# Fiat-Vehicle-Selection(LASSO-RIDGE)

# In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read_csv(r"C:\Users\prajapath Arjun\Downloads\fiat500_VehicleSelection_Dataset.csv")
print(df)
```

```
ID
                                      age in days
              model
                      engine power
                                                         km
                                                             previous owners
0
          1
             lounge
                                 51
                                               882
                                                      25000
                                                                             1
1
          2
                                 51
                                              1186
                                                     32500
                                                                             1
                pop
2
          3
              sport
                                 74
                                              4658
                                                    142228
                                                                             1
3
                                 51
                                                                             1
          4
             lounge
                                              2739
                                                    160000
4
          5
                pop
                                 73
                                              3074
                                                    106880
                                                                             1
                                               . . .
1533
      1534
              sport
                                 51
                                              3712
                                                    115280
                                                                             1
1534
      1535
             lounge
                                 74
                                              3835
                                                    112000
                                                                             1
                                                                             1
1535
      1536
                 pop
                                 51
                                              2223
                                                     60457
      1537
                                                     80750
                                                                             1
1536
             lounge
                                 51
                                              2557
      1538
                                 51
                                              1766
                                                     54276
                                                                             1
1537
                pop
             lat
                              price
                         lon
      44.907242
0
                    8.611560
                                8900
1
                                8800
```

```
45.666359
                  12.241890
2
      45.503300
                 11.417840
                               4200
3
      40.633171
                 17.634609
                               6000
4
      41.903221
                 12.495650
                               5700
                                . . .
. . .
             . . .
                         . . .
      45.069679
                   7.704920
                               5200
1533
1534
      45.845692
                   8.666870
                               4600
      45.481541
                   9.413480
                               7500
1535
                               5990
1536
      45.000702
                   7.682270
1537
      40.323410 17.568270
                               7900
```

[1538 rows x 9 columns]

#### In [2]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing,svm
```

#### In [3]:

```
df=df[['km','price']]
df.columns=['Km','Price']
```

# In [4]:

```
df.head(10)
```

# Out[4]:

	Km	Price
0	25000	8900
1	32500	8800
2	142228	4200
3	160000	6000
4	106880	5700
5	70225	7900
6	11600	10750
7	49076	9190
8	76000	5600
9	89000	6000

# In [5]:

```
df.tail()
```

# Out[5]:

	Km	Price
1533	115280	5200
1534	112000	4600
1535	60457	7500
1536	80750	5990
1537	54276	7900

# In [6]:

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1538 entries, 0 to 1537
Data columns (total 2 columns):
#
    Column Non-Null Count Dtype
    -----
---
0
    Κm
           1538 non-null
                          int64
    Price
           1538 non-null
                          int64
1
dtypes: int64(2)
memory usage: 24.2 KB
```

```
In [7]:
```

```
df.describe()
```

# Out[7]:

	Km	Price
count	1538.000000	1538.000000
mean	53396.011704	8576.003901
std	40046.830723	1939.958641
min	1232.000000	2500.000000
25%	20006.250000	7122.500000
50%	39031.000000	9000.000000
75%	79667.750000	10000.000000
max	235000.000000	11100.000000

# In [8]:

```
df.shape
```

# Out[8]:

(1538, 2)

# In [9]:

```
df.isnull().sum()
```

### Out[9]:

Km 0
Price 0
dtype: int64

# In [10]:

```
x=np.array(df['Km']).reshape(-1,1)
y=np.array(df['Price']).reshape(-1,1)
```

# In [11]:

```
df.dropna(inplace=True)
```

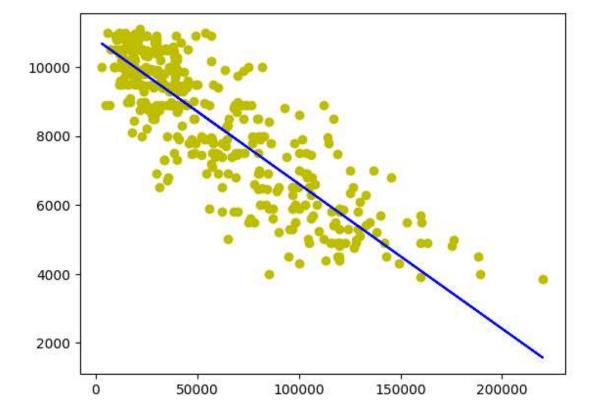
### In [12]:

```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
regr=LinearRegression()
regr.fit(X_train,y_train)
regr.fit(X_train,y_train)
print(regr.score(X_test,y_test))
```

### 0.7298610434355204

# In [13]:

```
y_pred=regr.predict(X_test)
plt.scatter(X_test,y_test,color='y')
plt.plot(X_test,y_pred,color='b')
plt.show()
```

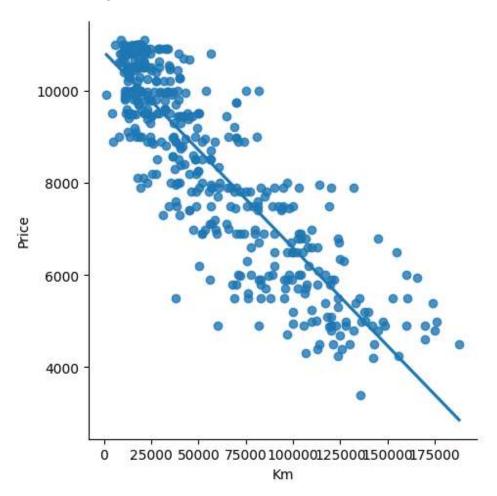


### In [14]:

```
udf=df[:][:500]
sns.lmplot(x="Km",y="Price",data=udf,order=1,ci=None)
```

# Out[14]:

<seaborn.axisgrid.FacetGrid at 0x233c9a08610>



### In [15]:

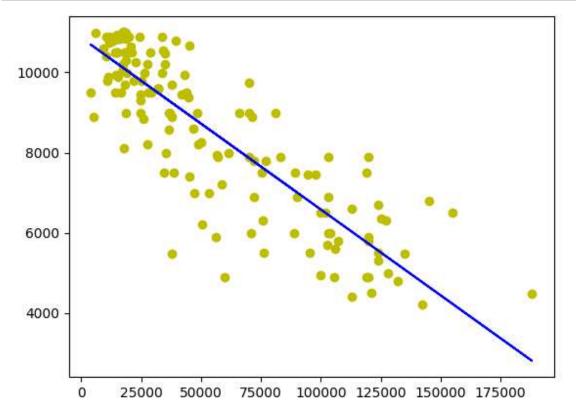
```
udf.fillna(method='ffill',inplace=True)
X=np.array(udf['Km']).reshape(-1,1)
y=np.array(udf['Price']).reshape(-1,1)
udf.dropna(inplace=True)
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3)
regr.fit(X_train,y_train)
```

### Out[15]:

```
LinearRegression
LinearRegression()
```

# In [16]:

```
y_pred=regr.predict(X_test)
plt.scatter(X_test,y_test,color='y')
plt.plot(X_test,y_pred,color='b')
plt.show()
```



# In [17]:

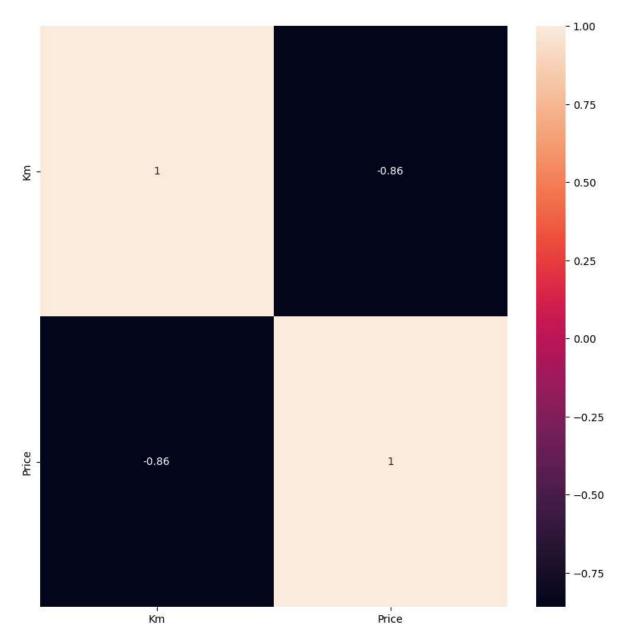
from sklearn.linear\_model import Ridge,Lasso,RidgeCV,LassoCV

# In [19]:

```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True)
```

# Out[19]:

# <Axes: >



#### In [20]:

```
from sklearn.preprocessing import StandardScaler
features=df.columns[0:2]
target=df.columns[-1]
X=df[features].values
y=df[target].values
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))
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 [21]:

```
#Linear regression model
regr=LinearRegression()
regr.fit(X_train,y_train)
actual=y_test #actual value
train_score_regr=regr.score(X_train,y_train)
test_score_regr=regr.score(X_test,y_test)
print("\nLinear model:\n")
print("The train score for Linear model is {}".format(train_score_regr))
print("The test score for Linear model is {}".format(test_score_regr))
```

### Linear model:

The train score for Linear model is 1.0 The test score for Linear model is 1.0

### In [22]:

```
#ridge regression model
ridgeReg=Ridge(alpha=10)
ridgeReg.fit(X_train,y_train)
#train and test score for 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 0.9997095924476732 The test score for ridge model is 0.9997198323998524

#### In [23]:

```
#using the linear cv model for ridge regression
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(ridge_cv.score(X_train,y_train))
print(ridge_cv.score(X_test,y_test))
```

- 0.99999999999668
- 0.9999999999968

### In [25]:

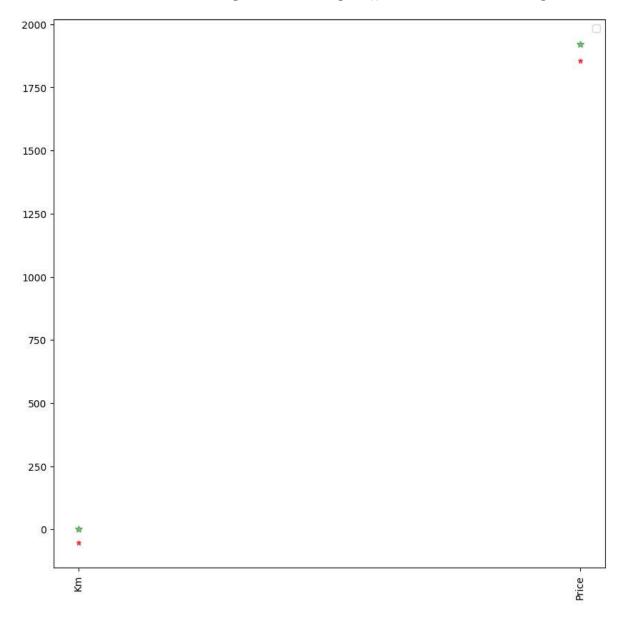
```
#using the linear cv model for lasso regression
from sklearn.linear_model import LassoCV
#lasso cross validation
lasso_cv=LassoCV(alphas=[0.0001,0.001,0.01,1,1,10],random_state=0).fit(X_train,y_train)
#score
print(lasso_cv.score(X_train,y_train))
print(lasso_cv.score(X_test,y_test))
```

- 0.9999999877496772
- 0.9999999874481674

### In [27]:

```
plt.figure(figsize=(10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='recolor:plt.plot(features,regr.coef_,alpha=0.5,linestyle='none',marker='*',markersize=7,color='green'
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

No artists with labels found to put in legend. Note that artists whose label s tart with an underscore are ignored when legend() is called with no argument.

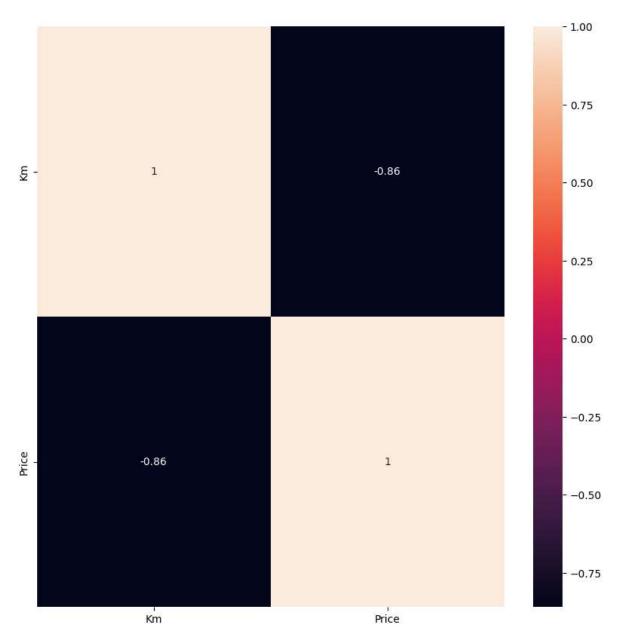


# In [28]:

```
#ridge regression
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True)
```

# Out[28]:

# <Axes: >



### In [29]:

```
#lasso regression model
lassoReg=Lasso(alpha=10)
lassoReg.fit(X_train,y_train)
#train and test score for ridge regression
train_score_lasso=lassoReg.score(X_train,y_train)
test_score_lasso=lassoReg.score(X_test,y_test)
print("\nLasso model:\n")
print("The train score for lasso model is {}".format(train_score_lasso))
print("The test score for lasso model is {}".format(test_score_lasso))
```

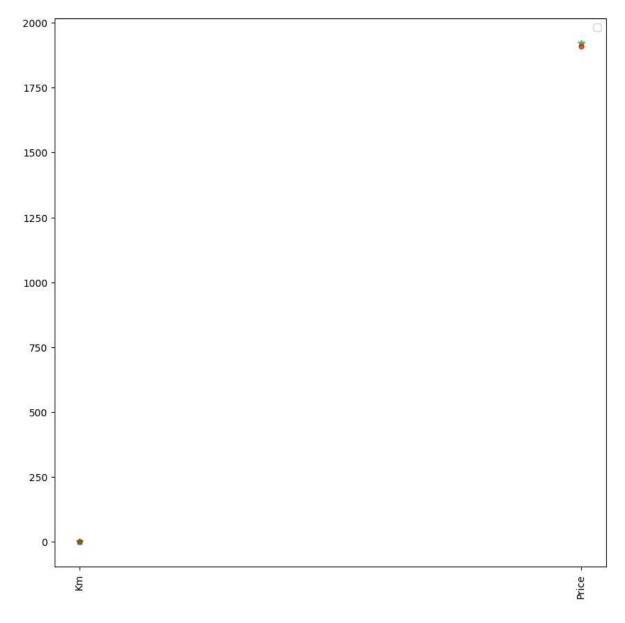
### Lasso model:

The train score for lasso model is 0.9999728562194999 The test score for lasso model is 0.9999728508562553

### In [30]:

```
plt.figure(figsize=(10,10))
plt.plot(features,lassoReg.coef_,alpha=0.7,linestyle='none',marker='o',markersize=5,color='recolor:plt.plot(features,regr.coef_,alpha=0.5,linestyle='none',marker='*',markersize=7,color='green'
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

No artists with labels found to put in legend. Note that artists whose label s tart with an underscore are ignored when legend() is called with no argument.

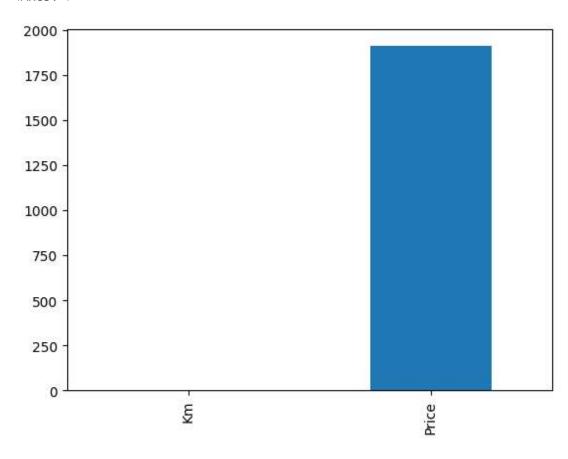


# In [31]:

pd.Series(lassoReg.coef\_,features).sort\_values(ascending=True).plot(kind="bar")

# Out[31]:

<Axes: >



#### In [32]:

```
#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
#add plot for lasso regression
plt.plot(features,lassoReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='ord
#add plot for linear model
plt.plot(features,regr.coef_,alpha=0.5,linestyle='none',marker='*',markersize=7,color='green'
#rotate axis
plt.xticks(rotation=90)
plt.legend()
plt.title("Comparison of Ridge,Lasso and Linear regression models")
plt.show()
```

No artists with labels found to put in legend. Note that artists whose label s tart with an underscore are ignored when legend() is called with no argument.

