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

In [2]:
```
vehicle=pd.read_excel("data.csv.xlsx")
vehicle
```

Out[2]:

	origin	cylinders	displacement	horsepower	weight	acceleration	year	name	Kilometer_per_liter
0	1	8	307.0	130	3504	12.0	1970	chevrolet chevelle malibu	7.652587
1	1	8	350.0	165	3693	11.5	1970	buick skylark 320	6.377156
2	1	8	318.0	150	3436	11.0	1970	plymouth satellite	7.652587
3	1	8	304.0	150	3433	12.0	1970	amc rebel sst	6.802299
4	1	8	302.0	140	3449	10.5	1970	ford torino	7.227443
...	...	...	...	...	...	...	...	...	...
393	1	4	140.0	86	2790	15.6	1982	ford mustang gl	11.478880
394	2	4	97.0	52	2130	24.6	1982	vw pickup	18.706323
395	1	4	135.0	84	2295	11.6	1982	dodge rampage	13.604599
396	1	4	120.0	79	2625	18.6	1982	ford ranger	11.904024
397	1	4	119.0	82	2720	19.4	1982	chevy s-10	13.179455

398 rows × 9 columns

from dataset Kilometer_per_liter seems to be dependent variable

In [3]:
```
vehicle_data=pd.DataFrame(vehicle)
vehicle_data
```

Out[3]:

	origin	cylinders	displacement	horsepower	weight	acceleration	year	name	Kilometer_per_liter
0	1	8	307.0	130	3504	12.0	1970	chevrolet chevelle malibu	7.652587
1	1	8	350.0	165	3693	11.5	1970	buick skylark 320	6.377156
2	1	8	318.0	150	3436	11.0	1970	plymouth satellite	7.652587
3	1	8	304.0	150	3433	12.0	1970	amc rebel sst	6.802299
4	1	8	302.0	140	3449	10.5	1970	ford torino	7.227443
...	...	...	...	...	...	...	...	...	...
393	1	4	140.0	86	2790	15.6	1982	ford mustang gl	11.478880
394	2	4	97.0	52	2130	24.6	1982	vw pickup	18.706323
395	1	4	135.0	84	2295	11.6	1982	dodge rampage	13.604599
396	1	4	120.0	79	2625	18.6	1982	ford ranger	11.904024
397	1	4	119.0	82	2720	19.4	1982	chevy s-10	13.179455

398 rows × 9 columns

In [4]:
```
vehicle.info()
```

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

no null values

In [5]:
```
#changing ? into null values and dropping them
vehicle=vehicle_data.replace({"?":np.nan}).dropna()
```

In [6]:
```
#changing datatype of horsepower into float
vehicle["horsepower"]=pd.to_numeric(vehicle["horsepower"],downcast="float")
```

In [7]:
```
#dropping unnessasary columns
vehicle.drop(columns=["year","name"],inplace=True)
```

In [8]:
```
vehicle
```

Out[8]:

	origin	cylinders	displacement	horsepower	weight	acceleration	Kilometer_per_liter
0	1	8	307.0	130.0	3504	12.0	7.652587
1	1	8	350.0	165.0	3693	11.5	6.377156
2	1	8	318.0	150.0	3436	11.0	7.652587
3	1	8	304.0	150.0	3433	12.0	6.802299
4	1	8	302.0	140.0	3449	10.5	7.227443
...	...	...	...	...	...	...	...
393	1	4	140.0	86.0	2790	15.6	11.478880
394	2	4	97.0	52.0	2130	24.6	18.706323
395	1	4	135.0	84.0	2295	11.6	13.604599
396	1	4	120.0	79.0	2625	18.6	11.904024
397	1	4	119.0	82.0	2720	19.4	13.179455

392 rows × 7 columns

In [9]:
```
vehicle.describe()
```

Out[9]:

	origin	cylinders	displacement	horsepower	weight	acceleration	Kilometer_per_liter
count	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000
mean	1.576531	5.471939	194.411990	104.469391	2977.584184	15.541327	9.967885
std	0.805518	1.705783	104.644004	38.491138	849.402560	2.758864	3.318250
min	1.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	3.826293
25%	1.000000	4.000000	105.000000	75.000000	2225.250000	13.775000	7.227443
50%	1.000000	4.000000	151.000000	93.500000	2803.500000	15.500000	9.672019
75%	2.000000	8.000000	275.750000	126.000000	3614.750000	17.025000	12.329168
max	3.000000	8.000000	455.000000	230.000000	5140.000000	24.800000	19.811697

Checking correlation

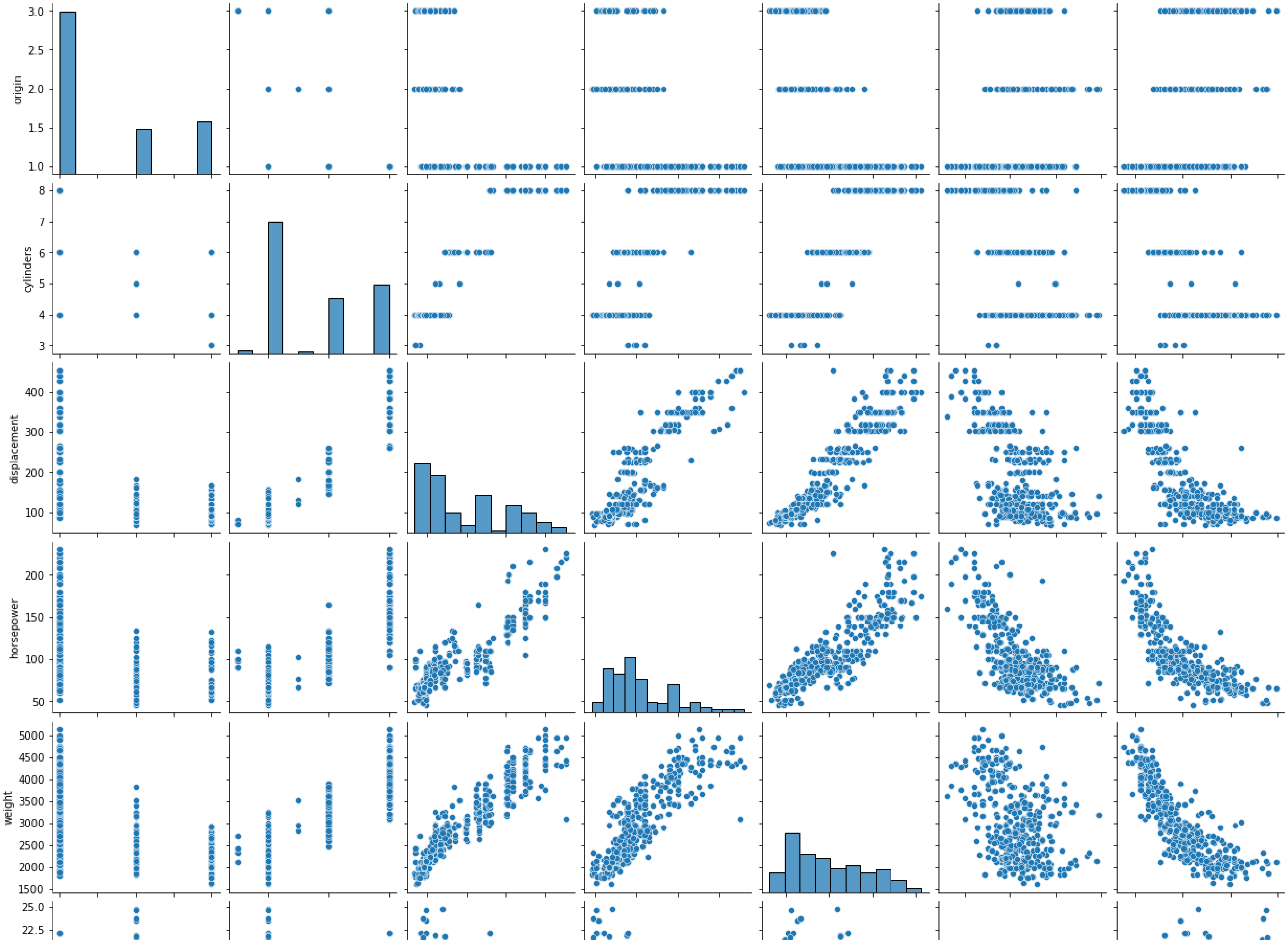
In [10]:
```
vehicle_corr=vehicle.corr()
vehicle_corr.round(2)
```

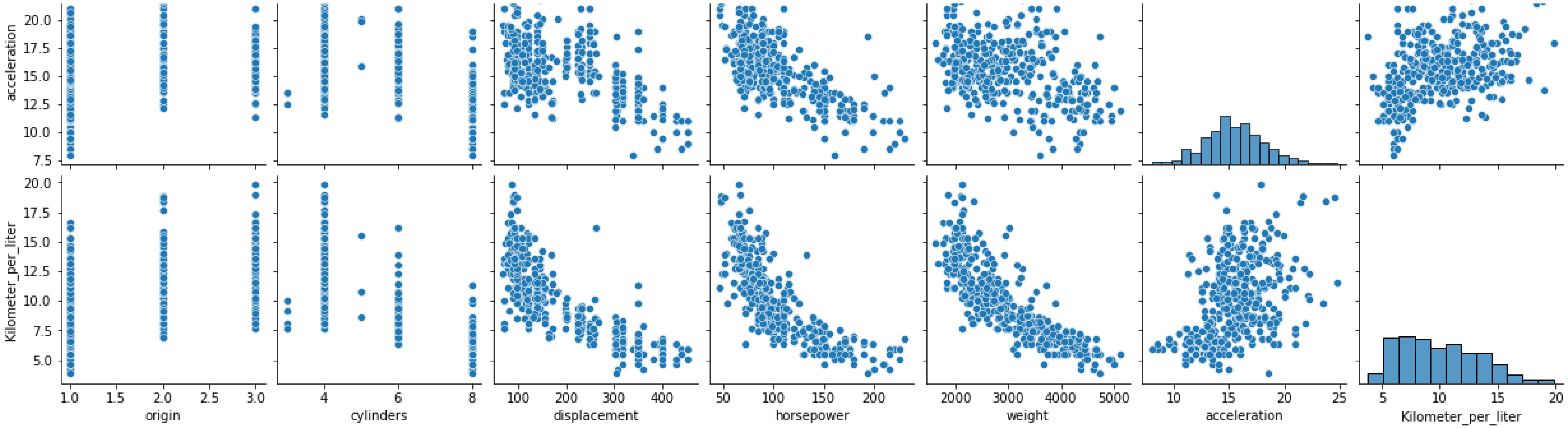
Out[10]:

	origin	cylinders	displacement	horsepower	weight	acceleration	Kilometer_per_liter
origin	1.00	-0.57	-0.61	-0.46	-0.59	0.21	0.57
cylinders	-0.57	1.00	0.95	0.84	0.90	-0.50	-0.78
displacement	-0.61	0.95	1.00	0.90	0.93	-0.54	-0.81
horsepower	-0.46	0.84	0.90	1.00	0.86	-0.69	-0.78
weight	-0.59	0.90	0.93	0.86	1.00	-0.42	-0.83
acceleration	0.21	-0.50	-0.54	-0.69	-0.42	1.00	0.42
Kilometer_per_liter	0.57	-0.78	-0.81	-0.78	-0.83	0.42	1.00

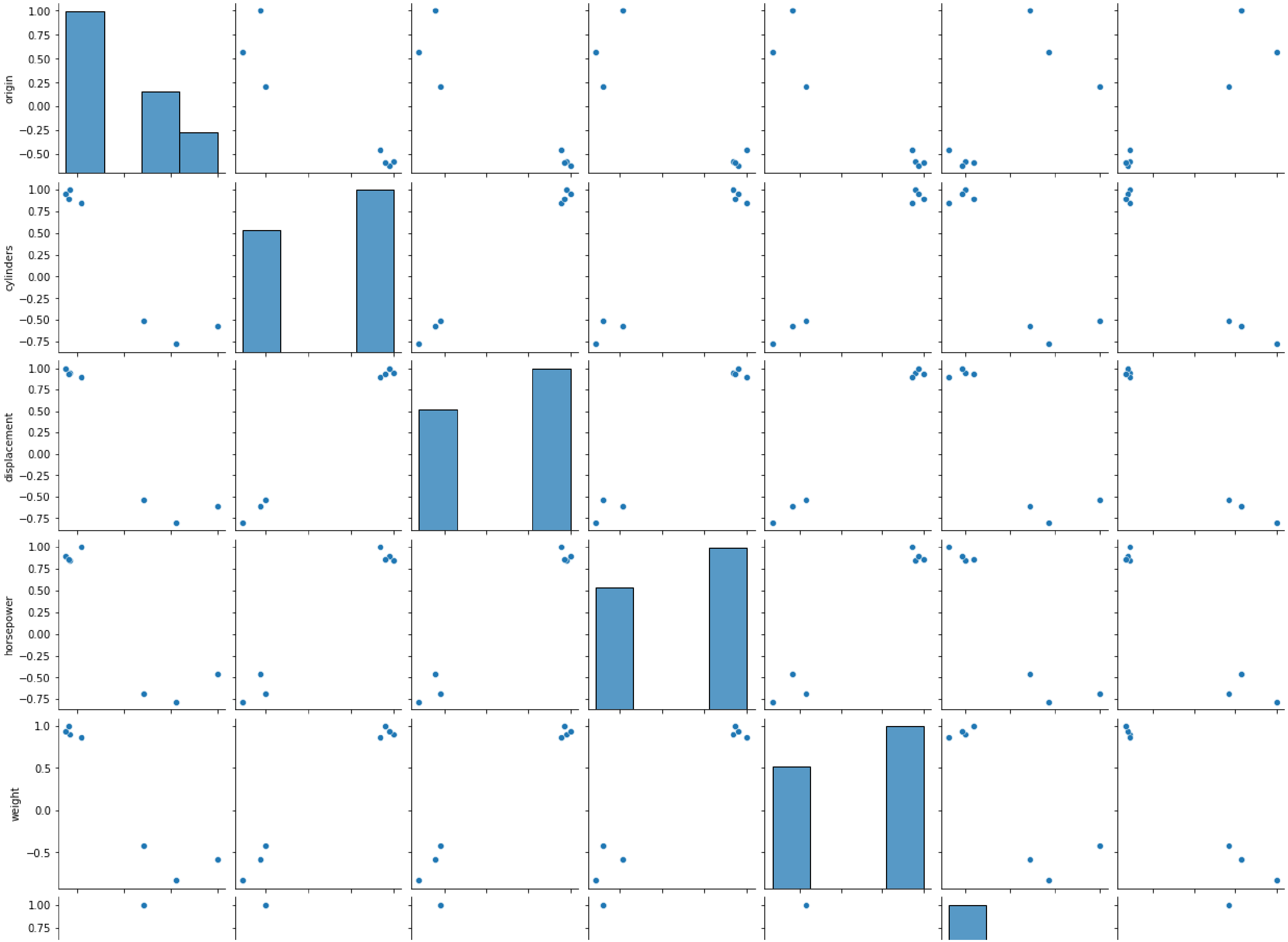
correlation seems to be high with origin by taking Kilometer_per_liter as dep variable

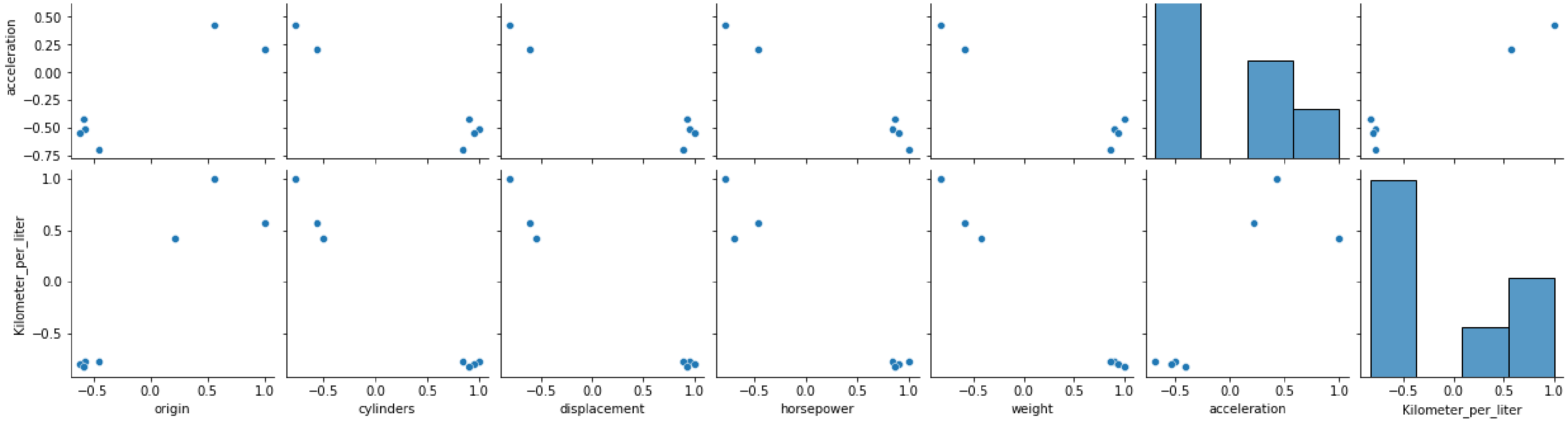
In [11]:
```
sns.pairplot(vehicle);
```




acceleration
Kilometer_per_liter
origin
cylinders
displacement
horsepower
weight
acceleration
Kilometer_per_liter

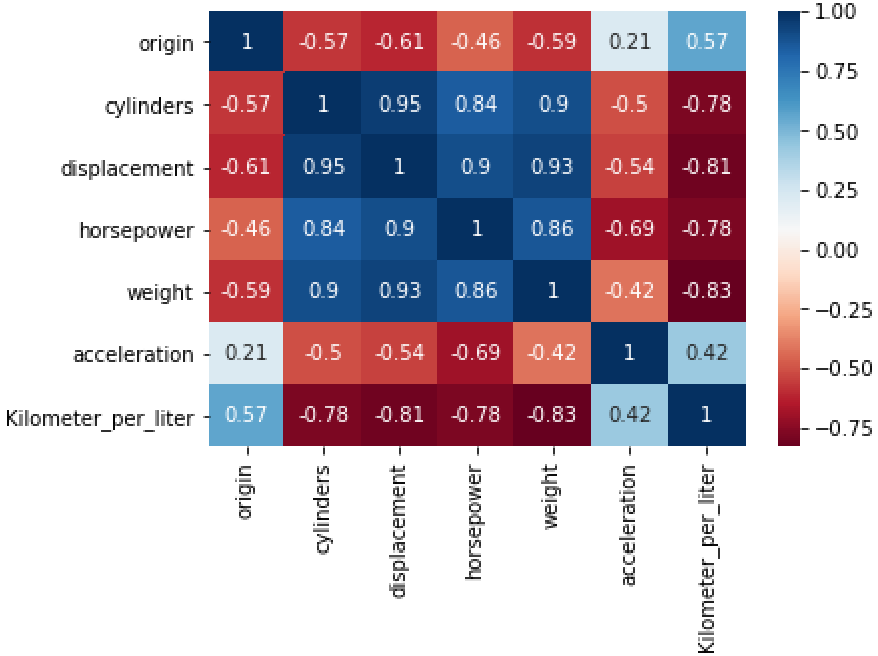
In [12]:
```
sns.pairplot(vehicle_corr);
```



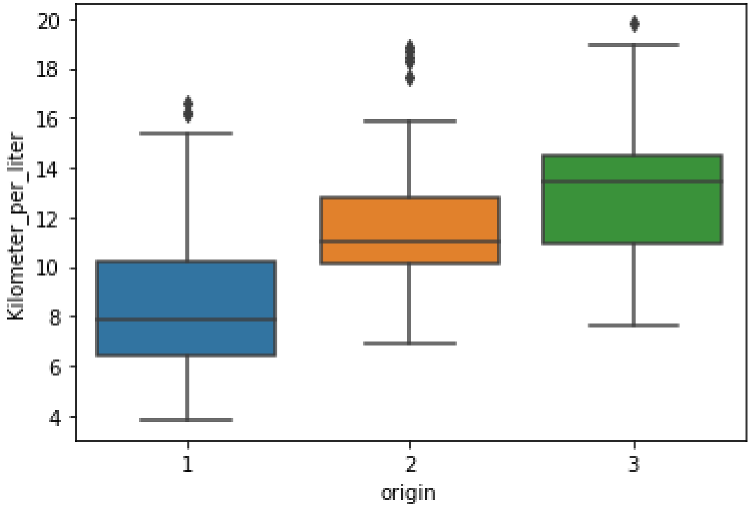


In [13]:

```
sns.heatmap(vehicle_corr,annot=True,cmap="RdBu");
```

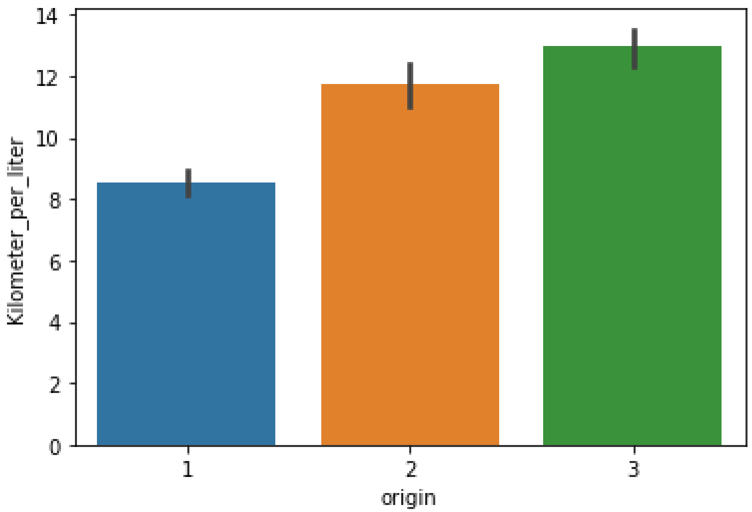


In [14]:
```
sns.boxplot(x="origin",y="Kilometer_per_liter",data=vehicle);
```

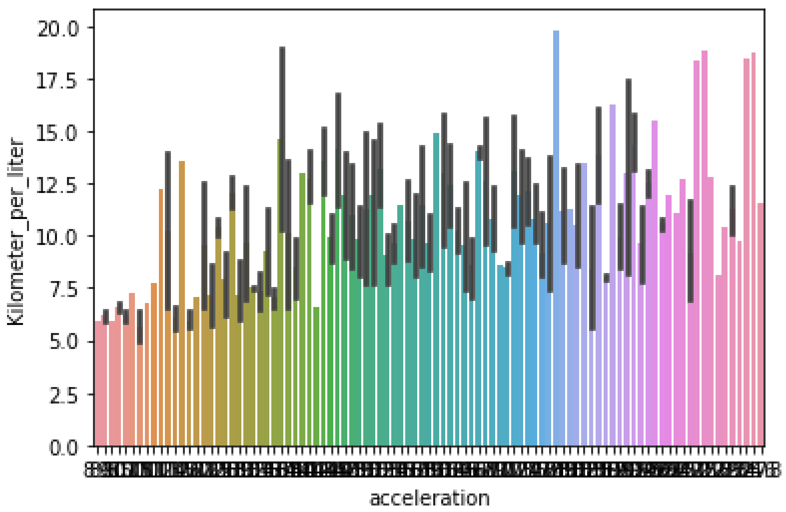


outlier seems to be high in origin=2

In [38]:
```
sns.barplot(x="origin",y="Kilometer_per_liter",data=vehicle);
```



In [41]:
```
sns.barplot(x="acceleration",y="Kilometer_per_liter",data=vehicle);
```



Seperation of dep and indep variables

In [42]:
```
y_dep=vehicle.Kilometer_per_liter
x_indep=vehicle.drop("Kilometer_per_liter",axis=1)
```

Model creation by finding OLS and fitting,then checking p,r-sq values

In [44]:
```
import statsmodels.api as sm
model=sm.OLS(y_dep,x_indep)
my_fit=model.fit()
```

In [45]:
```
my_fit.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	Kilometer_per_liter	**R-squared (uncentered):**	0.954
Model:	OLS	**Adj. R-squared (uncentered):**	0.953
Method:	Least Squares	**F-statistic:**	1326.
Date:	Wed, 25 Aug 2021	**Prob (F-statistic):**	4.64e-254
Time:	19:23:43	**Log-Likelihood:**	-875.83
No. Observations:	392	**AIC:**	1764.
Df Residuals:	386	**BIC:**	1787.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
origin	1.2389	0.184	6.741	0.000	0.878	1.600
cylinders	0.7222	0.207	3.486	0.001	0.315	1.130
displacement	-0.0125	0.005	-2.533	0.012	-0.022	-0.003
horsepower	0.0352	0.008	4.548	0.000	0.020	0.050
weight	-0.0025	0.000	-5.643	0.000	-0.003	-0.002
acceleration	0.6479	0.041	15.702	0.000	0.567	0.729

Omnibus:	17.389	**Durbin-Watson:**	1.132
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	21.608
Skew:	0.405	**Prob(JB):**	2.03e-05
Kurtosis:	3.816	**Cond. No.**	5.89e+03

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 5.89e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

here r-sq value is 0.954 so this dataset have strong correlation and no p value is greater than 0.5 so dont need to remove any variable

PREDICTION

In [48]:
```
y_pred=my_fit.predict(x_indep)
y_pred
```

Out[48]:
```
0       6.865118
1       6.769440
2       6.952690
3       7.782759
4       6.444008
         ...
393     8.610721
394    16.653761
395     7.236321
396    10.965974
397    11.367294
Length: 392, dtype: float64
```

so now we know the machine calculated values but we need to check if it is correct or not so we are using machine learning concepts

MACHINE LEARNING

In [50]:
```
import sklearn
from sklearn import model_selection
from sklearn.model_selection import train_test_split
```

splitting values for training and testing

In [92]:
```
x_train,x_test,y_train,y_test=train_test_split(x_indep,y_dep,test_size=0.3,random_state=1)
```

In [93]:
```
x_test
```

Out[93]:

	origin	cylinders	displacement	horsepower	weight	acceleration
82	3	4	120.0	97.0	2506	14.5
167	3	4	97.0	75.0	2171	16.0
356	3	4	108.0	75.0	2350	16.8
120	2	4	121.0	112.0	2868	15.5
385	3	4	91.0	67.0	1995	16.2
...	...	...	...	...	...	...
60	1	4	140.0	90.0	2408	19.5
12	1	8	400.0	150.0	3761	9.5
305	1	4	151.0	90.0	2670	16.0
165	1	8	262.0	110.0	3221	13.5
92	1	8	351.0	158.0	4363	13.0

118 rows × 6 columns

Importing linear regression for creating model and prediction

In [94]:
```
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
```

In [95]:
```
model=LinearRegression()
```

In [96]:
```
fit=model.fit(x_train,y_train)
fit
```

Out[96]:
```
LinearRegression()
```

In [97]:
```
y_pred1=fit.predict(x_test)
y_pred1
```

Out[97]:
```
array([11.79066114, 12.9581304 , 12.67076418, 10.15920544, 13.48334961,
       11.72763078, 12.53668204,  5.94872652, 12.46667823, 12.86910163,
        8.77450386, 12.25678153,  7.20647314, 13.56127707, 10.87363359,
        7.48469118, 10.97916848, 13.02522612,  4.49374821,  9.82579183,
       12.06625665,  8.32544117,  7.50985307,  5.61848152,  4.91004341,
        6.64222772, 13.56136732,  8.31875386,  9.28626959, 10.93855791,
        7.66678646, 10.39056823,  5.32105886,  9.67625544,  8.68174884,
        6.01469511,  8.21892906,  8.62016773, 13.45554163, 12.69143722,
        5.15305595,  5.28264137, 10.45862927,  9.85423824, 10.02143706,
        8.18887695,  4.55998135, 13.62865323,  9.05429607,  3.8544805 ,
        6.89794175,  9.43969121, 10.52831441, 11.03425326, 13.18142051,
        9.37809116,  9.65598267, 10.69555046, 10.5382758 , 14.05463235,
       10.07370594, 11.46894036, 13.79026489,  8.45036573,  9.76051827,
        9.43808014, 10.21647751,  6.71643208, 12.73925306,  3.83935124,
       12.07548048,  7.63654796,  6.96449292, 12.20548714, 11.294451  ,
       12.01621395,  7.25791425,  5.57052828,  5.51884679, 10.9268567 ,
        8.28016413, 12.10383694, 13.46417057, 12.18078416,  6.28611232,
        8.52581424, 13.61372941, 10.49871365, 13.75403991,  9.96389695,
       11.51808255,  8.91654273,  6.16045073,  4.44775315,  3.68987905,
        9.55082792,  6.06400324, 10.27922814,  9.69317147,  5.74081032,
       12.71584837, 10.83945926,  9.75795808, 12.92377246, 12.37563389,
       13.21646253,  9.69091408, 13.98123704,  6.12322736,  7.84610419,
       13.67622096, 10.32244716, 13.47122573, 11.31074172,  6.91412775,
       10.50688092,  8.61734791,  5.53480692])
```

In [98]:
```
model.score(x_test,y_test)
```

Out[98]: 0.7295775706920559

In [99]:
```
model.score(x_train,y_train)
```

Out[99]: 0.7104995419744988

BY checking accuracy i conclude test dataset have good accuracy

In [100]:
```
comp=pd.DataFrame({"actual":y_test,"predicted":y_pred1})
comp
```

Out[100]:

	actual	predicted
82	9.778305	11.790661
167	12.329168	12.958130
356	13.774656	12.670764
120	8.077730	10.159205
385	16.155461	13.483350
...	...	...
60	8.502874	11.310742
12	6.377156	6.914128
305	12.074081	10.506881
165	8.502874	8.617348
92	5.526868	5.534807

118 rows × 2 columns

calculating error

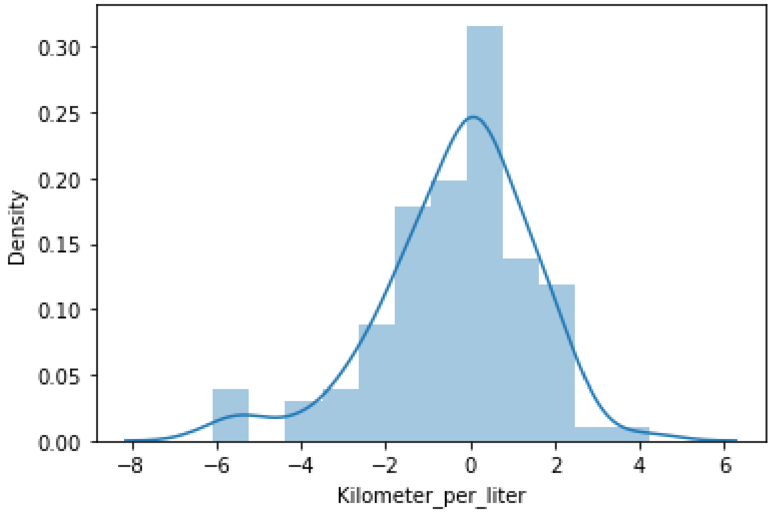
In [101]:
```
res=y_pred1-y_test
res
```

Out[101]:
```
82     2.012356
167    0.628963
356   -1.103892
120    2.081475
385   -2.672111
         ...
60     2.807868
12     0.536972
305   -1.567200
165    0.114474
92     0.007939
Name: Kilometer_per_liter, Length: 118, dtype: float64
```

In [102]:
```
sns.distplot(res)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated fun
ction 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[102]: <AxesSubplot:xlabel='Kilometer_per_liter', ylabel='Density'>



In [107]:
```
from sklearn.metrics import mean_squared_error as ms
mean_sqr=ms(y_test,y_pred1)
mean_sqr
```

Out[107]: 3.249585701022922

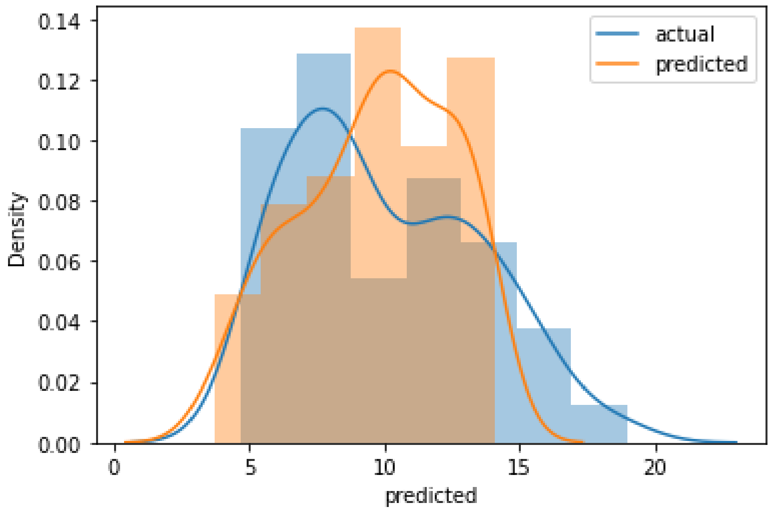
In [104]:
```
# RMSE
root_mean_sqr=np.sqrt(mean_sqr)
root_mean_sqr
```

Out[104]: 1.8026607282078684

In [105]:
```
sns.distplot(comp["actual"]);
sns.distplot(comp["predicted"]);
plt.legend(["actual","predicted"])
```

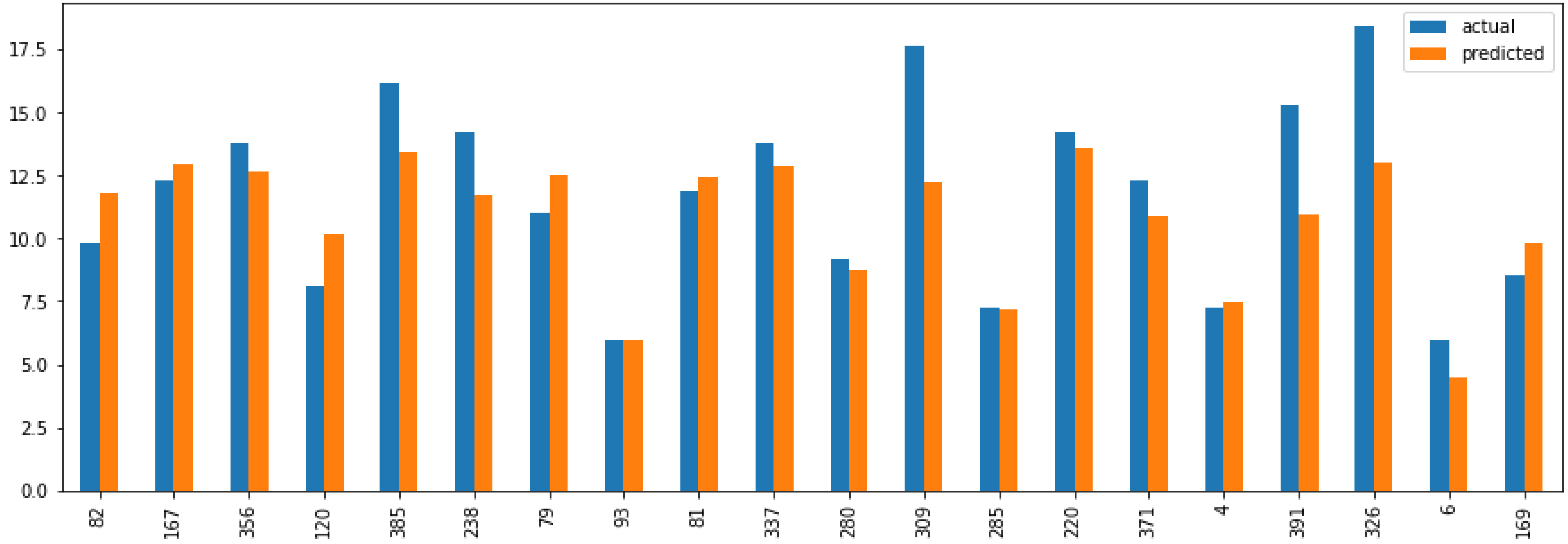
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated fun
ction 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[105]:
```
<matplotlib.legend.Legend at 0x1ea7d652ca0>
```



In [108]:
```
com_g=comp.head(20)
com_g.plot(kind="bar",figsize=[15,5])
```

Out[108]: <AxesSubplot:>



from barplot,predicted values are mostly nearer to actual values

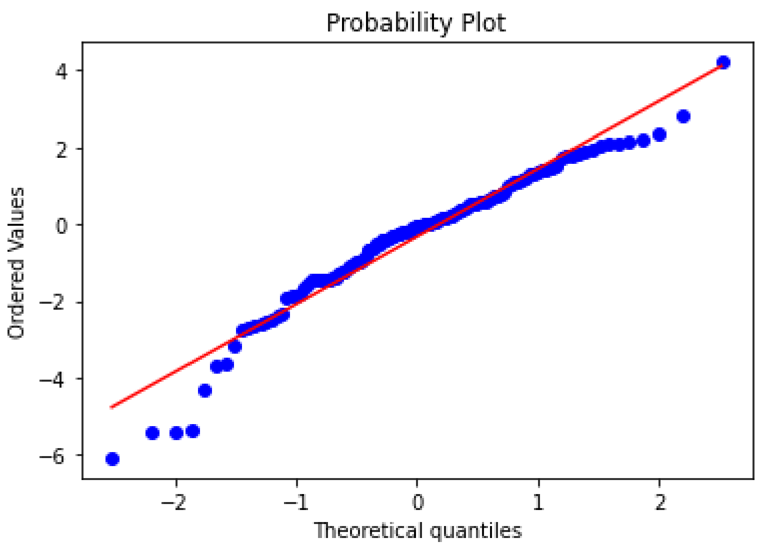
ASSUMPTIONS..

NORMALITY CHECK

In [110]:
```python
import scipy.stats as st
st.probplot(res,dist="norm",plot=plt)
```

Out[110]:
```
((array([-2.52065032, -2.19131491, -2.00161738, -1.86470486, -1.75581693,
         -1.66447993, -1.58523282, -1.51485025, -1.45126092, -1.39305187,
         -1.33921407, -1.2890006 , -1.24184226, -1.19729485, -1.15500461,
         -1.11468501, -1.0761005 , -1.03905491, -1.00338303, -0.96894431,
         -0.93561808, -0.90329991, -0.87189872, -0.84133459, -0.81153691,
         -0.78244296, -0.75399674, -0.72614796, -0.69885132, -0.67206575,
         -0.64575393, -0.61988179, -0.59441811, -0.56933416, -0.54460346,
         -0.52020147, -0.4961054 , -0.47229402, -0.44874749, -0.42544719,
         -0.40237564, -0.37951633, -0.35685365, -0.33437281, -0.31205971,
         -0.28990093, -0.2678836 , -0.24599539, -0.22422441, -0.20255921,
         -0.18098868, -0.15950204, -0.1380888 , -0.1167387 , -0.09544168,
         -0.07418787, -0.05296752, -0.031771  , -0.01058875,  0.01058875,
          0.031771  ,  0.05296752,  0.07418787,  0.09544168,  0.1167387 ,
          0.1380888 ,  0.15950204,  0.18098868,  0.20255921,  0.22422441,
          0.24599539,  0.2678836 ,  0.28990093,  0.31205971,  0.33437281,
          0.35685365,  0.37951633,  0.40237564,  0.42544719,  0.44874749,
          0.47229402,  0.4961054 ,  0.52020147,  0.54460346,  0.56933416,
          0.59441811,  0.61988179,  0.64575393,  0.67206575,  0.69885132,
          0.72614796,  0.75399674,  0.78244296,  0.81153691,  0.84133459,
          0.87189872,  0.90329991,  0.93561808,  0.96894431,  1.00338303,
          1.03905491,  1.0761005 ,  1.11468501,  1.15500461,  1.19729485,
          1.24184226,  1.2890006 ,  1.33921407,  1.39305187,  1.45126092,
          1.51485025,  1.58523282,  1.66447993,  1.75581693,  1.86470486,
          2.00161738,  2.19131491,  2.52065032]),
  array([-6.08175494e+00, -5.42601078e+00, -5.38668233e+00, -5.34767994e+00,
         -4.32600498e+00, -3.70403840e+00, -3.65483669e+00, -3.16141640e+00,
         -2.72946465e+00, -2.69991925e+00, -2.67211127e+00, -2.58815610e+00,
         -2.57034538e+00, -2.51468341e+00, -2.37694202e+00, -2.35117534e+00,
         -1.94005229e+00, -1.84895819e+00, -1.84302344e+00, -1.81575332e+00,
         -1.67238770e+00, -1.56720037e+00, -1.46711220e+00, -1.45826369e+00,
         -1.45553392e+00, -1.44411834e+00, -1.43667152e+00, -1.42531977e+00,
         -1.41184544e+00, -1.37570939e+00, -1.29305549e+00, -1.26237325e+00,
         -1.22293087e+00, -1.15022394e+00, -1.10389194e+00, -1.02617469e+00,
         -9.97404810e-01, -9.71245948e-01, -9.05554494e-01, -8.22831208e-01,
         -6.81037128e-01, -6.69370535e-01, -6.37052143e-01, -5.26211222e-01,
         -4.95972720e-01, -4.35083445e-01, -4.26848982e-01, -3.85941253e-01,
         -3.66085845e-01, -3.29501278e-01, -2.98865489e-01, -2.39552027e-01,
         -2.28827631e-01, -2.25330575e-01, -2.16704882e-01, -2.05809334e-01,
```

```
        -1.84120292e-01, -1.16599427e-01, -3.36971639e-02, -2.54526032e-02,
        -2.09698853e-02, -9.99405122e-03, -8.02140816e-03, -3.28538028e-03,
         7.93872789e-03,  3.65234398e-02,  4.36600828e-02,  1.14473761e-01,
         1.56651060e-01,  1.69340537e-01,  1.71215458e-01,  1.94784852e-01,
         2.40714606e-01,  2.57248159e-01,  3.23093873e-01,  3.58251735e-01,
         3.72491173e-01,  4.49198300e-01,  4.57408545e-01,  5.12138026e-01,
         5.36972137e-01,  5.37135040e-01,  5.62654426e-01,  5.66342324e-01,
         5.74584980e-01,  6.28962881e-01,  6.74723160e-01,  7.24245213e-01,
         7.59244127e-01,  7.64420178e-01,  8.50182359e-01,  1.01252026e+00,
         1.04380487e+00,  1.09612406e+00,  1.10301119e+00,  1.13269746e+00,
         1.21255712e+00,  1.30590234e+00,  1.32291768e+00,  1.36034970e+00,
         1.43401348e+00,  1.43762472e+00,  1.48294564e+00,  1.52314185e+00,
         1.72550443e+00,  1.76753261e+00,  1.77650780e+00,  1.81172133e+00,
         1.87003606e+00,  1.95575512e+00,  2.01235587e+00,  2.08147500e+00,
         2.10537135e+00,  2.13874707e+00,  2.17218491e+00,  2.36885032e+00,
         2.80786757e+00,  4.21297422e+00])),
 (1.7614951915979662, -0.33017033577661237, 0.9766485225426503))
```

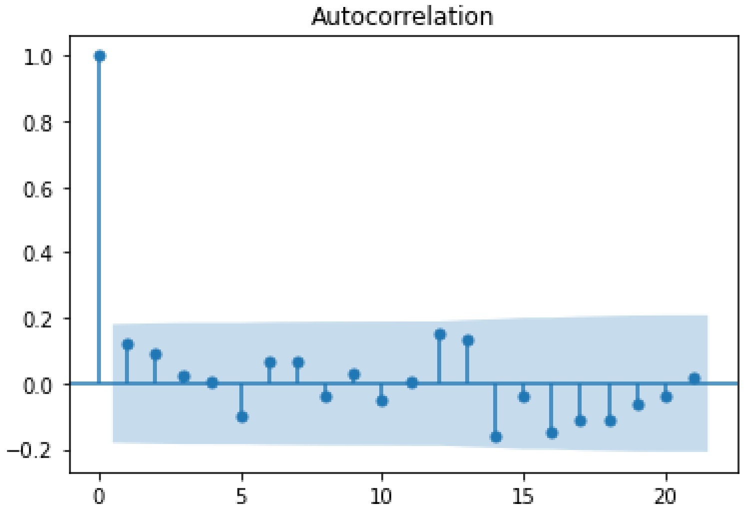


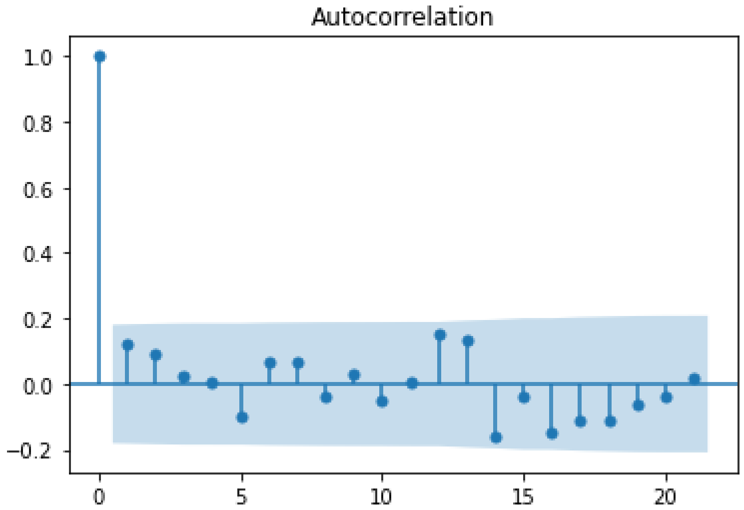
good accuracy of prediction

NO AUTOCORRELATION

In [114]:
```
import statsmodels.api as sm
sm.graphics.tsa.plot_acf(res)
```

Out[114]:





no values are greater than 0.5 so there is not equal values present in dependent

MULTI COLINEARITY

In [115]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor as vifm
def calculate_vif(x):
    vif=pd.DataFrame()
    vif['features']=x.columns
    vif['VIF_Values']=[vifm(x.values,i) for i in range(x.shape[1])]
    return(vif)
```

In [116]:
```
calculate_vif(vehicle)
```

Out[116]:

	features	VIF_Values
0	origin	8.937792
1	cylinders	109.908759
2	displacement	90.883447
3	horsepower	59.173992
4	weight	150.930316
5	acceleration	52.537059
6	Kilometer_per_liter	21.605023

cylinder and weight have high multi colinearity or in otherwords high impact on correlation

Using optimizer to find even the best fit for the model

L2 Ridge

In [118]:
```
from sklearn.linear_model import Ridge
```

In [127]:
```
ridge_model=Ridge(alpha=75,max_iter=100)
```

In [128]:
```
ridge_model.fit(x_train,y_train)
```

Out[128]:
```
Ridge(alpha=75, max_iter=100)
```

In [129]:
```
ridge_model.predict(x_test)
```

Out[129]:
```
array([11.52554309, 12.71179012, 12.37460767, 10.17943505, 13.24083927,
       12.04717596, 12.53148005,  5.9956792 , 12.24242475, 12.56853927,
        8.87269638, 12.30004305,  7.25071293, 13.33905774, 11.06134103,
        7.62549571, 11.2054543 , 12.92500081,  4.2916874 ,  9.88690255,
       12.05311108,  8.28395072,  7.61231286,  5.63763689,  4.73442021,
        6.56944636, 13.26874198,  8.37138731,  9.3819815 , 11.16580749,
        7.77588713, 10.52901189,  5.27780291,  9.77967724,  8.737844  ,
        6.10299612,  8.24319216,  8.64682724, 13.22795141, 12.4913248 ,
        5.03269058,  5.13196833, 10.30641582,  9.91555665, 10.09657883,
        8.1337868 ,  4.32253634, 13.37181172,  9.14128582,  3.65918941,
        7.03753302,  9.5684858 , 10.66596571, 11.27858493, 13.22314177,
        9.65679125, 10.01072632, 10.83872375, 10.71758848, 13.79801113,
        9.987606  , 11.48809076, 13.52569249,  8.61136027,  9.77847202,
        9.46124131, 10.10585104,  6.798151  , 12.81439401,  3.75386482,
       11.79830397,  7.80772616,  7.02516311, 12.24243597, 11.36302863,
       12.35001517,  7.07126889,  5.36566661,  5.51845505, 11.1187335 ,
        8.34242942, 12.13905842, 13.23160374, 12.20133867,  6.2922267 ,
        8.60589189, 13.40241729, 10.73518032, 13.51927608, 10.07255769,
       11.84068529,  8.95362927,  6.2136191 ,  4.63144694,  3.48644338,
        9.88463963,  6.12512076, 10.30456838,  9.82020446,  5.68297534,
       12.45920238, 11.01303674,  9.81857355, 12.64945556, 12.34584318,
       12.94526399,  9.8196444 , 13.7127381 ,  6.07790342,  7.81092631,
       13.41333644, 10.30593377, 13.23339902, 11.45393377,  6.75058238,
       10.65067704,  8.79792394,  5.50274628])
```

In [130]:
```
ridge_model.score(x_test,y_test)
```

Out[130]:
```
0.7291924297934178
```

accuracy is same as checked using linear regression so i conclude this is best fit

L1 LASSO

In [131]:
```
from sklearn.linear_model import Lasso
```

In [132]:
```
lasso_model=Lasso(alpha=75,max_iter=100)
lasso_model.fit(x_train,y_train)
```

Out[132]:
```
Lasso(alpha=75, max_iter=100)
```

In [133]:
```
lasso_model.predict(x_test)
```

Out[133]:
```
array([11.33363156, 12.35927508, 11.81124466, 10.22532423, 12.89812063,
       12.65319084, 12.30416588,  6.0339631 , 12.00106525, 11.99494201,
        9.07109257, 12.44193889,  7.24942721, 13.05120175, 11.27546073,
        8.44652159, 11.75001221, 11.857169  ,  5.67575327, 10.0844896 ,
       12.1296534 ,  7.88624468,  8.59960271,  6.25439991,  5.71555436,
        6.94326497, 12.74503951,  7.82807385,  9.70178679, 11.70408788,
        8.52000053, 10.61721191,  5.22263315, 10.32635777,  8.52000053,
        6.10131879,  7.41781645,  8.18322206, 12.98996931, 12.4848016 ,
        5.76454032,  5.58084297, 10.4120832 , 10.12429069, 10.46719241,
        7.58620568,  3.70713003, 12.97466119,  9.10783204,  4.50927512,
        7.76377978,  9.34663859, 10.8070325 , 11.9796339 , 13.357364  ,
        9.87017603, 11.06114716, 11.08564014, 11.18055044, 13.49513701,
        9.77526573, 11.4622197 , 12.95935308,  8.70369787,  9.56095216,
        9.17518773,  8.99455201,  7.956662  , 13.1124342 ,  3.83571818,
       11.55406838,  7.96890849,  7.50966512, 12.3072275 , 12.16639287,
       13.14305043,  9.55789054,  5.3389748 ,  5.92068307, 11.38261752,
        7.92298415, 12.2123172 , 12.82464169, 12.30110425,  7.30759804,
        8.55061675, 13.34205589, 10.83152548, 13.03589364,  9.7844506 ,
       12.38070644,  8.39753563,  5.856389  ,  5.59002784,  3.84490304,
       10.7396768 ,  5.85945062, 10.44882267,  9.6068765 ,  5.65738354,
       12.02861986, 11.15299584,  9.9895793 , 12.07148257, 12.39907617,
       12.46949349,  9.63749272, 12.92873686,  6.28807776,  7.07491473,
       12.82158007,  9.33133048, 12.92873686, 11.63367056,  7.49129538,
       10.83152548,  9.14457151,  5.64819867])
```

In [134]:
```
lasso_model.score(x_test,y_test)
```

Out[134]:
```
0.7124650229890934
```

this shows only one percent less than previous

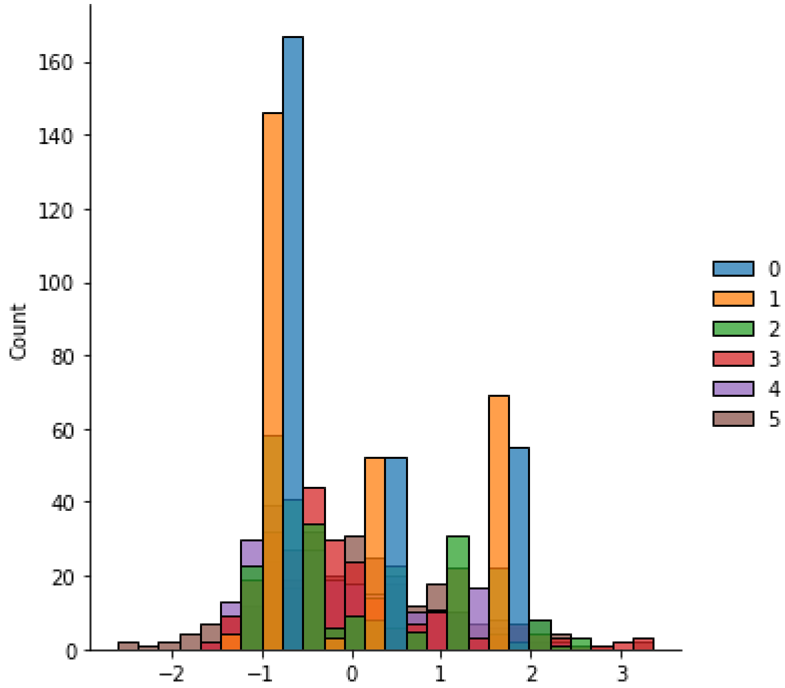
Now we can check our best fit even by using another optimizer

STOCHARTIC GRADIENT DESCENT(SGD)

In [135]:
```
from sklearn.preprocessing import StandardScaler
norm=StandardScaler()
x_train=norm.fit_transform(x_train)
x_test=norm.fit_transform(x_test)
```

the data is made into normally distributed with mean=0 and std with 1

In [138]:
```
sns.displot(x_train);
```



In [139]:
```
from sklearn.linear_model import SGDRegressor
model=SGDRegressor()
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
```

In [140]:
```
model.score(x_test,y_test)
```

Out[140]:
```
0.7356752087233532
```

By using SGD the accuracy is found to be good accuracy or in otherwords SGD found the best fit with 0.73 accuracy

In [ ]: