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

## IMPORTING THE ESSENTIAL LIBRARIES:-

In [1]:

```
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 [2]:

```
df=pd.read_csv(r"C:\Users\Prathyusha\Downloads\rainfall in india 1901-2015.csv")
df
```

Out[2]:

| | SUBDIVISION | YEAR | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | O |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | ANDAMAN & NICOBAR ISLANDS | 1901 | 49.2 | 87.1 | 29.2 | 2.3 | 528.8 | 517.5 | 365.1 | 481.1 | 332.6 | 38 |
| **1** | ANDAMAN & NICOBAR ISLANDS | 1902 | 0.0 | 159.8 | 12.2 | 0.0 | 446.1 | 537.1 | 228.9 | 753.7 | 666.2 | 19 |
| **2** | ANDAMAN & NICOBAR ISLANDS | 1903 | 12.7 | 144.0 | 0.0 | 1.0 | 235.1 | 479.9 | 728.4 | 326.7 | 339.0 | 18 |
| **3** | ANDAMAN & NICOBAR ISLANDS | 1904 | 9.4 | 14.7 | 0.0 | 202.4 | 304.5 | 495.1 | 502.0 | 160.1 | 820.4 | 22 |
| **4** | ANDAMAN & NICOBAR ISLANDS | 1905 | 1.3 | 0.0 | 3.3 | 26.9 | 279.5 | 628.7 | 368.7 | 330.5 | 297.0 | 26 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **4111** | LAKSHADWEEP | 2011 | 5.1 | 2.8 | 3.1 | 85.9 | 107.2 | 153.6 | 350.2 | 254.0 | 255.2 | 11 |
| **4112** | LAKSHADWEEP | 2012 | 19.2 | 0.1 | 1.6 | 76.8 | 21.2 | 327.0 | 231.5 | 381.2 | 179.8 | 14 |
| **4113** | LAKSHADWEEP | 2013 | 26.2 | 34.4 | 37.5 | 5.3 | 88.3 | 426.2 | 296.4 | 154.4 | 180.0 | 7 |
| **4114** | LAKSHADWEEP | 2014 | 53.2 | 16.1 | 4.4 | 14.9 | 57.4 | 244.1 | 116.1 | 466.1 | 132.2 | 16 |
| **4115** | LAKSHADWEEP | 2015 | 2.2 | 0.5 | 3.7 | 87.1 | 133.1 | 296.6 | 257.5 | 146.4 | 160.4 | 16 |

4116 rows × 19 columns

# DATA PREPROCESSING:-

In [3]:

```
df.head()
```

Out[3]:

| | SUBDIVISION | YEAR | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OCT | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 | 5 |
| **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 | 3 |
| **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 | 2 |
| **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 | 3 |
| **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 | |

In [4]:

```
df.tail()
```

Out[4]:

| | SUBDIVISION | YEAR | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4111** | LAKSHADWEEP | 2011 | 5.1 | 2.8 | 3.1 | 85.9 | 107.2 | 153.6 | 350.2 | 254.0 | 255.2 | 117. |
| **4112** | LAKSHADWEEP | 2012 | 19.2 | 0.1 | 1.6 | 76.8 | 21.2 | 327.0 | 231.5 | 381.2 | 179.8 | 145. |
| **4113** | LAKSHADWEEP | 2013 | 26.2 | 34.4 | 37.5 | 5.3 | 88.3 | 426.2 | 296.4 | 154.4 | 180.0 | 72. |
| **4114** | LAKSHADWEEP | 2014 | 53.2 | 16.1 | 4.4 | 14.9 | 57.4 | 244.1 | 116.1 | 466.1 | 132.2 | 169. |
| **4115** | LAKSHADWEEP | 2015 | 2.2 | 0.5 | 3.7 | 87.1 | 133.1 | 296.6 | 257.5 | 146.4 | 160.4 | 165. |

In [5]:

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

Out[5]:

```
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 [6]:

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

In [7]:

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

Out[7]:

```
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 [8]:

```
df.describe()
```

Out[8]:

| | YEAR | JAN | FEB | MAR | APR | MAY | |
|---|---|---|---|---|---|---|---|
| **count** | 4116.000000 | 4116.000000 | 4116.000000 | 4116.000000 | 4116.000000 | 4116.000000 | 4116.0( |
| **mean** | 1958.218659 | 18.957240 | 21.823251 | 27.415379 | 43.160641 | 85.788994 | 230.5( |
| **std** | 33.140898 | 33.576192 | 35.922602 | 47.045473 | 67.816588 | 123.220150 | 234.8! |
| **min** | 1901.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.4( |
| **25%** | 1930.000000 | 0.600000 | 0.600000 | 1.000000 | 3.000000 | 8.600000 | 70.4 |
| **50%** | 1958.000000 | 6.000000 | 6.700000 | 7.900000 | 15.700000 | 36.700000 | 138.9( |
| **75%** | 1987.000000 | 22.200000 | 26.800000 | 31.400000 | 50.125000 | 97.400000 | 306.1! |
| **max** | 2015.000000 | 583.700000 | 403.500000 | 605.600000 | 595.100000 | 1168.600000 | 1609.9( |

In [9]:

```
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 [10]:

```
df.columns
```

Out[10]:

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

In [11]:

```
df.shape
```

Out[11]:

```
(4116, 19)
```

In [12]:

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

Out[12]:

```
ANNUAL
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: count, Length: 3712, dtype: int64
```

In [13]:

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

Out[13]:

```
Jan-Feb
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: count, Length: 1220, dtype: int64
```

In [14]:

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

Out[14]:

```
Mar-May
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: count, Length: 2262, dtype: int64
```

In [15]:

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

Out[15]:

```
Jun-Sep
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: count, Length: 3683, dtype: int64
```

In [16]:

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

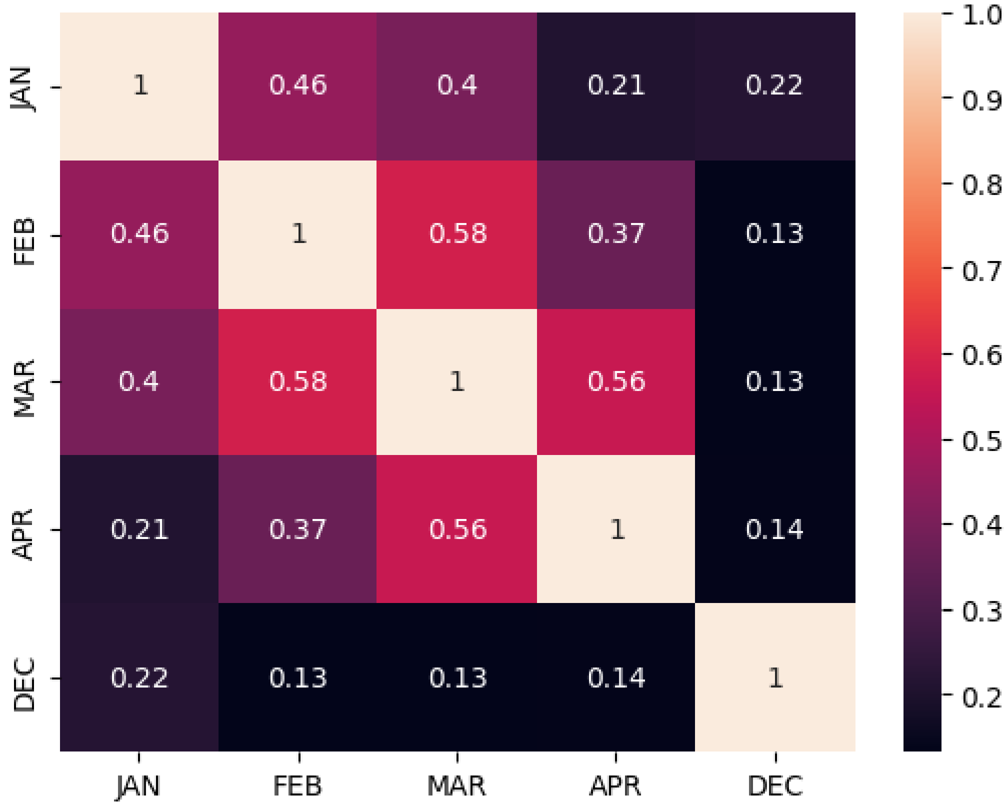
Out[16]:

```
Oct-Dec
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: count, Length: 2389, dtype: int64
```

## EXPLORATARY DATA ANALYSIS:-

In [19]:

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




In [20]:

```
df.columns
```

Out[20]:

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

In [21]:

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

## LINEAR REGRESSION:-

In [22]:

```
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=42)
```

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_
```

```
9.650666612303553
```

Out[23]:

| | coefficient |
|---|---|
| **FEB** | 0.442278 |

In [24]:

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

```
0.1793580786264921
```

In [25]:

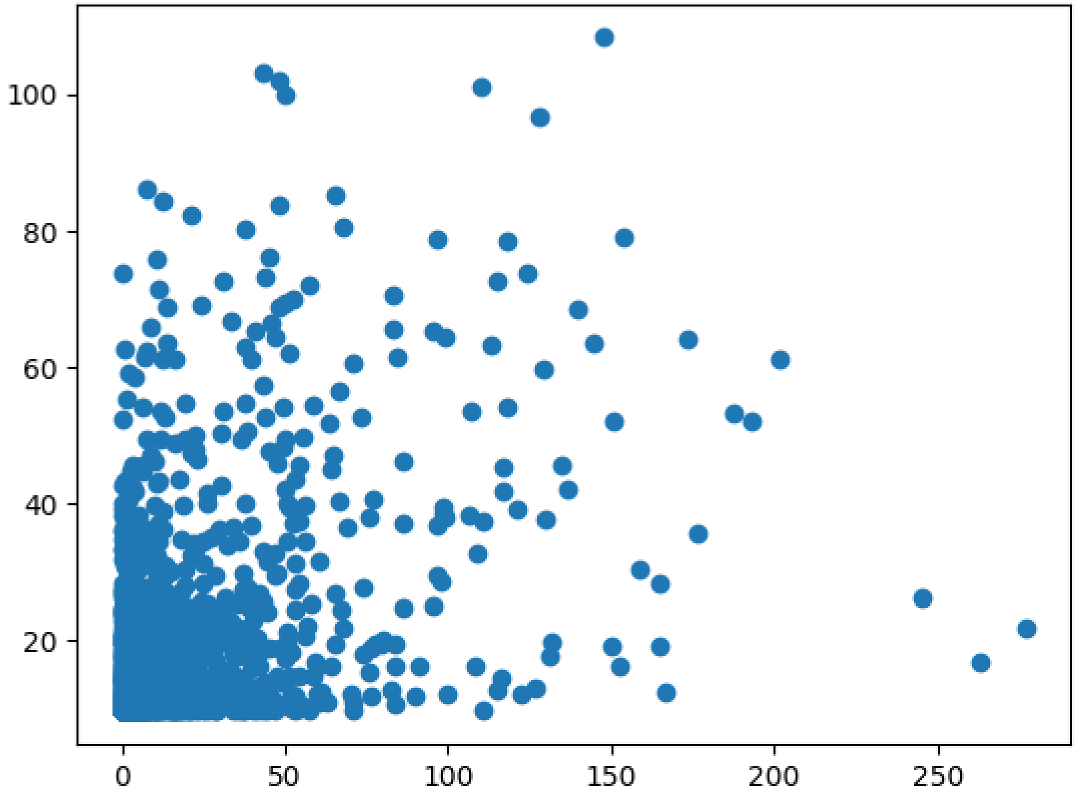
```
predictions=reg.predict(X_test)
```

In [26]:

```
plt.scatter(y_test,predictions)
```

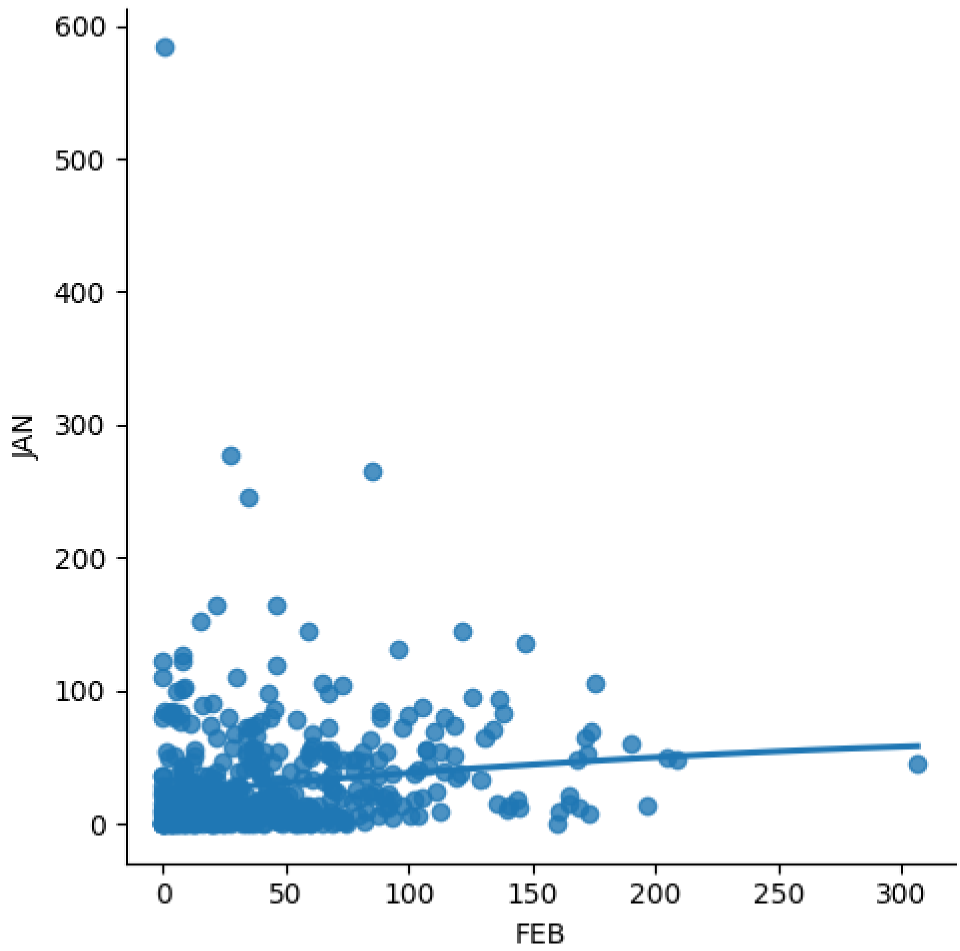
Out[26]:

```
<matplotlib.collections.PathCollection at 0x21831ba8710>
```



In [27]:

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




In [28]:

```
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[28]:

```
LinearRegression()
```

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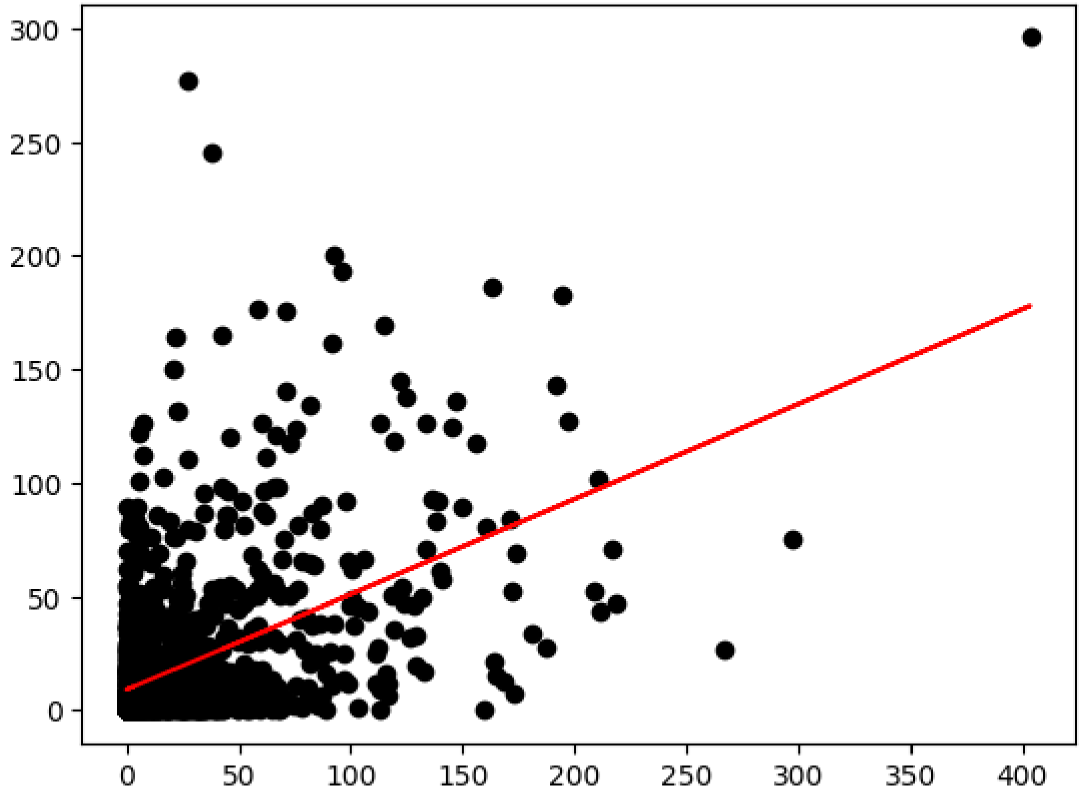
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [29]:

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




In [30]:

```
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: 0.2471525141287697
```

# RIDGE MODEL:-

In [31]:

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

In [32]:

```
features= df.columns[0:5]
target= df.columns[-5]
```

In [33]:

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

In [34]:

```
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)
```

In [35]:

```
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 [36]:

```
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))
```

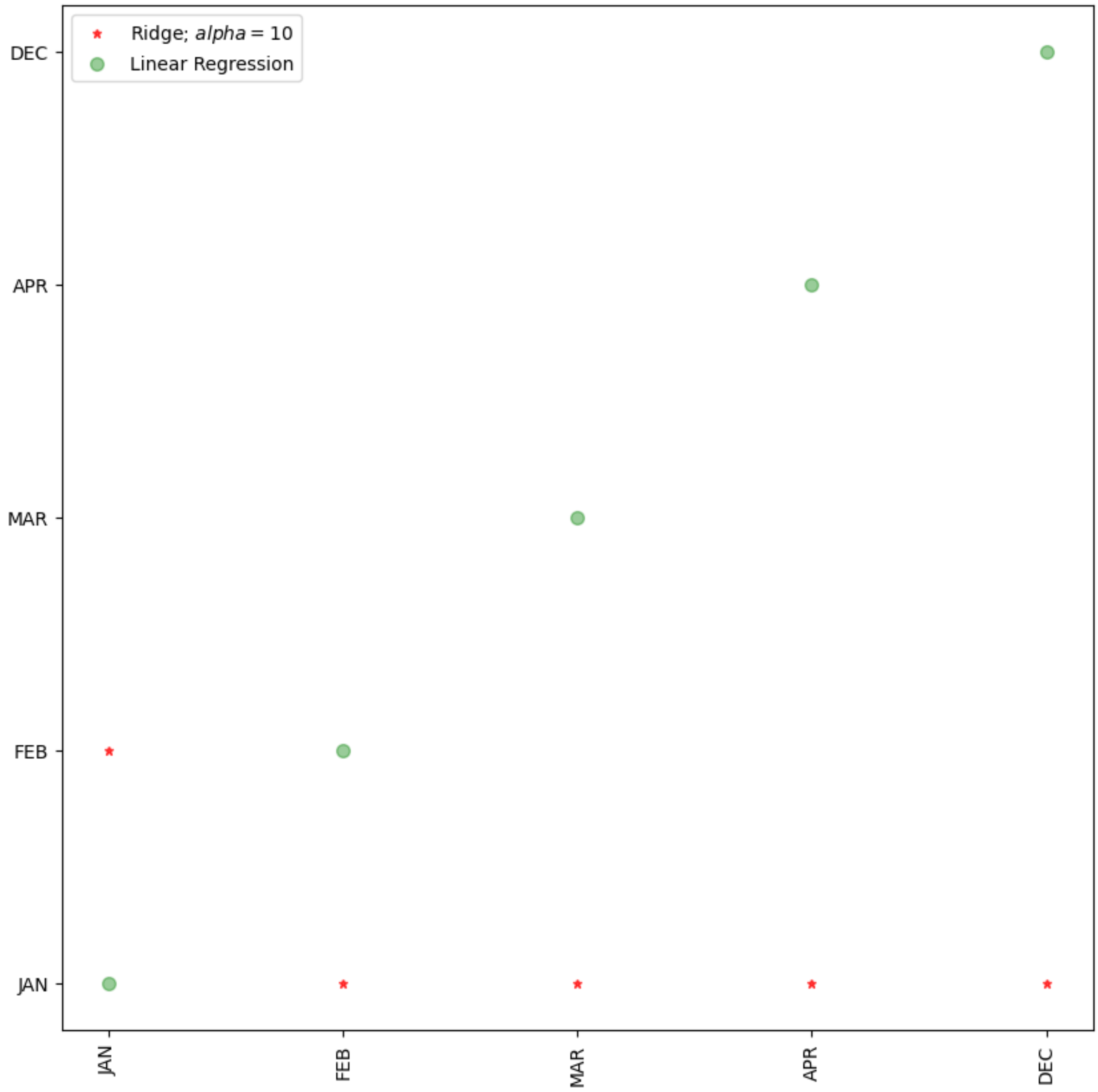
```
 Ridge Model:

the train score for ridge model is0.9999999999874192
the test score for ridge model is0.99999999998833
```

In [37]:

```
lr=LinearRegression()
```

In [38]:

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



## Lasso Regression:-

In [39]:

```
print("\n Lasso 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))
```

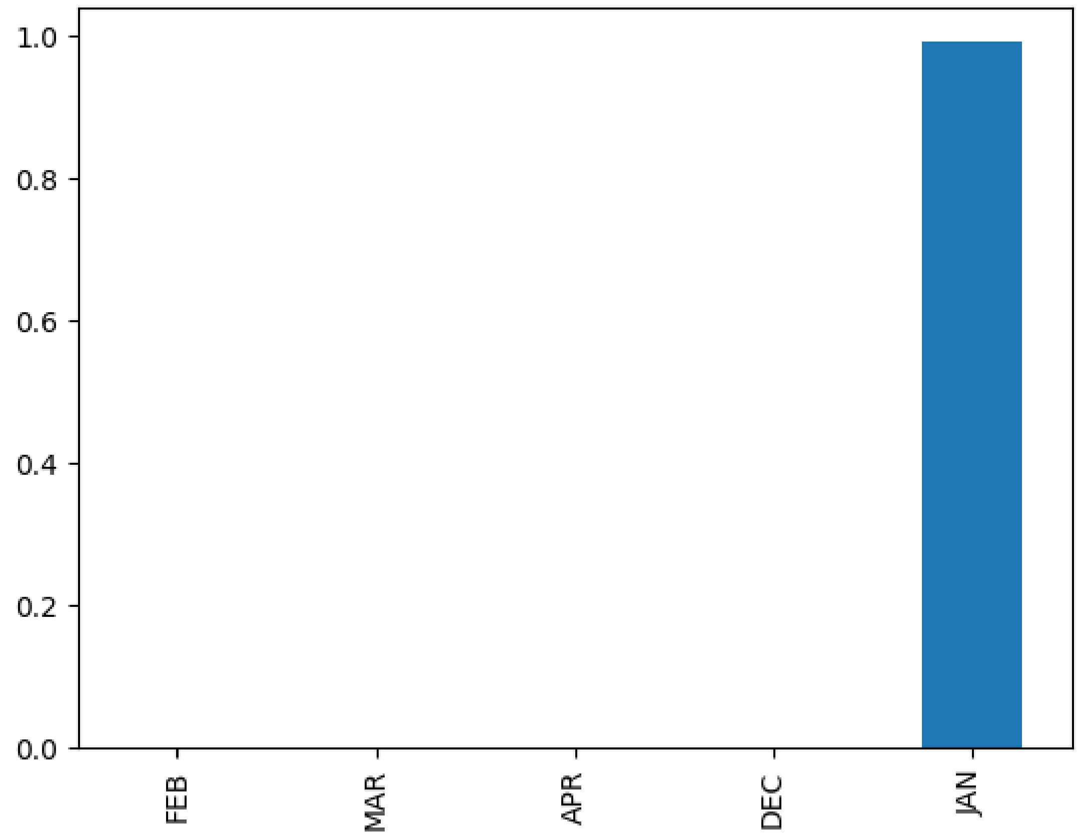
```
 Lasso Model:

The train score for ls model is 0.9999207747038827
The test score for ls model is0.9999206791315256
```

In [40]:

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

Out[40]:

<Axes: >



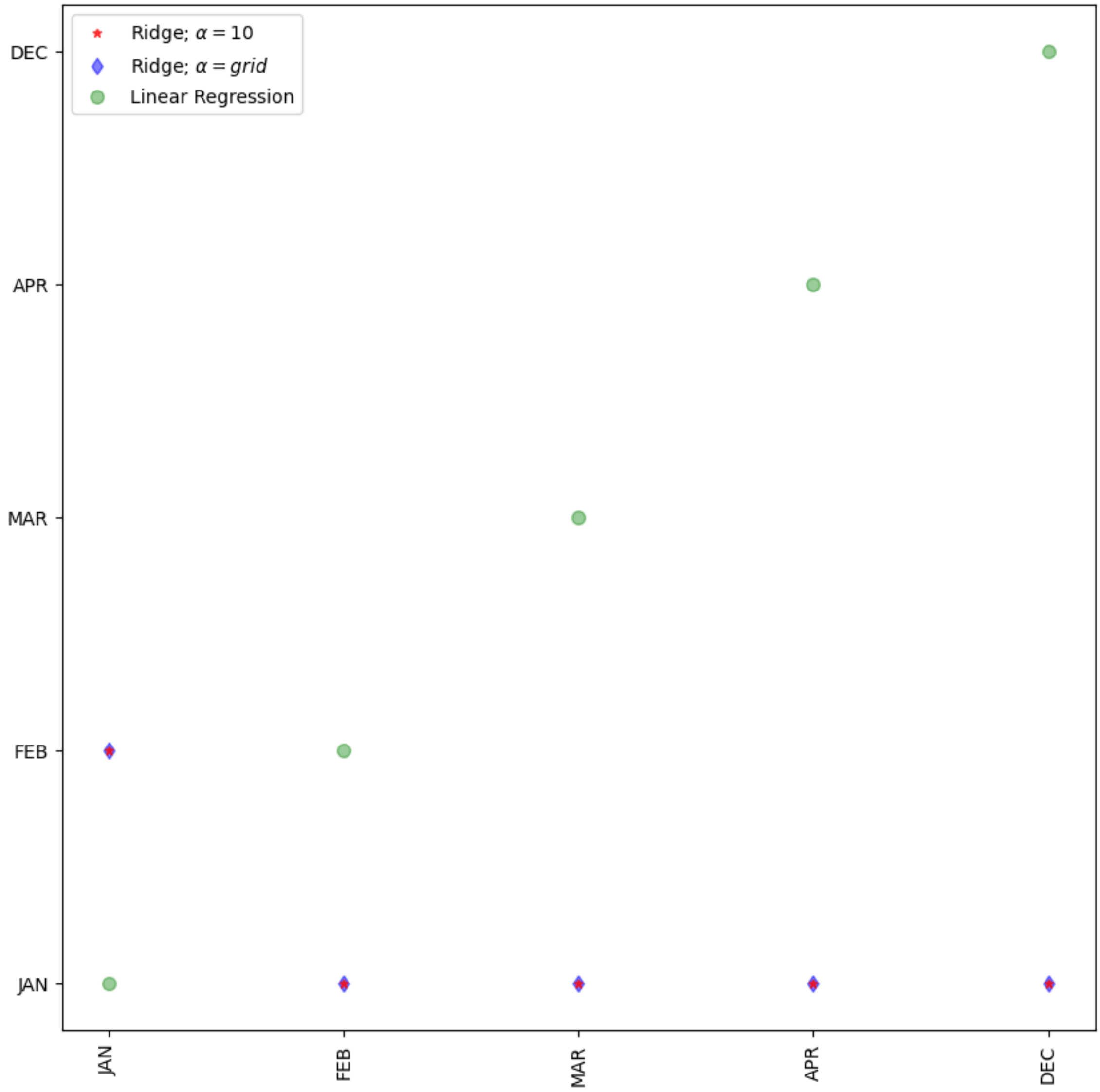
In [41]:

```
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))
```

```
0.9999999999999921
0.9999999999999921
```

In [44]:

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



## ELASTIC NET:-

In [50]:

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

```
[9.99098574e-01 0.00000000e+00 3.02728910e-05 0.00000000e+00
 0.00000000e+00]
0.01625860696662329
0.9999992160905338
```

In [51]:

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

```
0.0008816302333966198
```

## CONCLUSION:-

```
               THE SCORE OF LINEAR REGRESSION IS :- 0.1793580786264921
               THE SCORE OF RIDGE MODEL IS :- 0.99999999998833
               THE SCORE OF LASSO MODEL IS :- 0.999999999999992
               THE SCORE OF ELASTIC NET IS :- 0.9999992160905338
           *AMONG ALL MODELS LASSO YEILD HIGHEST ACCURACY.SO,WE PREFER LASSO MODEL
   FO
```

R THIS DATA SET*