DATA COLLECTION

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

In [2]:
```python
# 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	lo
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611559
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	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495650
...	...	...	...	...	...	...	...	
1544	NaN	NaN	NaN	NaN	NaN	NaN	NaN	leng
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	pop	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	pop	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

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  
---  ------           --------------  -----  
 0   ID               1538 non-null   float64
 1   model            1538 non-null   object 
 2   engine_power     1538 non-null   float64
 3   age_in_days      1538 non-null   float64
 4   km               1538 non-null   float64
 5   previous_owners  1538 non-null   float64
 6   lat              1538 non-null   float64
 7   lon              1549 non-null   object 
 8   price            1549 non-null   object 
 9   Unnamed: 9       0 non-null      float64
 10  Unnamed: 10      1 non-null      object 
dtypes: float64(7), object(4)
memory usage: 133.2+ KB
```

In [5]:
```
# to display summary of statistics
sd.describe()
```

Out[5]:

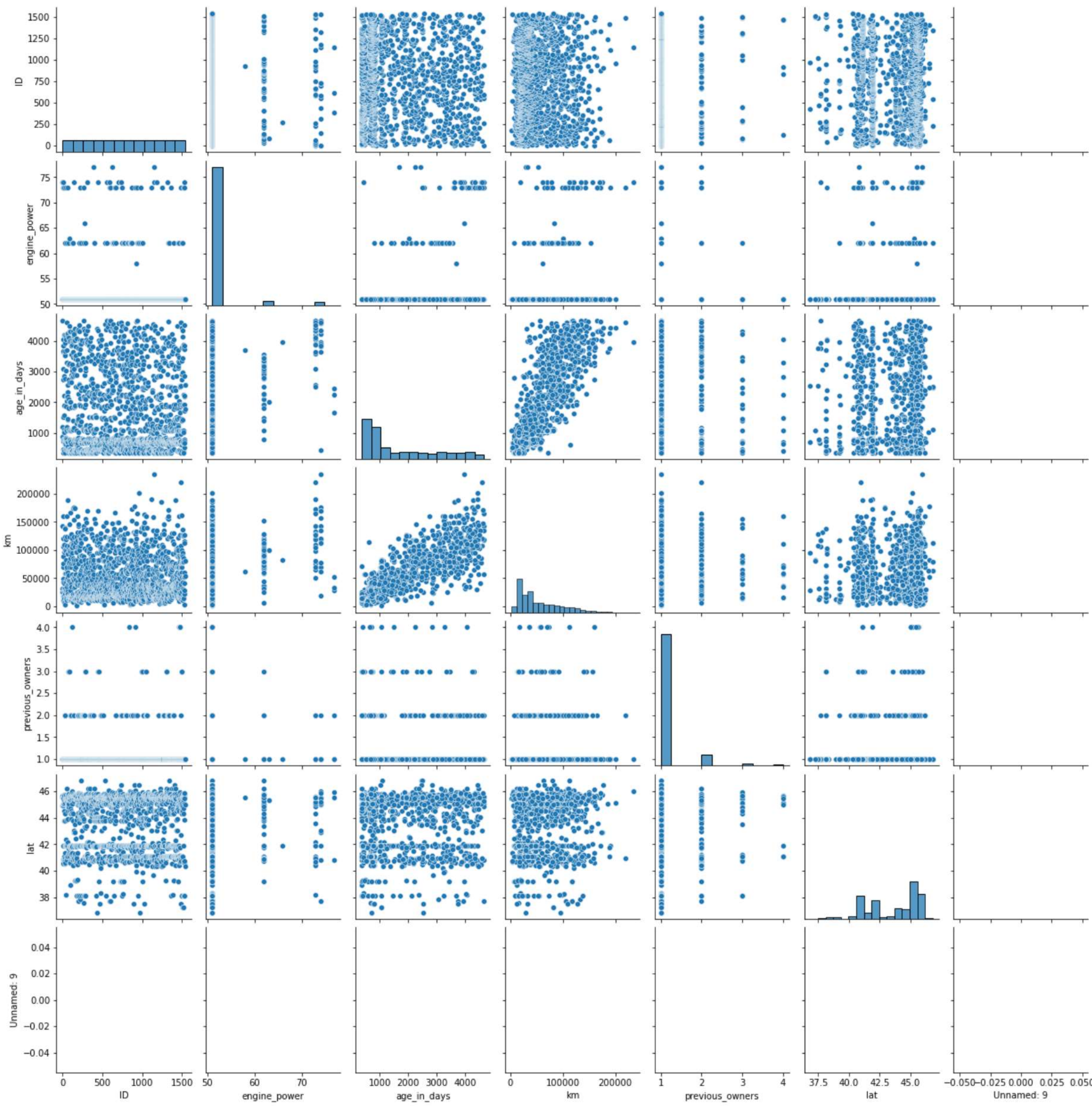
	ID	engine_power	age_in_days	km	previous_owners	lat	U
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	
mean	769.500000	51.904421	1650.980494	53396.011704	1.123537	43.541361	
std	444.126671	3.988023	1289.522278	40046.830723	0.416423	2.133518	
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.855839	
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	
75%	1153.750000	51.000000	2616.000000	79667.750000	1.000000	45.467960	
max	1538.000000	77.000000	4658.000000	235000.000000	4.000000	46.795612	

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

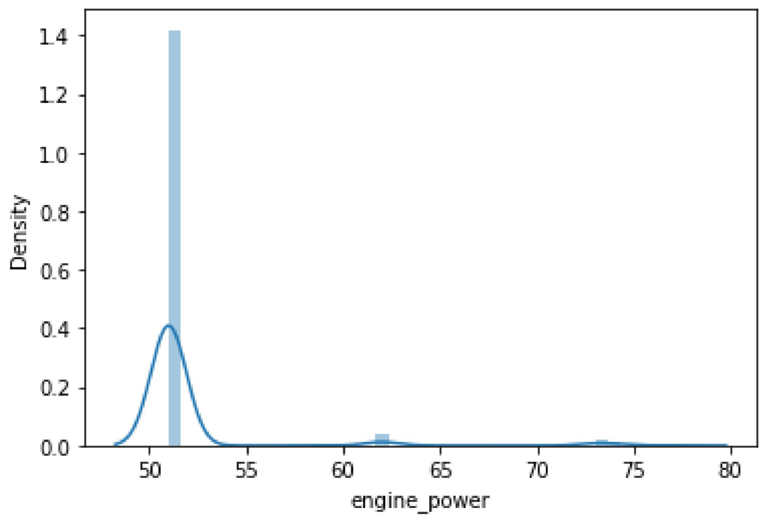
In [7]:
```
sns.pairplot(sd)
```
Out[7]: <seaborn.axisgrid.PairGrid at 0x26c71926ca0>



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

```
C:\ProgramData\Anaconda3\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)
```

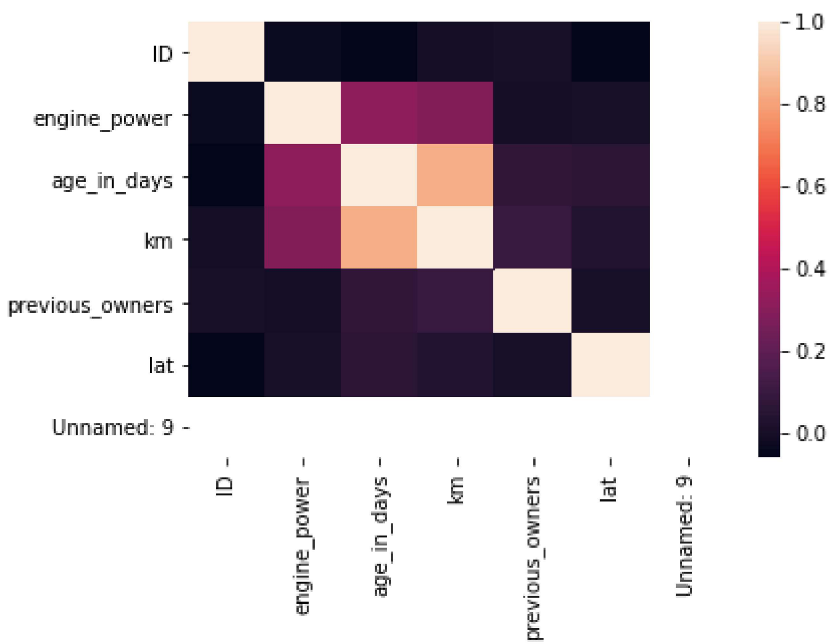
Out[8]: <AxesSubplot:xlabel='engine_power', ylabel='Density'>



In [9]:
```python
sd1=sd[['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owners',
        'lat', 'lon', 'price', 'Unnamed: 9', 'Unnamed: 10']]
```

In [10]:
```python
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]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lo
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611559
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	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495650
...	...	...	...	...	...	...	...	
195	196.0	lounge	51.0	517.0	9150.0	1.0	44.411758	12.20405
196	197.0	pop	51.0	1552.0	52026.0	1.0	45.069679	7.704919
197	198.0	lounge	51.0	2282.0	145150.0	2.0	45.386841	11.790889
198	199.0	lounge	51.0	397.0	19783.0	2.0	38.122070	13.361120
199	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_)
```

54.50483260332787

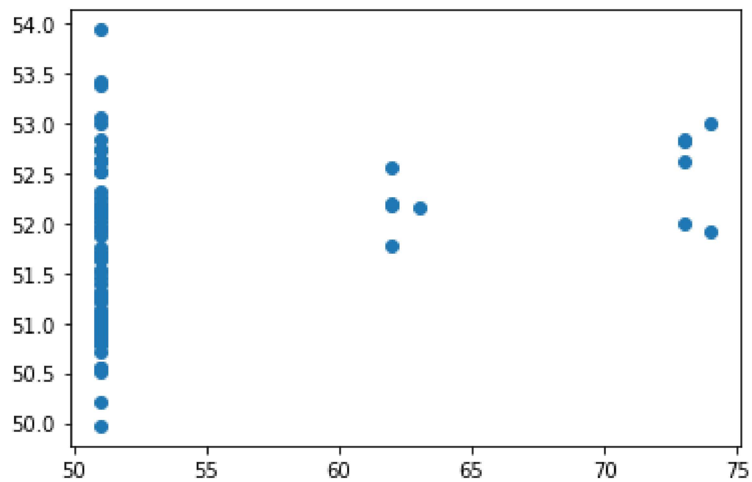
In [16]:
```
coeff= pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[16]:

	Co-efficient
age_in_days	0.000093
km	0.000014
previous_owners	-0.633241
lat	-0.073178

In [17]:
```
prediction = lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[17]: <matplotlib.collections.PathCollection at 0x26c757a4100>



In [18]:
```
print(lr.score(x_test,y_test))
```

```
-0.0022158901133071396
```

In [19]:
```
lr.score(x_train,y_train)
```

Out[19]: 0.06105953613687165

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]: -0.005705362898171584

In [23]:
```
dr.score(x_train,y_train)
```
Out[23]:
```
0.06033618425619769
```
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]:
```
-0.01685904140581518
```
In [26]:
```
la.score(x_train,y_train)
```
Out[26]:
```
0.05171978236019881
```
ElasticNet

In [27]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```
Out[27]:
```
ElasticNet()
```
In [28]:
```
print(en.coef_)
```
```
[ 6.34599666e-05  1.44256114e-05 -0.00000000e+00 -0.00000000e+00]
```
In [29]:
```
print(en.intercept_)
```
```
50.64771418373925
```
In [30]:
```
prediction=en.predict(x_test)
```
In [31]:
```
print(en.score(x_test,y_test))
```
```
-0.015401598358145474
```
Evaluation metrics

In [32]:
```
from sklearn import metrics
```
In [34]:
```
print("mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
```
```
mean Absolute Error: 2.8182440628473038
```

In [35]:
```
print("mean squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
mean squared Error: 40.24480772492612
```

In [36]:
```
print("Root mean Absolytre Error:",np.sqrt(metrics.mean_squared_error(y_test,pr
```

```
Root mean Absolytre Error: 6.34387954842509
```

In [ ]: