Advertising Datasset

In [30]:
```
import pandas as pd
import numpy as np
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 [31]:
```
data=pd.read_csv(r"C:\Users\91949\Downloads\Advertising.csv")
data
```

Out[31]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9
...	...	...	...	...
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	18.4

200 rows × 4 columns

In [32]:
```
data.head()
```

Out[32]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

In [33]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   TV         200 non-null    float64
 1   Radio      200 non-null    float64
 2   Newspaper  200 non-null    float64
 3   Sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
```

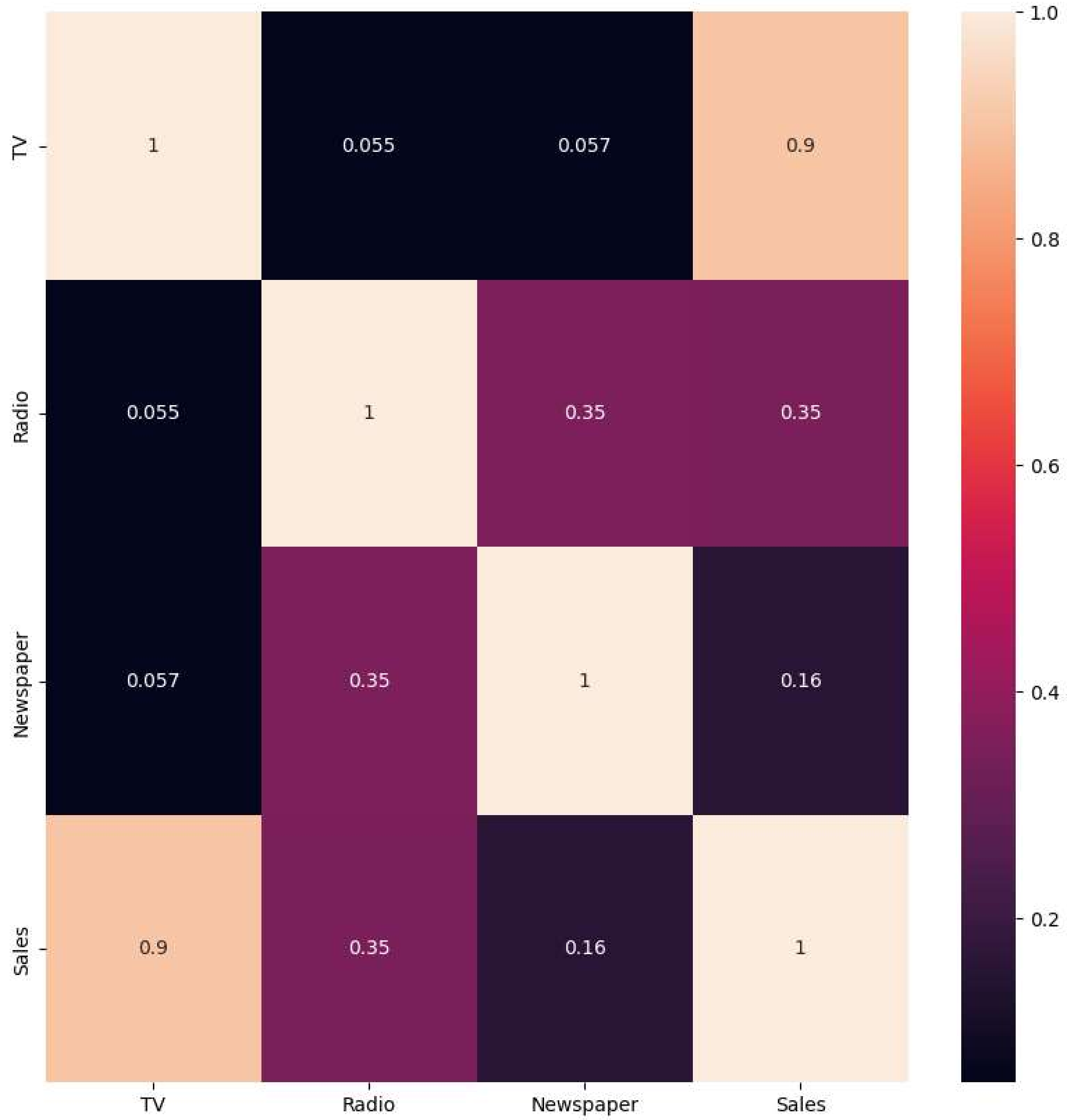
In [34]:
```
data.describe()
```

Out[34]:

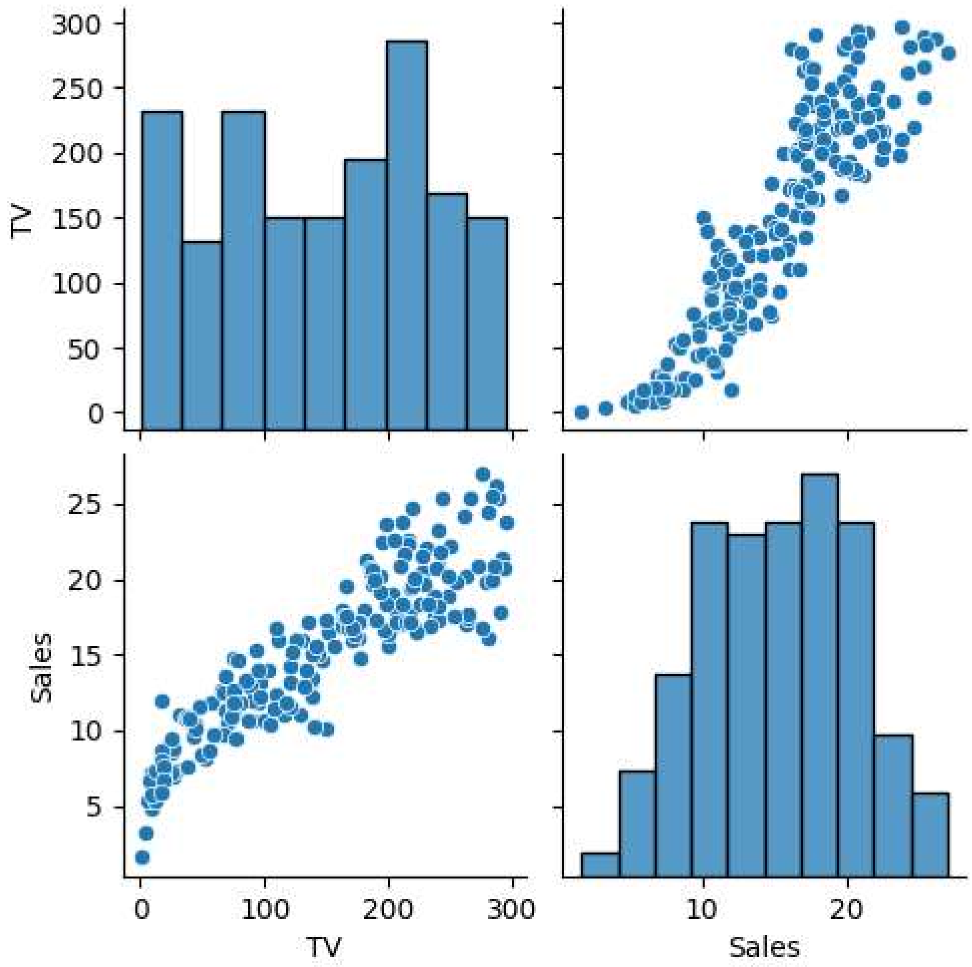
	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

In [35]:
```
plt.figure(figsize = (10, 10))
sns.heatmap(data.corr(), annot = True)
```

Out[35]: <Axes: >



In [36]:
```
data.drop(columns = ["Radio", "Newspaper"], inplace = True)
#pairplot
sns.pairplot(data)
data.Sales = np.log(data.Sales)
```



In [37]:
```
features = data.columns[0:2]
target = data.columns[-1]
#X and y values
X = data[features].values
y = data[target].values
#splot
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))
#Scale features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
The dimension of X_train is (140, 2)
The dimension of X_test is (60, 2)
```

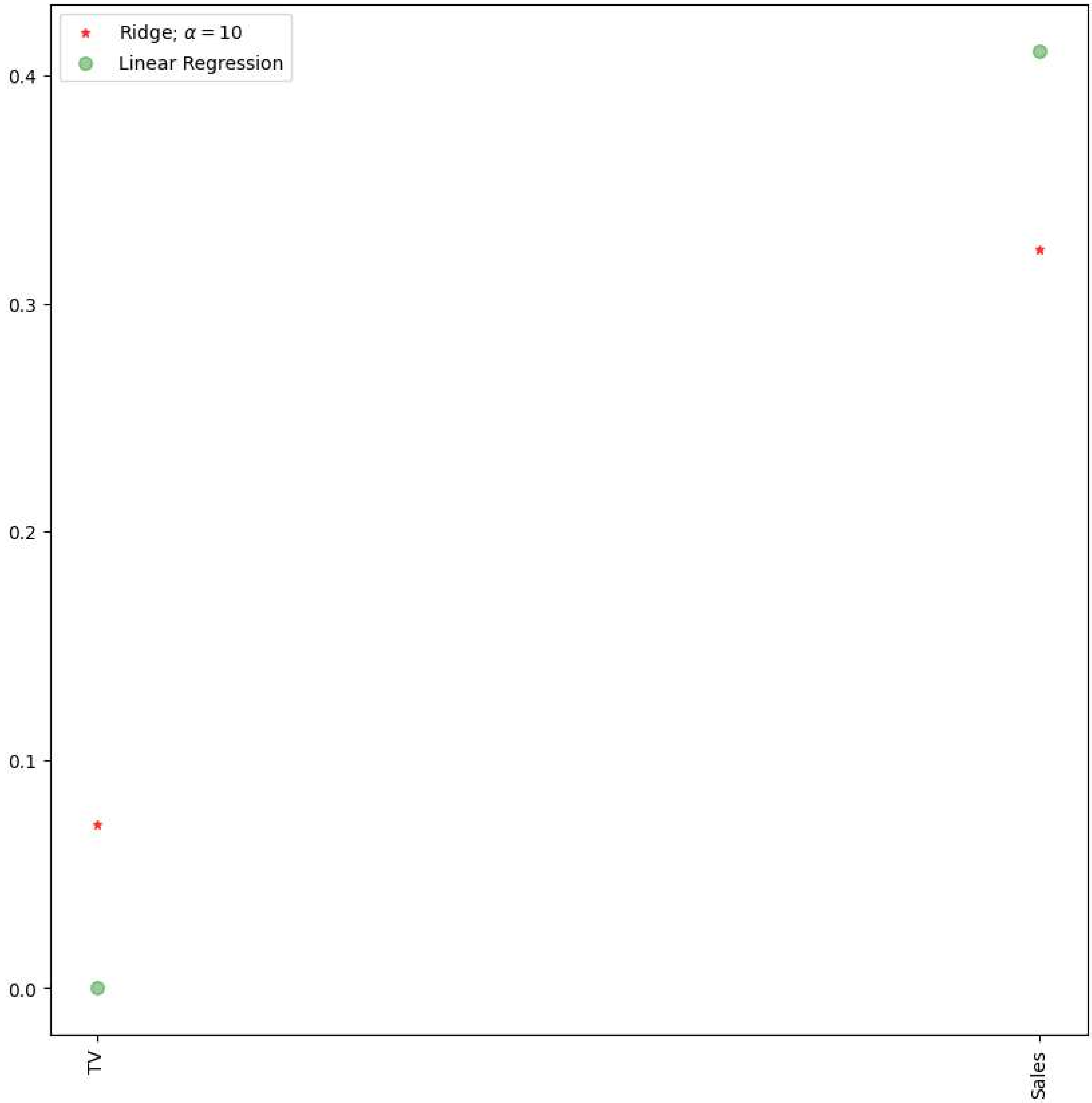
In [38]:
```
#Model
lr = LinearRegression()
#Fit model
lr.fit(X_train, y_train)
#predict
#prediction = lr.predict(X_test)
#actual
actual = y_test
train_score_lr = lr.score(X_train, y_train)
test_score_lr = lr.score(X_test, y_test)
print("\nLinear Regression Model:\n")
print("The train score for lr model 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 [39]:
```
#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 0.990287139194161
The test score for ridge model is 0.9844266285141221
```

In [40]:
```
plt.figure(figsize = (10, 10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge; $\
#plt.plot(rr100.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'Ridge; $\alpha = 10
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regress
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```

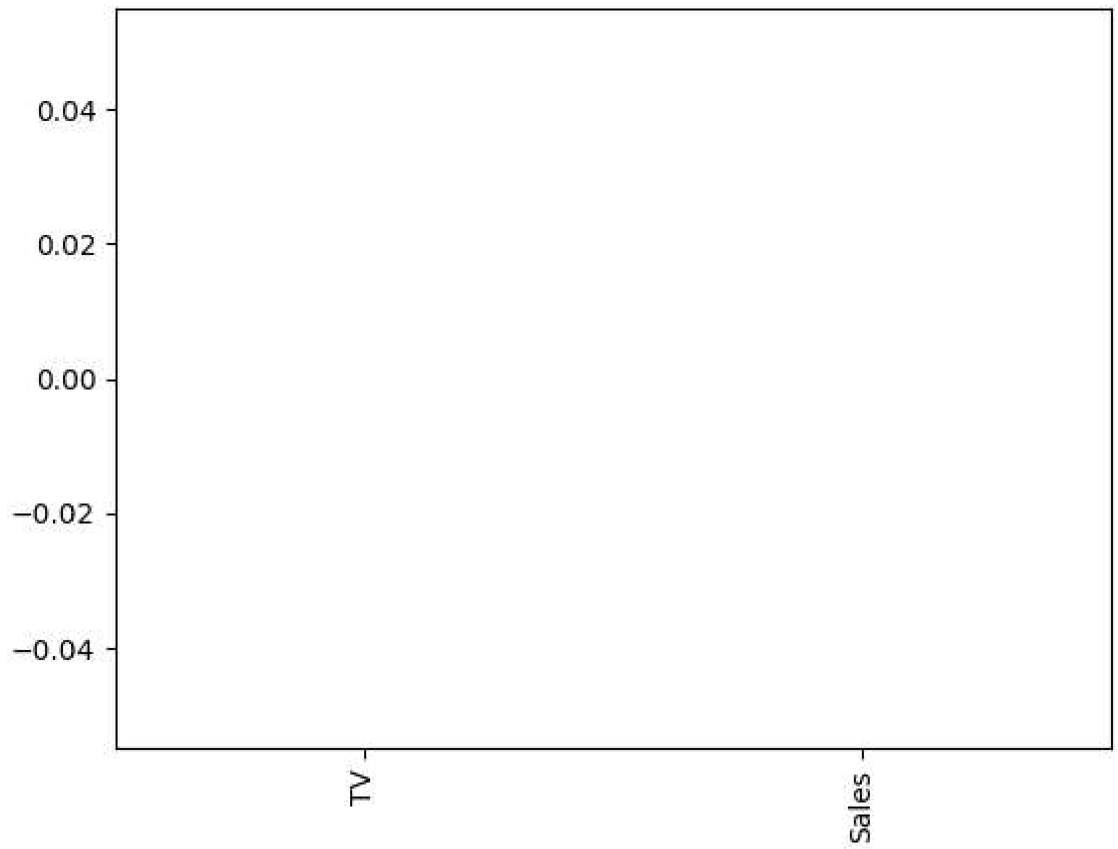


In [41]:
```
#Lasso regression model
print("\nLasso Model: \n")
lasso = Lasso(alpha = 10)
lasso.fit(X_train,y_train)
train_score_ls =lasso.score(X_train,y_train)
test_score_ls =lasso.score(X_test,y_test)
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for ls model is 0.0
The test score for ls model is -0.0042092253233847465
```

In [42]:
```
pd.Series(lasso.coef_, features).sort_values(ascending = True).plot(kind = "bar")
```

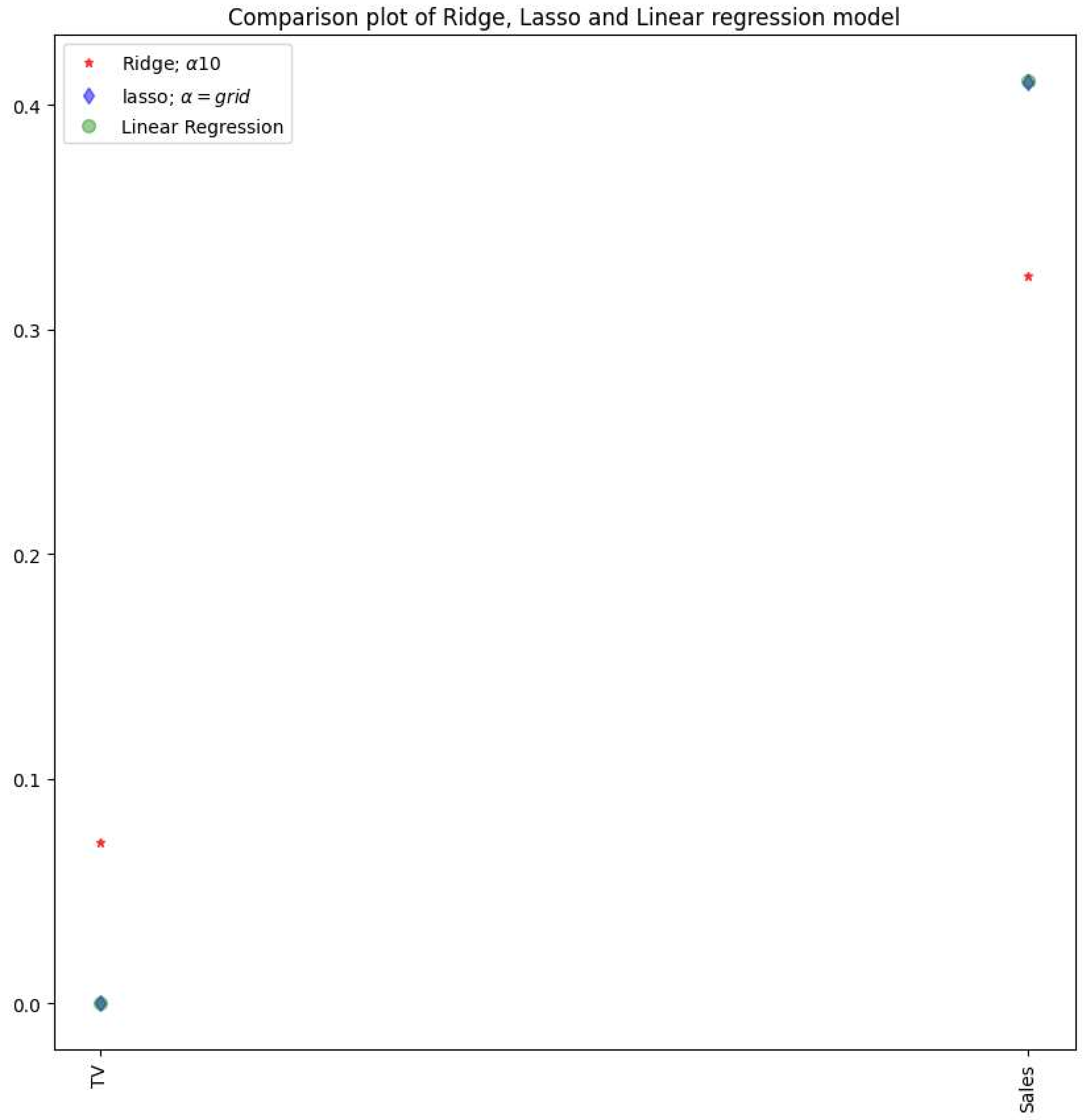
Out[42]: <Axes: >



In [43]:
```
#Using the linear CV model
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).fit(X_train, y_train)

#score
print(lasso_cv.score(X_train, y_train))
print(lasso_cv.score(X_test, y_test))
```

```
0.9999999343798134
0.9999999152638072
```

In [44]:
```
#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; $\
#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 =
#add plot for linear model
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regress
#rotate axis
plt.xticks(rotation = 90)
plt.legend()
plt.title("Comparison plot of Ridge, Lasso and Linear regression model")
plt.show()
```



In [45]:
```
#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_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 0.999999999997627
The train score for ridge model is 0.9999999999962467
```

Elastic Net Regression

In [46]:
```
from sklearn.linear_model import ElasticNet
regr=ElasticNet()
regr.fit(x,y)
print(regr.coef_)
print(regr.intercept_)
```

```
[0.00417976 0.        ]
2.026383919311004
```

In [47]:
```
y_pred_elastic=regr.predict(X_train)
```

In [48]:
```
mean_squared_error=np.mean((y_pred_elastic-y_train)**2)
print("Mean Squared Error on test set",mean_squared_error)
```

```
Mean Squared Error on test set 0.5538818050142158
```

vehicles dataset

In [1]:
```
import pandas as pd
import numpy as np
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 [2]:
```
df=pd.read_csv(r"C:\Users\91949\Downloads\fiat500_VehicleSelection_Dataset.csv")
df
```

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.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 [4]:
```
df.describe()
```

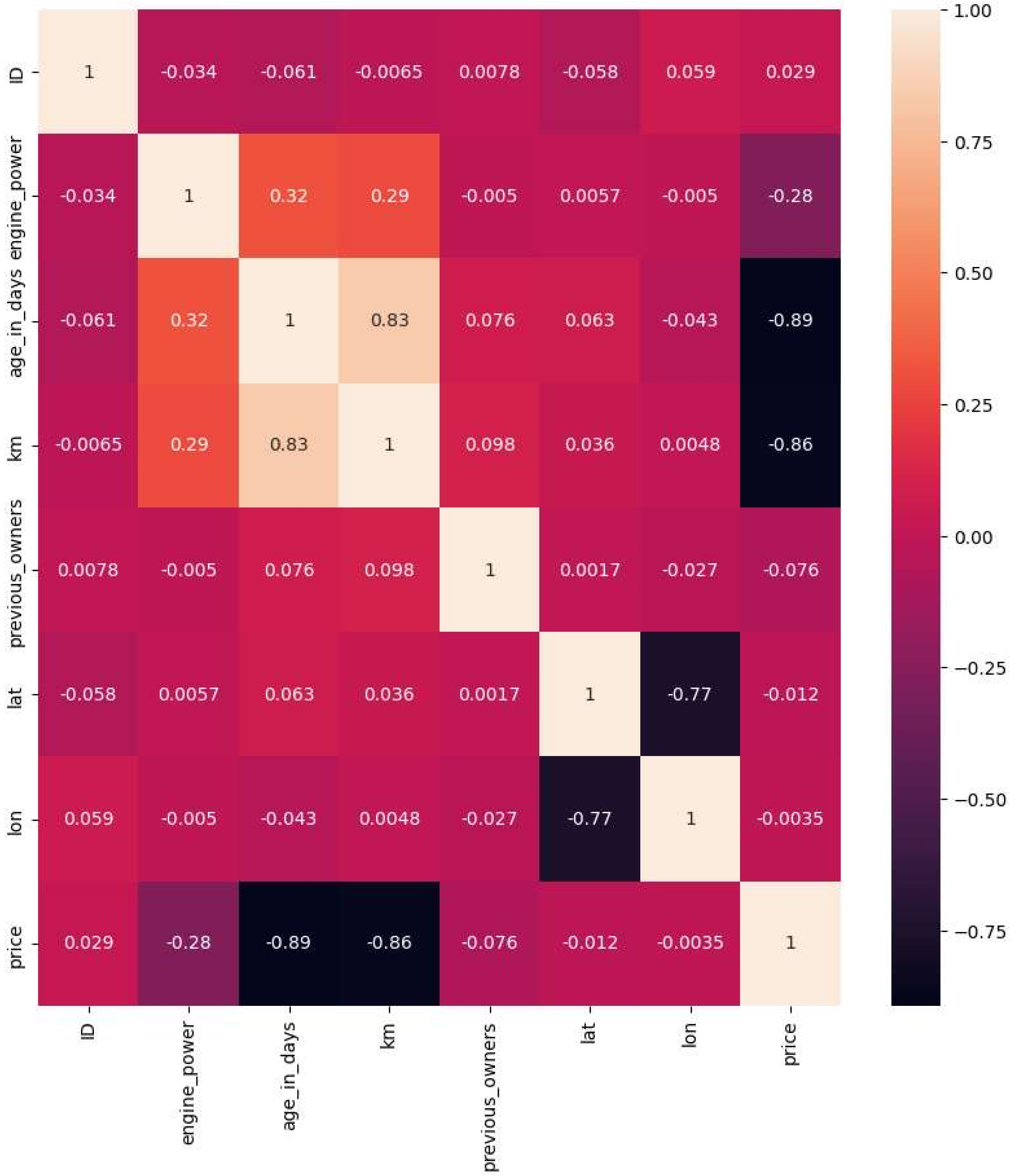
Out[4]:

	ID	engine_power	age_in_days	km	previous_owners	lat	lon	price
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000
mean	769.500000	51.904421	1650.980494	53396.011704	1.123537	43.541361	11.563428	8576.003901
std	444.126671	3.988023	1289.522278	40046.830723	0.416423	2.133518	2.328190	1939.958641
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.855839	7.245400	2500.000000
25%	385.250000	51.000000	670.000000	20006.250000	1.000000	41.802990	9.505090	7122.500000
50%	769.500000	51.000000	1035.000000	39031.000000	1.000000	44.394096	11.869260	9000.000000
75%	1153.750000	51.000000	2616.000000	79667.750000	1.000000	45.467960	12.769040	10000.000000
max	1538.000000	77.000000	4658.000000	235000.000000	4.000000	46.795612	18.365520	11100.000000

In [5]:
```
df.drop(columns=['model'],inplace=True)
```

In [6]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot = True)
```

Out[6]: <Axes: >



In [7]:

```
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_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 (1076, 2)
The dimension of X_test is (462, 2)
```

In [8]:

```
#Model
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))
```

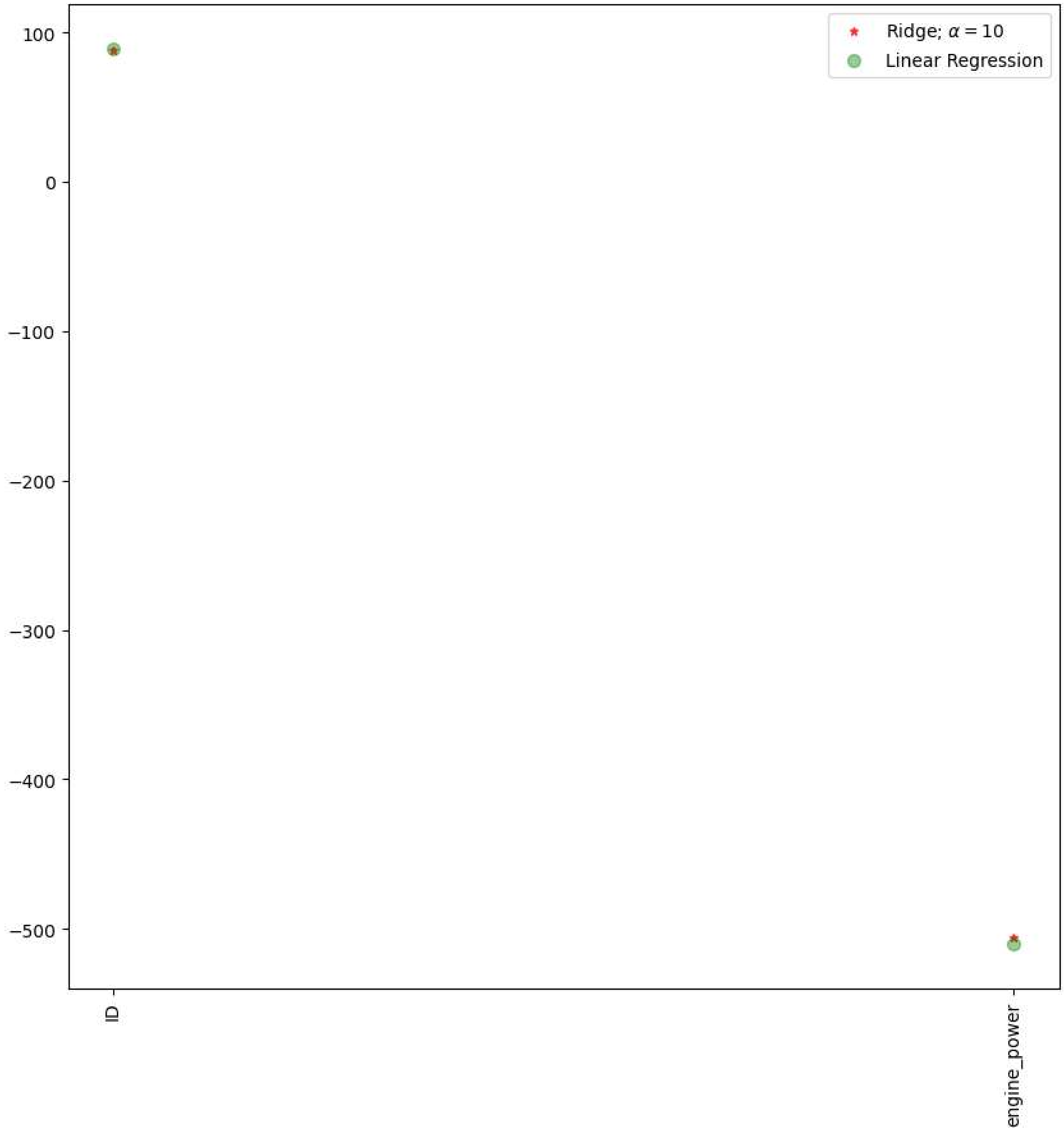
```

Linear Regression Model:

The train score for lr model is 0.07448634159905865
The test score for lr model is 0.07913288661070894
```

In [9]:

```
#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 0.07448028989896427
The test score for ridge model is 0.07885996726883082
```

In [10]:
```
plt.figure(figsize = (10, 10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge; $\
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regress
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



In [12]:
```
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).fit(x_train,y_train)
#score
print(lasso_cv.score(x_train, y_train))
print(lasso_cv.score(x_test, y_test))
```

```
0.07448634159905387
0.07913288806451946
```

Elastic Net

In [13]:
```
from sklearn.linear_model import ElasticNet
regr=ElasticNet()
regr.fit(x,y)
print(regr.coef_)
print(regr.intercept_)
```

```
[ 8.46751882e-02 -1.30405006e+02]
15279.442735227916
```

In [14]:
```
y_pred_elastic=regr.predict(x_train)
```

In [37]:
```
mse=np.mean(y_pred_elastic-y_train)
print("Mean Squared Error on test set",mse)
```

```
Mean Squared Error on test set 6695.057976863604
```

temperature dataset

In [39]:
```
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 [40]:

```
d=pd.read_csv(r"C:\Users\91949\Downloads\bottle.csv.zip")
d
```

```
C:\Users\91949\AppData\Local\Temp\ipykernel_17404\4268028596.py:1: DtypeWarning: Columns (47,73) have mixed types. S
pecify dtype option on import or set low_memory=False.
  d=pd.read_csv(r"C:\Users\91949\Downloads\bottle.csv.zip")
```

Out[40]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R_PHAEO	R_PRES	R_SAMP	DIC1	DIC
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.500	33.4400	NaN	25.64900	NaN	...	NaN	0	NaN	NaN	NaN
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.460	33.4400	NaN	25.65600	NaN	...	NaN	8	NaN	NaN	NaN
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	10.460	33.4370	NaN	25.65400	NaN	...	NaN	10	NaN	NaN	NaN
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.450	33.4200	NaN	25.64300	NaN	...	NaN	19	NaN	NaN	NaN
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	10.450	33.4210	NaN	25.64300	NaN	...	NaN	20	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
864858	34404	864859	093.4 026.4	20-1611SR-MX-310-2239-09340264-0000A-7	0	18.744	33.4083	5.805	23.87055	108.74	...	0.18	0	NaN	NaN	NaN
864859	34404	864860	093.4 026.4	20-1611SR-MX-310-2239-09340264-0002A-3	2	18.744	33.4083	5.805	23.87072	108.74	...	0.18	2	4.0	NaN	NaN
864860	34404	864861	093.4 026.4	20-1611SR-MX-310-2239-09340264-0005A-3	5	18.692	33.4150	5.796	23.88911	108.46	...	0.18	5	3.0	NaN	NaN
864861	34404	864862	093.4 026.4	20-1611SR-MX-310-2239-09340264-0010A-3	10	18.161	33.4062	5.816	24.01426	107.74	...	0.31	10	2.0	NaN	NaN
864862	34404	864863	093.4 026.4	20-1611SR-MX-310-2239-09340264-0015A-3	15	17.533	33.3880	5.774	24.15297	105.66	...	0.61	15	1.0	NaN	NaN

864863 rows × 74 columns

In [41]:
```
d.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  float64
 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(65), int64(5), object(4)
memory usage: 488.3+ MB
```

In [42]:
```
d.describe()
```

Out[42]:

	Cst_Cnt	Btl_Cnt	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	Oxy_µmol/Kg
count	864863.000000	864863.000000	864863.000000	853900.000000	817509.000000	696201.000000	812174.000000	661274.000000	661268.000000
mean	17138.790958	432432.000000	226.831951	10.799677	33.840350	3.392468	25.819394	57.103779	148.808694
std	10240.949817	249664.587269	316.050259	4.243825	0.461843	2.073256	1.167787	37.094137	90.187533
min	1.000000	1.000000	0.000000	1.440000	28.431000	-0.010000	20.934000	-0.100000	-0.434900
25%	8269.000000	216216.500000	46.000000	7.680000	33.488000	1.360000	24.965000	21.100000	60.915470
50%	16848.000000	432432.000000	125.000000	10.060000	33.863000	3.440000	25.996000	54.400000	151.064150
75%	26557.000000	648647.500000	300.000000	13.880000	34.196900	5.500000	26.646000	97.600000	240.379600
max	34404.000000	864863.000000	5351.000000	31.140000	37.034000	11.130000	250.784000	214.100000	485.701800

8 rows × 70 columns

In [43]:
```
d.isna().any()
```

Out[43]:
```
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
```

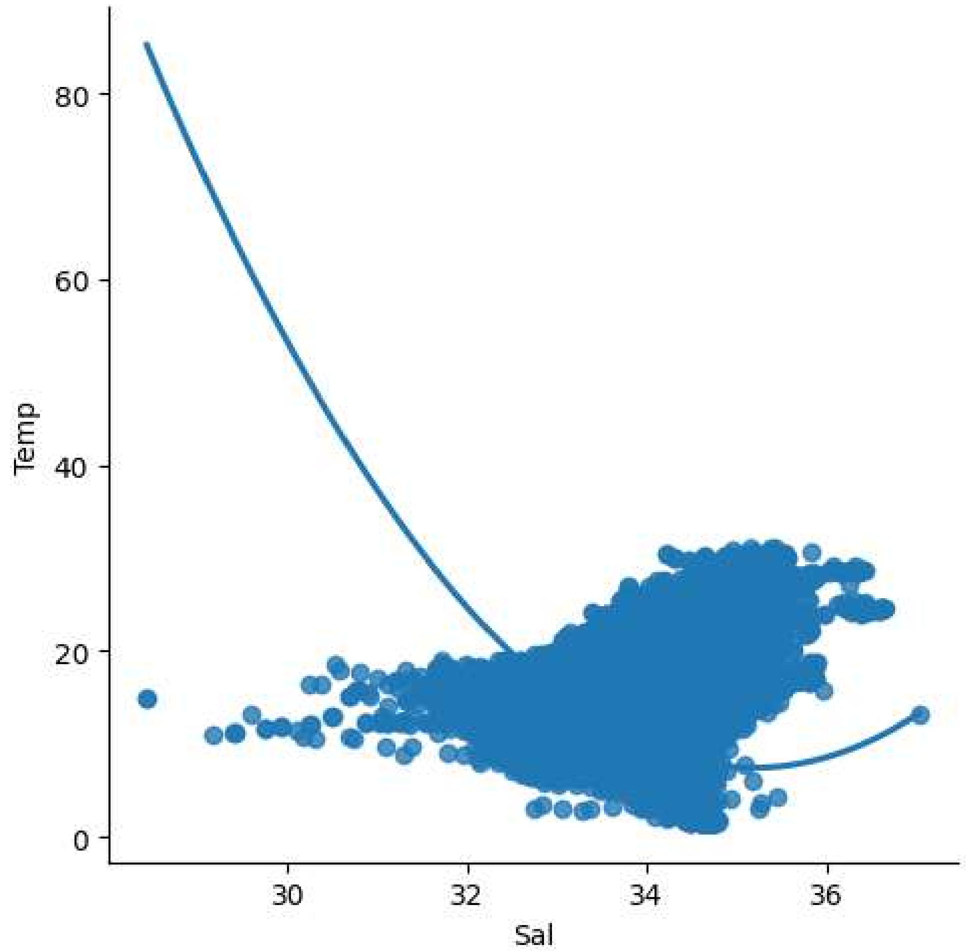
In [44]:
```
d.isnull().sum()
```

Out[44]:
```
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 [45]:
```
d=d[['Salnty', 'T_degC']]
d.columns=['Sal', 'Temp']
```

In [46]:
```
sns.lmplot(x='Sal',y='Temp',data=d,order=2,ci=None)
```

Out[46]: <seaborn.axisgrid.FacetGrid at 0x1118968ae90>



In [47]:
```
d.fillna (method='ffill')
```

Out[47]:

	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 [48]:
```
d.fillna(value=0,inplace=True)
```

```
C:\Users\91949\AppData\Local\Temp\ipykernel_17404\4235753077.py:1: SettingWithCopyWarning:
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/stable/user_guide/indexing.html#returnin
g-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versu
s-a-copy)
  d.fillna(value=0,inplace=True)
```

In [49]:
```
x=np.array(d['Sal']).reshape(-1,1)
y=np.array(d[ 'Temp']).reshape(-1,1)
```

In [50]:
```
d.dropna (inplace=True)
```

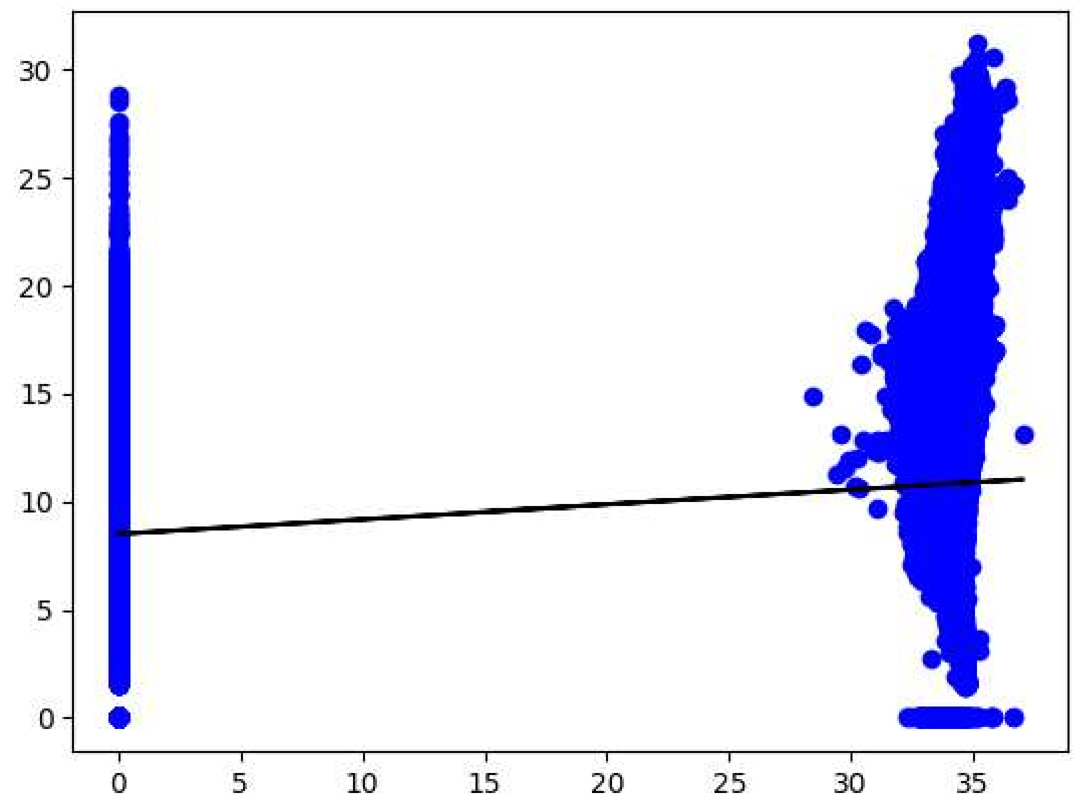
```
C:\Users\91949\AppData\Local\Temp\ipykernel_17404\2818693002.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

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

In [51]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

In [52]:
```
regr=LinearRegression()
regr.fit(x_train,y_train)
print(regr.score (x_test,y_test))
```

```
0.013838527337843964
```

In [53]:
```
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 [54]:
```
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: 0.013838527337843964
```

In [55]:
```
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_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 (1076, 2)
The dimension of X_test is (462, 2)
```

Elastic Net

In [56]:
```
from sklearn.linear_model import ElasticNet
regr=ElasticNet()
regr.fit(x,y)
print(regr.coef_)
print(regr.intercept_)
```

```
[ 8.46751882e-02 -1.30405006e+02]
15279.442735227916
```

In [57]:
```
y_pred_elastic=regr.predict(x_train)
```

In [60]:
```
mean_squared_error=np.mean(y_pred_elastic-y_train)
print("Mean Squared Error on test set",mean_squared_error)
```

```
Mean Squared Error on test set 6695.057976863604
```