```
In [26]: import numpy as np
   import pandas as pd
   import seaborn as sns
   import matplotlib.pyplot as plt
   from sklearn import preprocessing,svm
   from sklearn.model_selection import train_test_split
   from sklearn.linear_model import LinearRegression
In [27]: df=pd.read_csv(r"C:\Users\rubin\Downloads\fiat500_VehicleSelection_Dataset.xls.csv")
```

Out[27]:

	#NAME?	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

In [28]: df.head()

1538 rows × 9 columns

Out[28]:

	#NAME?	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

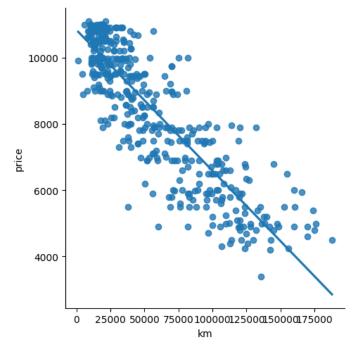
In [29]: df.shape

Out[29]: (1538, 9)

```
In [30]: df.describe
                                                           model engine_power age_in_days
Out[30]: <bound method NDFrame.describe of
                                                  #NAME?
                                                                                                 km previous owners
                    1 lounge
         0
                                                     882
                                                           25000
                                                                                 1
         1
                    2
                          pop
                                         51
                                                     1186
                                                            32500
                                                                                 1
                                                          142228
         2
                    3
                        sport
                                         74
                                                     4658
                                                                                 1
         3
                                         51
                                                           160000
                    4
                       lounge
                                                     2739
                                                                                 1
         4
                                         73
                                                     3074
                                                          106880
                                                                                 1
                          pop
                                         . . .
         1533
                 1534
                        sport
                                         51
                                                     3712
                                                           115280
                                                                                 1
         1534
                 1535
                       lounge
                                         74
                                                     3835
                                                          112000
                                                                                 1
                                         51
                                                            60457
         1535
                 1536
                          pop
                                                     2223
                                                                                 1
         1536
                 1537
                       lounge
                                         51
                                                     2557
                                                            80750
                                                                                 1
         1537
                 1538
                                         51
                                                     1766
                                                            54276
                                                                                 1
                          pop
                                     price
                     lat
                                lon
               44.907242
                                      8900
         0
                           8.611560
         1
               45.666359 12.241890
                                       8800
         2
               45.503300 11.417840
                                      4200
                                       6000
         3
               40.633171 17.634609
         4
               41.903221 12.495650
                                      5700
         1533 45.069679
                           7.704920
                                       5200
         1534 45.845692
                           8.666870
                                       4600
         1535 45.481541
                           9.413480
                                      7500
               45.000702
                           7.682270
                                       5990
         1536
         1537 40.323410 17.568270
                                       7900
         [1538 rows x 9 columns]>
In [31]: df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1538 entries, 0 to 1537
         Data columns (total 9 columns):
          #
              Column
                               Non-Null Count Dtype
          0
              #NAME?
                               1538 non-null
                                                int64
          1
              model
                               1538 non-null
                                                object
          2
                               1538 non-null
              engine power
                                                int64
                               1538 non-null
          3
                                                int64
              age_in_days
          4
              km
                               1538 non-null
                                                int64
              previous_owners 1538 non-null
          5
                                                int64
                               1538 non-null
          6
              lat
                                                float64
              lon
                               1538 non-null
                                                float64
              price
          8
                               1538 non-null
                                                int64
         dtypes: float64(2), int64(6), object(1)
         memory usage: 108.3+ KB
In [32]: df.isna().any()
Out[32]: #NAME?
                            False
         model
                            False
         engine_power
                            False
         age_in_days
                            False
         km
                            False
         previous_owners
                            False
         lat
                            False
         lon
                            False
         price
                            False
         dtype: bool
```

```
In [33]: sns.lmplot(x='km',y='price',data=df,order=2,ci=None)
         plt.show()
             10000
              8000
          price
              6000
              4000
                             50000
                                       100000
                                                 150000
                                                           200000
                      0
                                            km
In [34]: x=np.array(df['km']).reshape(-1,1)
         y=np.array(df['price']).reshape(-1,1)
In [35]: df.dropna(inplace=True)
In [36]: |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))
         0.7002560851710697
In [37]: y_pred=regr.predict(x_test)
         plt.scatter(x_test,y_test,color='b')
         plt.plot(x_test,y_pred,color='k')
         plt.show()
          10000
            8000
            6000
            4000
            2000
                              50000
                                          100000
                                                      150000
                                                                   200000
```

```
In [38]: df500=df[:][:500]
sns.lmplot(x="km",y="price",data=df500,order=1,ci=None)
plt.show()
```



```
In [39]: from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

```
In [40]: #train model
    model=LinearRegression()
    model.fit(x_train,y_train)
    #Evaluation the model on the test set
    y_pred=model.predict(x_test)
    r2=r2_score(y_test,y_pred)
    print("R2 score:",r2)
```

R2 score: 0.7002560851710697

```
In [41]: from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

```
In [42]: features=df.columns[0:1]
    target=df.columns[-1]
```

In [43]: converter={"model":{"sport":1,"lounge":2,"pop":3}}
df=df.replace(converter)
df

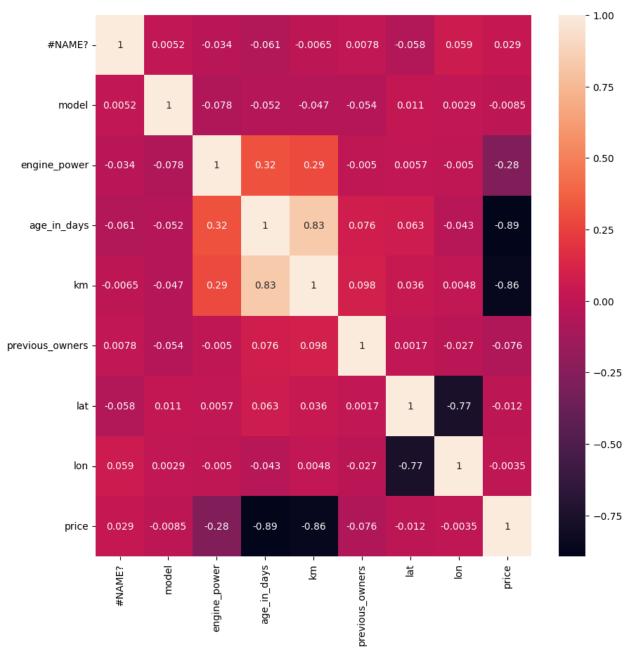
Out[43]:

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

1538 rows × 9 columns

```
In [46]: plt.figure(figsize = (10, 10))
sns.heatmap(df.corr(), annot = True)
```

Out[46]: <Axes: >



```
In [47]: #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=0.25, 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 (1153, 1)
The dimension of X_test is (385, 1)
```

```
In [48]: 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 0.00310286926477088
         The test score for 1r model is -0.008405634316406507
In [49]: #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 [50]: plt.figure(figsize=(10,10))
Out[50]: <Figure size 1000x1000 with 0 Axes>
         <Figure size 1000x1000 with 0 Axes>
In [52]: plt.plot(features, ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color='red',label=r'Ridge;$\alpha=10$
         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.show()
                                                 Ridge; \alpha = 10
                                                                  LinearRegression
           107.0
           106.8
           106.6
           106.4
           106.2
                                                 #NAME?
```

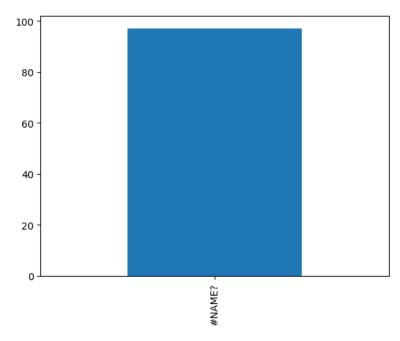
```
In [53]: #Lasso regression model
print("\nLasso Model: \n")
lasso = Lasso(alpha = 10)
lasso.fit(X_train,y_train)
train_score_ls =lasso.score(X_train,y_train)
test_score_ls =lasso.score(X_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model 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 [54]: pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar")
```

Out[54]: <Axes: >



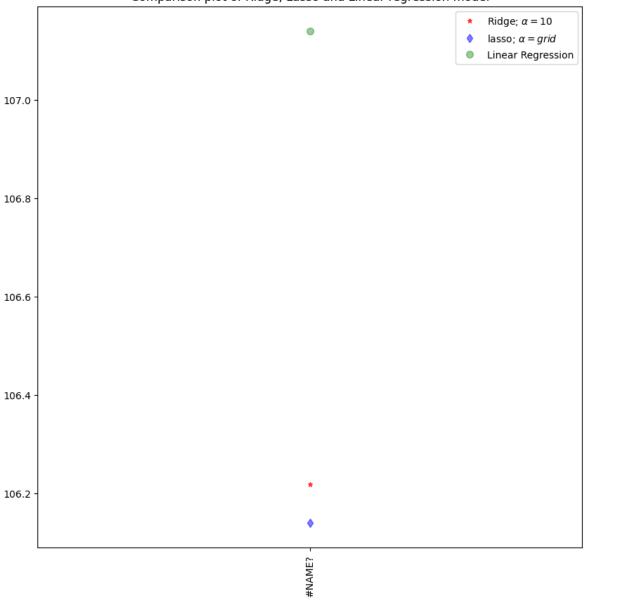
```
In [55]: #Using the Linear CV model
    from sklearn.linear_model import LassoCV
    #Lasso Cross validation
    lasso_cv = LassoCV(alphas = [0.0001, 0.001, 0.01, 1, 10], random_state=0).fit(X_train, y_train)
    #score
    print(lasso_cv.score(X_train, y_train))
    print(lasso_cv.score(X_test, y_test))
```

0.00310259895673648 -0.008299466692577973

```
In [56]: #plot size

plt.figure(figsize = (10, 10))
    #add plot for ridge regression
plt.plot(features, ridgeReg.coef_, alpha=0.7, linestyle='none', marker='*', markersize=5, color='red', label=r'Ridge; $\alpha=10!
    #add plot for Lasso regression
plt.plot(lasso_cv.coef_, alpha=0.5, linestyle='none', marker='d', markersize=6, color='blue', label=r'lasso; $\alpha= grid$')
    #add plot for Linear model
plt.plot(features, lr.coef_, alpha=0.4, linestyle='none', marker='o', markersize=7, color='green', label='Linear Regression')
    #rotate axis
plt.xticks(rotation = 90)
plt.legend()
plt.title("Comparison plot of Ridge, Lasso and Linear regression model")
plt.show()
```

Comparison plot of Ridge, Lasso and Linear regression model



```
In [57]: #Using the Linear CV model
from sklearn.linear_model import RidgeCV
#Ridge Cross validation
ridge_cv = RidgeCV(alphas = [0.0001, 0.001, 0.01, 1, 10]).fit(X_train, y_train)
#score
print("The train score for ridge model is {}".format(ridge_cv.score(X_train, y_train)))
print("The train score for ridge model is {}".format(ridge_cv.score(X_test, y_test)))
```

The train score for ridge model is 0.0031026398591535997 The train score for ridge model is -0.008307809466002958 In []: