Data collection

Importing libraries

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

Importing dataset

In [2]:
```
data=pd.read_csv(r"C:\Users\user\Downloads\fiat500_VehicleSelection_Dataset (2).csv")
data
```

Out[2]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	p
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611559868	8
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.24188995	8
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.41784	4
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.63460922	6
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.49565029	5
...	...	...	...	...	...	...	...	...	
1544	NaN	NaN	NaN	NaN	NaN	NaN	NaN	length	
1545	NaN	NaN	NaN	NaN	NaN	NaN	NaN	concat	lonp
1546	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Null values	
1547	NaN	NaN	NaN	NaN	NaN	NaN	NaN	find	
1548	NaN	NaN	NaN	NaN	NaN	NaN	NaN	search	

1549 rows × 11 columns

head

In [3]:
```
# to display first 8 dataset values
da=data.head(8)
da
```

Out[3]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price	U
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.611559868	8900	
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.24188995	8800	
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.41784	4200	
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.63460922	6000	
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.49565029	5700	
5	6.0	pop	74.0	3623.0	70225.0	1.0	45.000702	7.68227005	7900	
6	7.0	lounge	51.0	731.0	11600.0	1.0	44.907242	8.611559868	10750	
7	8.0	lounge	51.0	1521.0	49076.0	1.0	41.903221	12.49565029	9190	

info

In [4]:

```
# to identify missing values
data.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
```

describe

In [5]:

```
# to display summary of the dataset
data.describe()
```

Out[5]:

	ID	engine_power	age_in_days	km	previous_owners	lat	Unnamed: g
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	0.0
mean	769.500000	51.904421	1650.980494	53396.011704	1.123537	43.541361	NaN
std	444.126671	3.988023	1289.522278	40046.830723	0.416423	2.133518	NaN

	ID	engine_power	age_in_days	km	previous_owners	lat	Unnamed: 9
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.855839	NaN
25%	385.250000	51.000000	670.000000	20006.250000	1.000000	41.802990	NaN
50%	769.500000	51.000000	1035.000000	39031.000000	1.000000	44.394096	NaN
75%	1153.750000	51.000000	2616.000000	79667.750000	1.000000	45.467960	NaN
max	1538.000000	77.000000	4658.000000	235000.000000	4.000000	46.795612	NaN

columns

In [6]:
```
# to display headings of the dataset
data.columns
```

Out[6]:
```
Index(['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owners',
       'lat', 'lon', 'price', 'Unnamed: 9', 'Unnamed: 10'],
      dtype='object')
```

In [7]:
```
a=data.dropna(axis=1,how='any')
a
b=a.head(8)
b
```

Out[7]:

	lon	price
0	8.611559868	8900
1	12.24188995	8800
2	11.41784	4200
3	17.63460922	6000
4	12.49565029	5700
5	7.68227005	7900
6	8.611559868	10750
7	12.49565029	9190

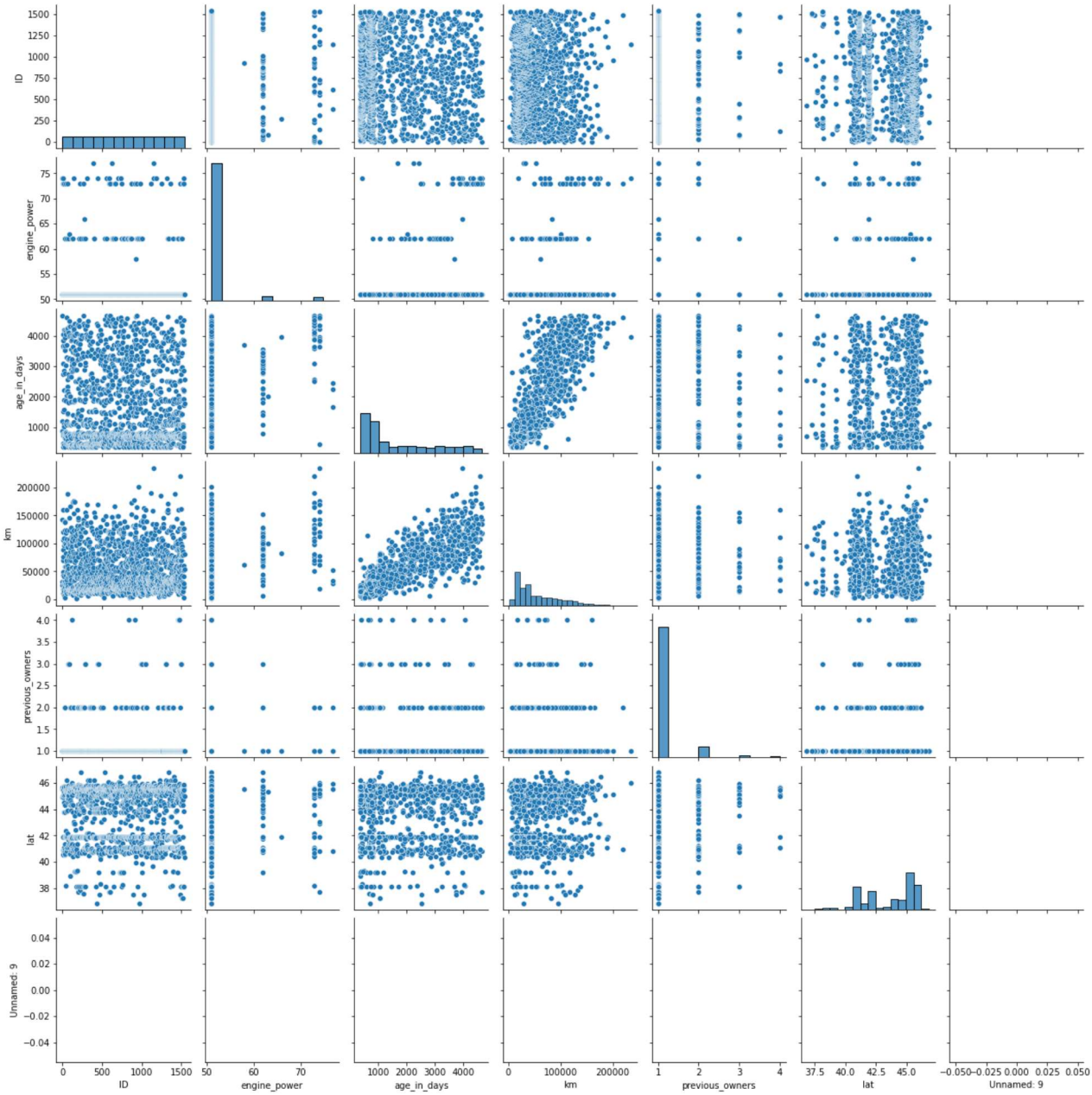
In [8]:
```
a.columns
```

Out[8]:
```
Index(['lon', 'price'], dtype='object')
```

EDA and Visualization

In [9]:
```
sns.pairplot(data)
```

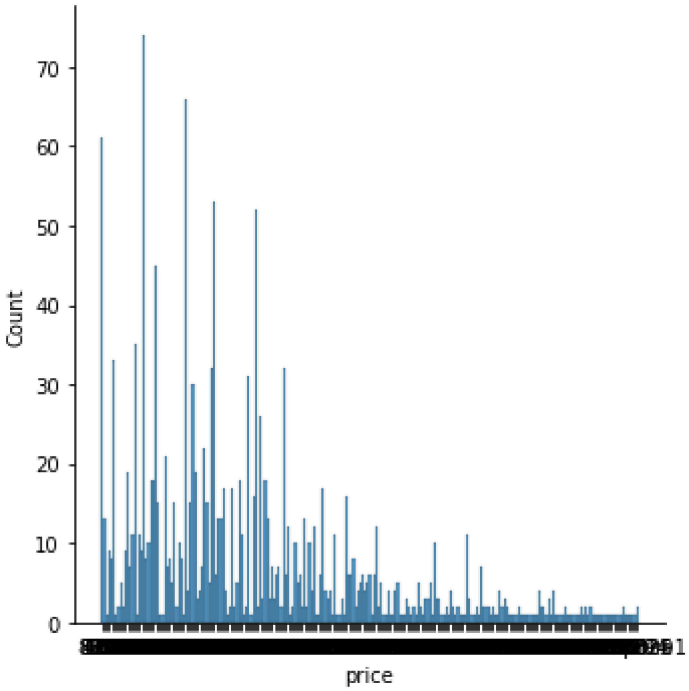
Out[9]: <seaborn.axisgrid.PairGrid at 0x1c09f580760>



distribution plot

In [10]:
```
sns.displot(a["price"])
```

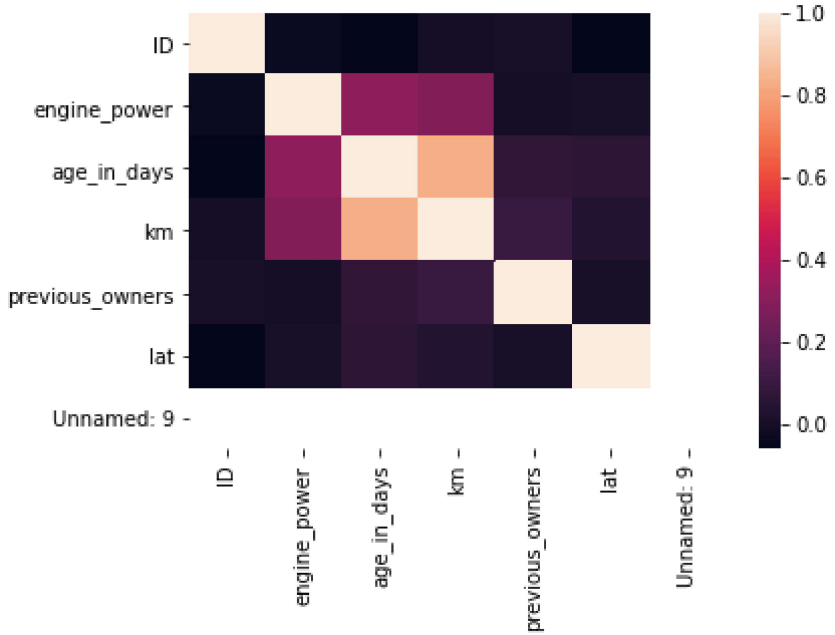
Out[10]: <seaborn.axisgrid.FacetGrid at 0x1c0a13c5760>



correlation

In [11]:
```
dat=data[['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owners',
       'lat', 'lon', 'price', 'Unnamed: 9', 'Unnamed: 10']]
sns.heatmap(dat.corr())
```

Out[11]: <AxesSubplot:>



To train the model-Model Building

In [12]:
```
x=b[['price']]
y=b['price']
```

In [13]:
```
# to split my dataset into training 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=0.3)
```

In [14]:
```
from sklearn.linear_model import LinearRegression
lr= LinearRegression()
lr.fit(x_train,y_train)
```

Out[14]:
```
LinearRegression()
```

In [15]:
```
print(lr.intercept_)
```

```
-1.8189894035458565e-12
```

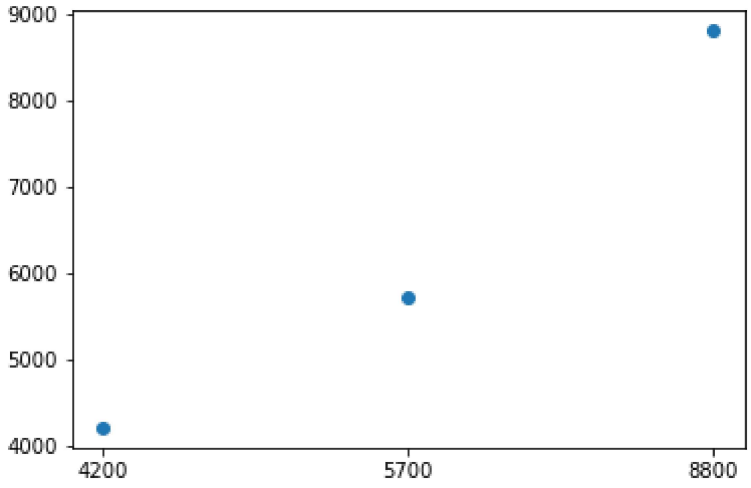
In [16]:
```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[16]:

	Co-efficient
price	1.0

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

Out[17]:
```
<matplotlib.collections.PathCollection at 0x1c0a3772850>
```



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

```
1.0
```

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

Out[19]:
```
1.0
```

Ridge regression

In [20]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [21]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
rr.score(x_test,y_test)
```

Out[21]: 0.999999999998373

In [22]:
```
rr.score(x_train,y_train)
```

Out[22]: 0.9999999999993388

Lasso regression

In [23]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
la.score(x_train,y_train)
```

Out[23]: 0.9999999999834676

In [24]:
```
la.score(x_test,y_test)
```

Out[24]: 0.9999999999593253

In [25]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[25]: ElasticNet()

In [26]:
```
print(en.coef_)
```

```
[0.99999959]
```

In [27]:
```
print(en.intercept_)
```

```
0.0034756211480271304
```

In [28]:
```
predict=en.predict(x_test)
```

In [29]:
```
print(en.score(x_test,y_test))
```

```
0.9999999999995932
```

In [30]:
```
from sklearn import metrics
```

In [31]:
```
print("Mean Absolute error:",metrics.mean_absolute_error(y_test,predict))
```

```
Mean Absolute error: 0.0010094535297563805
```

In [32]:
```
print("Mean Squared error:",metrics.mean_squared_error(y_test,predict))
```

```
Mean Squared error: 1.492308530760009e-06
```

In [33]:
```
print("Root squared error:",np.sqrt(metrics.mean_squared_error(y_test,predict)))
```

```
Root squared error: 0.0012216008066303857
```

In [ ]:
```

```