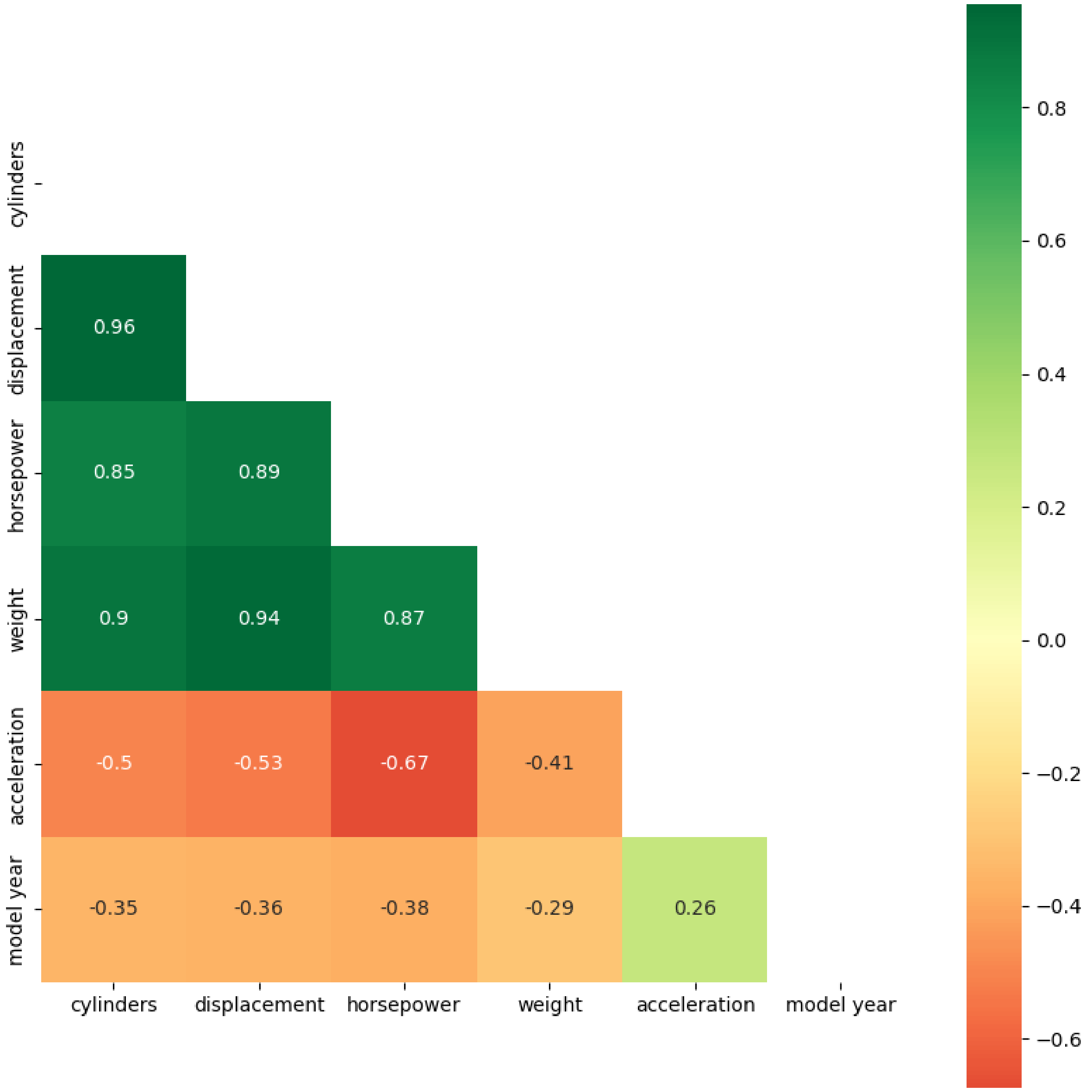


In [53]:
```
from statsmodels.stats.stattools import durbin_watson
durbin_watson(df['residuals'])
```

Out[53]:
```
2.2289894982698764
```

Multi-collinearity

In [54]:
```
plt.figure(figsize=(10,10))
mask = np.triu(np.ones_like(x_train.corr(), dtype=bool))
p = sns.heatmap(x_train.corr(), mask = mask, annot = True, cmap = 'RdYlGn', square
```



In [55]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_data = pd.DataFrame()
vif_data['feature'] = x_train.columns
vif_data['VIF'] = [variance_inflation_factor(x_train.values, i)
                          for i in range(len(x_train.columns))]
vif_data
```

Out[55]:

	feature	VIF
0	cylinders	126.237998
1	displacement	93.582674
2	horsepower	59.910827
3	weight	147.846492
4	acceleration	68.083819
5	model year	103.231342

In [56]:
```
df.head()
```

Out[56]:

	cylinders	displacement	horsepower	weight	acceleration	model year	mpg	y_pred	residual
350	4	105.0	63.0	2215	14.9	81	34.7	32.611112	2.08888
59	4	97.0	54.0	2254	23.5	72	23.0	25.479167	-2.47916
120	4	121.0	112.0	2868	15.5	73	19.0	21.363441	-2.36344
12	8	400.0	150.0	3761	9.5	70	15.0	14.403729	0.59627
349	4	91.0	68.0	1985	16.0	81	34.1	34.097768	0.00223

FIX 1

In [57]:
```
x['c_d'] = x['cylinders']*x['displacement']
x.drop(columns = ['cylinders', 'displacement'], inplace = True)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_
model = sm.OLS(y_train, sm.add_constant(x_train, prepend = False))
result = model.fit()
result.summary()
#LOWER THE 'AIC' VALUE, BETTER THE MODEL
```

Out[57]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.806
Model:	OLS	**Adj. R-squared:**	0.803
Method:	Least Squares	**F-statistic:**	226.4
Date:	Sun, 26 Mar 2023	**Prob (F-statistic):**	1.03e-94
Time:	23:44:44	**Log-Likelihood:**	-739.97
No. Observations:	278	**AIC:**	1492.
Df Residuals:	272	**BIC:**	1514.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
horsepower	-0.0203	0.017	-1.221	0.223	-0.053	0.012
weight	-0.0081	0.001	-10.635	0.000	-0.010	-0.007
acceleration	0.0733	0.118	0.619	0.537	-0.160	0.307
model year	0.8121	0.063	12.940	0.000	0.689	0.936
c_d	0.0022	0.001	3.296	0.001	0.001	0.004
const	-15.8569	5.465	-2.902	0.004	-26.616	-5.098

Omnibus:	21.373	**Durbin-Watson:**	2.199
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	31.807
Skew:	0.512	**Prob(JB):**	1.24e-07
Kurtosis:	4.303	**Cond. No.**	8.80e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.8e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [58]:

```
vif_data_2 = pd.DataFrame()
vif_data_2['feature'] = x_train.columns

vif_data_2['VIF'] = [variance_inflation_factor(x_train.values, i)
                          for i in range(len(x_train.columns))]

vif_data_2
```

Out[58]:

	feature	VIF
0	horsepower	61.673700
1	weight	119.856562
2	acceleration	66.550538
3	model year	100.688356
4	c_d	24.029190

FIX 2

In [59]:

```
x['h_w'] = x['horsepower']*x['weight']
x.drop(columns=['weight','horsepower'], inplace = True)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_
model = sm.OLS(y_train, sm.add_constant(x_train, prepend = False))
result = model.fit()
result.summary()
```

Out[59]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.715
Model:	OLS	**Adj. R-squared:**	0.711
Method:	Least Squares	**F-statistic:**	171.0
Date:	Sun, 26 Mar 2023	**Prob (F-statistic):**	4.32e-73
Time:	23:44:44	**Log-Likelihood:**	-793.73
No. Observations:	278	**AIC:**	1597.
Df Residuals:	273	**BIC:**	1616.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
acceleration	-0.2971	0.113	-2.632	0.009	-0.519	-0.075
model year	0.7164	0.075	9.613	0.000	0.570	0.863
c_d	-0.0022	0.001	-2.895	0.004	-0.004	-0.001
h_w	-1.68e-05	3.47e-06	-4.844	0.000	-2.36e-05	-9.97e-06
const	-17.8680	6.038	-2.959	0.003	-29.755	-5.981

Omnibus:	33.032	**Durbin-Watson:**	2.203
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	44.695
Skew:	0.795	**Prob(JB):**	1.97e-10
Kurtosis:	4.154	**Cond. No.**	9.39e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.39e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

FIX 4

In [60]:
```
x = pd.concat([x, df['weight']], axis = 1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_
model = sm.OLS(y_train, sm.add_constant(x_train, prepend = False))
result = model.fit()
result.summary()
```

Out[60]:

OLS Regression Results

Dep. Variable:	mpg	**R-squared:**	0.812
Model:	OLS	**Adj. R-squared:**	0.809
Method:	Least Squares	**F-statistic:**	235.2
Date:	Sun, 26 Mar 2023	**Prob (F-statistic):**	1.55e-96
Time:	23:44:44	**Log-Likelihood:**	-735.67
No. Observations:	278	**AIC:**	1483.
Df Residuals:	272	**BIC:**	1505.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
acceleration	0.3113	0.105	2.961	0.003	0.104	0.518
model year	0.8544	0.062	13.850	0.000	0.733	0.976
c_d	0.0013	0.001	1.863	0.064	-7.16e-05	0.003
h_w	1.176e-05	3.71e-06	3.174	0.002	4.47e-06	1.91e-05
weight	-0.0103	0.001	-11.876	0.000	-0.012	-0.009
const	-21.1258	4.916	-4.297	0.000	-30.805	-11.447

Omnibus:	18.051	**Durbin-Watson:**	2.181
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	25.939
Skew:	0.454	**Prob(JB):**	2.33e-06
Kurtosis:	4.190	**Cond. No.**	9.40e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.4e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [61]:
```
vif_data_3 = pd.DataFrame()
vif_data_3['feature'] = x_train.columns

vif_data_3['VIF'] = [variance_inflation_factor(x_train.values, i)
                          for i in range(len(x_train.columns))]

vif_data_3
```

Out[61]:

	feature	VIF
0	acceleration	60.912078
1	model year	69.470275
2	c_d	25.343398
3	h_w	49.028539
4	weight	164.712937

In [ ]: