```
In [1]: 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
```

Out[2]:

	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 [3]: df.head()

Out[3]:

	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	рор	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 [4]: df.tail()

Out[4]:

	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	pop	51	1766	54276	1	40.323410	17.56827	7900

In [5]: df.shape

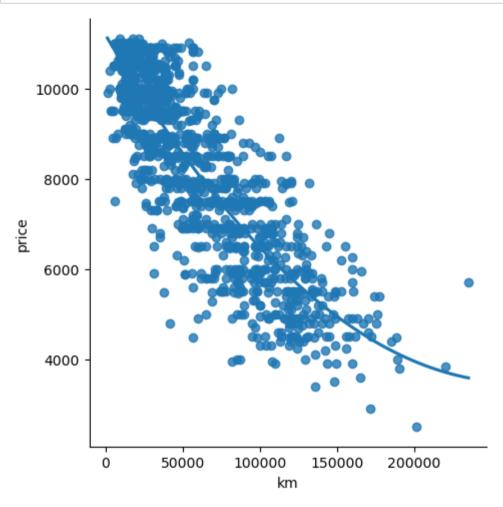
Out[5]: (1538, 9)

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

```
In [7]: df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1538 entries, 0 to 1537
        Data columns (total 9 columns):
             Column
                             Non-Null Count Dtype
                              _____
             ID
                             1538 non-null
                                             int64
                             1538 non-null
         1
             model
                                             obiect
                             1538 non-null
                                             int64
             engine power
                             1538 non-null
                                             int64
             age in days
         3
                             1538 non-null
                                             int64
             km
             previous owners 1538 non-null
                                             int64
                             1538 non-null
             lat
                                             float64
                                            float64
             lon
                             1538 non-null
             price
                             1538 non-null
                                            int64
        dtypes: float64(2), int64(6), object(1)
        memory usage: 108.3+ KB
In [8]: df.isna().any()
Out[8]: ID
                           False
                           False
        model
        engine power
                           False
                           False
        age_in_days
                           False
        previous_owners
                           False
        lat
                           False
        lon
                          False
        price
                          False
        dtype: bool
```

```
In [9]: df.isna().any()
Out[9]: ID
                          False
        model
                          False
        engine_power
                          False
                          False
        age_in_days
                          False
        km
                          False
        previous_owners
        lat
                          False
        lon
                          False
        price
                          False
        dtype: bool
```

```
In [10]: sns.lmplot(x='km',y='price',data=df,order=2,ci=None)
plt.show()
```



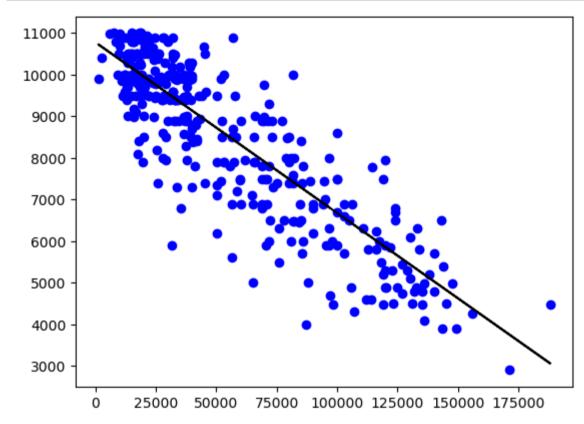
```
In [22]: x=np.array(df['km']).reshape(-1,1)
y=np.array(df['price']).reshape(-1,1)
```

```
In [23]: df.dropna(inplace=True)

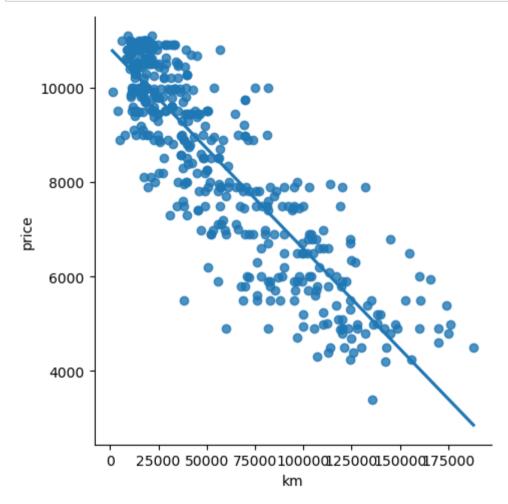
In [24]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
#splitting data into train and test
regr=LinearRegression()
regr.fit(x_train,y_train)
print(regr.score(x_test,y_test))
```

0.7703956212905387

```
In [25]: 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 [26]: df500=df[:][:500]
    sns.lmplot(x="km",y="price",data=df500,order=1,ci=None)
    plt.show()
```



In [27]: from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

```
In [28]: #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)
```

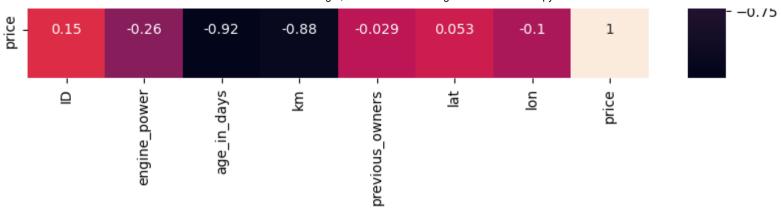
R2 score: 0.7703956212905387

Ridge and Lasso

```
In [29]: from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

```
In [30]: plt.figure(figsize = (10, 10))
    sns.heatmap(df500.corr(), annot = True)
    plt.show()
```





```
In [37]: features=df.columns[0:1]
target=df.columns[-1]
```

```
In [38]: #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 [39]: | lr = LinearRegression()
         #Fit model
         lr.fit(X_train, y_train)
         #predict
         #prediction = lr.predict(X test)
         #actual
         actual = v 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 [40]: #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 [41]: plt.figure(figsize=(10,10))
Out[41]: <Figure size 1000x1000 with 0 Axes>
```

```
In [42]: 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='LinearRegression')
    plt.xticks(rotation=90)
    plt.legend()
    plt.show()
```





```
In [43]: #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 1s model is 0.003075838461310987 The test score for 1s model is -0.007367578602064828

```
In [44]: pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar")
```

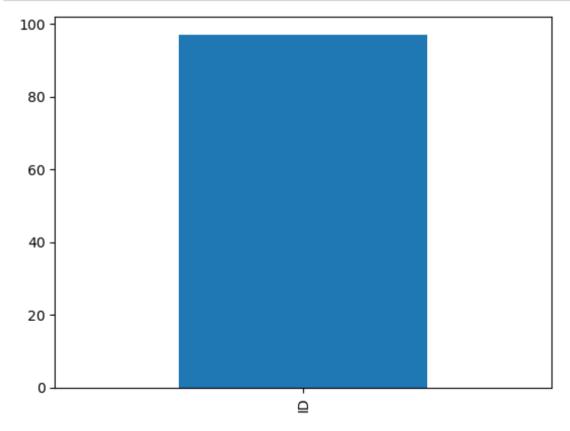
Out[44]: <AxesSubplot:>

```
In [45]: #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))
```

0.0031025989567363688

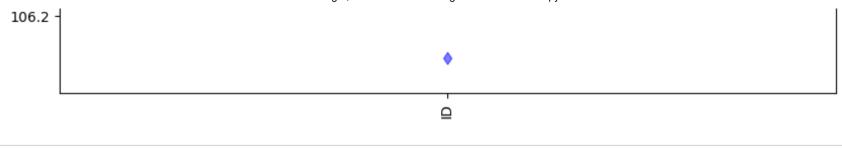
-0.008299466692577973

```
In [46]: #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 #add plot for Lasso regression
    plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso; $\alpha = grid$\frac{\pi}{\pidot} #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 [47]: #Using the Linear CV model
    from sklearn.linear_model import RidgeCV
    #Ridge Cross validation
    ridge_cv = RidgeCV(alphas = [0.0001, 0.001, 0.1, 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 -0.008307809466001403
```

Elastic

```
In [48]: from sklearn.linear_model import ElasticNet
    regr=ElasticNet()
    regr.fit(X,y)
    print(regr.coef_)
    print(regr.intercept_)
```

[0.12455754] 8480.156871173602

```
In [49]: y_pred_elastic=regr.predict(X_train)
```

```
In [50]: mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
    print(mean_squared_error)
```

3708273.194830543

In []: