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

In [2]: df=pd.read_csv(r"C:\\Users\\Admin\\Downloads\\fiat500_VehicleSelection_Dataset
 df

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	рор	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]: df.head()

Out[3]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	F
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	ł
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	1

```
In [4]: df.describe()
```

Out[4]:

	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	
4							

In [5]: df.info()

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

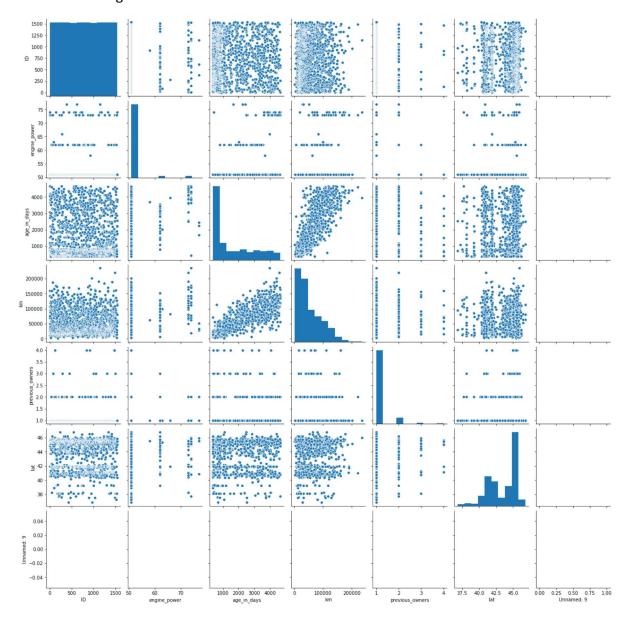
```
Column
                       Non-Null Count
                                         Dtype
                        _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _
                                         ----
     ID
                                         float64
 0
                       1538 non-null
     model
 1
                       1538 non-null
                                         object
 2
     engine_power
                       1538 non-null
                                         float64
 3
     age_in_days
                       1538 non-null
                                         float64
 4
                       1538 non-null
                                         float64
 5
     previous_owners 1538 non-null
                                         float64
                       1538 non-null
                                         float64
 6
     lat
 7
     lon
                       1549 non-null
                                         object
 8
     price
                       1549 non-null
                                         object
                                         float64
 9
     Unnamed: 9
                       0 non-null
 10 Unnamed: 10
                       1 non-null
                                         object
dtypes: float64(7), object(4)
```

memory usage: 133.2+ KB

```
In [6]: df.columns
```

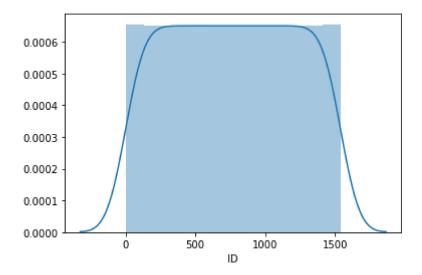
In [7]: sns.pairplot(df)

Out[7]: <seaborn.axisgrid.PairGrid at 0x1c73a71ff40>



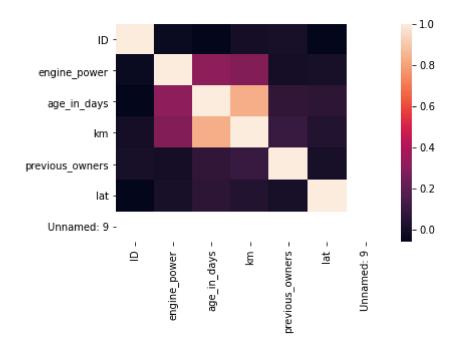
```
In [8]: sns.distplot(df['ID'])
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1c73bdc4b80>



In [9]: sns.heatmap(df.corr())

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1c73d45f460>



```
In [10]: df1=df.fillna(value=1)
```

```
In [11]: x=df1[[ 'age_in_days']]
y=df1['km']
```

In [12]: 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 [13]: | from sklearn.linear_model import LinearRegression
         lr= LinearRegression()
         lr.fit(x_train,y_train)
Out[13]: LinearRegression()
In [14]:
         print(lr.intercept_)
         10107.496918795696
In [15]: | prediction= lr.predict(x_test)
         plt.scatter(y_test,prediction)
Out[15]: <matplotlib.collections.PathCollection at 0x1c73df4c130>
          120000
          100000
           80000
           60000
           40000
           20000
                         50000
                                  100000
                                          150000
                                                   200000
In [16]:
         print(lr.score(x_test,y_test))
         0.6909047947917997
In [17]:
         print(lr.score(x_train,y_train))
         0.7039740472013478
In [18]: from sklearn.linear_model import Ridge,Lasso
         rr=Ridge(alpha=10)
In [19]:
         rr.fit(x_train,y_train)
Out[19]: Ridge(alpha=10)
In [20]: rr.score(x_test,y_test)
Out[20]: 0.6909047949621456
```

```
la=Lasso(alpha=10)
In [21]:
         la.fit(x_train,y_train)
Out[21]: Lasso(alpha=10)
         la.score(x_test,y_test)
In [22]:
Out[22]: 0.6909048008397267
In [23]:
         from sklearn.linear_model import ElasticNet
         en=ElasticNet()
         en.fit(x_train,y_train)
Out[23]: ElasticNet()
In [24]:
         print(en.intercept_)
         10107.510543888835
In [25]:
         print(en.predict(x_test))
                            30046.03367764 108047.00147518
                                                             30778,68282167
          [ 43547.71076034
           27638.75791871
                            26853.77669297
                                             26042.62942638
                                                             19684.2814979
          123197.13913193
                            31589.83008826 127174.37734234 104095.92930563
           22039.22517511 125604.41489086
                                             72225.69154065
                                                             27638.75791871
           75417.94852532
                            38000.51009846
                                             30778.68282167
                                                             88134.64438228
          120789.863373
                            56316.73869902
                                             26042.62942638
                                                             29234.88641105
           46739.96774501 110454.27723411 102499.8008133
                                                             72225,69154065
           20495.42876449
                            38000.51009846
                                             28449.90518531
                                                             28449.90518531
           116053.80997771
                            68274.6193711
                                            115242.66271112
                                                             30778.68282167
                            88945.79164888
                                                             26853.77669297
           19684.2814979
                                             31589.83008826
           29234.88641105
                            64271.21511984
                                             84183.57221273
                                                             84968.55343847
          100903.67232096
                            19684.2814979
                                             69007.26851513 119193.73488067
           122412.15790619
                            21228.07790852
                                             29234.88641105
                                                             30778.68282167
           48336.09623735
                            30046.03367764
                                             19684.2814979
                                                             49906.05868882
           19684.2814979
                            68274.6193711
                                             21228.07790852
                                                             21228.07790852
           47551.11501161
                            53124.48171435
                                             67463.47210451
                                                             85779.70070507
           28449.90518531
                            69818.41578172
                                             26042.62942638
                                                             54720.61020669
                                             36404.38160612
           65867.34361217
                            58724.01445795
                                                             19684.2814979
           74632.96729958 125604.41489086
                                             20495.42876449
                                                             22039.22517511
                                                             07605 24020542
In [26]:
         print(en.score(x_test,y_test))
```

0.6909048030066923

Evaluation

In [27]: from sklearn import metrics
 print("Mean Absolute Error", metrics.mean_absolute_error(y_test, prediction))
 print("Mean Squared Error", metrics.mean_squared_error(y_test, prediction))
 print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction))
 Mean Absolute Error 15844.679730165151
 Mean Squared Error 507836061.28438807
 Root Mean Squared Error: 22535.218243549098
In []: