DATA COLLECTION

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

In [2]: # To Import Dataset
sd=pd.read_csv(r"c:\Users\user\Downloads\\VehicleSelection.csv")
sd

Out[2]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	le
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.6115598
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.241889
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.417
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.634609
4	5.0	рор	73.0	3074.0	106880.0	1.0	41.903221	12.495650
			•••	•••				
1544	NaN	NaN	NaN	NaN	NaN	NaN	NaN	lenç
1545	NaN	NaN	NaN	NaN	NaN	NaN	NaN	conc
1546	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Null valu
1547	NaN	NaN	NaN	NaN	NaN	NaN	NaN	fi
1548	NaN	NaN	NaN	NaN	NaN	NaN	NaN	sear

1549 rows × 11 columns

In [3]: # to display top 10 rows
sd.head(10)

Out[3]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611559868
1	2.0	рор	51.0	1186.0	32500.0	1.0	45.666359	12.24188995
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.41784
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.63460922
4	5.0	рор	73.0	3074.0	106880.0	1.0	41.903221	12.49565029
5	6.0	pop	74.0	3623.0	70225.0	1.0	45.000702	7.68227005
6	7.0	lounge	51.0	731.0	11600.0	1.0	44.907242	8.611559868
7	8.0	lounge	51.0	1521.0	49076.0	1.0	41.903221	12.49565029
8	9.0	sport	73.0	4049.0	76000.0	1.0	45.548000	11.54946995
9	10.0	sport	51.0	3653.0	89000.0	1.0	45.438301	10.99170017
4 0		_			_)	•

DATA CLEANING AND PRE_PROCESSING

In [4]: sd.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1549 entries, 0 to 1548
Data columns (total 11 columns):

Column	Non-Null Count	Dtype
ID	1538 non-null	float64
model	1538 non-null	object
engine_power	1538 non-null	float64
age_in_days	1538 non-null	float64
km	1538 non-null	float64
previous_owners	1538 non-null	float64
lat	1538 non-null	float64
lon	1549 non-null	object
price	1549 non-null	object
Unnamed: 9	0 non-null	float64
Unnamed: 10	1 non-null	object
	ID model engine_power age_in_days km previous_owners lat lon price Unnamed: 9	ID 1538 non-null model 1538 non-null engine_power 1538 non-null age_in_days 1538 non-null km 1538 non-null previous_owners 1538 non-null lat 1538 non-null lon 1549 non-null price 1549 non-null Unnamed: 9 0 non-null

dtypes: float64(7), object(4)

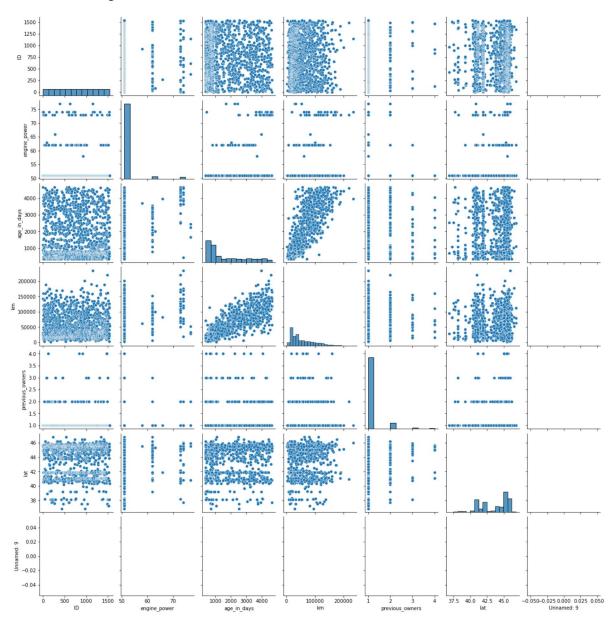
memory usage: 133.2+ KB

```
In [5]: # to display summary of statistics
         sd.describe()
Out[5]:
                                                                                                    U
                                                                                                lat
                          ID engine_power age_in_days
                                                                  km previous_owners
          count 1538.000000
                               1538.000000
                                            1538.000000
                                                          1538.000000
                                                                           1538.000000
                                                                                       1538.000000
                  769.500000
                                 51.904421
                                            1650.980494
                                                         53396.011704
                                                                              1.123537
                                                                                          43.541361
           mean
             std
                  444.126671
                                  3.988023
                                            1289.522278
                                                         40046.830723
                                                                              0.416423
                                                                                          2.133518
                    1.000000
                                 51.000000
                                             366.000000
                                                          1232.000000
                                                                              1.000000
                                                                                          36.855839
            min
            25%
                  385.250000
                                 51.000000
                                             670.000000
                                                         20006.250000
                                                                              1.000000
                                                                                          41.802990
            50%
                  769.500000
                                 51.000000
                                            1035.000000
                                                         39031.000000
                                                                              1.000000
                                                                                          44.394096
                 1153.750000
                                                                              1.000000
           75%
                                 51.000000
                                            2616.000000
                                                         79667.750000
                                                                                          45.467960
                 1538.000000
                                 77.000000
                                            4658.000000
                                                        235000.000000
                                                                              4.000000
                                                                                          46.795612
            max
In [6]:
         #to display colums heading
         sd.columns
Out[6]: Index(['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owners',
                  'lat', 'lon', 'price', 'Unnamed: 9', 'Unnamed: 10'],
                dtype='object')
```

EDA and visualization

In [7]: sns.pairplot(sd)

Out[7]: <seaborn.axisgrid.PairGrid at 0x24c385f4c40>

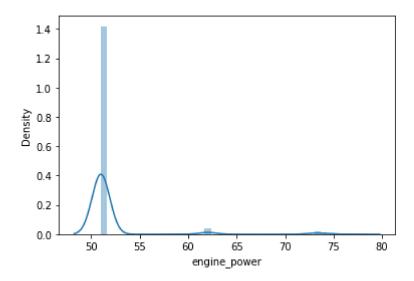


```
In [8]: sns.distplot(sd['engine_power'])
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fut ureWarning: `distplot` is a deprecated function and will be removed in a futu re version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

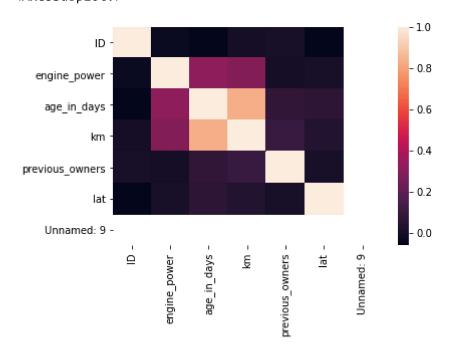
warnings.warn(msg, FutureWarning)

Out[8]: <AxesSubplot:xlabel='engine_power', ylabel='Density'>



In [10]: sns.heatmap(sd1.corr())

Out[10]: <AxesSubplot:>



TO TRAIN THE MODEL MODEL BUILDING

we are goint train Liner Regression model; we need to split out the data into two varibles x and y where x is independent on x (output) and y is dependent on x(output) adress coloumn as it is not required our model

```
In [11]: dss=sd.head(200)
          dss
Out[11]:
                      model engine_power age_in_days
                                                                                        lat
                                                                                                    k
                                                             km previous_owners
             0
                  1.0
                      lounge
                                      51.0
                                                  882.0
                                                         25000.0
                                                                              1.0
                                                                                 44.907242 8.61155980
             1
                  2.0
                                      51.0
                                                 1186.0
                                                         32500.0
                                                                             1.0 45.666359 12.2418899
                         pop
             2
                  3.0
                        sport
                                      74.0
                                                 4658.0
                                                       142228.0
                                                                             1.0 45.503300
                                                                                               11.417
             3
                                      51.0
                                                 2739.0
                                                        160000.0
                                                                                  40.633171
                                                                                            17.634609;
                  4.0
                      lounge
             4
                                                        106880.0
                                                                             1.0 41.903221
                  5.0
                                      73.0
                                                 3074.0
                                                                                            12.495650;
                         pop
             ...
                                                     ...
                                                                              ...
           195
                196.0
                                      51.0
                                                  517.0
                                                          9150.0
                                                                             1.0 44.411758
                                                                                             12.204059
                      lounge
           196
               197.0
                                      51.0
                                                 1552.0
                                                         52026.0
                                                                                 45.069679
                                                                                           7 7049198
                                                        145150.0
                                                                                  45.386841
            197 198.0
                      lounge
                                      51.0
                                                 2282.0
                                                                                            11.790889
                                      51.0
                                                  397.0
                                                         19783.0
                                                                                 38.122070
           198
               199.0
                      lounge
                                                                             2.0
                                                                                            13.361120:
               200.0 lounge
                                      51.0
                                                 3743.0 105610.0
                                                                             2.0 37.727879
                                                                                            12.887470;
          200 rows × 11 columns
In [12]: | x= dss[['age_in_days', 'km', 'previous_owners',
                   'lat']]
          y=dss[ 'engine_power']
In [13]: # To split my dataset into training data and test data
          from sklearn .model_selection import train_test_split
          x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.4)
In [14]: from sklearn.linear_model import LinearRegression
          lr=LinearRegression()
          lr.fit(x_train,y_train)
Out[14]: LinearRegression()
In [15]:
          print(lr.intercept_)
          57.287116485755654
```

```
In [16]: coeff= pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
          coeff
Out[16]:
                          Co-efficient
                            0.001218
              age_in_days
                            0.000010
                     km
          previous_owners
                           -1.237513
                           -0.137091
                      lat
In [17]:
         prediction = lr.predict(x_test)
          plt.scatter(y_test,prediction)
Out[17]: <matplotlib.collections.PathCollection at 0x24c3c455c40>
           57
           56
           55
           53
           52
           51
           50
                      55
                               60
                                        65
                                                 70
         print(lr.score(x_test,y_test))
In [18]:
          -0.19302825676216084
In [19]: |lr.score(x_train,y_train)
Out[19]: 0.16182642739380004
In [20]:
         from sklearn.linear_model import Ridge,Lasso
In [21]: | dr=Ridge(alpha=10)
         dr.fit(x_train,y_train)
Out[21]: Ridge(alpha=10)
In [22]: dr.score(x_test,y_test)
Out[22]: -0.2064739917770242
```

```
In [23]: dr.score(x_train,y_train)
Out[23]: 0.1607460504381495
In [24]: la=Lasso(alpha=10)
la.fit(x_train,y_train)
Out[24]: Lasso(alpha=10)
In [25]: la.score(x_test,y_test)
Out[25]: -0.22672079753185526
In [26]: la.score(x_train,y_train)
Out[26]: 0.1508021612247673
In [ ]:
```