In [25]: import pandas as pd
 import numpy as np
 import seaborn as sns
 import matplotlib.pyplot as plt
 from sklearn.model_selection import train_test_split
 from sklearn.linear_model import LinearRegression
 from sklearn.linear_model import Ridge,RidgeCV,Lasso
 from sklearn.preprocessing import StandardScaler

In [26]: df=pd.read_csv(r"C:\Users\SASIDHAR ROYAL\Downloads\fiat500_VehicleSelection_Dataset.csv")
df

Out[26]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
0	1	lounge	51	882	25000	1	44.907242	8.611560	8900
1	2	pop	51	1186	32500	1	45.666359	12.241890	8800
2	3	sport	74	4658	142228	1	45.503300	11.417840	4200
3	4	lounge	51	2739	160000	1	40.633171	17.634609	6000
4	5	pop	73	3074	106880	1	41.903221	12.495650	5700
1533	1534	sport	51	3712	115280	1	45.069679	7.704920	5200
1534	1535	lounge	74	3835	112000	1	45.845692	8.666870	4600
1535	1536	pop	51	2223	60457	1	45.481541	9.413480	7500
1536	1537	lounge	51	2557	80750	1	45.000702	7.682270	5990
1537	1538	pop	51	1766	54276	1	40.323410	17.568270	7900

1538 rows × 9 columns

In [27]: df.head()

Out[27]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
0	1	lounge	51	882	25000	1	44.907242	8.611560	8900
1	2	pop	51	1186	32500	1	45.666359	12.241890	8800
2	3	sport	74	4658	142228	1	45.503300	11.417840	4200
3	4	lounge	51	2739	160000	1	40.633171	17.634609	6000
4	5	pop	73	3074	106880	1	41.903221	12.495650	5700

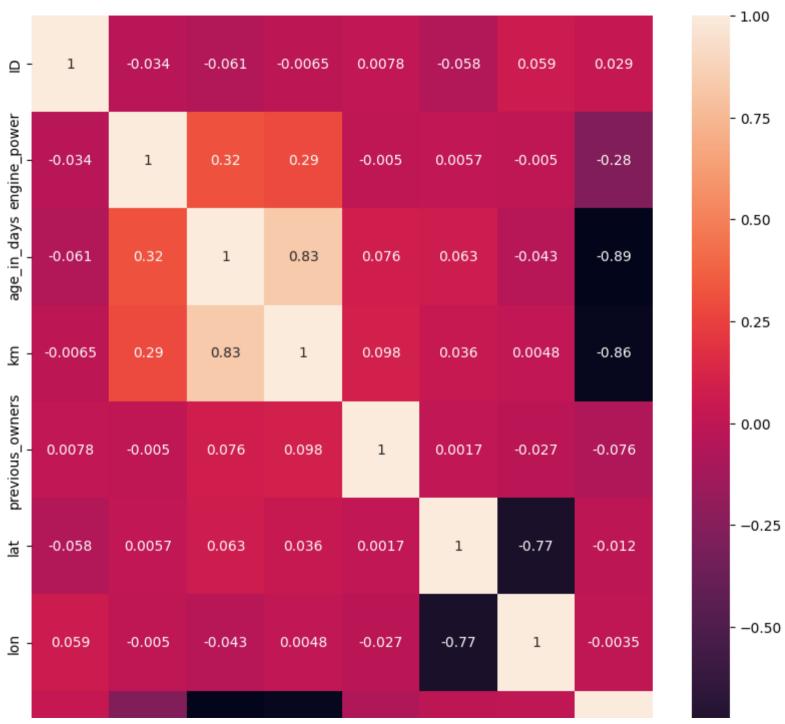
In [28]: df.tail()

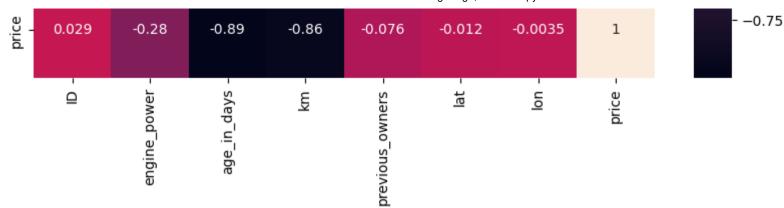
Out[28]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
1533	1534	sport	51	3712	115280	1	45.069679	7.70492	5200
1534	1535	lounge	74	3835	112000	1	45.845692	8.66687	4600
1535	1536	pop	51	2223	60457	1	45.481541	9.41348	7500
1536	1537	lounge	51	2557	80750	1	45.000702	7.68227	5990
1537	1538	gog	51	1766	54276	1	40.323410	17.56827	7900

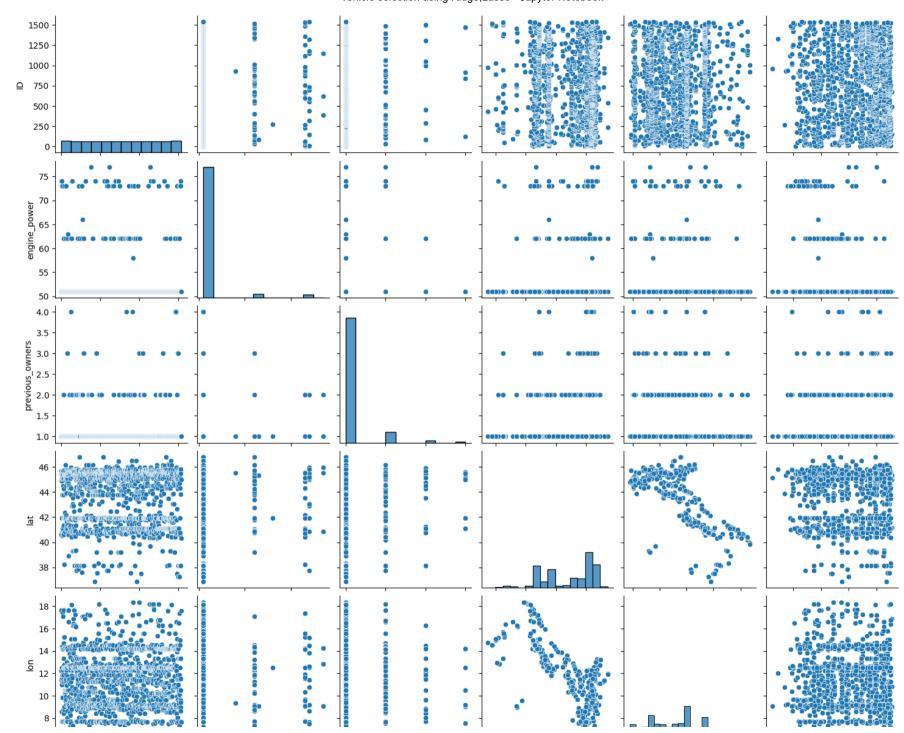
```
In [29]: df.describe()
Out[29]:
                              engine_power age_in_days
                                                                   km previous owners
                                                                                                 lat
                                                                                                            lon
                                                                                                                        price
            count 1538.000000
                                1538.000000
                                            1538.000000
                                                           1538.000000
                                                                                        1538.000000 1538.000000
                                                                                                                  1538.000000
                                                                            1538.000000
                   769.500000
                                             1650.980494
            mean
                                  51.904421
                                                          53396.011704
                                                                               1.123537
                                                                                          43.541361
                                                                                                       11.563428
                                                                                                                  8576.003901
                   444.126671
                                   3.988023
                                             1289.522278
                                                                               0.416423
                                                                                                        2.328190
              std
                                                          40046.830723
                                                                                           2.133518
                                                                                                                  1939.958641
                     1.000000
                                  51.000000
                                              366.000000
                                                           1232.000000
                                                                               1.000000
                                                                                          36.855839
                                                                                                        7.245400
                                                                                                                  2500.000000
             min
             25%
                   385.250000
                                  51.000000
                                              670.000000
                                                          20006.250000
                                                                               1.000000
                                                                                          41.802990
                                                                                                        9.505090
                                                                                                                  7122.500000
             50%
                   769.500000
                                  51.000000
                                             1035.000000
                                                          39031.000000
                                                                               1.000000
                                                                                          44.394096
                                                                                                       11.869260
                                                                                                                  9000.000000
             75% 1153.750000
                                  51.000000
                                             2616.000000
                                                                               1.000000
                                                                                                       12.769040
                                                          79667.750000
                                                                                          45.467960
                                                                                                                 10000.000000
             max 1538.000000
                                  77.000000
                                            4658.000000
                                                                               4.000000
                                                         235000.000000
                                                                                          46.795612
                                                                                                       18.365520 11100.000000
In [30]:
          df.shape
Out[30]: (1538, 9)
In [31]: | df.columns
Out[31]: Index(['ID', 'model', 'engine power', 'age in days', 'km', 'previous owners',
                   'lat', 'lon', 'price'],
                  dtype='object')
         a=df
In [32]:
          a.drop(columns=["model"],inplace=True)
```

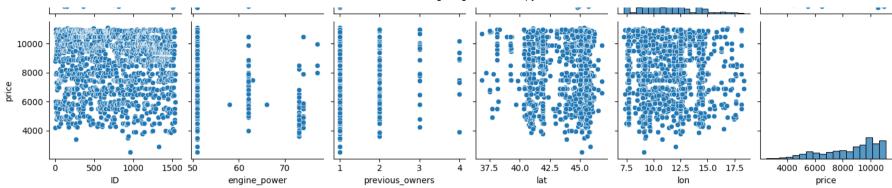
```
In [33]: plt.figure(figsize = (10, 10))
sns.heatmap(df.corr(), annot = True)
Out[33]: <Axes: >
```





```
In [34]: df.drop(columns = ["km", "age_in_days"], inplace = True)
#pairplot
sns.pairplot(df)
df.price=np.log(df.price)
```



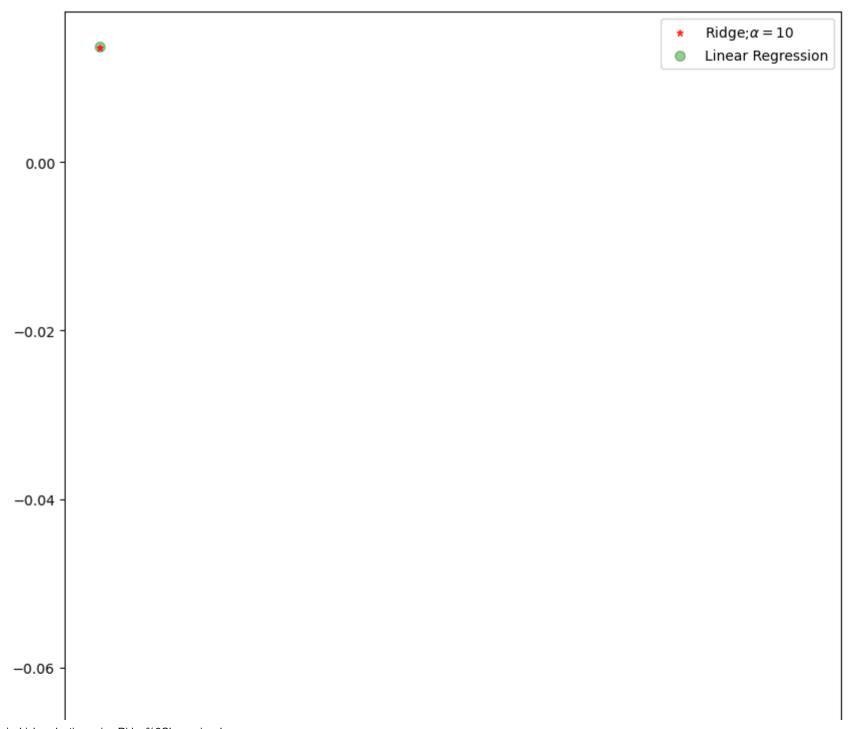


```
In [35]: features = df.columns[0:2]
    target = df.columns[-1]
    #X and y values
    X = df[features].values
    y = df[target].values
    #splot
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=17)
    print("The dimension of X_train is {}".format(X_train.shape))
    print("The dimension of X_test is {}".format(X_test.shape))
    #Scale features
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test=scaler.transform(X_test)
```

The dimension of X_train is (1076, 2) The dimension of X_test is (462, 2)

```
In [36]: #Model
         lr = LinearRegression()
         #Fit model
         lr.fit(X train, y train)
         #predict
         #prediction = lr.predict(X test)
         #actual
         actual = y test
         train score lr = lr.score(X train, y train)
         test score lr = lr.score(X test, y test)
         print("\nLinear Regression Model:\n")
         print("The train score for lr model is {}".format(train score lr))
         print("The test score for lr model is {}".format(test score lr))
         Linear Regression Model:
         The train score for lr model is 0.07906758951709636
         The test score for 1r model is 0.08573839649638304
In [37]: | ridgeReg = Ridge(alpha=10)
         ridgeReg.fit(X train,y train)
         #train and test scorefor ridge regression
         train score ridge = ridgeReg.score(X train, y train)
         test score ridge = ridgeReg.score(X_test, y_test)
         print("\nRidge Model:\n")
         print("The train score for ridge model is {}".format(train score ridge))
         print("The test score for ridge model is {}".format(test score ridge))
         Ridge Model:
         The train score for ridge model is 0.07906120163510788
         The test score for ridge model is 0.08541192691344546
```

```
In [38]: plt.figure(figsize=(10,10))
    plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;$\alpha=
    plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regression')
    plt.xticks(rotation=90)
    plt.legend()
    plt.show()
```



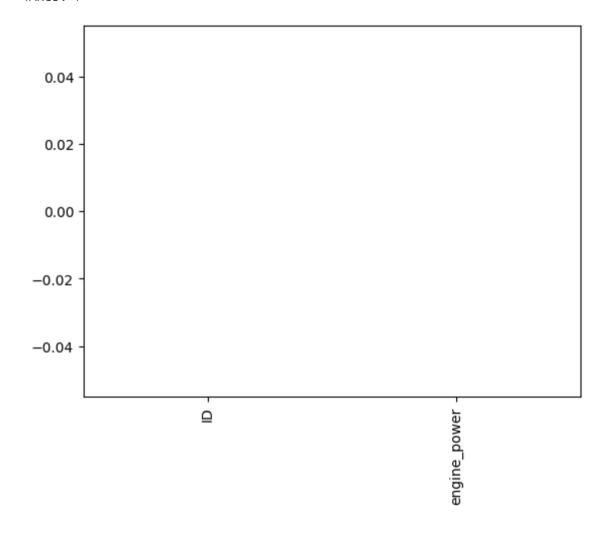
```
In [39]: lassoReg=Lasso(alpha=10)
    lassoReg.fit(X_train,y_train)
        train_score_lasso=lassoReg.score(X_train,y_train)
        test_score_lasso=lassoReg.score(X_test,y_test)
        print("\nRidge model\:\n")
        print("The train score for lasso model is {}".format(train_score_ridge))
        print("The train score for lasso model is {}".format(test_score_ridge))
```

Ridge model\:

The train score for lasso model is 0.07906120163510788
The train score for lasso model is 0.08541192691344546

In [40]: pd.Series(lassoReg.coef_,features).sort_values(ascending=True).plot(kind="bar")

Out[40]: <Axes: >

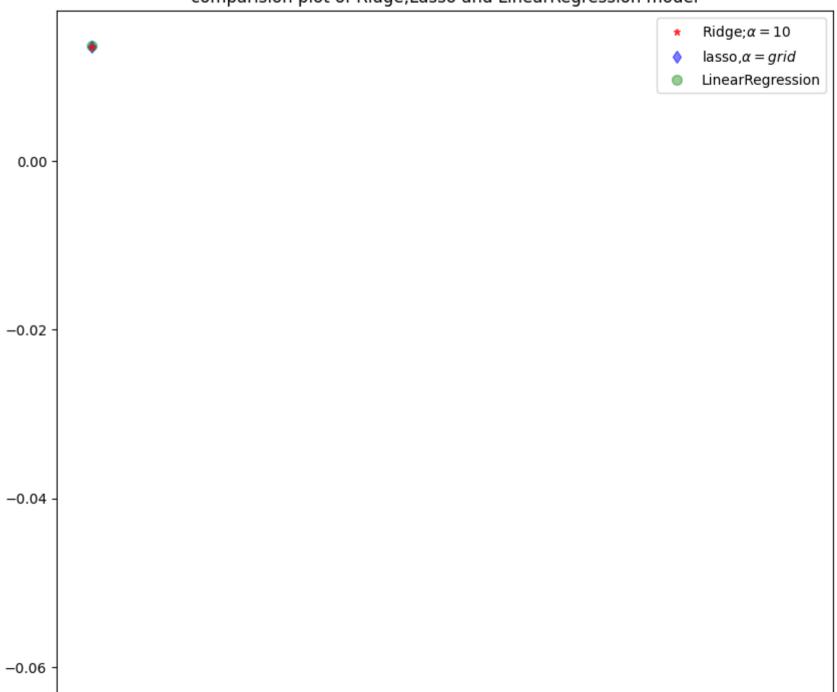


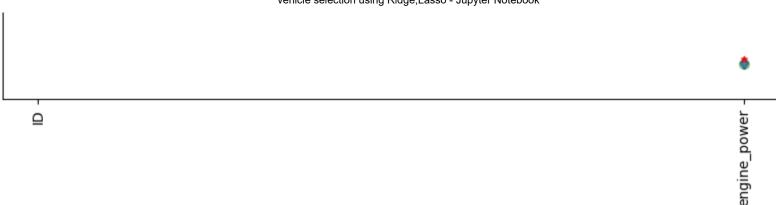
```
In [41]: from sklearn.linear_model import LassoCV
    lasso_CV=LassoCV(alphas=[0.0001,0.001,0.01,1,10]).fit(X_train,y_train)
    print("The train score for lasso model is{}".format(lasso_CV.score(X_train,y_train)))
    print("The test score for lasso model is{}".format(lasso_CV.score(X_test,y_test)))
```

The train score for lasso model is0.07906730311134957 The test score for lasso model is0.08575009503364805

```
In [42]: plt.figure(figsize=(10,10))
    plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;$\alpha=plt.plot(features,lasso_CV.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso,$\alpha=plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='LinearRegression')
    plt.xticks(rotation=90)
    plt.legend()
    plt.title("comparision plot of Ridge,Lasso and LinearRegression model")
    plt.show()
```

comparision plot of Ridge,Lasso and LinearRegression model





```
In [43]: from sklearn.linear_model import RidgeCV
    ridge_CV=RidgeCV(alphas=[0.0001,0.001,0.1,1,10]).fit(X_train,y_train)
    print("The train score for ridge model is{}".format(ridge_CV.score(X_train,y_train)))
    print("The test score for ridge model is{}".format(ridge_CV.score(X_test,y_test)))
```

The train score for ridge model is0.07906120163510788
The test score for ridge model is0.08541192691344601

```
In [ ]:
```