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
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
df=pd.read_csv(r"C:\Users\DELL\Downloads\bottle1.csv")
df
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_7856\3734436603.py:1: DtypeWarnin
g: Columns (47,73) have mixed types. Specify dtype option on import or set lo
w_memory=False.
  df=pd.read_csv(r"C:\Users\DELL\Downloads\bottle1.csv")
```

Out[2]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sa
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.500	33.4400	NaN	25.64900	Na
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.460	33.4400	NaN	25.65600	Na
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	10.460	33.4370	NaN	25.65400	Na
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.450	33.4200	NaN	25.64300	Na
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	10.450	33.4210	NaN	25.64300	Na
...	...	...	...	...	...	...	...	...	...	.
864858	34404	864859	093.4 026.4	20-1611SR-MX-310-2239-09340264-0000A-7	0	18.744	33.4083	5.805	23.87055	108.7
864859	34404	864860	093.4 026.4	20-1611SR-MX-310-2239-09340264-0002A-3	2	18.744	33.4083	5.805	23.87072	108.7
864860	34404	864861	093.4 026.4	20-1611SR-MX-310-2239-09340264-0005A-3	5	18.692	33.4150	5.796	23.88911	108.4
864861	34404	864862	093.4 026.4	20-1611SR-MX-310-2239-09340264-0010A-3	10	18.161	33.4062	5.816	24.01426	107.7

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sa
864862	34404	864863	093.4 026.4	20-1611SR-MX-310-2239-09340264-0015A-3	15	17.533	33.3880	5.774	24.15297	105.6

864863 rows × 74 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 864863 entries, 0 to 864862
Data columns (total 74 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   Cst_Cnt              864863 non-null  int64  
 1   Btl_Cnt              864863 non-null  int64  
 2   Sta_ID               864863 non-null  object 
 3   Depth_ID             864863 non-null  object 
 4   Depthm               864863 non-null  int64  
 5   T_degC               853900 non-null  float64
 6   Salnty               817509 non-null  float64
 7   O2ml_L               696201 non-null  float64
 8   STheta               812174 non-null  float64
 9   O2Sat                661274 non-null  float64
 10  Oxy_µmol/Kg          661268 non-null  float64
 11  BtlNum               118667 non-null  float64
 12  RecInd               864863 non-null  int64  
 13  T_prec               853900 non-null  float64
 14  T_qual               23127 non-null   float64
 15  S_prec               817509 non-null  float64
 16  S_qual               74914 non-null   float64
 17  P_qual               673755 non-null  float64
 18  O_qual               184676 non-null  float64
 19  SThtaq               65823 non-null   float64
 20  O2Satq               217797 non-null  float64
 21  ChlorA               225272 non-null  float64
 22  Chlqua               639166 non-null  float64
 23  Phaeop               225271 non-null  float64
 24  Phaqua               639170 non-null  float64
 25  PO4uM                413317 non-null  float64
 26  PO4q                 451786 non-null  float64
 27  SiO3uM               354091 non-null  float64
 28  SiO3qu               510866 non-null  float64
 29  NO2uM                337576 non-null  float64
 30  NO2q                 529474 non-null  float64
 31  NO3uM                337403 non-null  float64
 32  NO3q                 529933 non-null  float64
 33  NH3uM                64962 non-null   float64
 34  NH3q                 808299 non-null  float64
 35  C14As1               14432 non-null   float64
 36  C14A1p               12760 non-null   float64
 37  C14A1q               848605 non-null  float64
 38  C14As2               14414 non-null   float64
 39  C14A2p               12742 non-null   float64
 40  C14A2q               848623 non-null  float64
 41  DarkAs               22649 non-null   float64
 42  DarkAp               20457 non-null   float64
 43  DarkAq               840440 non-null  float64
 44  MeanAs               22650 non-null   float64
 45  MeanAp               20457 non-null   float64
 46  MeanAq               840439 non-null  float64
 47  IncTim               14437 non-null   object 
 48  LightP               18651 non-null   float64
 49  R_Depth              864863 non-null  int64  
 50  R_TEMP               853900 non-null  float64
 51  R_POTEMP             818816 non-null  float64
```

```
 52  R_SALINITY            817509 non-null  float64
 53  R_SIGMA               812007 non-null  float64
 54  R_SVA                 812092 non-null  float64
 55  R_DYNHT               818206 non-null  float64
 56  R_O2                  696201 non-null  float64
 57  R_O2Sat               666448 non-null  float64
 58  R_SIO3                354099 non-null  float64
 59  R_PO4                 413325 non-null  float64
 60  R_NO3                 337411 non-null  float64
 61  R_NO2                 337584 non-null  float64
 62  R_NH4                 64982 non-null   float64
 63  R_CHLA                225276 non-null  float64
 64  R_PHAEO               225275 non-null  float64
 65  R_PRES                864863 non-null  int64
 66  R_SAMP                122006 non-null  float64
 67  DIC1                  1999 non-null    float64
 68  DIC2                  224 non-null     float64
 69  TA1                   2084 non-null    float64
 70  TA2                   234 non-null     float64
 71  pH2                   10 non-null      float64
 72  pH1                   84 non-null      float64
 73  DIC Quality Comment   55 non-null      object
dtypes: float64(64), int64(6), object(4)
memory usage: 488.3+ MB
```

In [3]:
```
df.describe()
```

Out[3]:

	Cst_Cnt	Btl_Cnt	Depthm	T_degC	Salnty	O2ml_
count	864863.000000	864863.000000	864863.000000	853900.000000	817509.000000	696201.00000
mean	17138.790958	432432.000000	226.831951	10.799677	33.840350	3.39246
std	10240.949817	249664.587269	316.050259	4.243825	0.461843	2.07325
min	1.000000	1.000000	0.000000	1.440000	28.431000	-0.01000
25%	8269.000000	216216.500000	46.000000	7.680000	33.488000	1.36000
50%	16848.000000	432432.000000	125.000000	10.060000	33.863000	3.44000
75%	26557.000000	648647.500000	300.000000	13.880000	34.196900	5.50000
max	34404.000000	864863.000000	5351.000000	31.140000	37.034000	11.13000

8 rows × 70 columns

In [4]:
```
df.isna().any()
```

Out[4]:
```
Cst_Cnt                False
Btl_Cnt                False
Sta_ID                 False
Depth_ID               False
Depthm                 False
                       ...
TA1                     True
TA2                     True
pH2                     True
pH1                     True
DIC Quality Comment     True
Length: 74, dtype: bool
```

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
Cst_Cnt                    0
Btl_Cnt                    0
Sta_ID                     0
Depth_ID                   0
Depthm                     0
                         ...
TA1                   862779
TA2                   864629
pH2                   864853
pH1                   864779
DIC Quality Comment   864808
Length: 74, dtype: int64
```

In [6]:
```
df=df[['Salnty','T_degC']]
df.columns=['Sal','Temp']
```

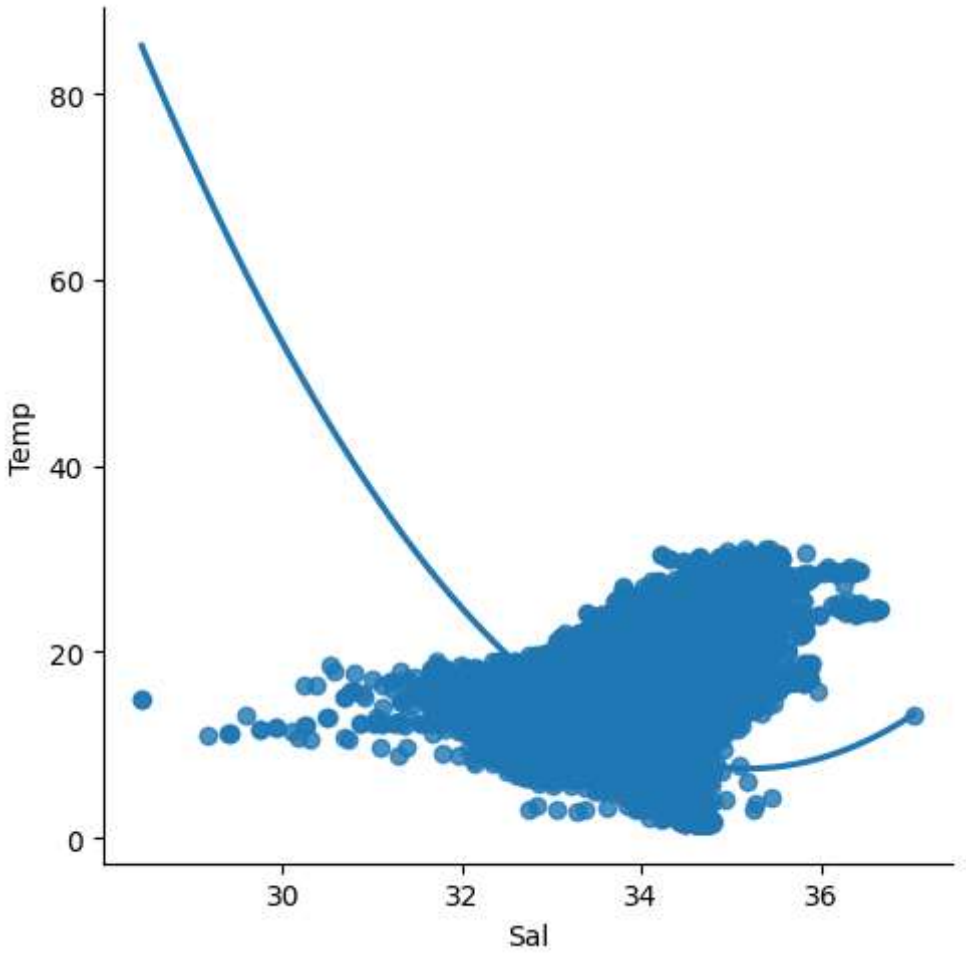
In [7]:
```
df.head(20)
```

Out[7]:

	Sal	Temp
0	33.440	10.50
1	33.440	10.46
2	33.437	10.46
3	33.420	10.45
4	33.421	10.45
5	33.431	10.45
6	33.440	10.45
7	33.424	10.24
8	33.420	10.06
9	33.494	9.86
10	33.510	9.83
11	33.580	9.67
12	33.640	9.50
13	33.689	9.32
14	33.847	8.76
15	33.860	8.71
16	33.876	8.53
17	NaN	8.45
18	33.926	8.26
19	33.980	7.96

In [8]:
```
sns.lmplot(x='Sal',y='Temp',data=df,order=2,ci=None)
```

Out[8]:
```
<seaborn.axisgrid.FacetGrid at 0x1aff6ac7550>
```



In [9]:
```
df.fillna(method='ffill')
```

Out[9]:

	Sal	Temp
0	33.4400	10.500
1	33.4400	10.460
2	33.4370	10.460
3	33.4200	10.450
4	33.4210	10.450
...	...	...
864858	33.4083	18.744
864859	33.4083	18.744
864860	33.4150	18.692
864861	33.4062	18.161
864862	33.3880	17.533

864863 rows × 2 columns

In [10]:
```
df.fillna(value=0,inplace=True)
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_7856\1434098079.py:1: SettingWithC
opyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  df.fillna(value=0,inplace=True)
```

In [11]:
```
x=np.array(df['Sal']).reshape(-1,1)
y=np.array(df['Temp']).reshape(-1,1)
```

In [12]:
```
df.dropna(inplace=True)
```

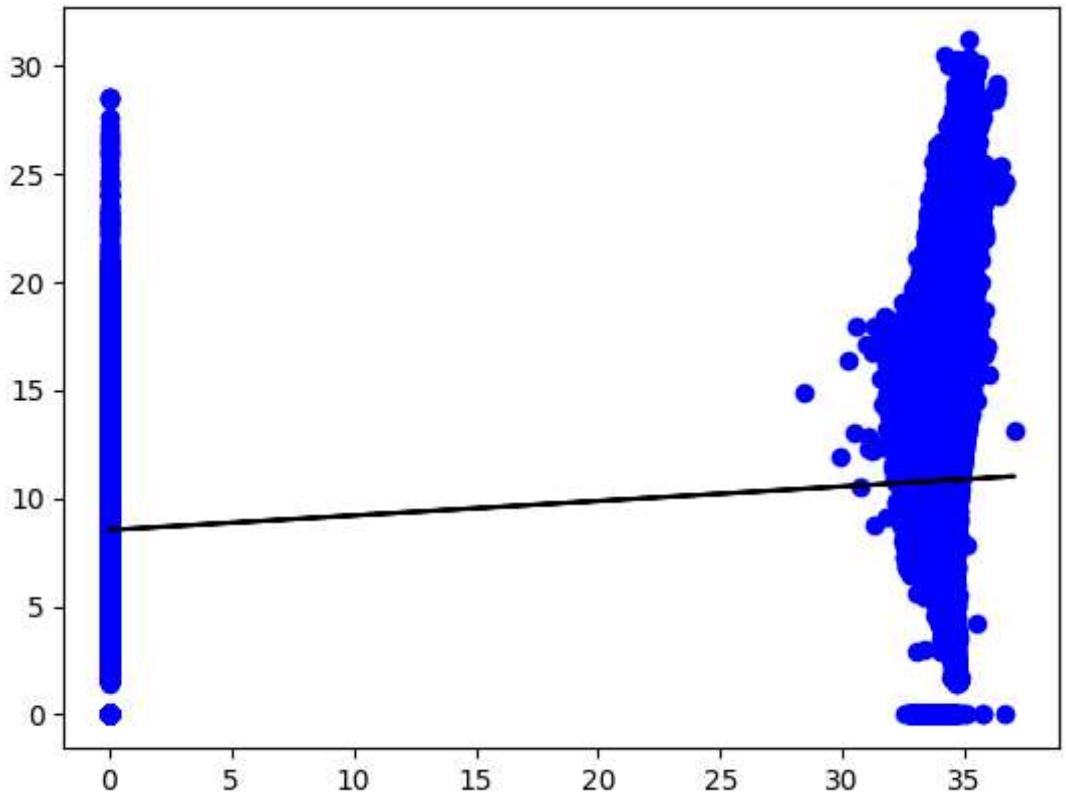
```
C:\Users\DELL\AppData\Local\Temp\ipykernel_7856\1379821321.py:1: SettingWithC
opyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  df.dropna(inplace=True)
```

In [13]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

In [14]:
```
regr=LinearRegression()
regr.fit(x_train,y_train)
print(regr.score(x_test,y_test))
```

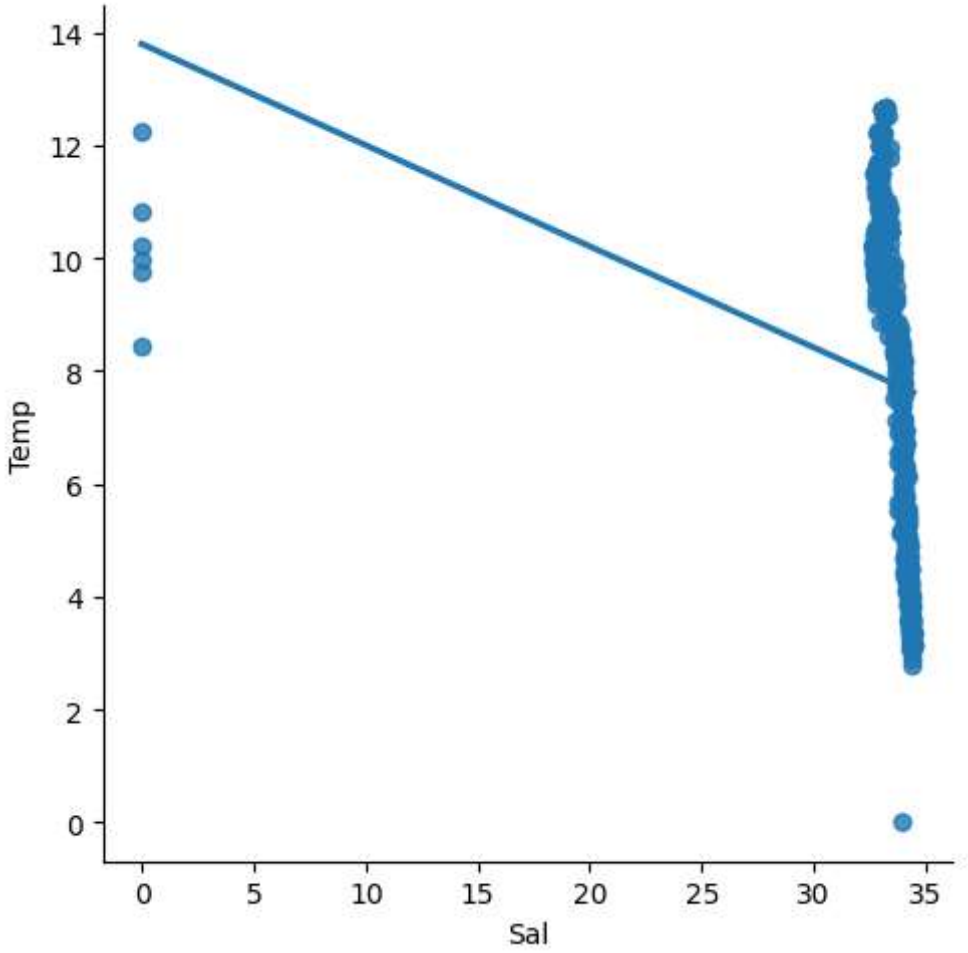
```
0.01496724141753003
```

In [15]:
```
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



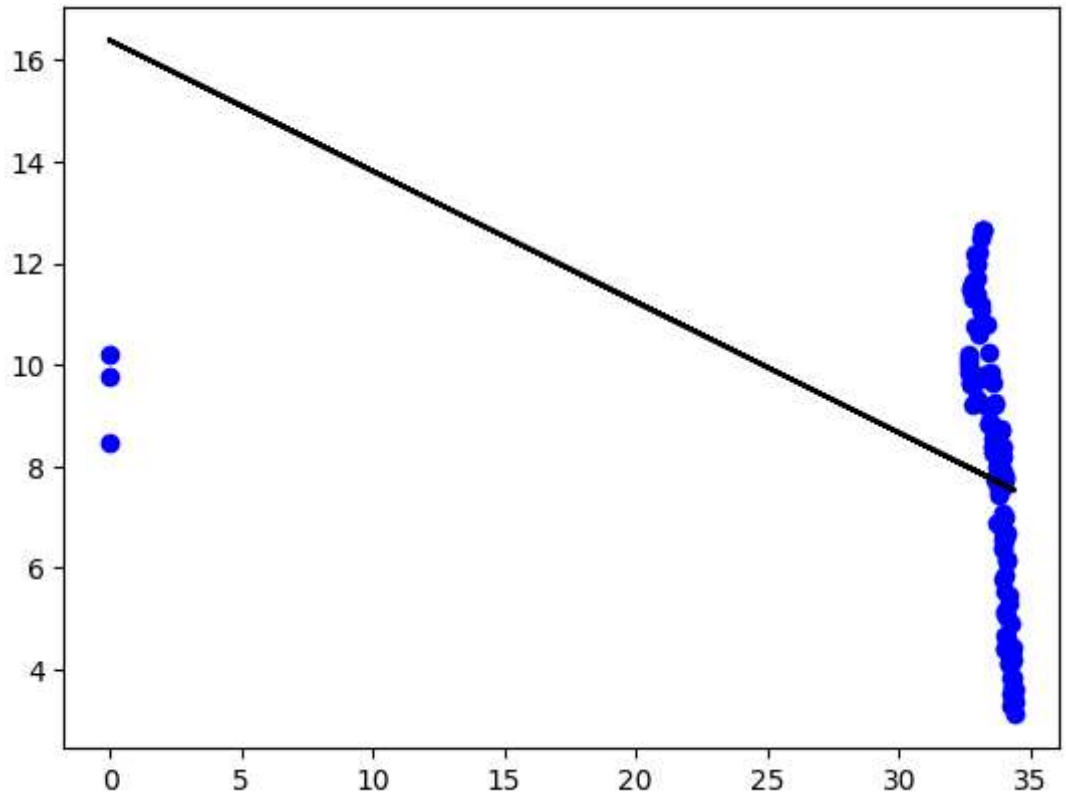
In [16]:
```
df500=df[:][:500]
sns.lmplot(x='Sal',y='Temp',data=df500,order=1,ci=None)
```

Out[16]: <seaborn.axisgrid.FacetGrid at 0x1af8b25e010>



In [17]:
```
df500.fillna(method='ffill',inplace=True)
x=np.array(df500['Sal']).reshape(-1,1)
y=np.array(df500['Temp']).reshape(-1,1)
df500.dropna(inplace=True)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
regr=LinearRegression()
regr.fit(x_train,y_train)
print("Regression:",regr.score(x_test,y_test))
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```

```
Regression: -0.057733985937520105
```



In [18]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
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)
```

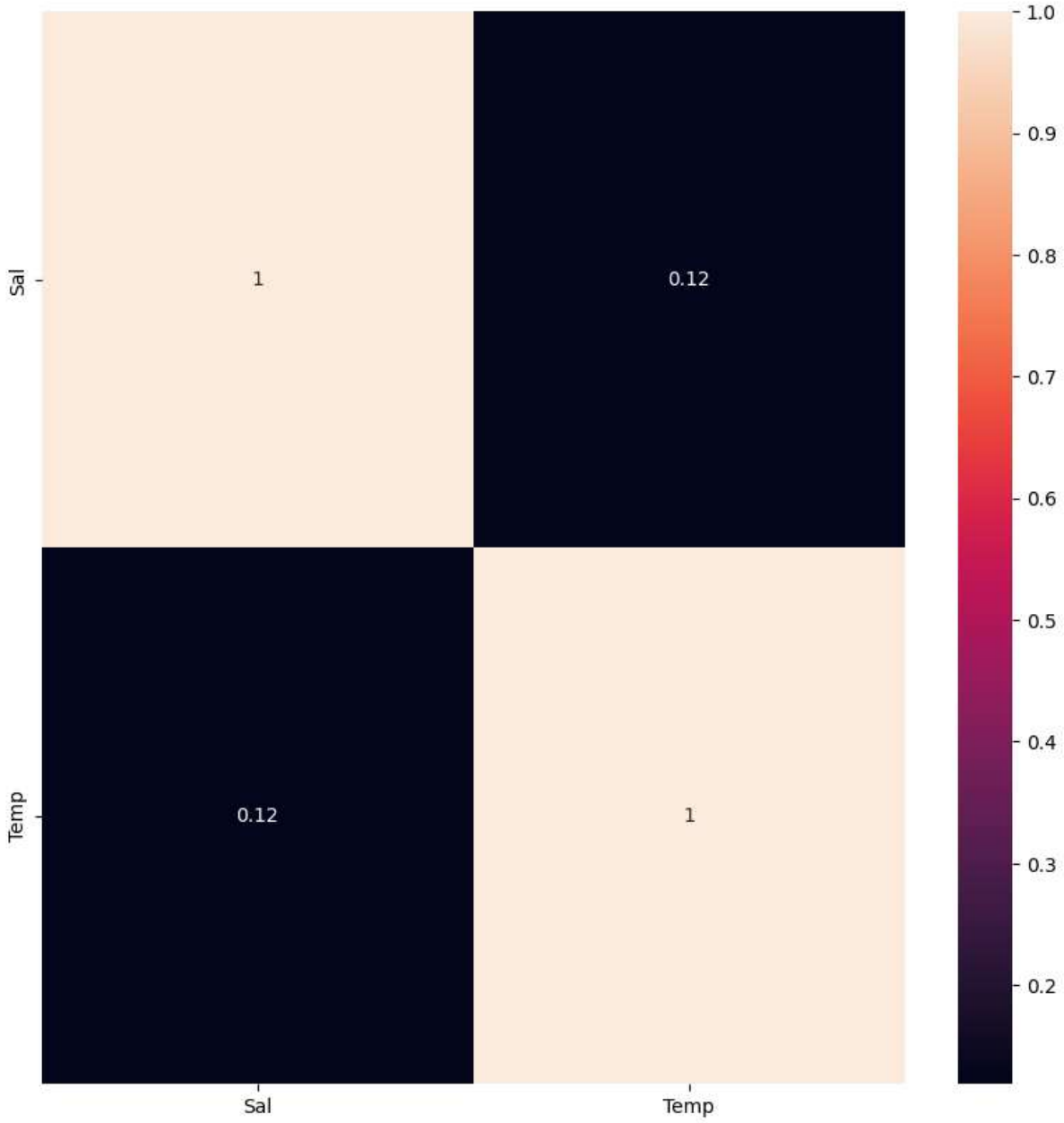
```
R2 score: -0.057733985937520105
```

In [19]:
```
#conclusion: Linear regression is not fit for the model
```

Ridge and lasso

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

Out[20]: <Axes: >



In [21]:
```
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
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 (605404, 2)
The dimension of X_test is (259459, 2)
```

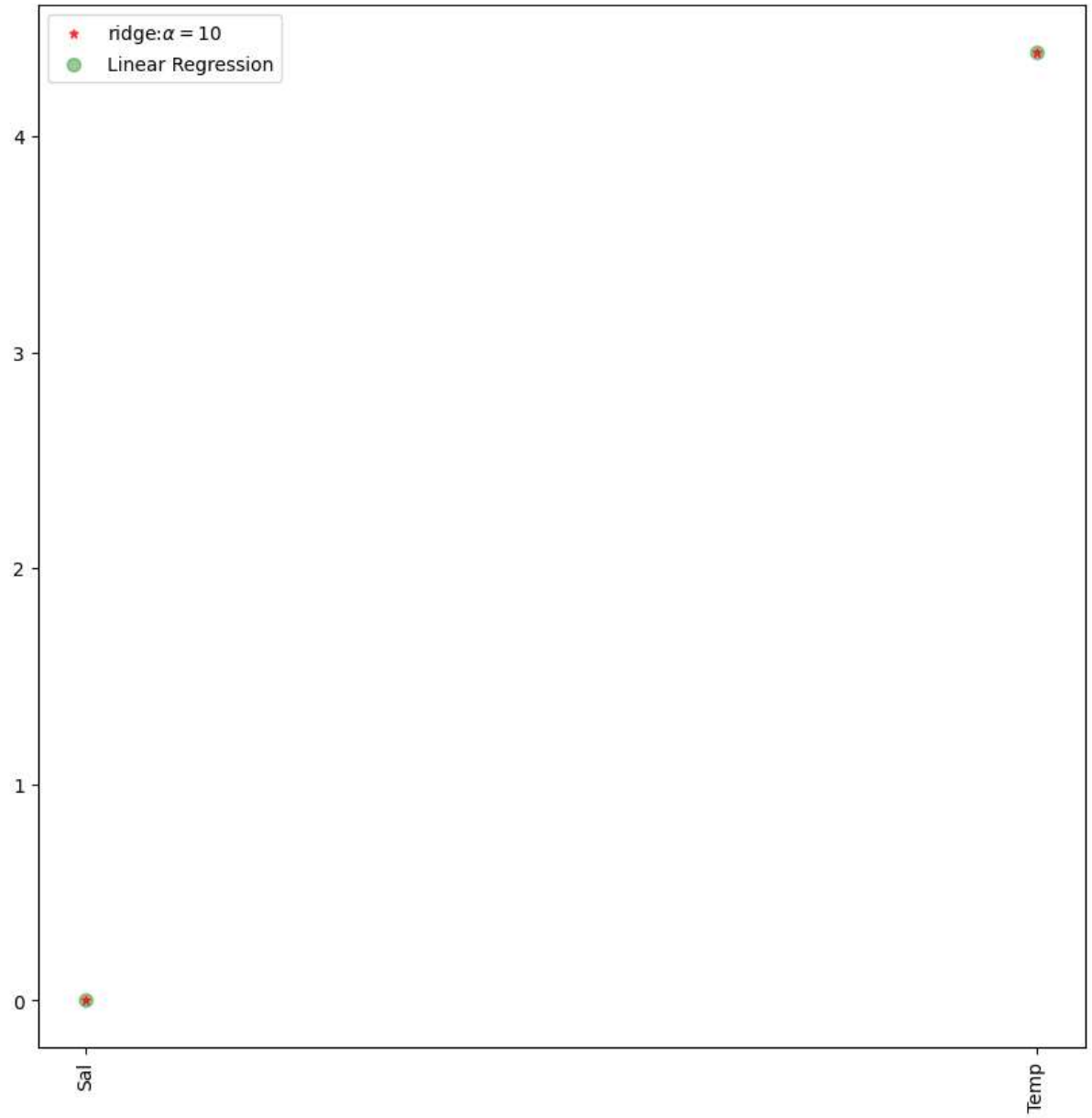
In [22]:
```
lr = LinearRegression()
#Fit model
lr.fit(X_train, y_train)
#predict
#prediction = lr.predict(X_test)
#actual
actual = y_test
train_score_lr = lr.score(X_train, y_train)
test_score_lr = lr.score(X_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model is {}".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 1.0
The test score for lr model is 1.0
```

In [23]:
```
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 0.999999999723243
The test score for ridge model is 0.9999999997231402
```

In [24]:
```
plt.figure(figsize=(10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

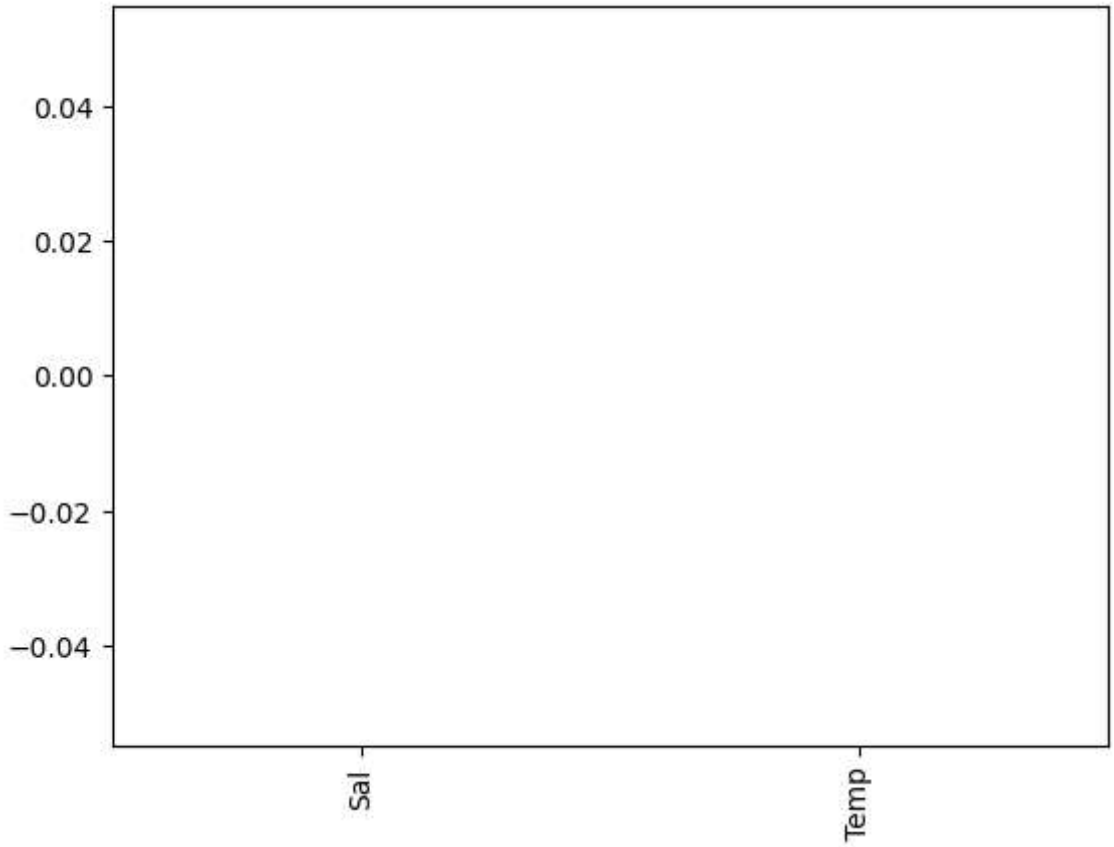


In [25]:
```
#Lasso regression model
print("\nLasso Model: \n")
lasso = Lasso(alpha = 10)
lasso.fit(X_train,y_train)
train_score_ls =lasso.score(X_train,y_train)
test_score_ls =lasso.score(X_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for ls model is 0.0
The test score for ls model is -1.9031696447013857e-05
```

In [26]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar
```

Out[26]:
```
<Axes: >
```



In [27]:
```
from sklearn.linear_model import LassoCV
#Lasso Cross validation
lasso_cv = LassoCV(alphas = [0.0001, 0.001,0.01, 0.1, 1, 10], random_state=0).f
#score
print(lasso_cv.score(X_train, y_train))
print(lasso_cv.score(X_test, y_test))
```

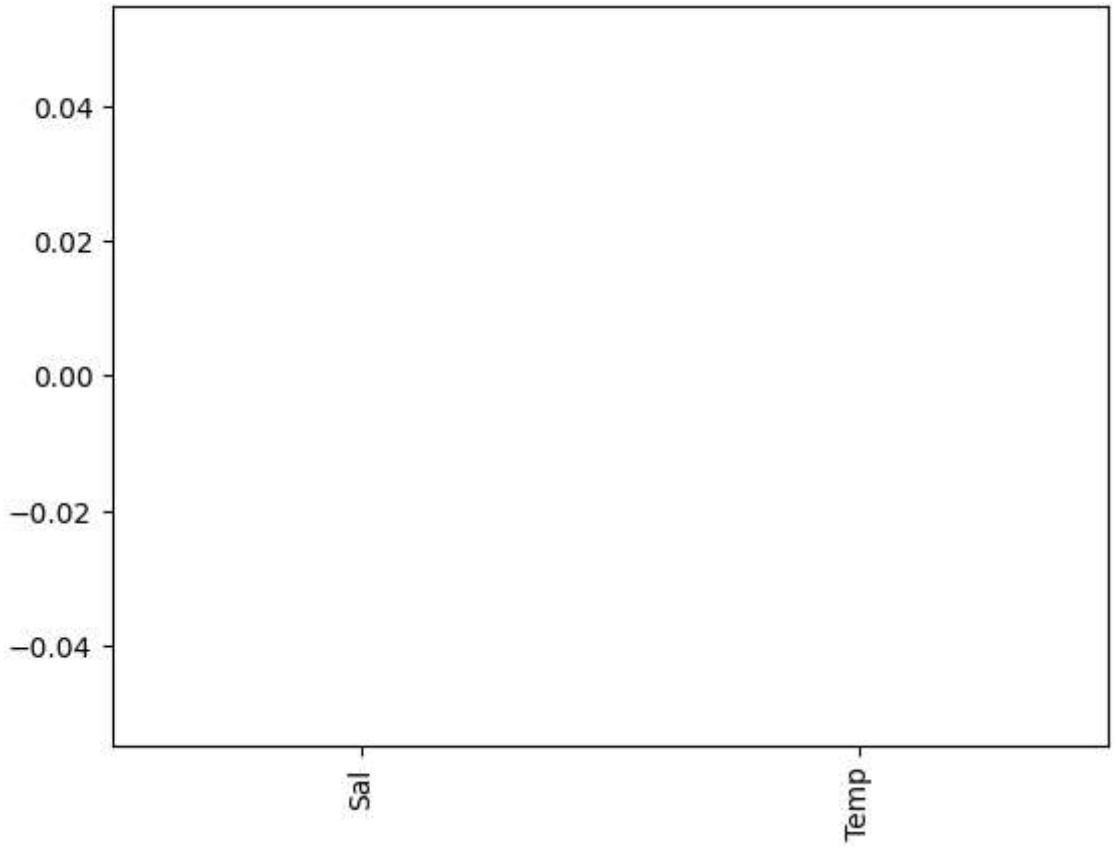
```
0.9999999994806811
0.9999999994806712
```

In [28]:
```
#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 0.0
The test score for ls model is -1.9031696447013857e-05
```

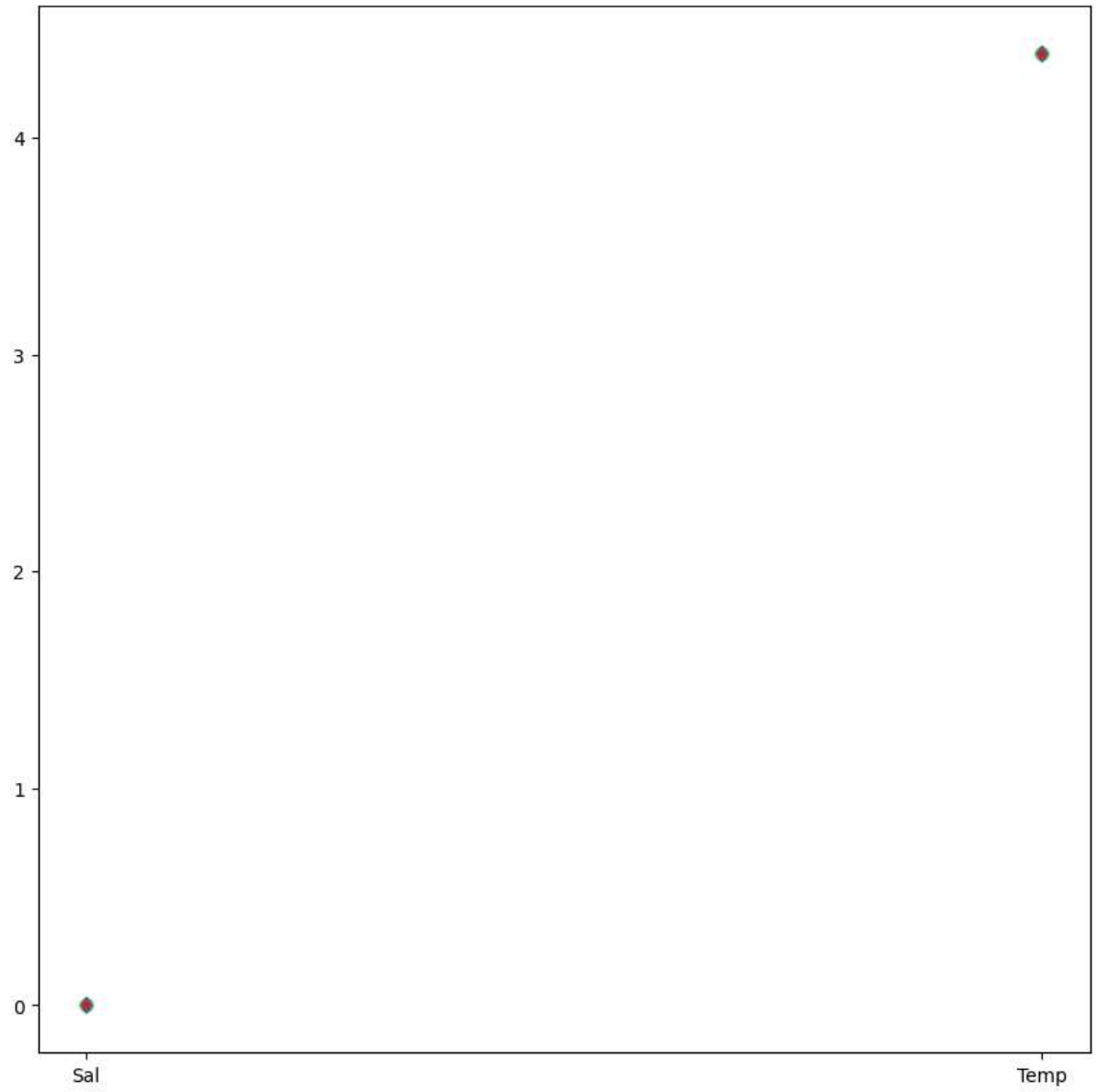
In [29]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar
```

Out[29]:
```
<Axes: >
```



In [30]:
```
#plot size
plt.figure(figsize = (10, 10))
#add plot for ridge regression
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
#add plot for lasso regression
plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,colo
#add plot for linear model
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
```

Out[30]:
```
[<matplotlib.lines.Line2D at 0x1af8fc93990>]
```



dataset-2

In [31]:
```
#vehicles dataset
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
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.preprocessing import StandardScaler



d=pd.read_csv(r"C:\Users\DELL\Downloads\fiat500_VehicleSelection_Dataset1.excel
d
```

Out[31]:

	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 [32]:
```
d.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1538 entries, 0 to 1537
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ID               1538 non-null   int64  
 1   model            1538 non-null   object 
 2   engine_power     1538 non-null   int64  
 3   age_in_days      1538 non-null   int64  
 4   km               1538 non-null   int64  
 5   previous_owners  1538 non-null   int64  
 6   lat              1538 non-null   float64
 7   lon              1538 non-null   float64
 8   price            1538 non-null   int64  
dtypes: float64(2), int64(6), object(1)
memory usage: 108.3+ KB
```

In [33]:
```
d.describe()
```

Out[33]:

	ID	engine_power	age_in_days	km	previous_owners	lat	
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1
mean	769.500000	51.904421	1650.980494	53396.011704	1.123537	43.541361	
std	444.126671	3.988023	1289.522278	40046.830723	0.416423	2.133518	
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.855839	
25%	385.250000	51.000000	670.000000	20006.250000	1.000000	41.802990	
50%	769.500000	51.000000	1035.000000	39031.000000	1.000000	44.394096	
75%	1153.750000	51.000000	2616.000000	79667.750000	1.000000	45.467960	
max	1538.000000	77.000000	4658.000000	235000.000000	4.000000	46.795612	

In [34]:
```
d.isna().any()
```

Out[34]:
```
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 [35]:
```
d.isnull().sum()
```

Out[35]:
```
ID                0
model             0
engine_power      0
age_in_days       0
km                0
previous_owners   0
lat               0
lon               0
price             0
dtype: int64
```

In [36]:
```
d.isnull()
```

Out[36]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
1533	False	False	False	False	False	False	False	False	False
1534	False	False	False	False	False	False	False	False	False
1535	False	False	False	False	False	False	False	False	False
1536	False	False	False	False	False	False	False	False	False
1537	False	False	False	False	False	False	False	False	False

1538 rows × 9 columns

In [37]:
```
d.loc[:10,["ID","price"]]
```

Out[37]:

	ID	price
0	1	8900
1	2	8800
2	3	4200
3	4	6000
4	5	5700
5	6	7900
6	7	10750
7	8	9190
8	9	5600
9	10	6000
10	11	8950

In [38]:
```
d=d[["engine_power","price"]]
d.columns=["engine","price"]
```

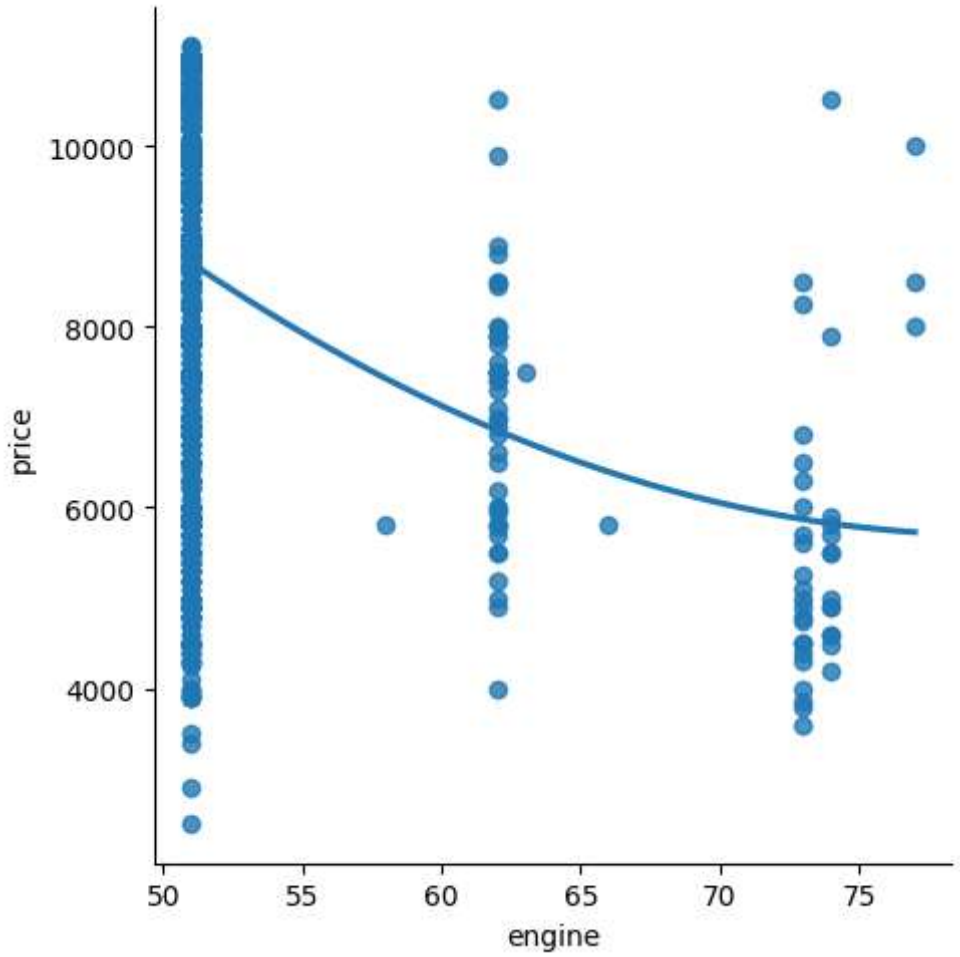
In [39]:
```
d.head(10)
```

Out[39]:

	engine	price
0	51	8900
1	51	8800
2	74	4200
3	51	6000
4	73	5700
5	74	7900
6	51	10750
7	51	9190
8	73	5600
9	51	6000

In [41]:
```
sns.lmplot(x='engine',y='price',data=d,order=2,ci=None)
```

Out[41]:
```
<seaborn.axisgrid.FacetGrid at 0x1af93903d90>
```



In [42]:
```
d.fillna(method='ffill')
```

Out[42]:

	engine	price
0	51	8900
1	51	8800
2	74	4200
3	51	6000
4	73	5700
...	...	...
1533	51	5200
1534	74	4600
1535	51	7500
1536	51	5990
1537	51	7900

1538 rows × 2 columns

In [43]:
```
x=np.array(d['engine']).reshape(-1,1)
y=np.array(d['price']).reshape(-1,1)
```

In [44]:
```
d.dropna(inplace=True)
```

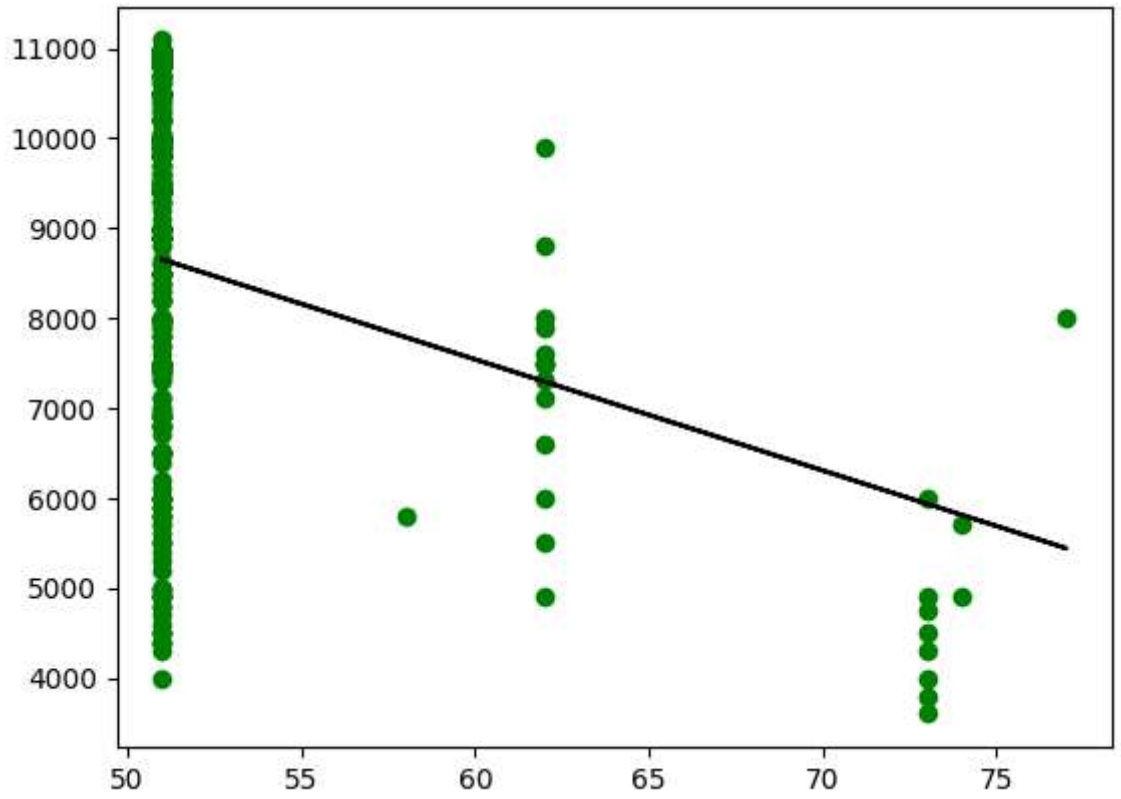
```
C:\Users\DELL\AppData\Local\Temp\ipykernel_7856\1307611603.py:1: SettingWithC
opyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  d.dropna(inplace=True)
```

In [45]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

In [46]:
```
regr=LinearRegression()
regr.fit(x_train,y_train)
print(regr.score(x_test,y_test))
```

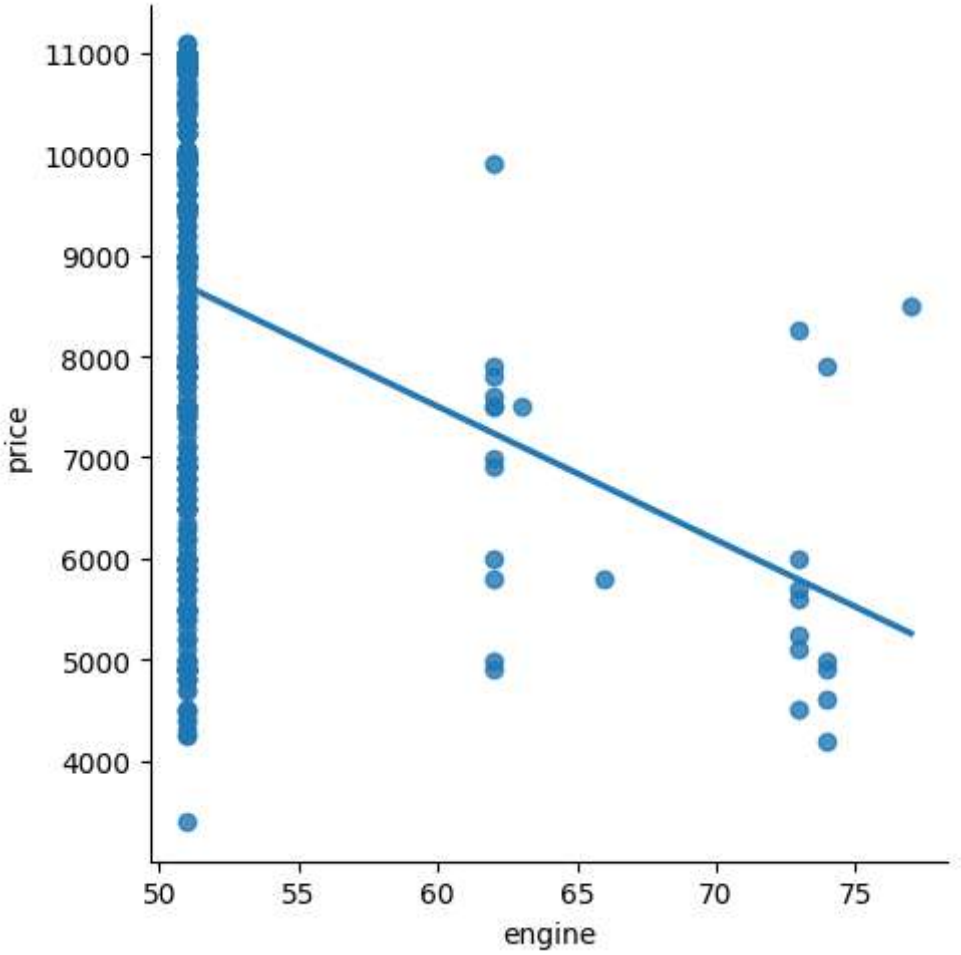
```
0.12099803064802517
```

In [47]:
```
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='g')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



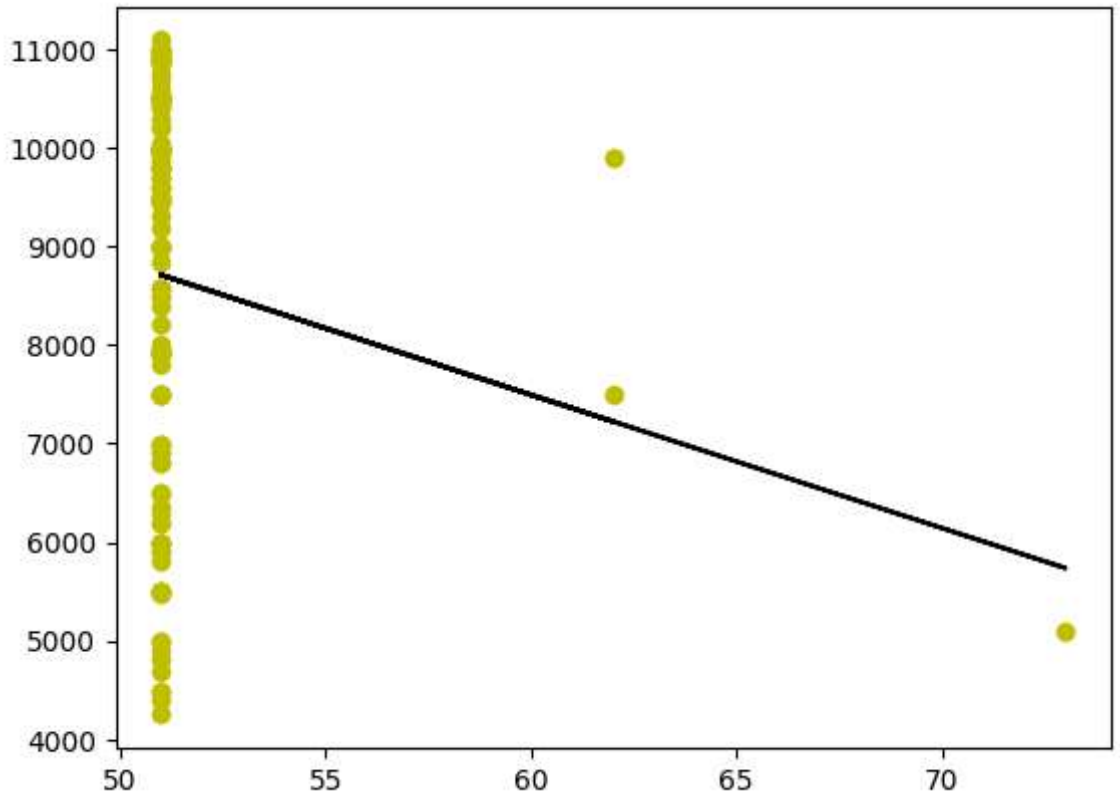
In [48]:
```
d500=d[:][:500]
sns.lmplot(x='engine',y='price',data=d500,order=1,ci=None)
```

Out[48]: <seaborn.axisgrid.FacetGrid at 0x1af8fc83ed0>



In [49]:
```
d500.fillna(method='ffill',inplace=True)
x=np.array(d500['engine']).reshape(-1,1)
y=np.array(d500['price']).reshape(-1,1)
d500.dropna(inplace=True)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
regr=LinearRegression()
regr.fit(x_train,y_train)
print("Regression:",regr.score(x_test,y_test))
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='y')
plt.plot(x_test,y_pred,color='k')
plt.show()
```

```
Regression: 0.013442580179974017
```



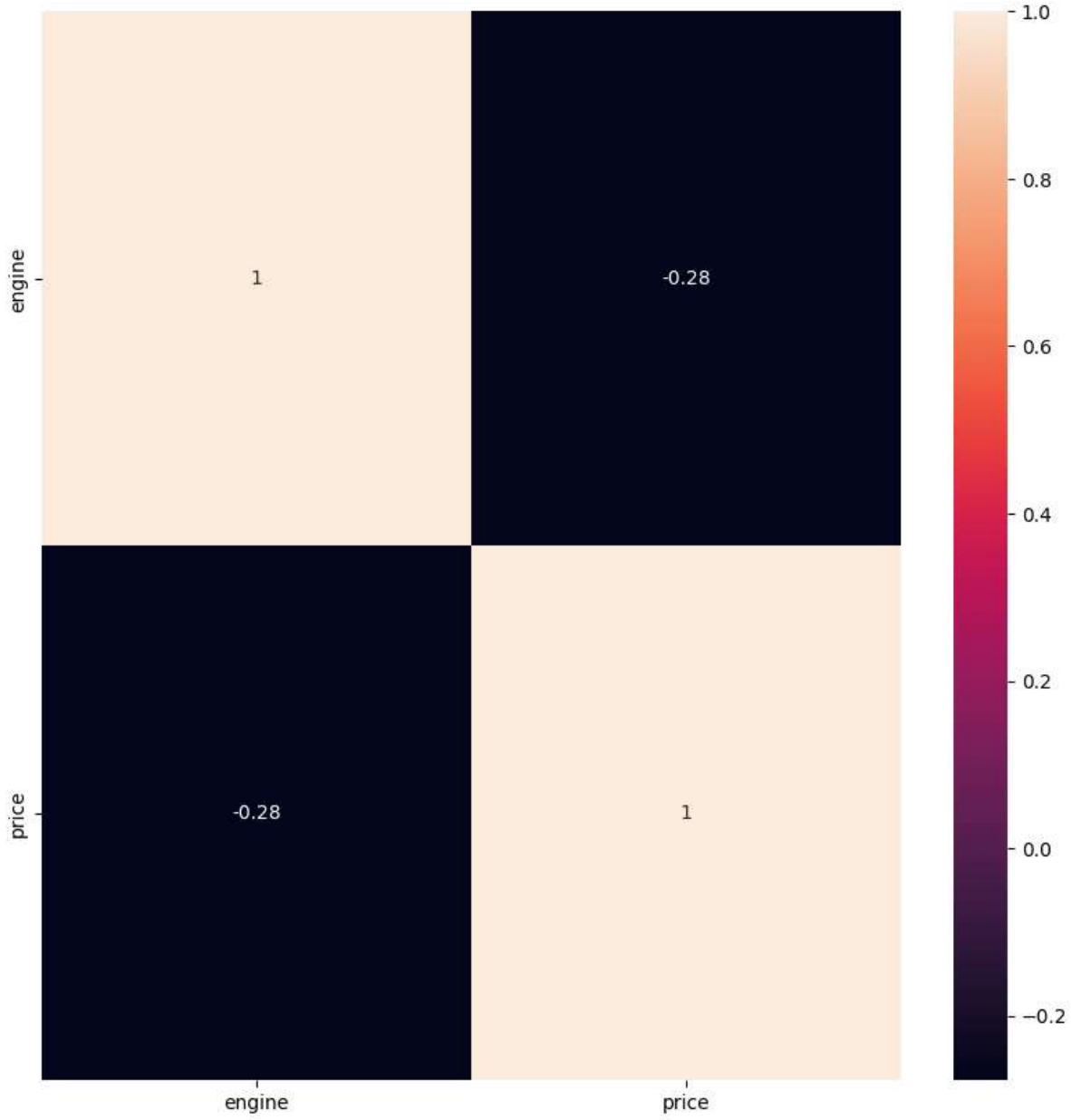
In [50]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
model=LinearRegression()
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
r2=r2_score(y_test,y_pred)
print("R2 score:",r2)
```

```
R2 score: 0.013442580179974017
```

Ridge regresssion and lasso

In [52]:
```
plt.figure(figsize = (10, 10))
sns.heatmap(d.corr(), annot = True)
```

Out[52]: <Axes: >



In [53]:
```
features = d.columns[0:2]
target = d.columns[-1]
#X and y values
X = d[features].values
y = d[target].values
#splot
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random
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)
```

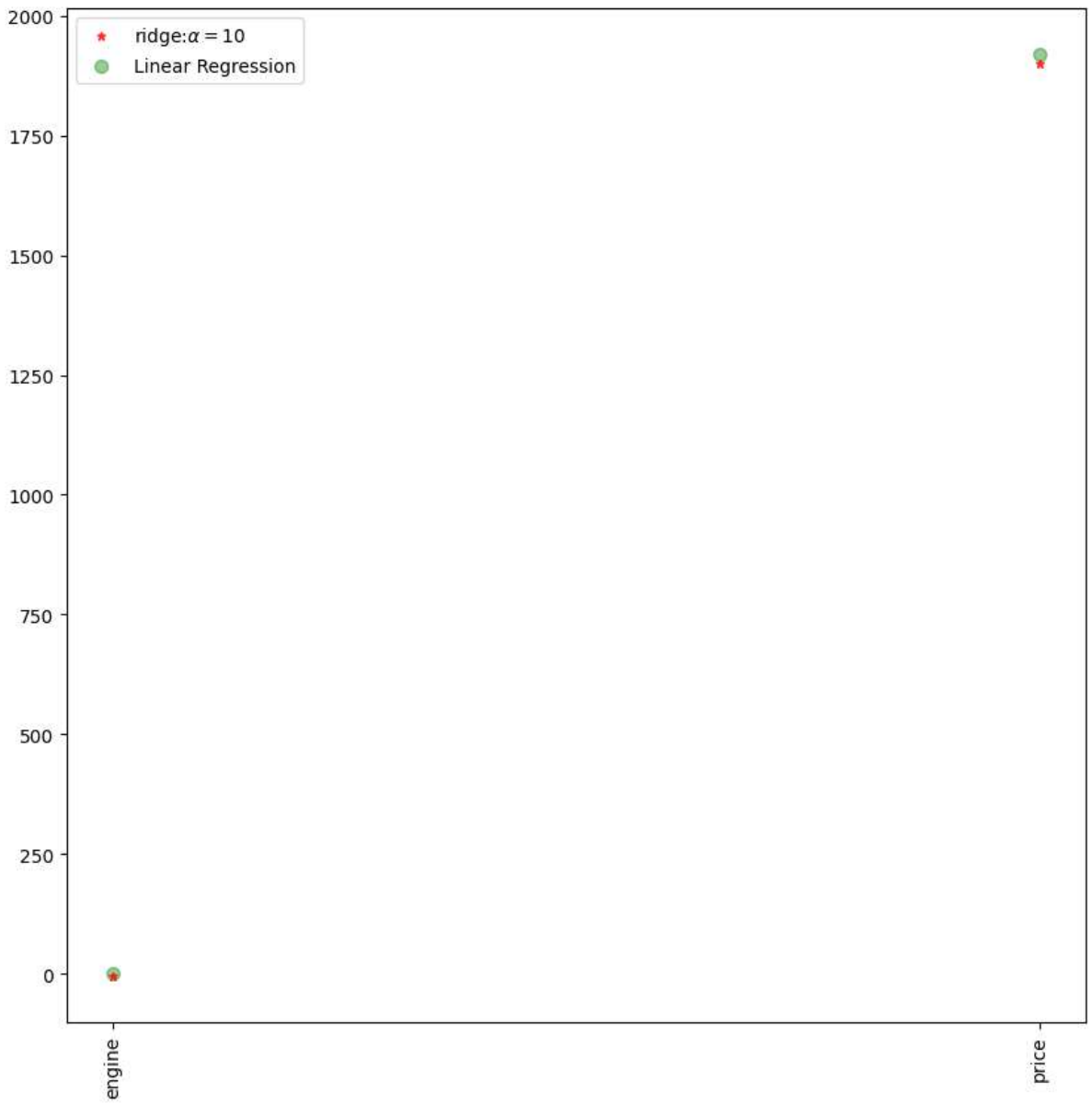
In [54]:
```
lr = LinearRegression()
#Fit model
lr.fit(X_train, y_train)
#predict
#prediction = lr.predict(X_test)
#actual
actual = y_test
train_score_lr = lr.score(X_train, y_train)
test_score_lr = lr.score(X_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model is {}".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 1.0
The test score for lr model is 1.0
```

In [55]:
```
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 0.9999088581979684
The test score for ridge model is 0.9999100853681022
```

In [56]:
```
plt.figure(figsize=(10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

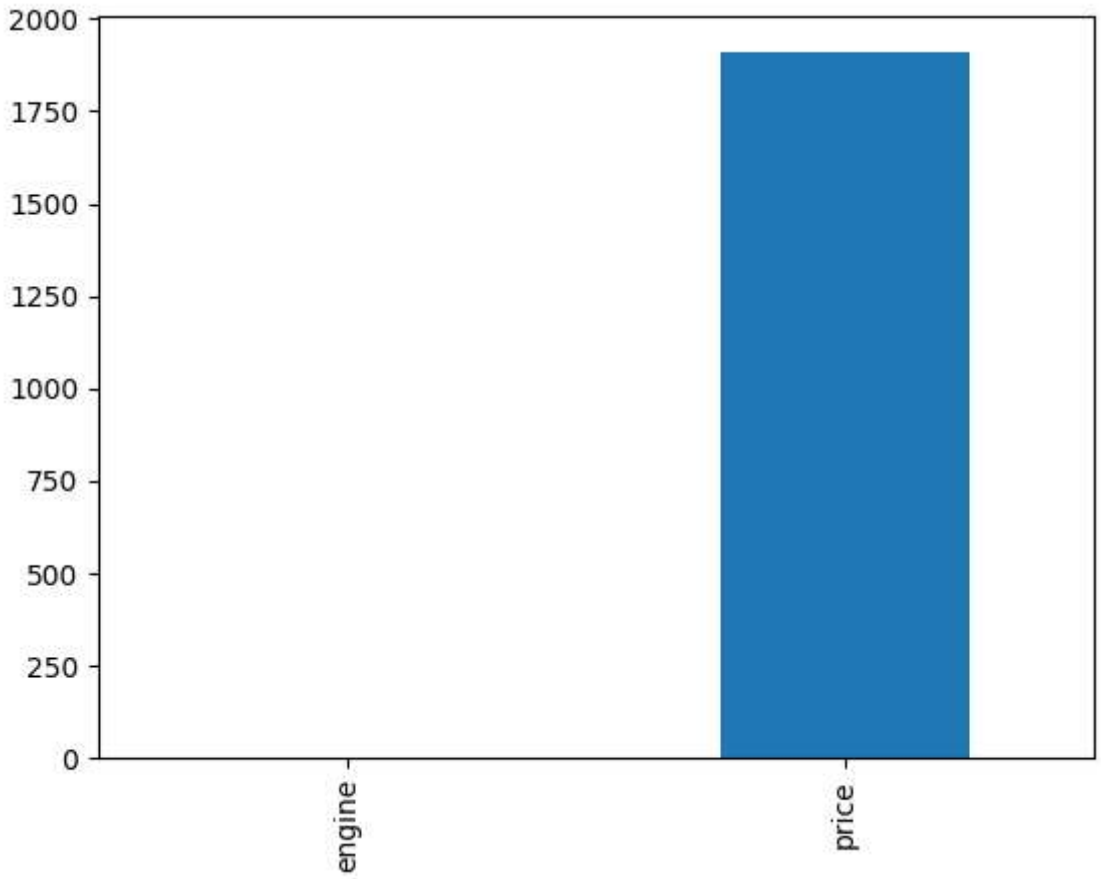


In [57]:
```
#Lasso regression model
print("\nLasso Model: \n")
lasso = Lasso(alpha = 10)
lasso.fit(X_train,y_train)
train_score_ls =lasso.score(X_train,y_train)
test_score_ls =lasso.score(X_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for ls model is 0.9999728562194999
The test score for ls model is 0.9999728508562553
```

In [58]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar
```

Out[58]: <Axes: >



In [59]:
```
from sklearn.linear_model import LassoCV
#Lasso Cross validation
lasso_cv = LassoCV(alphas = [0.0001, 0.001,0.01, 0.1, 1, 10], random_state=0).f
#score
print(lasso_cv.score(X_train, y_train))
print(lasso_cv.score(X_test, y_test))
```

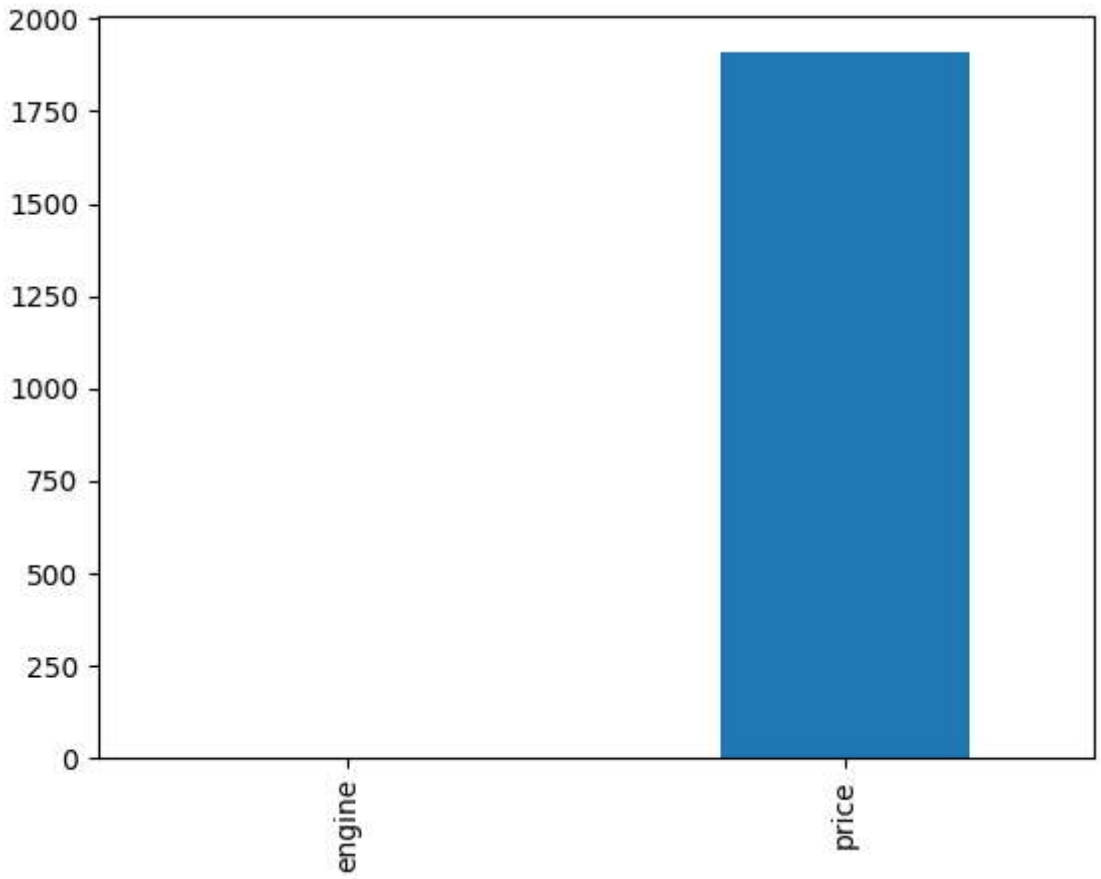
```
0.9999999999501757
0.9999999999638806
```

In [60]:
```
#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 0.9999728562194999
The test score for ls model is 0.9999728508562553
```

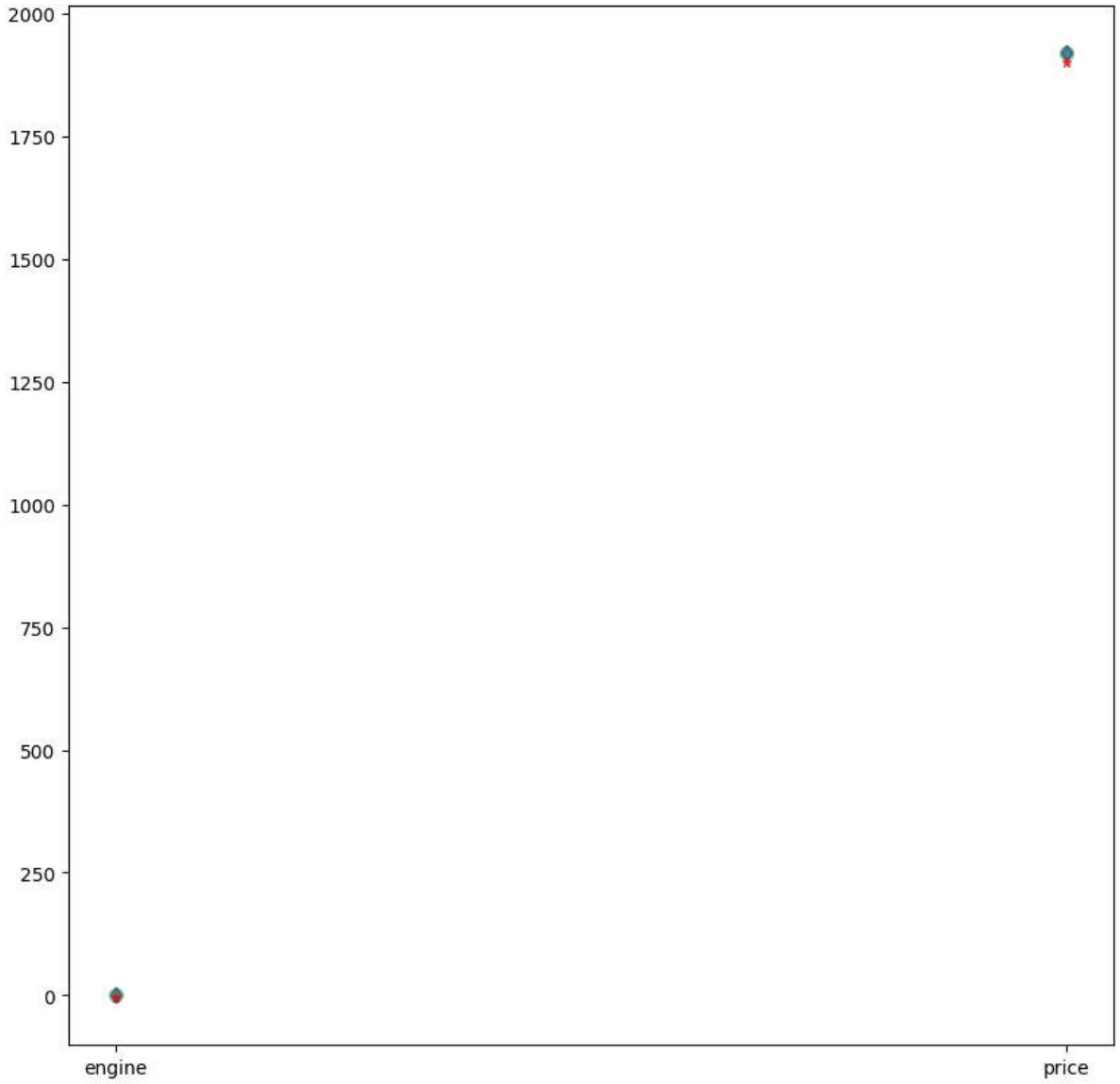
In [61]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar
```

Out[61]: <Axes: >



In [62]:
```
#plot size
plt.figure(figsize = (10, 10))
#add plot for ridge regression
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
#add plot for lasso regression
plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,colo
#add plot for linear model
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
```

Out[62]: [<matplotlib.lines.Line2D at 0x1af90318410>]



In [50]:
```
#conclusion: the above model is fit for linear regression.
```

dataset-3

In [63]:
```
#dataset-3
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
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.preprocessing import StandardScaler
ds=pd.read_csv(r"C:\Users\DELL\Downloads\data.csv")
ds
```

Out[63]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	2014-05-02 00:00:00	3.130000e+05	3.0	1.50	1340	7912	1.5	0	0
1	2014-05-02 00:00:00	2.384000e+06	5.0	2.50	3650	9050	2.0	0	4
2	2014-05-02 00:00:00	3.420000e+05	3.0	2.00	1930	11947	1.0	0	0
3	2014-05-02 00:00:00	4.200000e+05	3.0	2.25	2000	8030	1.0	0	0
4	2014-05-02 00:00:00	5.500000e+05	4.0	2.50	1940	10500	1.0	0	0
...	...	...	...	...	...	...	...	...	...
4595	2014-07-09 00:00:00	3.081667e+05	3.0	1.75	1510	6360	1.0	0	0
4596	2014-07-09 00:00:00	5.343333e+05	3.0	2.50	1460	7573	2.0	0	0
4597	2014-07-09 00:00:00	4.169042e+05	3.0	2.50	3010	7014	2.0	0	0
4598	2014-07-10 00:00:00	2.034000e+05	4.0	2.00	2090	6630	1.0	0	0
4599	2014-07-10 00:00:00	2.206000e+05	3.0	2.50	1490	8102	2.0	0	0

4600 rows × 18 columns

In [64]:
```
ds.describe()
```

Out[64]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wate
count	4.600000e+03	4600.000000	4600.000000	4600.000000	4.600000e+03	4600.000000	4600.0
mean	5.519630e+05	3.400870	2.160815	2139.346957	1.485252e+04	1.512065	0.0
std	5.638347e+05	0.908848	0.783781	963.206916	3.588444e+04	0.538288	0.0
min	0.000000e+00	0.000000	0.000000	370.000000	6.380000e+02	1.000000	0.0
25%	3.228750e+05	3.000000	1.750000	1460.000000	5.000750e+03	1.000000	0.0
50%	4.609435e+05	3.000000	2.250000	1980.000000	7.683000e+03	1.500000	0.0
75%	6.549625e+05	4.000000	2.500000	2620.000000	1.100125e+04	2.000000	0.0
max	2.659000e+07	9.000000	8.000000	13540.000000	1.074218e+06	3.500000	1.0

In [65]:
```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           4600 non-null   object 
 1   price          4600 non-null   float64
 2   bedrooms       4600 non-null   float64
 3   bathrooms      4600 non-null   float64
 4   sqft_living    4600 non-null   int64  
 5   sqft_lot       4600 non-null   int64  
 6   floors         4600 non-null   float64
 7   waterfront     4600 non-null   int64  
 8   view           4600 non-null   int64  
 9   condition      4600 non-null   int64  
 10  sqft_above     4600 non-null   int64  
 11  sqft_basement  4600 non-null   int64  
 12  yr_built       4600 non-null   int64  
 13  yr_renovated   4600 non-null   int64  
 14  street         4600 non-null   object 
 15  city           4600 non-null   object 
 16  statezip       4600 non-null   object 
 17  country        4600 non-null   object 
dtypes: float64(4), int64(9), object(5)
memory usage: 647.0+ KB
```

In [66]:
```
ds.isna().any()
```

Out[66]:
```
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront       False
view             False
condition        False
sqft_above       False
sqft_basement    False
yr_built         False
yr_renovated     False
street           False
city             False
statezip         False
country          False
dtype: bool
```

In [67]:
```
ds.isnull().sum()
```

Out[67]:
```
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
street           0
city             0
statezip         0
country          0
dtype: int64
```

In [68]:
```
ds.loc[:10,["price","floors"]]
```

Out[68]:

	price	floors
0	313000.0	1.5
1	2384000.0	2.0
2	342000.0	1.0
3	420000.0	1.0
4	550000.0	1.0
5	490000.0	1.0
6	335000.0	1.0
7	482000.0	2.0
8	452500.0	1.0
9	640000.0	1.5
10	463000.0	1.0

In [69]:
```
ds=ds[["price","floors"]]
ds.columns=["pri","flo"]
```

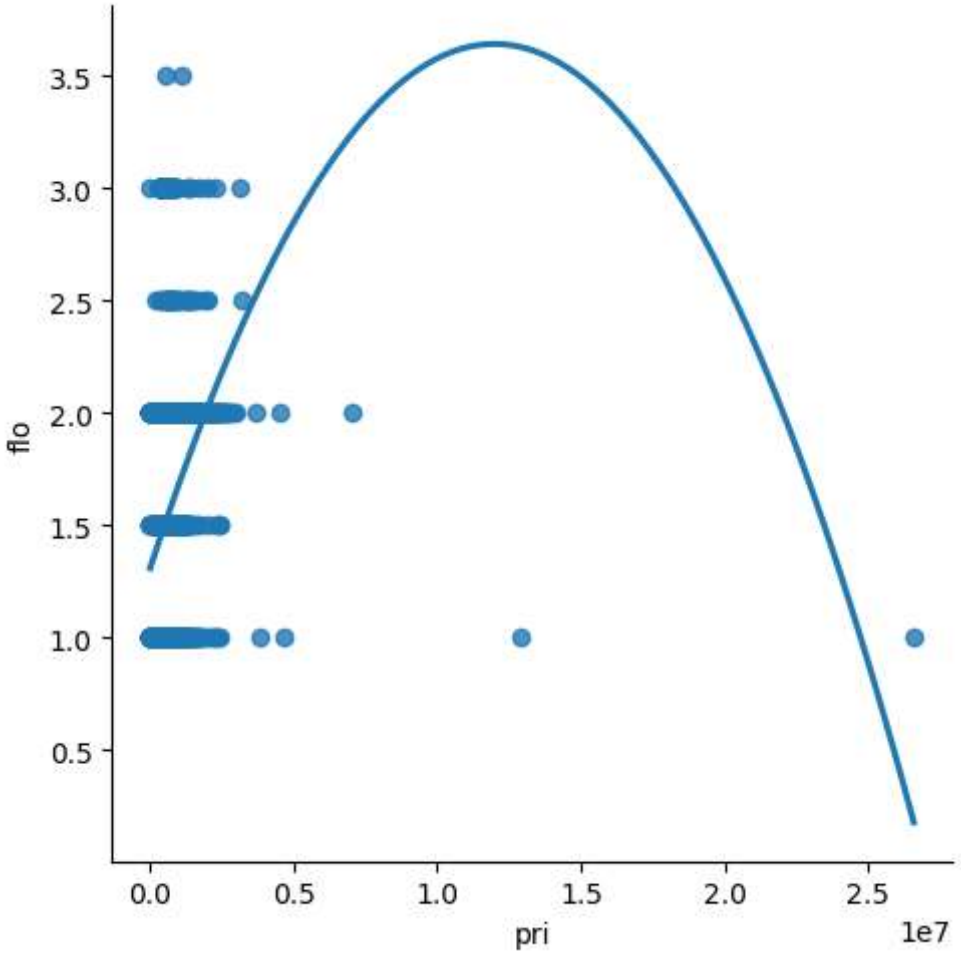
In [70]:
```
ds.head(10)
```

Out[70]:

	pri	flo
0	313000.0	1.5
1	2384000.0	2.0
2	342000.0	1.0
3	420000.0	1.0
4	550000.0	1.0
5	490000.0	1.0
6	335000.0	1.0
7	482000.0	2.0
8	452500.0	1.0
9	640000.0	1.5

In [71]:
```
sns.lmplot(x='pri',y='flo',data=ds,order=2,ci=None)
```

Out[71]:
```
<seaborn.axisgrid.FacetGrid at 0x1af902d9b90>
```



In [72]:
```
ds.fillna(method='ffill')
```

Out[72]:

	pri	flo
0	3.130000e+05	1.5
1	2.384000e+06	2.0
2	3.420000e+05	1.0
3	4.200000e+05	1.0
4	5.500000e+05	1.0
...	...	...
4595	3.081667e+05	1.0
4596	5.343333e+05	2.0
4597	4.169042e+05	2.0
4598	2.034000e+05	1.0
4599	2.206000e+05	2.0

4600 rows × 2 columns

In [73]:
```
x=np.array(ds['pri']).reshape(-1,1)
y=np.array(ds['flo']).reshape(-1,1)
```

In [74]:
```
ds.dropna(inplace=True)
```

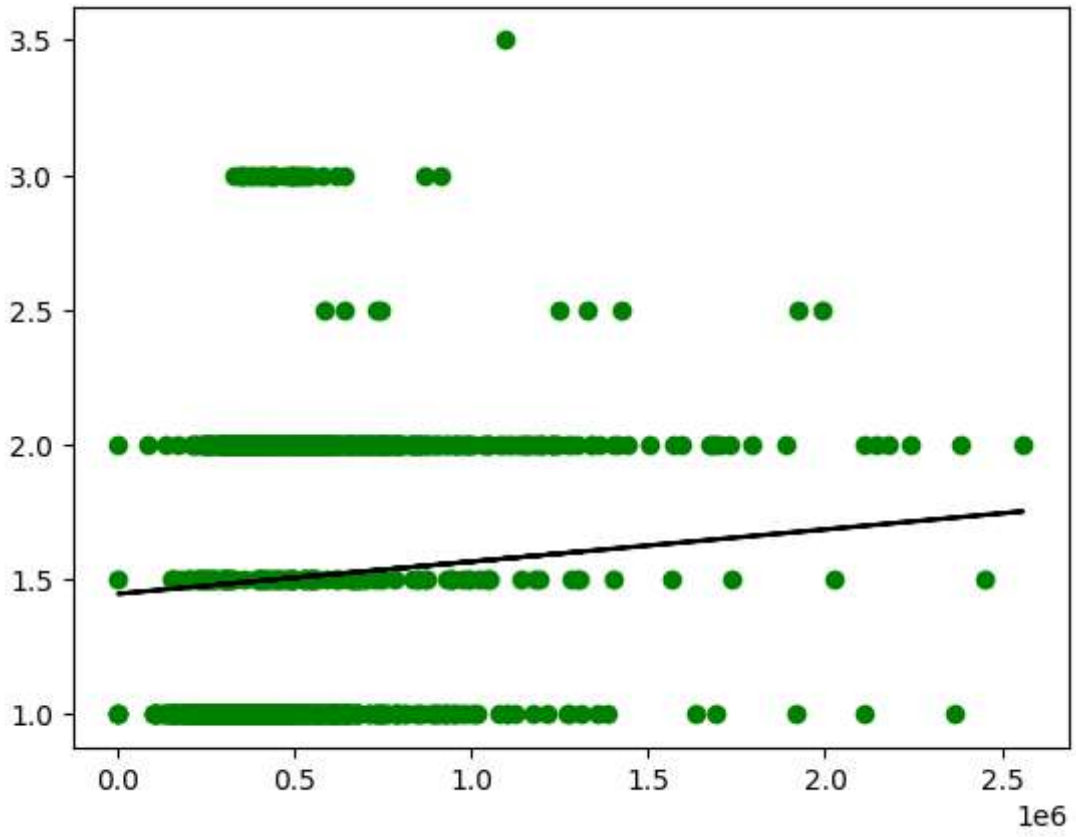
```
C:\Users\DELL\AppData\Local\Temp\ipykernel_7856\2725967003.py:1: SettingWithC
opyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  ds.dropna(inplace=True)
```

In [75]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

In [76]:
```
regr=LinearRegression()
regr.fit(x_train,y_train)
print(regr.score(x_test,y_test))
```

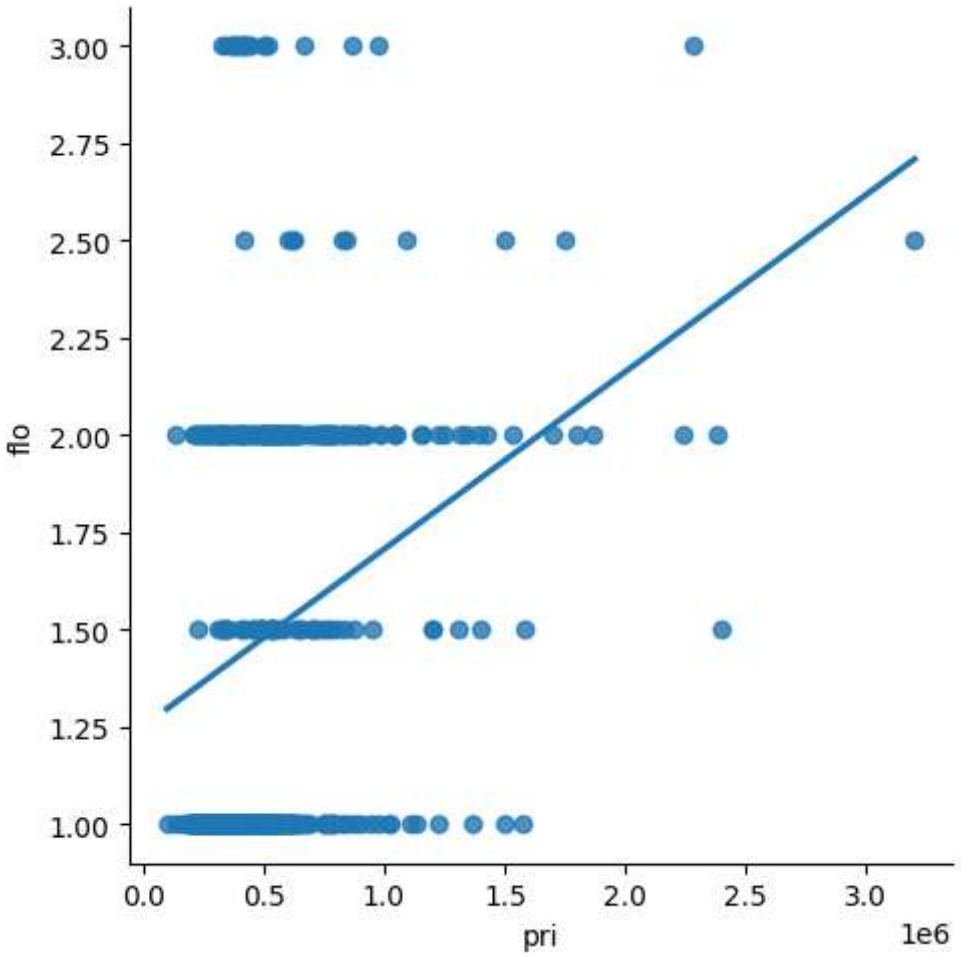
```
0.032764610913919245
```

In [77]:
```
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='g')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



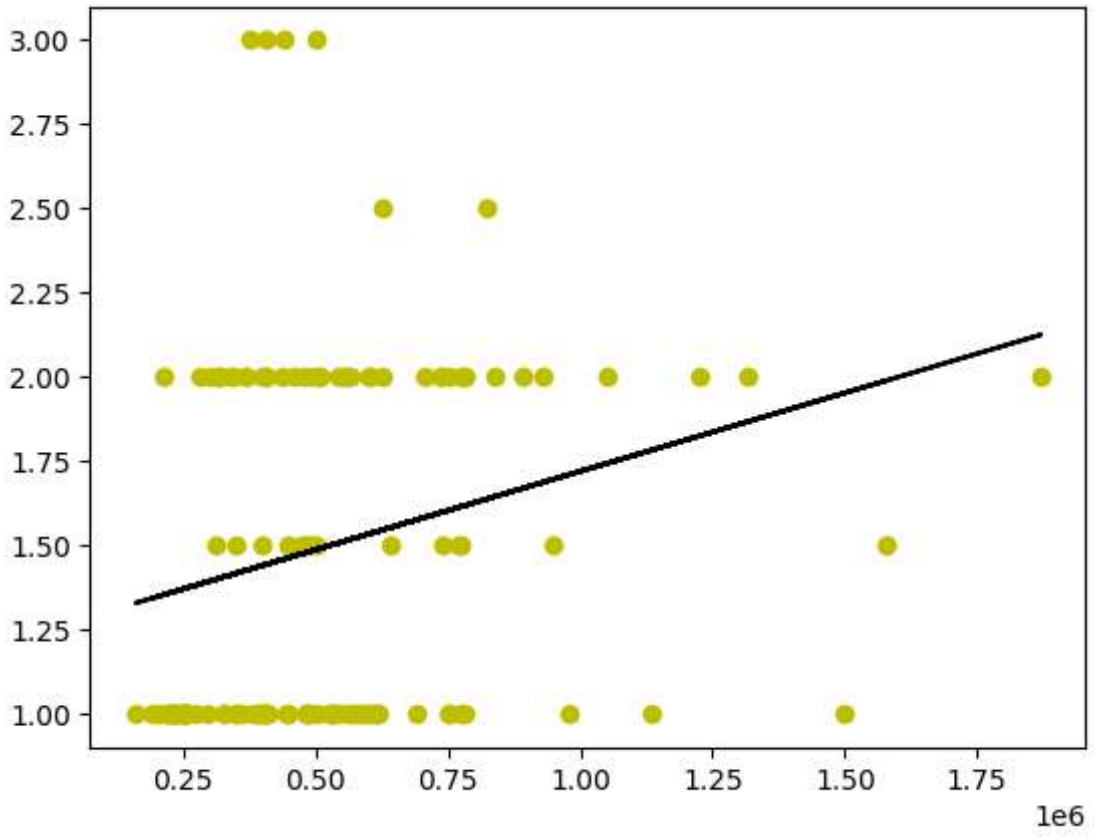
In [78]:
```
ds500=ds[:][:500]
sns.lmplot(x='pri',y='flo',data=ds500,order=1,ci=None)
```

Out[78]: <seaborn.axisgrid.FacetGrid at 0x1af93e4e750>



In [79]:
```
ds500.fillna(method='ffill',inplace=True)
x=np.array(ds500['pri']).reshape(-1,1)
y=np.array(ds500['flo']).reshape(-1,1)
ds500.dropna(inplace=True)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
regr=LinearRegression()
regr.fit(x_train,y_train)
print("Regression:",regr.score(x_test,y_test))
y_pred=regr.predict(x_test)
plt.scatter(x_test,y_test,color='y')
plt.plot(x_test,y_pred,color='k')
plt.show()
```

```
Regression: 0.03848039945992765
```



In [80]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
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)
```

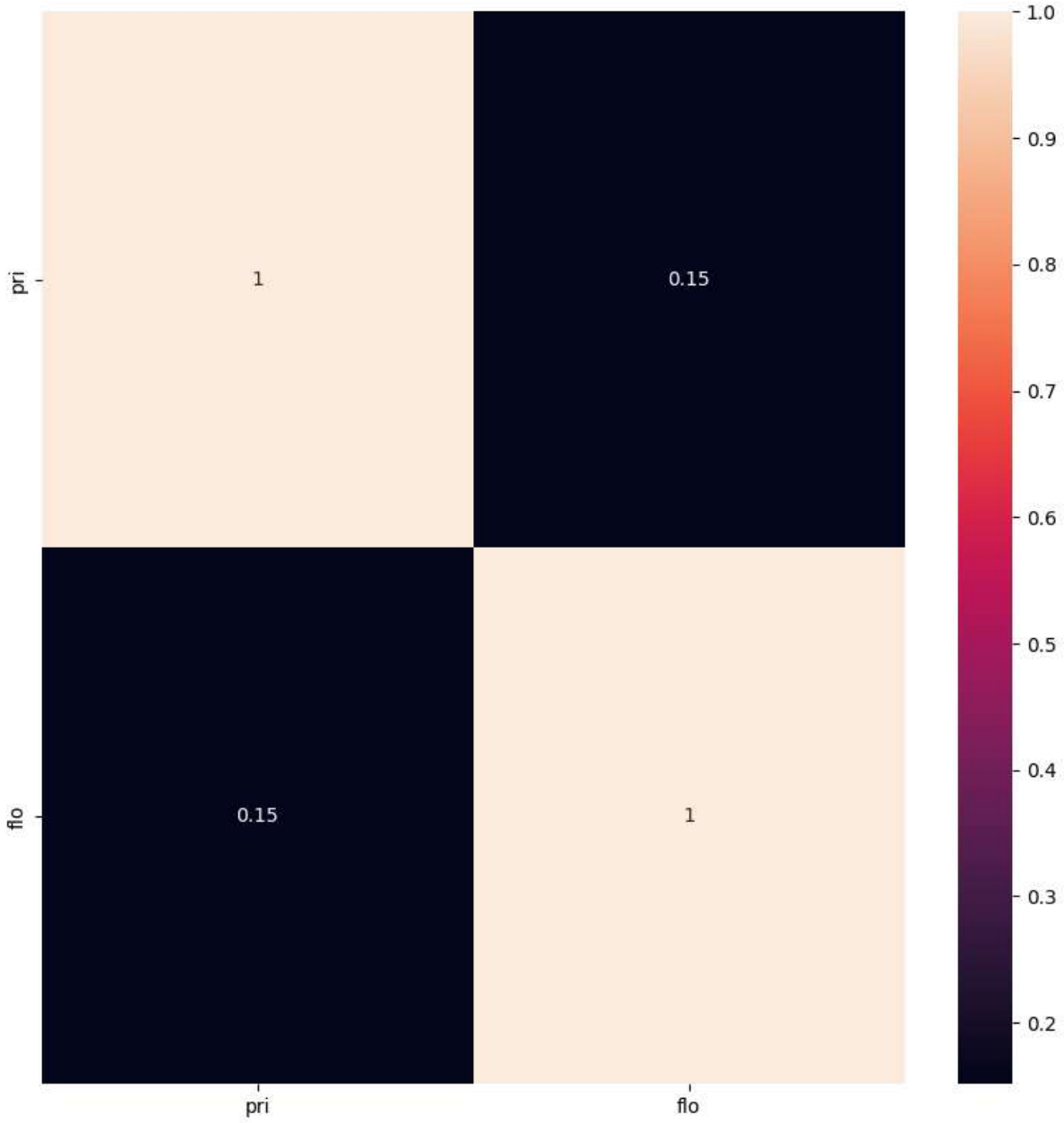
```
R2 score: 0.03848039945992765
```

In [81]:
```
#conclusion:the model is best fit for linear regression
```

Ridge and lasso

In [82]:
```
plt.figure(figsize = (10, 10))
sns.heatmap(ds.corr(), annot = True)
```

Out[82]: <Axes: >



In [83]:
```
features = ds.columns[0:2]
target = ds.columns[-1]
#X and y values
X = ds[features].values
y = ds[target].values
#splot
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random
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 (3220, 2)
The dimension of X_test is (1380, 2)
```

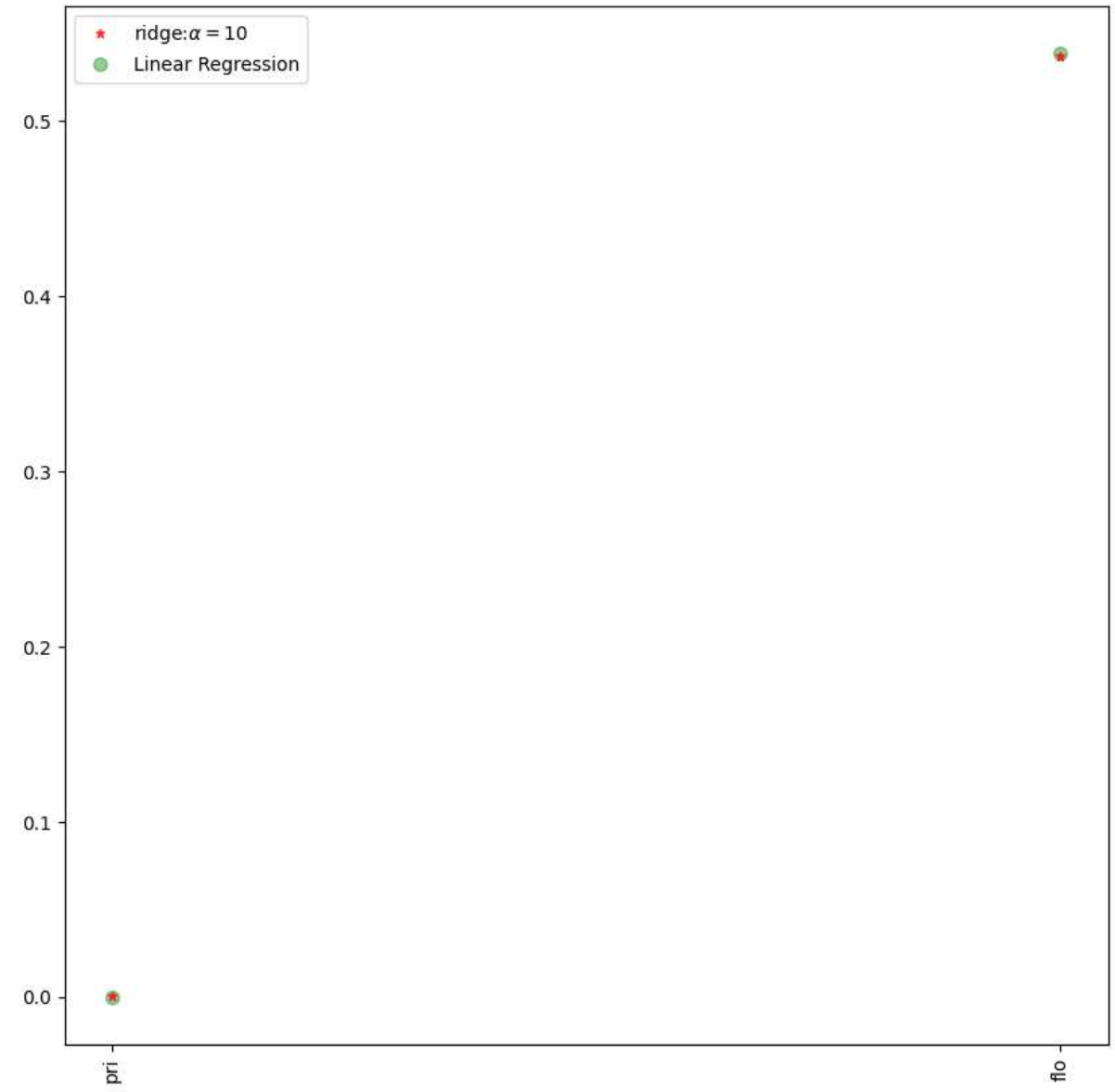
In [84]:
```
lr = LinearRegression()
#Fit model
lr.fit(X_train, y_train)
#predict
#prediction = lr.predict(X_test)
#actual
actual = y_test
train_score_lr = lr.score(X_train, y_train)
test_score_lr = lr.score(X_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model is {}".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 1.0
The test score for lr model is 1.0
```

In [85]:
```
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 0.9999902268703251
The test score for ridge model is 0.9999903260461295
```

In [86]:
```
plt.figure(figsize=(10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

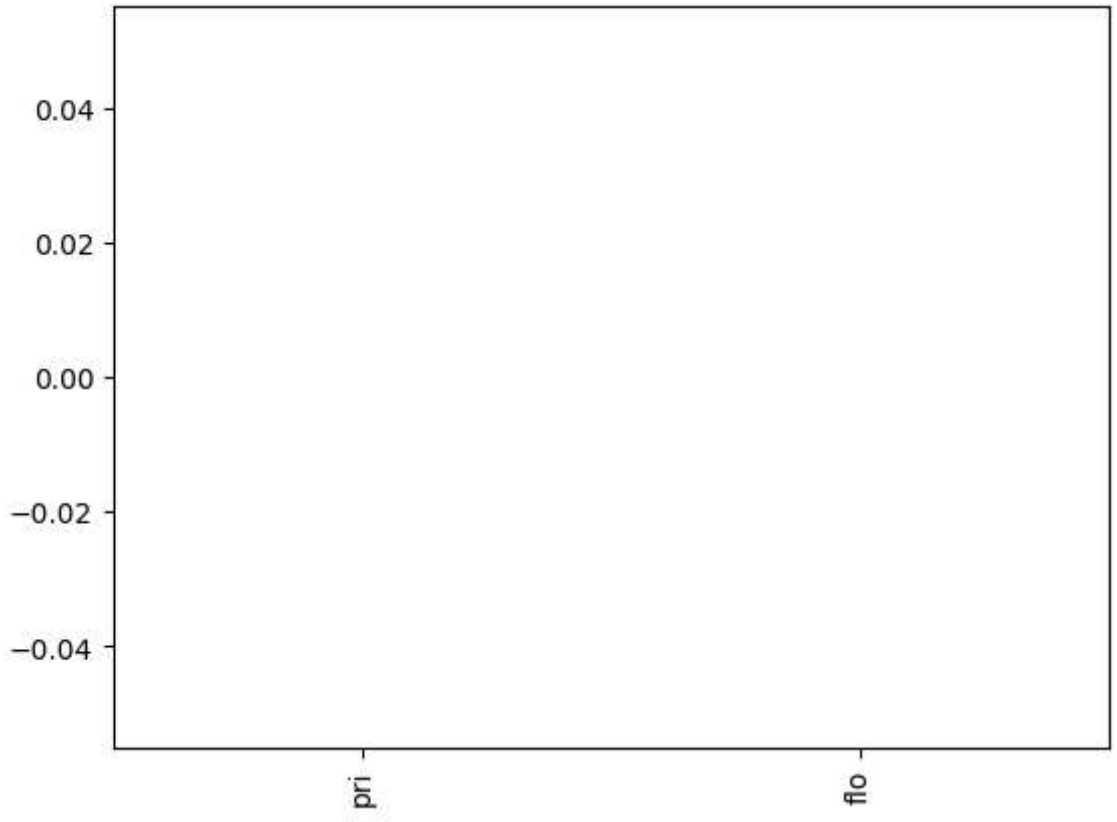


In [87]:
```
#Lasso regression model
print("\nLasso Model: \n")
lasso = Lasso(alpha = 10)
lasso.fit(X_train,y_train)
train_score_ls =lasso.score(X_train,y_train)
test_score_ls =lasso.score(X_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for ls model is 0.0
The test score for ls model is -0.000324420787036761
```

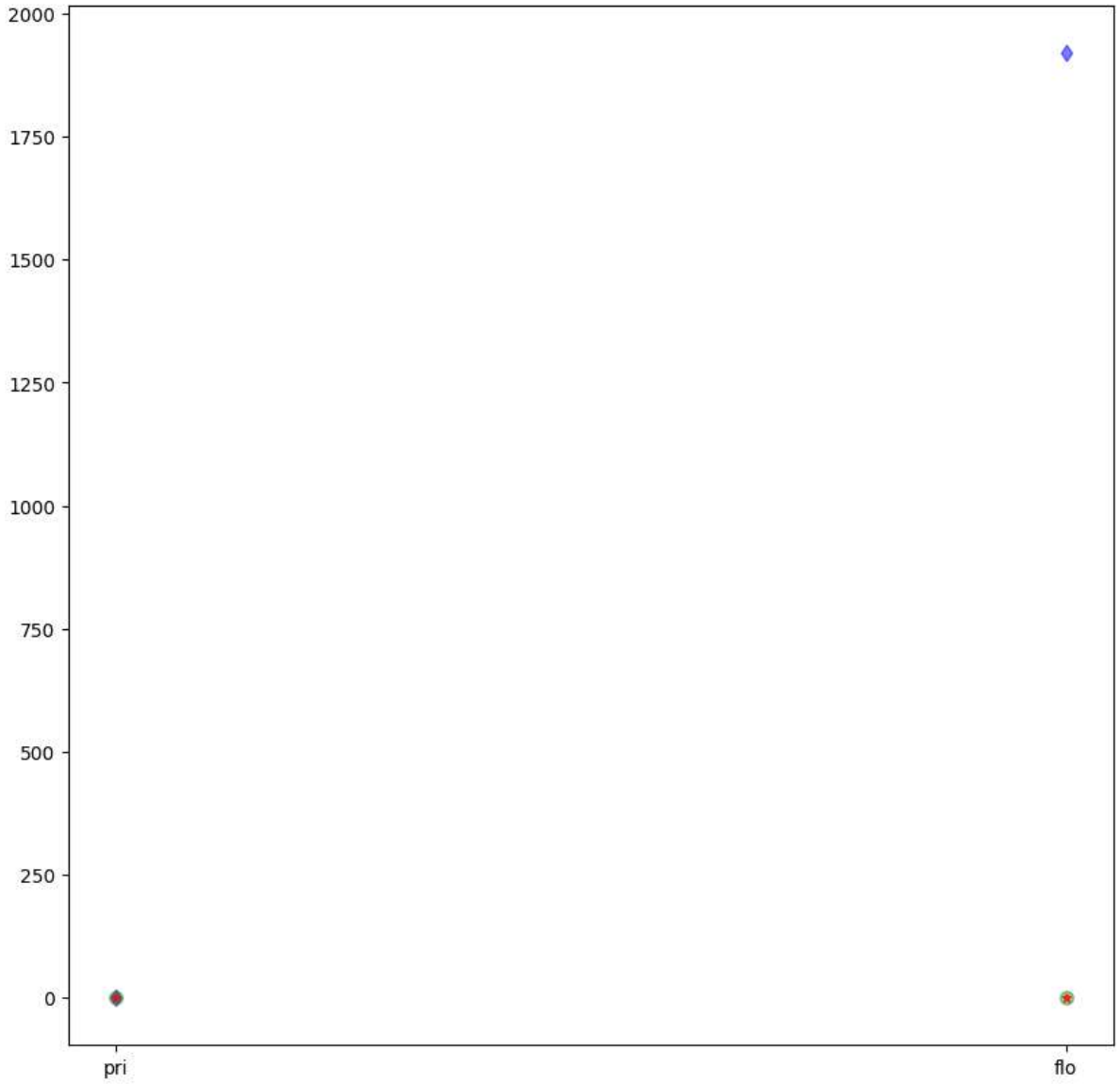
In [88]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar
```

Out[88]:
```
<Axes: >
```



In [89]:
```
#plot size
plt.figure(figsize = (10, 10))
#add plot for ridge regression
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersi
#add plot for lasso regression
plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,colo
#add plot for linear model
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
```

Out[89]:
```
[<matplotlib.lines.Line2D at 0x1af90409a90>]
```



In [ ]: