In [1]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```python
a=pd.read_csv(r"C:\Users\user\Downloads\fiat500_VehicleSelection_Dataset (1).csv")
a
```

Out[2]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.241
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.634
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495
...	...	...	...	...	...	...	...	
1544	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1545	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1546	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Null
1547	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1548	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

1549 rows × 11 columns

In [3]:

```
b=a.head(100)
b
```

Out[3]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.61155
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.2418
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.4
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.6346
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.4956
...	...	...	...	...	...	...	...	
95	96.0	sport	51.0	4292.0	165600.0	1.0	44.715408	11.3083
96	97.0	pop	51.0	1066.0	28000.0	1.0	41.769051	12.6628
97	98.0	sport	51.0	2009.0	86000.0	2.0	40.633171	17.6346
98	99.0	lounge	51.0	456.0	18592.0	2.0	45.393600	10.4822
99	100.0	pop	51.0	731.0	41558.0	2.0	45.571220	9.15913

100 rows × 11 columns

In [4]:

```
b.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ID               100 non-null    float64
 1   model            100 non-null    object 
 2   engine_power     100 non-null    float64
 3   age_in_days      100 non-null    float64
 4   km               100 non-null    float64
 5   previous_owners  100 non-null    float64
 6   lat              100 non-null    float64
 7   lon              100 non-null    object 
 8   price            100 non-null    object 
 9   Unnamed: 9       0 non-null      float64
 10  Unnamed: 10      0 non-null      object 
dtypes: float64(7), object(4)
memory usage: 8.7+ KB
```

In [5]:

```
b.describe()
```

Out[5]:

	ID	engine_power	age_in_days	km	previous_owners	lat
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
mean	50.500000	53.010000	1935.300000	58812.180000	1.180000	43.612648
std	29.011492	6.014284	1414.251278	44728.034639	0.500101	2.083451
min	1.000000	51.000000	366.000000	4000.000000	1.000000	38.218128
25%	25.750000	51.000000	723.500000	19781.750000	1.000000	41.744165
50%	50.500000	51.000000	1446.000000	44032.000000	1.000000	44.831066
75%	75.250000	51.000000	3265.500000	95075.750000	1.000000	45.396568
max	100.000000	74.000000	4658.000000	188000.000000	3.000000	46.176498

In [6]:

```
c=b.dropna(axis=1)
c
```

Out[6]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.6115
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.241
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.4
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.634
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495
...	...	...	...	...	...	...	...	
95	96.0	sport	51.0	4292.0	165600.0	1.0	44.715408	11.308
96	97.0	pop	51.0	1066.0	28000.0	1.0	41.769051	12.662
97	98.0	sport	51.0	2009.0	86000.0	2.0	40.633171	17.634
98	99.0	lounge	51.0	456.0	18592.0	2.0	45.393600	10.482
99	100.0	pop	51.0	731.0	41558.0	2.0	45.571220	9.1591

100 rows × 9 columns

In [7]:

```
c.columns
```

Out[7]:

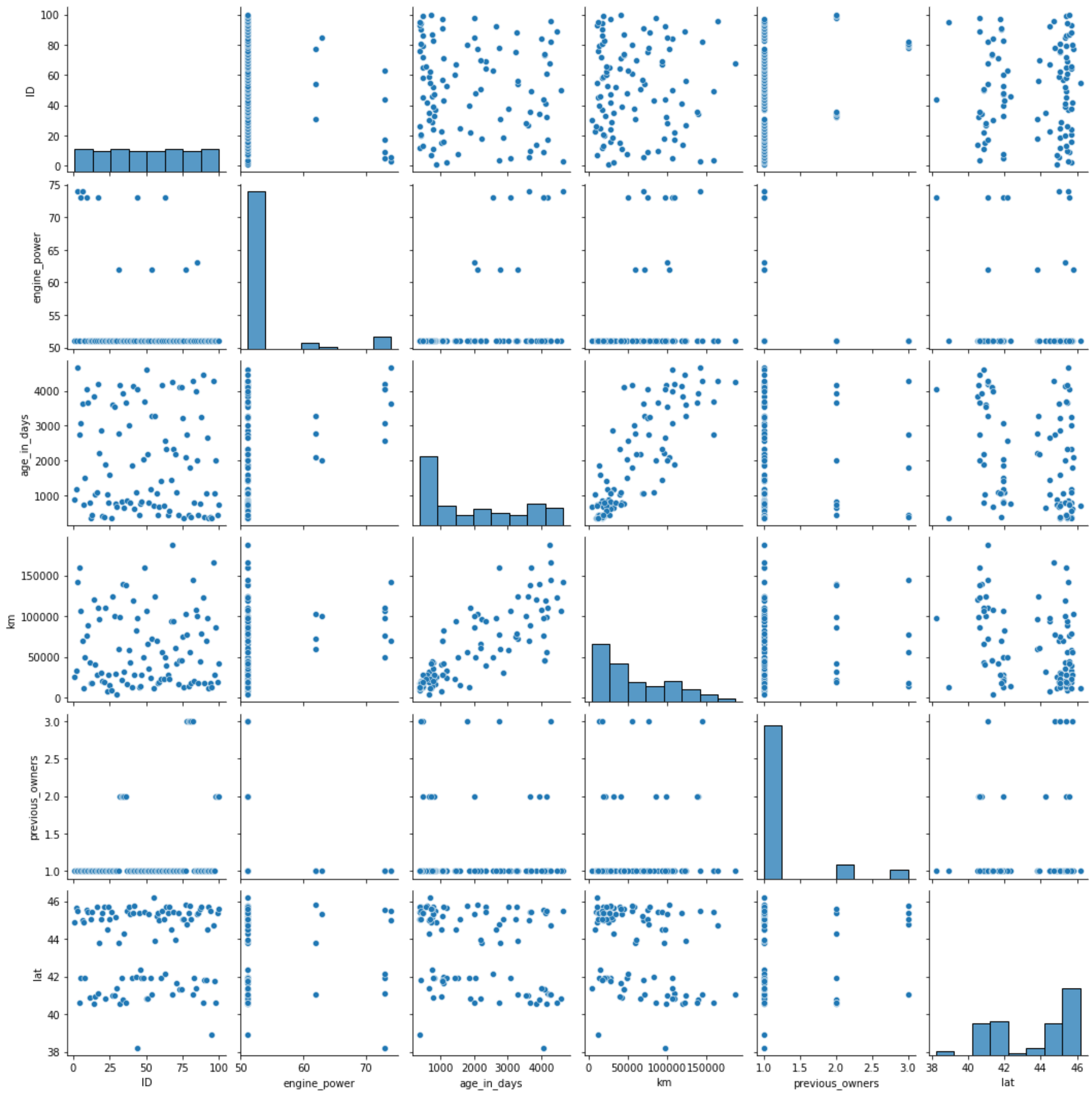
```
Index(['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owner
s',
       'lat', 'lon', 'price'],
      dtype='object')
```

In [8]:

```
sns.pairplot(c)
```

Out[8]:

```
<seaborn.axisgrid.PairGrid at 0x27032bf0c70>
```



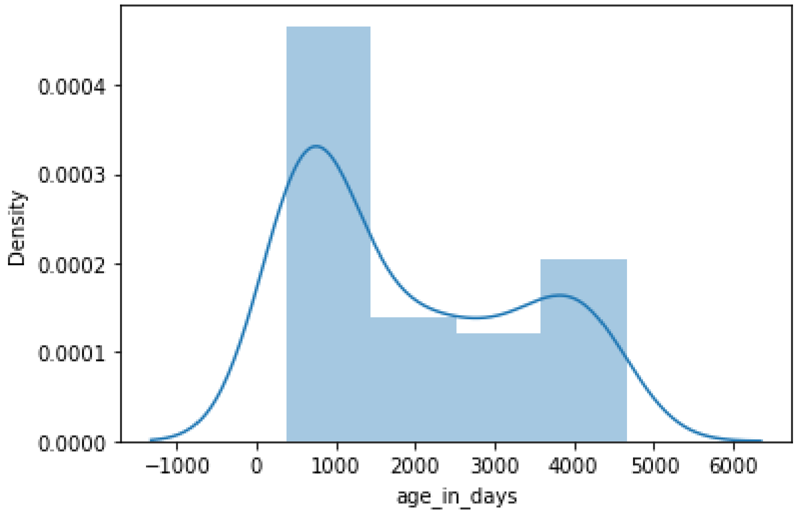
In [9]:

```
sns.distplot(c['age_in_days'])
```

```
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 fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[9]:

<AxesSubplot:xlabel='age_in_days', ylabel='Density'>



In [10]:

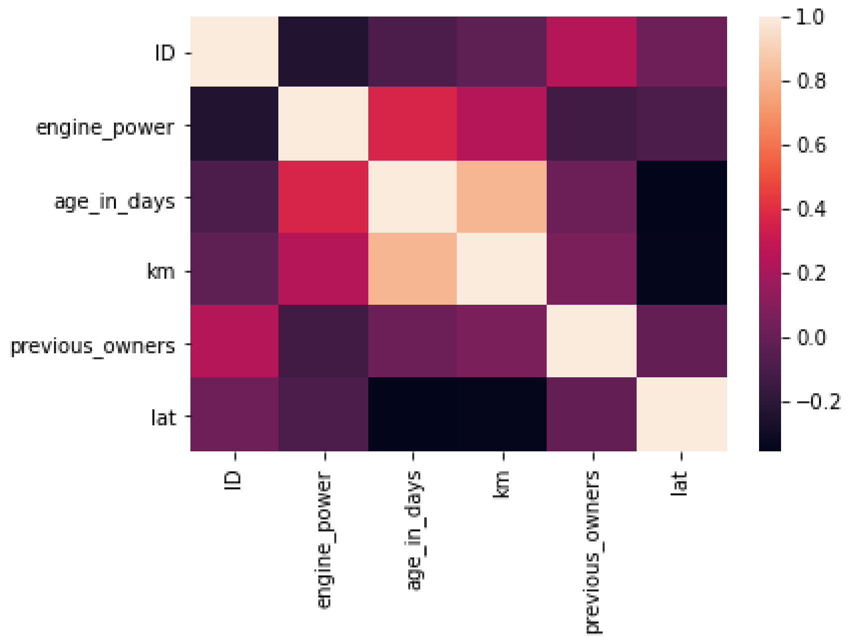
```
f=c[['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owners',
       'lat', 'lon', 'price']]
```

In [11]:

```
sns.heatmap(f.corr())
```

Out[11]:

```
<AxesSubplot:>
```



In [12]:

```
x=f[['ID','engine_power','km', 'previous_owners',
       'lat', 'lon', 'price']]
y=f['age_in_days']
```

In [13]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.5)
```

In [14]:

```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[14]:

```
LinearRegression()
```

In [15]:

```
print(lr.intercept_)
```

```
6896.681856091886
```

In [16]:

```
r=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
r
```

Out[16]:

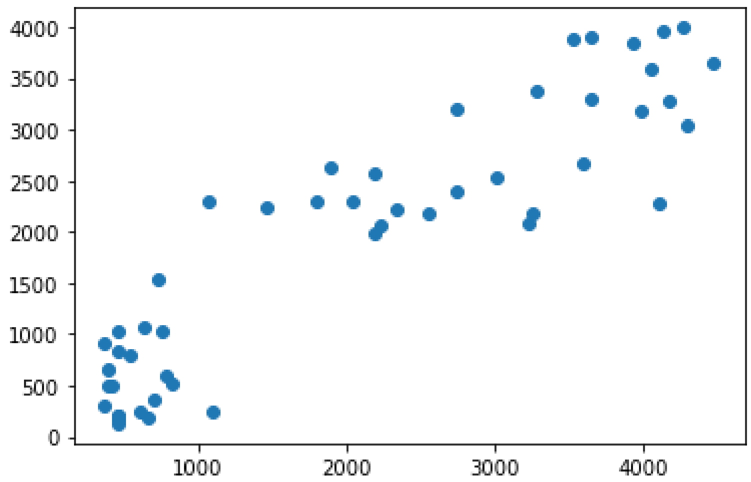
	Co-efficient
ID	-3.021181
engine_power	17.469947
km	-0.000558
previous_owners	165.049390
lat	-13.430399
lon	-21.678906
price	-0.620086

In [17]:

```
u=lr.predict(x_test)
plt.scatter(y_test,u)
```

Out[17]:

<matplotlib.collections.PathCollection at 0x2703521fb80>



In [18]:

```
print(lr.score(x_test,y_test))
```

0.8236052465600654

In [19]:

```
lr.score(x_train,y_train)
```

Out[19]:

0.8554274608268977

RIDGE REGRESSION

In [20]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [21]:

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[21]:

```
Ridge(alpha=10)
```

In [22]:

```
rr.score(x_test,y_test)
```

Out[22]:

```
0.8285017241960643
```

LASSO REGRESSION

In [23]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[23]:

```
Lasso(alpha=10)
```

In [24]:

```
la.score(x_test,y_test)
```

Out[24]:

```
0.8249223223241258
```

ELASTIC NET

In [25]:

```
from sklearn.linear_model import ElasticNet
p=ElasticNet()
p.fit(x_train,y_train)
```

Out[25]:

```
ElasticNet()
```

In [26]:

```
print(p.coef_)
```

```
[-2.57150661e+00  1.64724226e+01 -2.26919036e-04  5.22363640e+01
 -5.96119328e+00 -1.40467836e+01 -6.14410250e-01]
```

In [27]:

```
print(p.intercept_)
```

```
6586.73754164688
```

In [28]:

```
print(p.predict(x_test))
```

```
[ 534.69330542 3230.73561288 3899.69912776 2135.09156192 1045.28991093
  640.36875073 3284.45983865 2281.55023196 3767.8667207  3379.48686212
  966.71728847 4057.55919624 3321.43056837 2589.03223299  820.19949251
 2655.63509893 3578.3273058  2311.12233595 2082.57420273  407.96270267
  866.62473865 2099.8057086   288.76544001  157.59228188  330.59010419
  210.93087482 3963.07151446 3845.40545871 3256.08115958 1075.55784732
  987.98095935 3721.75037752 2718.87031935  175.15443212  194.57449918
 2180.72530995 2193.44122312 3113.48160811 1463.74145497  535.74522519
 2230.93206031  267.70141967 2305.17155892  245.55587025  536.75110676
  689.39157829 2289.77152188 2016.21723854 2335.00574079 2549.31018213]
```

In [35]:

```
prediction=p.predict(x_test)
print(p.score(x_test,y_test))
```

```
0.830116976100481
```

EVALUATION METRICS

In [36]:

```
from sklearn import metrics
```

In [37]:

```
print("Mean Absolytre Error:",metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolytre Error: 475.27204122558624
```

In [38]:

```
print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
Mean Squared Error: 354735.83604626363
```

In [39]:

```
print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Root Mean Squared Error: 595.5970416701746
```

In [ ]:

```

```