In [2]: import numpy as np
import pandas as pd
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 [3]: df=pd.read_csv(r"C:\Users\HP\Downloads\fiat500_VehicleSelection_Dataset (2).cs
 df

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

1538 rows × 9 columns

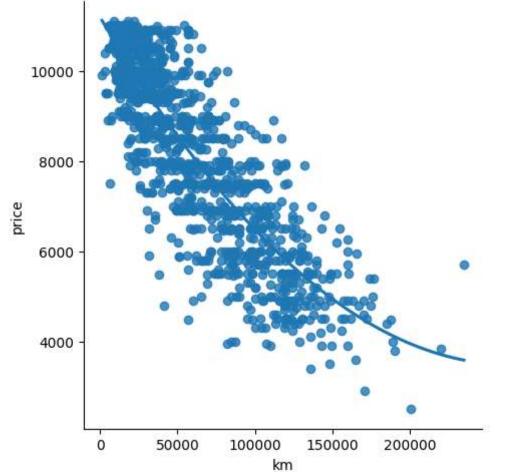
In [4]: df.head()

Out[4]:		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	рор	73	3074	106880	1	41.903221	12.495650	5700

```
In [5]: df.tail()
Out[5]:
                  ID
                      model engine power age in days
                                                          km
                                                              previous owners
                                                                                     lat
                                                                                              lon
          1533 1534
                                                 3712 115280
                                                                            1 45.069679
                                                                                          7.70492
                       sport
                                       51
          1534
               1535 lounge
                                                 3835 112000
                                                                                          8.66687
                                       74
                                                                              45.845692
          1535 1536
                                       51
                                                 2223
                                                        60457
                                                                            1 45.481541
                                                                                          9.41348
                        pop
               1537 lounge
                                                        80750
                                                                            1 45.000702
          1536
                                       51
                                                 2557
                                                                                          7.68227
          1537 1538
                                                 1766
                                                        54276
                                                                              40.323410 17.56827
                        pop
                                       51
In [6]: df.shape
Out[6]: (1538, 9)
In [7]: df.describe
Out[7]: <bound method NDFrame.describe of</pre>
                                                         ID
                                                               model
                                                                       engine power
                                                                                       age_in_da
         ys
                  km
                       previous_owners
         0
                                           51
                                                         882
                                                                25000
                   1
                       lounge
                                                                                        1
                                                                                           \
                   2
         1
                                           51
                                                        1186
                                                                32500
                                                                                        1
                          pop
         2
                   3
                        sport
                                           74
                                                        4658
                                                               142228
                                                                                        1
                                           51
                                                                                        1
         3
                   4
                                                        2739
                                                               160000
                       lounge
         4
                   5
                                           73
                                                                                        1
                          pop
                                                        3074
                                                               106880
                                           . . .
         . . .
                 . . .
                          . . .
                                                                                      . . .
         1533
                1534
                                           51
                                                        3712
                                                               115280
                                                                                        1
                        sport
         1534
                1535
                       lounge
                                           74
                                                        3835
                                                               112000
                                                                                        1
         1535
                1536
                                                        2223
                                                                                        1
                          pop
                                           51
                                                                60457
                                                                                        1
         1536
                1537
                       lounge
                                           51
                                                        2557
                                                                80750
                                                                                        1
         1537
                1538
                                           51
                                                        1766
                                                                54276
                          pop
                       lat
                                   lon
                                         price
         0
                44.907242
                              8.611560
                                          8900
         1
                45.666359
                             12.241890
                                          8800
         2
                45.503300
                             11.417840
                                          4200
         3
                40.633171
                             17.634609
                                          6000
         4
                41.903221
                                          5700
                             12.495650
                                           . . .
         1533
                45.069679
                              7.704920
                                          5200
         1534
                45.845692
                              8.666870
                                          4600
         1535
                45.481541
                              9.413480
                                          7500
         1536
                45.000702
                              7.682270
                                          5990
         1537
                40.323410
                                          7900
                            17.568270
```

[1538 rows x 9 columns]>

```
In [8]: df.isna().any()
Out[8]: ID
                            False
        model
                            False
        engine_power
                            False
        age_in_days
                            False
        km
                            False
        previous_owners
                            False
        lat
                            False
        lon
                            False
        price
                            False
        dtype: bool
In [9]: sns.lmplot(x='km',y='price',data=df,order=2,ci=None)
        plt.show()
            10000
```



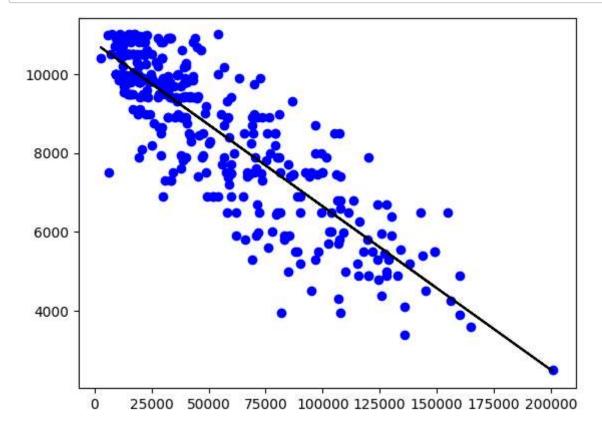
```
In [10]: x=np.array(df['km']).reshape(-1,1)
y=np.array(df['price']).reshape(-1,1)
```

```
In [11]: df.dropna(inplace=True)
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
    #splitting data into train and test
    regr=LinearRegression()
    regr.fit(x_train,y_train)
    print(regr.score(x_test,y_test))
```

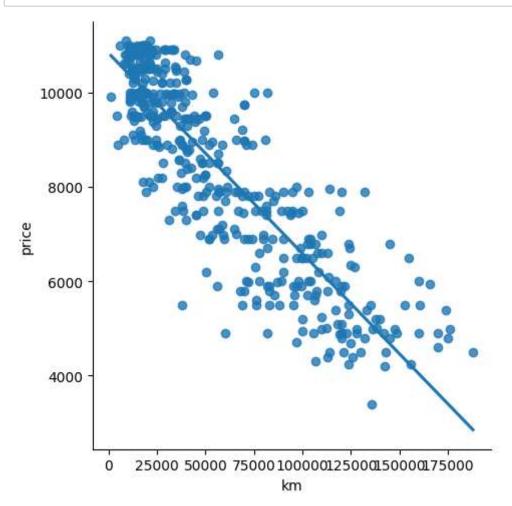
0.741062312488328

```
In [12]: y_pred=regr.predict(x_test)

plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



```
In [13]: df500=df[:][:500]
sns.lmplot(x="km",y="price",data=df500,order=1,ci=None)
plt.show()
```



```
In [14]: from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

```
In [15]: model=LinearRegression()
    model.fit(x_train,y_train)
    y_pred=model.predict(x_test)
    r2=r2_score(y_test,y_pred)
    print("R2 score:",r2)
```

R2 score: 0.741062312488328

```
In [16]: from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

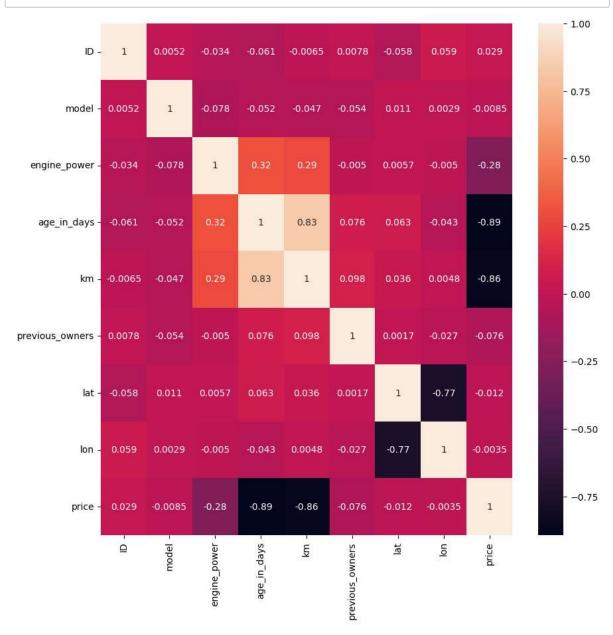
```
In [19]: converter={"model":{"sport":1,"lounge":2,"pop":3}}
df=df.replace(converter)
df
```

04	[40]	Ι.
Out	19	1

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

1538 rows × 9 columns

In [20]: plt.figure(figsize = (10, 10))
sns.heatmap(df.corr(), annot = True)
plt.show()



```
In [21]: features=df.columns[0:1]
         target=df.columns[-1]
         X = df[features].values
         y = df[target].values
         #splot
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rand
         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 (1153, 1)
         The dimension of X_test is (385, 1)
In [22]: | 1r = 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 0.00310286926477088
         The test score for lr model is -0.008405634316406507
```

```
In [23]: #Ridge Regression Model
    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:

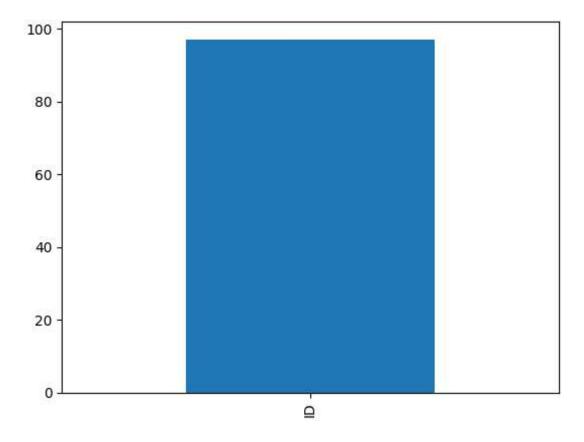
The train score for ridge model is 0.0031026398591535997 The test score for ridge model is -0.008307809466001403

```
In [24]: plt.figure(figsize=(10,10))
Out[24]: <Figure size 1000x1000 with 0 Axes>
         <Figure size 1000x1000 with 0 Axes>
         plt.plot(features, ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markers
In [26]:
         plt.plot(features, lr.coef_, alpha=0.4, linestyle='none', marker="o", markersize=7,
         plt.xticks(rotation=90)
         plt.legend()
         plt.show()
                                                                   Ridge; \alpha = 10
                                                                   LinearRegression
           107.0 -
           106.8 -
           106.6 -
           106.4
           106.2
                                                  \Box
In [27]: #Lasso regression model
         print("\nLasso Model: \n")
         lasso = Lasso(alpha = 10)
         lasso.fit(X_train,y_train)
         train_score_ls =lasso.score(X_train,y_train)
         test_score_ls =lasso.score(X_test,y_test)
         print("The train score for ls model is {}".format(train_score_ls))
         print("The test score for ls model is {}".format(test_score ls))
         Lasso Model:
```

The train score for ls model is 0.003075838461310987 The test score for ls model is -0.007367578602064606

```
In [37]: pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "ba
```

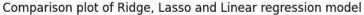
Out[37]: <Axes: >

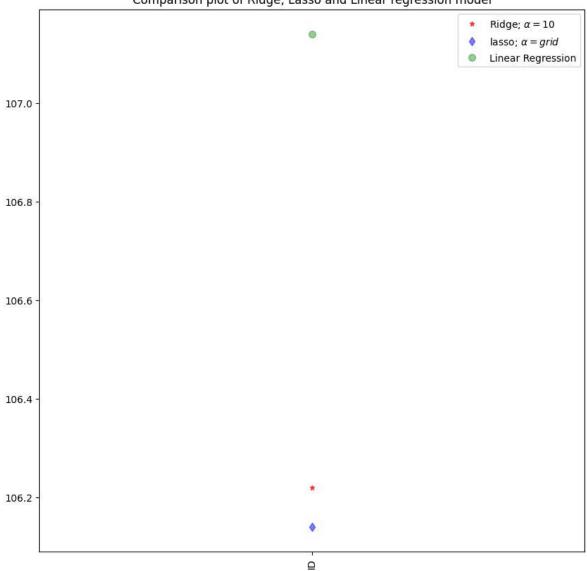


```
In [29]: #Using the Linear CV model
    from sklearn.linear_model import LassoCV
    #Lasso Cross validation
    lasso_cv = LassoCV(alphas = [0.0001, 0.001, 0.01, 1, 10], random_state=0).
    #score
    print(lasso_cv.score(X_train, y_train))
    print(lasso_cv.score(X_test, y_test))
```

0.0031025989567363688
-0.008299466692577973

In [34]: #plot size plt.figure(figsize = (10, 10)) #add plot for ridge regression plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markers #add plot for lasso regression plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,col #add plot for linear model plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7, #rotate axis plt.xticks(rotation = 90) plt.legend() plt.title("Comparison plot of Ridge, Lasso and Linear regression model") plt.show()





```
In [38]: #Using the linear CV model
         from sklearn.linear_model import RidgeCV
         #Ridge Cross validation
         ridge_cv = RidgeCV(alphas = [0.0001, 0.001, 0.01, 0.1, 1, 10]).fit(X_train, y_t
         #score
         print("The train score for ridge model is {}".format(ridge_cv.score(X_train, y
         print("The train score for ridge model is {}".format(ridge_cv.score(X_test, y_
         The train score for ridge model is 0.0031026398591535997
         The train score for ridge model is -0.008307809466003402
In [39]: from sklearn.linear_model import ElasticNet
         regr=ElasticNet()
         regr.fit(X,y)
         print(regr.coef_)
         print(regr.intercept_)
         [0.12455754]
         8480.156871173602
In [40]: y_pred_elastic=regr.predict(X_train)
         mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
```

3708273.194830543

print(mean_squared_error)