PROBLEM STATEMENT:- TO PREDICT THE RAINFALL BASED ON VARIOUS FEATURES OF THEDATASET

```
# IMPORTING THE ESSENTIAL LIBRARIES
```

In [3]:

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing,svm
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:

```
df=pd.read_csv(r"C:\Users\shaik\Desktop\202U1A3344\rainfall in india 1901-2015.csv")
df
```

Out[4]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNU
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388.5	558.2	33.6	337
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197.2	359.0	160.5	352
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181.2	284.4	225.0	295
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222.2	308.7	40.1	307
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260.7	25.4	344.7	256
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	184.3	14.9	153
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	12.4	8.8	140
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	78.1	26.7	142
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	59.0	62.3	139
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	231.0	159.0	164

4116 rows × 19 columns

```
# DATA PREPROCESSING
```

In [5]:

```
df.head()
```

Out[5]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	'
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388.5	558.2	33.6	3373.2	1
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197.2	359.0	160.5	3520.7	1
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181.2	284.4	225.0	2957.4	1
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222.2	308.7	40.1	3079.6	
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260.7	25.4	344.7	2566.7	

In [6]:

```
df.tail()
```

Out[6]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	184.3	14.9	1533.7
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	12.4	8.8	1405.5
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	78.1	26.7	1426.3
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	59.0	62.3	1395.0
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	231.0	159.0	1642.9

In [7]:

```
df.isnull().any()
```

Out[7]:

```
SUBDIVISION    False
YEAR           False
JAN             True
FEB             True
MAR             True
APR             True
MAY             True
JUN             True
JUL             True
AUG             True
SEP             True
OCT             True
NOV             True
DEC             True
ANNUAL          True
Jan-Feb         True
Mar-May         True
Jun-Sep         True
Oct-Dec         True
dtype: bool
```

In [8]:

```
df.fillna(method='ffill',inplace=True)
df.isnull().sum()
```

Out[8]:

```
SUBDIVISION    0
YEAR           0
JAN            0
FEB            0
MAR            0
APR            0
MAY            0
JUN            0
JUL            0
AUG            0
SEP            0
OCT            0
NOV            0
DEC            0
ANNUAL         0
Jan-Feb        0
Mar-May        0
Jun-Sep        0
Oct-Dec        0
dtype: int64
```

In [9]:

```
df.describe()
```

Out[9]:

	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	
count	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	4116.000000	411
mean	1958.218659	18.957240	21.823251	27.415379	43.160641	85.788994	230.567979	347.177235	29
std	33.140898	33.576192	35.922602	47.045473	67.816588	123.220150	234.896056	269.321089	18
min	1901.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.400000	0.000000	
25%	1930.000000	0.600000	0.600000	1.000000	3.000000	8.600000	70.475000	175.900000	15
50%	1958.000000	6.000000	6.700000	7.900000	15.700000	36.700000	138.900000	284.800000	25
75%	1987.000000	22.200000	26.800000	31.400000	50.125000	97.400000	306.150000	418.325000	37
max	2015.000000	583.700000	403.500000	605.600000	595.100000	1168.600000	1609.900000	2362.800000	166

In [10]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4116 entries, 0 to 4115
Data columns (total 19 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   SUBDIVISION  4116 non-null   object 
 1   YEAR         4116 non-null   int64  
 2   JAN          4116 non-null   float64
 3   FEB          4116 non-null   float64
 4   MAR          4116 non-null   float64
 5   APR          4116 non-null   float64
 6   MAY          4116 non-null   float64
 7   JUN          4116 non-null   float64
 8   JUL          4116 non-null   float64
 9   AUG          4116 non-null   float64
 10  SEP          4116 non-null   float64
 11  OCT          4116 non-null   float64
 12  NOV          4116 non-null   float64
 13  DEC          4116 non-null   float64
 14  ANNUAL       4116 non-null   float64
 15  Jan-Feb      4116 non-null   float64
 16  Mar-May      4116 non-null   float64
 17  Jun-Sep      4116 non-null   float64
 18  Oct-Dec      4116 non-null   float64
dtypes: float64(17), int64(1), object(1)
memory usage: 611.1+ KB
```

In [11]:

```
df.columns
```

Out[11]:

```
Index(['SUBDIVISION', 'YEAR', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
       'AUG', 'SEP', 'OCT', 'NOV', 'DEC', 'ANNUAL', 'Jan-Feb', 'Mar-May',
       'Jun-Sep', 'Oct-Dec'],
      dtype='object')
```

In [12]:

```
df.shape
```

Out[12]:

```
(4116, 19)
```

In [13]:

```
df['ANNUAL'].value_counts()
```

Out[13]:

```
790.5     4
770.3     4
1836.2    4
1024.6    4
1926.5    3
         ..
443.9     1
689.0     1
605.2     1
509.7     1
1642.9    1
Name: ANNUAL, Length: 3712, dtype: int64
```

In [14]:

```
df['Jan-Feb'].value_counts()
```

Out[14]:

```
0.0     238
0.1      80
0.2      52
0.3      38
0.4      32
       ...
23.3      1
95.2      1
76.9      1
66.5      1
69.3      1
Name: Jan-Feb, Length: 1220, dtype: int64
```

In [15]:

```
df['Mar-May'].value_counts()
```

Out[15]:

```
0.0      29
0.1      13
0.3      11
8.3      11
11.5     10
         ..
246.3     1
248.1     1
151.3     1
249.5     1
223.9     1
Name: Mar-May, Length: 2262, dtype: int64
```

In [16]:

```
df['Jun-Sep'].value_counts()
```

Out[16]:

```
434.3     4
334.8     4
573.8     4
613.3     4
1082.3    3
         ..
301.6     1
380.9     1
409.3     1
229.4     1
958.5     1
Name: Jun-Sep, Length: 3683, dtype: int64
```

In [17]:

```
df['Oct-Dec'].value_counts()
```

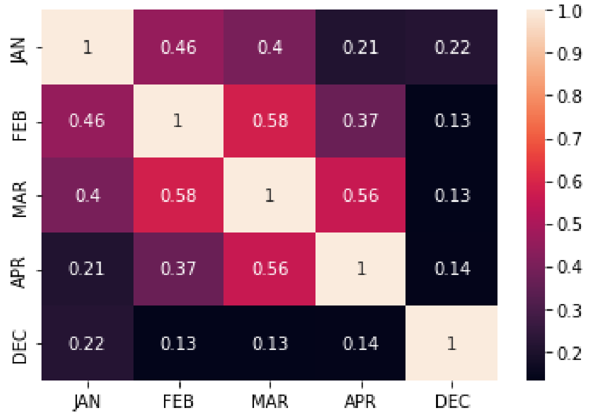
Out[17]:

```
0.0      16
0.1      15
0.5      13
0.6      12
0.7      11
         ..
191.5     1
124.5     1
139.1     1
41.5      1
555.4     1
Name: Oct-Dec, Length: 2389, dtype: int64
```

```
    # EXPLORATARY DATA ANALYSIS:
```

In [18]:

```
df=df[['JAN','FEB','MAR','APR','DEC']]
sns.heatmap(df.corr(),annot=True)
plt.show()
```



In [19]:

```
df.columns
```

Out[19]:

```
Index(['JAN', 'FEB', 'MAR', 'APR', 'DEC'], dtype='object')
```

In [20]:

```
x=df[["FEB"]]
y=df["JAN"]
```

Now we are fitting our data to all models

Linear Regression

In [21]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=44)
```

In [23]:

```
from sklearn.linear_model import LinearRegression
reg=LinearRegression()
reg.fit(X_train,y_train)
print(reg.intercept_)
coeff_=pd.DataFrame(reg.coef_,x.columns,columns=['coefficient'])
coeff_
```

```
9.892556121805407
```

Out[23]:

	coefficient
FEB	0.403596

In [24]:

```
score=reg.score(X_test,y_test)
print(score)
```

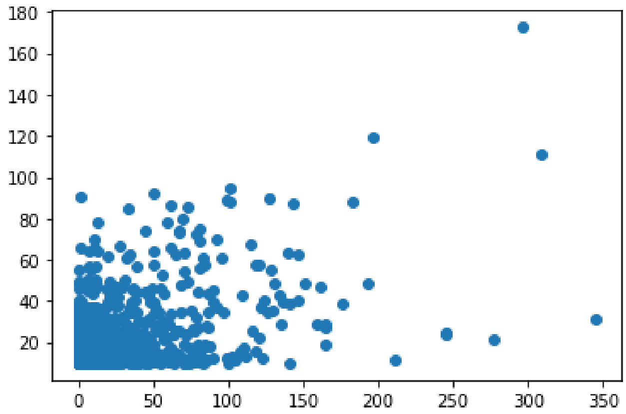
```
0.2383295717256828
```

In [26]:

```
predictions=reg.predict(X_test)
plt.scatter(y_test,predictions)
```

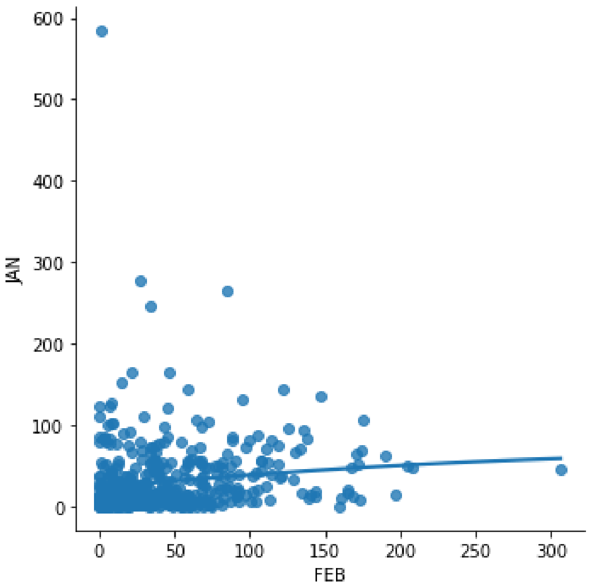
Out[26]:

```
<matplotlib.collections.PathCollection at 0x1c2330b3bb0>
```



In [27]:

```
df500=df[:][:500]
sns.lmplot(x="FEB",y="JAN",order=2,ci=None,data=df500)
plt.show()
```



In [29]:

```
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.33)
reg.fit(X_train,y_train)
reg.fit(X_test,y_test)
```

Out[29]:

```
LinearRegression()
```

In [31]:

```
y_pred=reg.predict(X_test)
plt.scatter(X_test,y_test,color='black')
plt.plot(X_test,y_pred,color='r')
plt.show()
```

```
   3631 # GH#42269

File ~\anaconda3\lib\site-packages\pandas\core\indexes\base.py:5637, in Index._check_index
ing_error(self, key)
   5633 def _check_indexing_error(self, key):
   5634     if not is_scalar(key):
   5635         # if key is not a scalar, directly raise an error (the code below
   5636         # would convert to numpy arrays and raise later any way) - GH29926
-> 5637         raise InvalidIndexError(key)

InvalidIndexError: (slice(None, None, None), None)
```

In [33]:

```
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: 0.18265421008098348
```

ridge model:

In [34]:

```
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
features= df.columns[0:5]
target= df.columns[-5]
```

In [35]:

```
x=np.array(df['JAN']).reshape(-1,1)
y=np.array(df['FEB']).reshape(-1,2)
```

In [36]:

```
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=18)
```

In [37]:

```
ridgeReg=Ridge(alpha=10)
ridgeReg.fit(x_train,y_train)
train_score_ridge=ridgeReg.score(x_train,y_train)
test_score_ridge=ridgeReg.score(x_test,y_test)
```

In [38]:

```
print("\n Ridge 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))
```

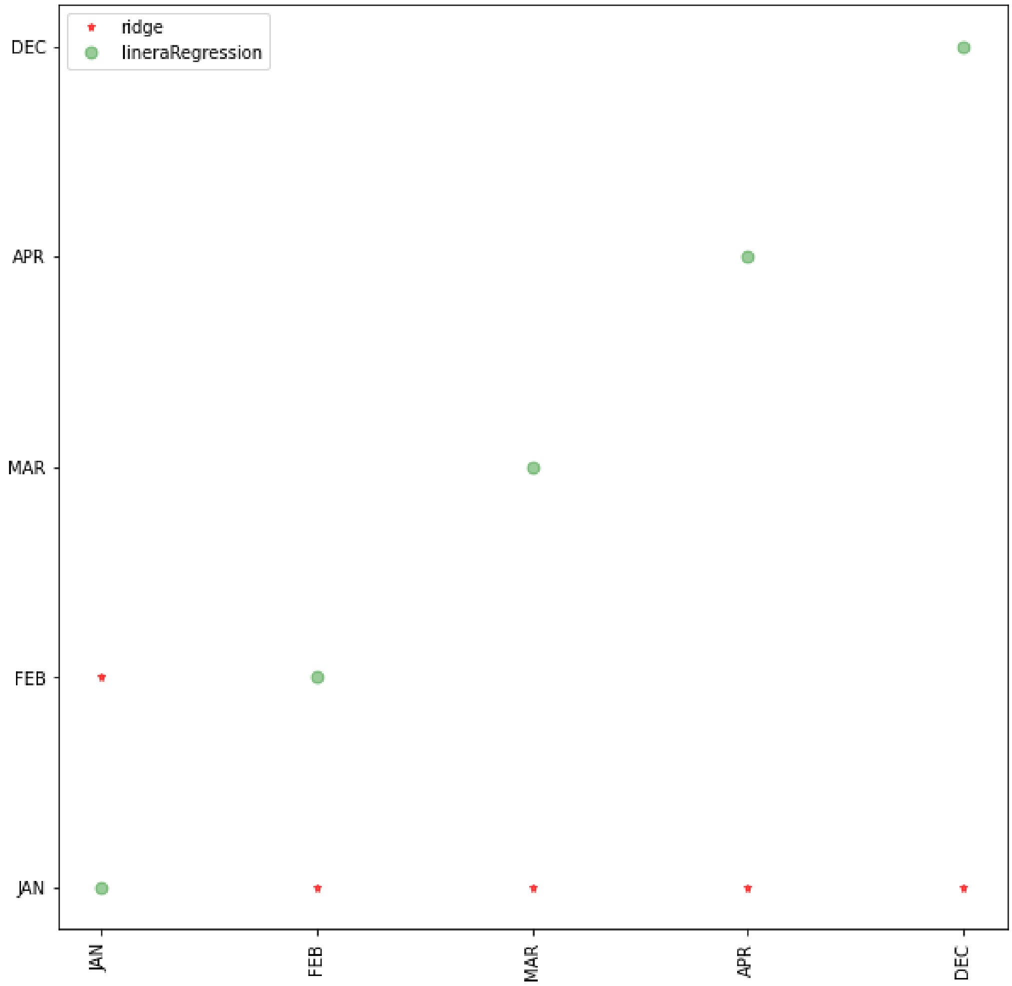
```
 Ridge Model:

the train score for ridge model is0.999999999984547
the test score for ridge model is0.9999999999809215
```

In [39]:

```
lr=LinearRegression()
```

In [40]:

```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color="red",label="ridg
plt.plot(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color="green",label="lineraRegression"
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



LASSO MODEL:

In [41]:

```
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))
```

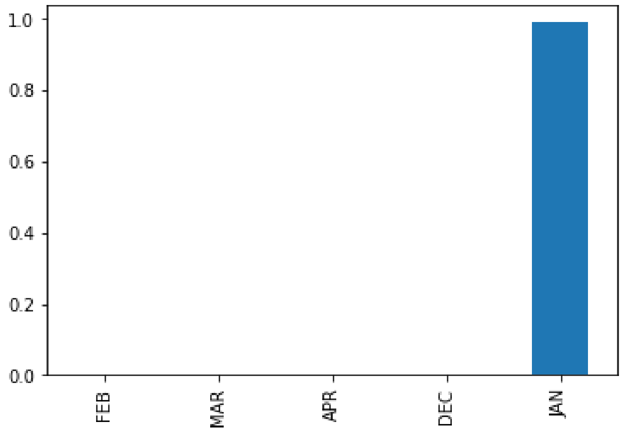
```
The train score for ls model is 0.9999116675344395
The test score for ls model is0.9999116271603994
```

In [42]:

```
pd.Series(lasso.coef_,features).sort_values(ascending=True).plot(kind="bar")
```

Out[42]:

```
<AxesSubplot:>
```



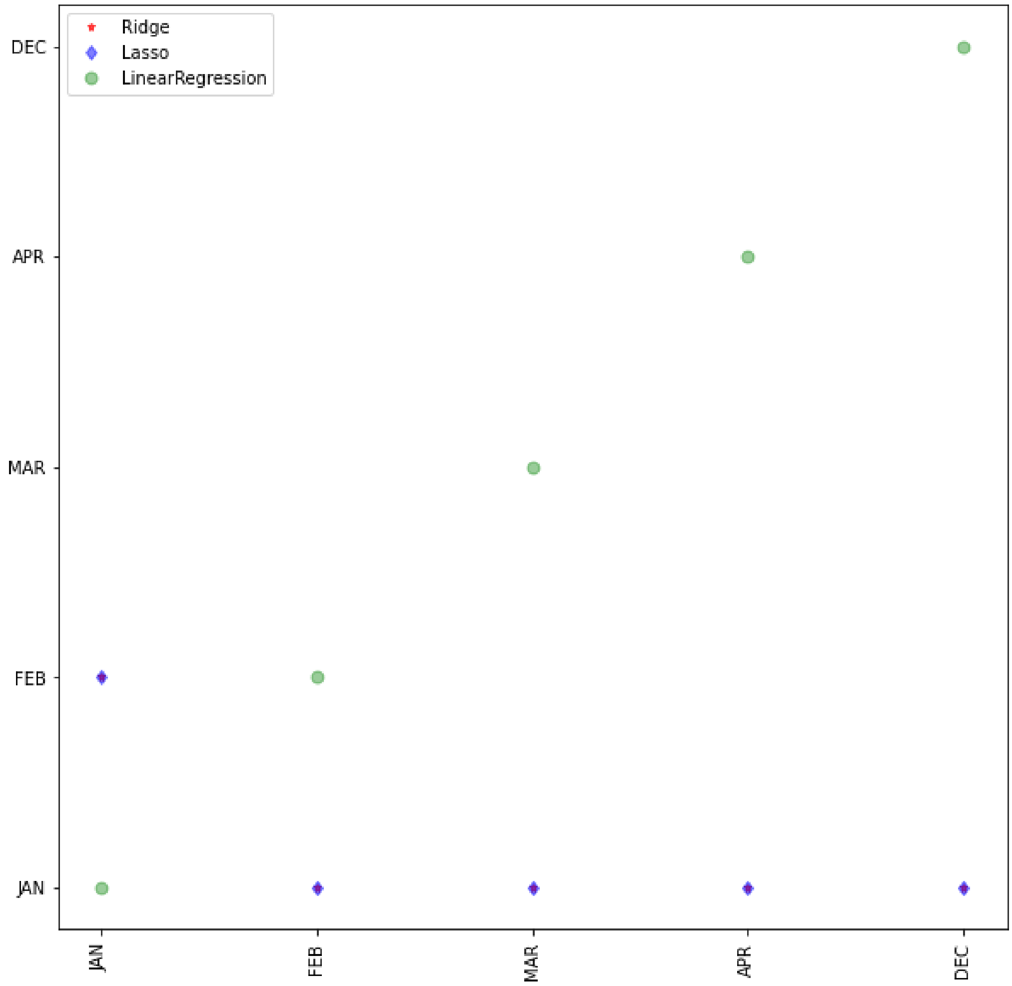
In [43]:

```
from sklearn.linear_model import LassoCV
lasso_cv=LassoCV(alphas=[0.0001,0.001,0.01,1,10],random_state=0).fit(x_train,y_train)
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999911
0.9999999999999911
```

In [44]:

```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",markersize=5,color="red",label="Ridge
plt.plot(lasso_cv.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label="Lasso")
plt.plot(features,alpha=0.4,linestyle='none',marker='o',markersize=7,color="green",label="LinearRegression"
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



ELASTIC NET

In [45]:

```
from sklearn.linear_model import ElasticNet
eln=ElasticNet()
eln.fit(x,y)
print(eln.coef_)
print(eln.intercept_)
print(eln.score(x,y))
```

```
[9.99098574e-01 0.00000000e+00 3.02728910e-05 0.00000000e+00
 0.00000000e+00]
0.016258606966616185
0.9999992160905338
```

In [51]:

```
y_pred_elastic = eln.predict(x_train)
mean_squared_error=np.mean((y_pred_elastic - y_train)**2)
print(mean_squared_error)
```

```
0.0008307258312266487
```

CONCLUSION:

In [ ]:

```
Here we concluded that with respect to all other models we getting LassoModel for best accuracy
```