RAINFALL

June 15, 2023

#PROBLEM STATEMENT:- TO PREDICT THE RAIN FALL BASED ON VARIOUS FEATURES OF THE DATASET WHICH IS GIVEN BELOW

IMPORTING THE ESSENTIAL LIBRARIES:-

[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
```

[5]:
```
df=pd.read_csv(r"/content/RAIN FALL.csv")
df
```

[5]:
```
                   SUBDIVISION  YEAR   JAN    FEB   MAR    APR    MAY    JUN  \
0     ANDAMAN & NICOBAR ISLANDS  1901  49.2   87.1  29.2    2.3  528.8  517.5
1     ANDAMAN & NICOBAR ISLANDS  1902   0.0  159.8  12.2    0.0  446.1  537.1
2     ANDAMAN & NICOBAR ISLANDS  1903  12.7  144.0   0.0    1.0  235.1  479.9
3     ANDAMAN & NICOBAR ISLANDS  1904   9.4   14.7   0.0  202.4  304.5  495.1
4     ANDAMAN & NICOBAR ISLANDS  1905   1.3    0.0   3.3   26.9  279.5  628.7
…                             …   …     …     …    …      …      …      …
4111               LAKSHADWEEP  2011   5.1    2.8   3.1   85.9  107.2  153.6
4112               LAKSHADWEEP  2012  19.2    0.1   1.6   76.8   21.2  327.0
4113               LAKSHADWEEP  2013  26.2   34.4  37.5    5.3   88.3  426.2
4114               LAKSHADWEEP  2014  53.2   16.1   4.4   14.9   57.4  244.1
4115               LAKSHADWEEP  2015   2.2    0.5   3.7   87.1  133.1  296.6

        JUL    AUG    SEP    OCT    NOV    DEC  ANNUAL  Jan-Feb  Mar-May  \
0     365.1  481.1  332.6  388.5  558.2   33.6  3373.2    136.3    560.3
1     228.9  753.7  666.2  197.2  359.0  160.5  3520.7    159.8    458.3
2     728.4  326.7  339.0  181.2  284.4  225.0  2957.4    156.7    236.1
3     502.0  160.1  820.4  222.2  308.7   40.1  3079.6     24.1    506.9
4     368.7  330.5  297.0  260.7   25.4  344.7  2566.7      1.3    309.7
…       …     …      …      …      …      …      …        …
4111  350.2  254.0  255.2  117.4  184.3   14.9  1533.7      7.9    196.2
4112  231.5  381.2  179.8  145.9   12.4    8.8  1405.5     19.3     99.6
4113  296.4  154.4  180.0   72.8   78.1   26.7  1426.3     60.6    131.1
```

```
4114  116.1  466.1  132.2  169.2   59.0   62.3  1395.0     69.3     76.7
4115  257.5  146.4  160.4  165.4  231.0  159.0  1642.9      2.7    223.9

      Jun-Sep  Oct-Dec
0      1696.3    980.3
1      2185.9    716.7
2      1874.0    690.6
3      1977.6    571.0
4      1624.9    630.8
…         …       …
4111   1013.0    316.6
4112   1119.5    167.1
4113   1057.0    177.6
4114    958.5    290.5
4115    860.9    555.4

[4116 rows x 19 columns]
```

DATA PREPROCESSING:-

[6]:
```
df.head()
```

[6]:
```
                SUBDIVISION  YEAR   JAN    FEB   MAR    APR    MAY    JUN  \
0  ANDAMAN & NICOBAR ISLANDS  1901  49.2   87.1  29.2    2.3  528.8  517.5
1  ANDAMAN & NICOBAR ISLANDS  1902   0.0  159.8  12.2    0.0  446.1  537.1
2  ANDAMAN & NICOBAR ISLANDS  1903  12.7  144.0   0.0    1.0  235.1  479.9
3  ANDAMAN & NICOBAR ISLANDS  1904   9.4   14.7   0.0  202.4  304.5  495.1
4  ANDAMAN & NICOBAR ISLANDS  1905   1.3    0.0   3.3   26.9  279.5  628.7

     JUL    AUG    SEP    OCT    NOV    DEC  ANNUAL  Jan-Feb  Mar-May  \
0  365.1  481.1  332.6  388.5  558.2   33.6  3373.2    136.3    560.3
1  228.9  753.7  666.2  197.2  359.0  160.5  3520.7    159.8    458.3
2  728.4  326.7  339.0  181.2  284.4  225.0  2957.4    156.7    236.1
3  502.0  160.1  820.4  222.2  308.7   40.1  3079.6     24.1    506.9
4  368.7  330.5  297.0  260.7   25.4  344.7  2566.7      1.3    309.7

   Jun-Sep  Oct-Dec
0   1696.3    980.3
1   2185.9    716.7
2   1874.0    690.6
3   1977.6    571.0
4   1624.9    630.8
```

[7]:
```
df.tail()
```

[7]:
```
      SUBDIVISION  YEAR   JAN  FEB  MAR   APR    MAY    JUN    JUL    AUG  \
4111  LAKSHADWEEP  2011   5.1  2.8  3.1  85.9  107.2  153.6  350.2  254.0
```

```
4112  LAKSHADWEEP  2012  19.2   0.1   1.6  76.8   21.2  327.0  231.5  381.2
4113  LAKSHADWEEP  2013  26.2  34.4  37.5   5.3   88.3  426.2  296.4  154.4
4114  LAKSHADWEEP  2014  53.2  16.1   4.4  14.9   57.4  244.1  116.1  466.1
4115  LAKSHADWEEP  2015   2.2   0.5   3.7  87.1  133.1  296.6  257.5  146.4

        SEP    OCT    NOV    DEC  ANNUAL  Jan-Feb  Mar-May  Jun-Sep  Oct-Dec
4111  255.2  117.4  184.3   14.9  1533.7      7.9    196.2   1013.0    316.6
4112  179.8  145.9   12.4    8.8  1405.5     19.3     99.6   1119.5    167.1
4113  180.0   72.8   78.1   26.7  1426.3     60.6    131.1   1057.0    177.6
4114  132.2  169.2   59.0   62.3  1395.0     69.3     76.7    958.5    290.5
4115  160.4  165.4  231.0  159.0  1642.9      2.7    223.9    860.9    555.4
```

[8]:
```python
df.isnull().any()
```

[8]:
```
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
```

[9]:
```python
df.fillna(method='ffill',inplace=True)
```

[10]:
```python
df.describe()
```

[10]:
```
              YEAR          JAN          FEB          MAR          APR  \
count  4116.000000  4116.000000  4116.000000  4116.000000  4116.000000
mean   1958.218659    18.957240    21.823251    27.415379    43.160641
std      33.140898    33.576192    35.922602    47.045473    67.816588
min    1901.000000     0.000000     0.000000     0.000000     0.000000
25%    1930.000000     0.600000     0.600000     1.000000     3.000000
50%    1958.000000     6.000000     6.700000     7.900000    15.700000
75%    1987.000000    22.200000    26.800000    31.400000    50.125000
```

```
max    2015.000000   583.700000   403.500000   605.600000   595.100000

               MAY          JUN          JUL          AUG          SEP  \
count  4116.000000  4116.000000  4116.000000  4116.000000  4116.000000
mean     85.788994   230.567979   347.177235   290.239796   197.524781
std     123.220150   234.896056   269.321089   188.785639   135.509037
min       0.000000     0.400000     0.000000     0.000000     0.100000
25%       8.600000    70.475000   175.900000   155.850000   100.575000
50%      36.700000   138.900000   284.800000   259.400000   174.000000
75%      97.400000   306.150000   418.325000   377.800000   266.225000
max    1168.600000  1609.900000  2362.800000  1664.600000  1222.000000

               OCT          NOV          DEC       ANNUAL      Jan-Feb  \
count  4116.000000  4116.000000  4116.000000  4116.000000  4116.000000
mean     95.724198    40.081997    19.042225  1417.221769    40.768975
std      99.689878    68.851397    42.655830   907.547328    59.302112
min       0.000000     0.000000     0.000000    62.300000     0.000000
25%      14.600000     0.700000     0.100000   806.450000     4.100000
50%      65.750000     9.700000     3.100000  1124.650000    19.200000
75%     148.600000    46.325000    17.600000  1660.425000    50.425000
max     948.300000   648.900000   617.500000  6331.100000   699.500000

           Mar-May      Jun-Sep      Oct-Dec
count  4116.000000  4116.000000  4116.000000
mean    156.579155  1065.552114   154.957070
std     202.056770   707.840186   167.807169
min       0.000000    57.400000     0.000000
25%      24.200000   574.375000    34.200000
50%      75.150000   881.750000    98.800000
75%     197.700000  1291.125000   215.775000
max    1745.800000  4536.900000  1252.500000
```

[11]:
```python
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
```

[12]:
```
df.columns
```

[12]:
```
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')
```

[13]:
```
df.shape
```

[13]:
```
(4116, 19)
```

[14]:
```
df['ANNUAL'].value_counts()
```

[14]:
```
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
```

[15]:
```
df['Jan-Feb'].value_counts()
```

[15]:
```
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
```

[16]:
```python
df['Mar-May'].value_counts()
```

[16]:
```
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
```

[17]:
```python
df['Jun-Sep'].value_counts()
```

[17]:
```
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
```

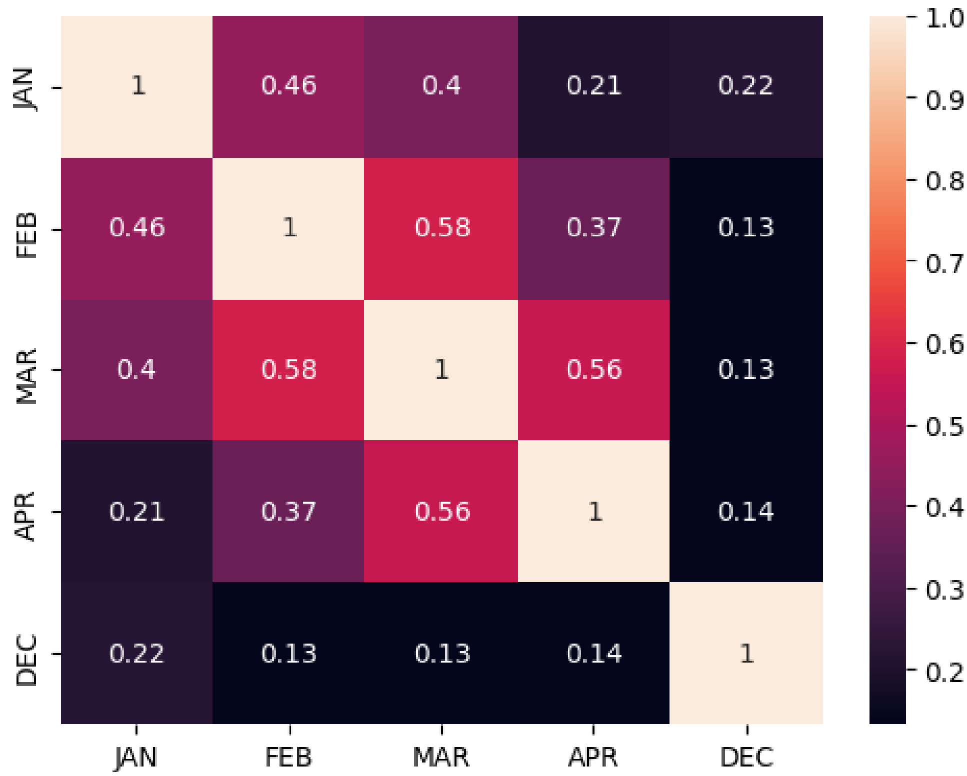
[18]:
```python
df['Oct-Dec'].value_counts()
```

[18]:
```
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:-

[19]:
```python
df=df[['JAN','FEB','MAR','APR','DEC']]
sns.heatmap(df.corr(),annot=True)
plt.show()
```



[20]:
```python
df.columns
```

[20]:
```
Index(['JAN', 'FEB', 'MAR', 'APR', 'DEC'], dtype='object')
```

[21]:
```python
x=df[["FEB"]]
y=df["JAN"]
```

LINEAR REGRESSION:-

[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)
```

[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

[23]:

	coefficient
FEB	0.442278

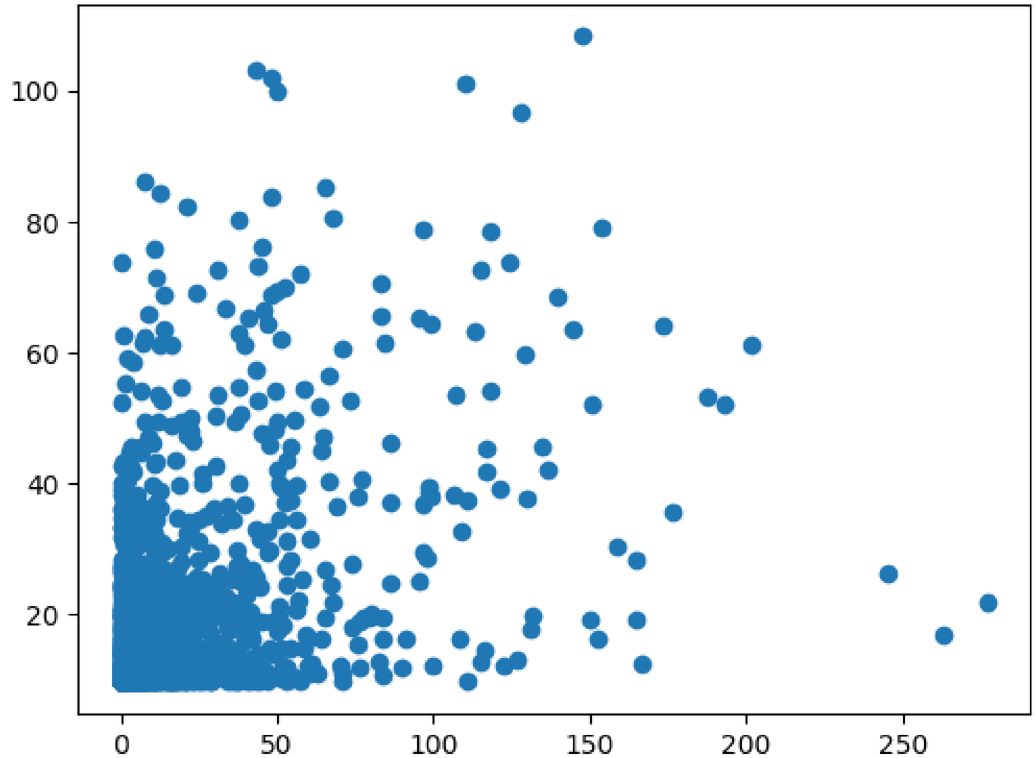
[24]:
```
score=reg.score(X_test,y_test)
print(score)
```

0.1793580786264921

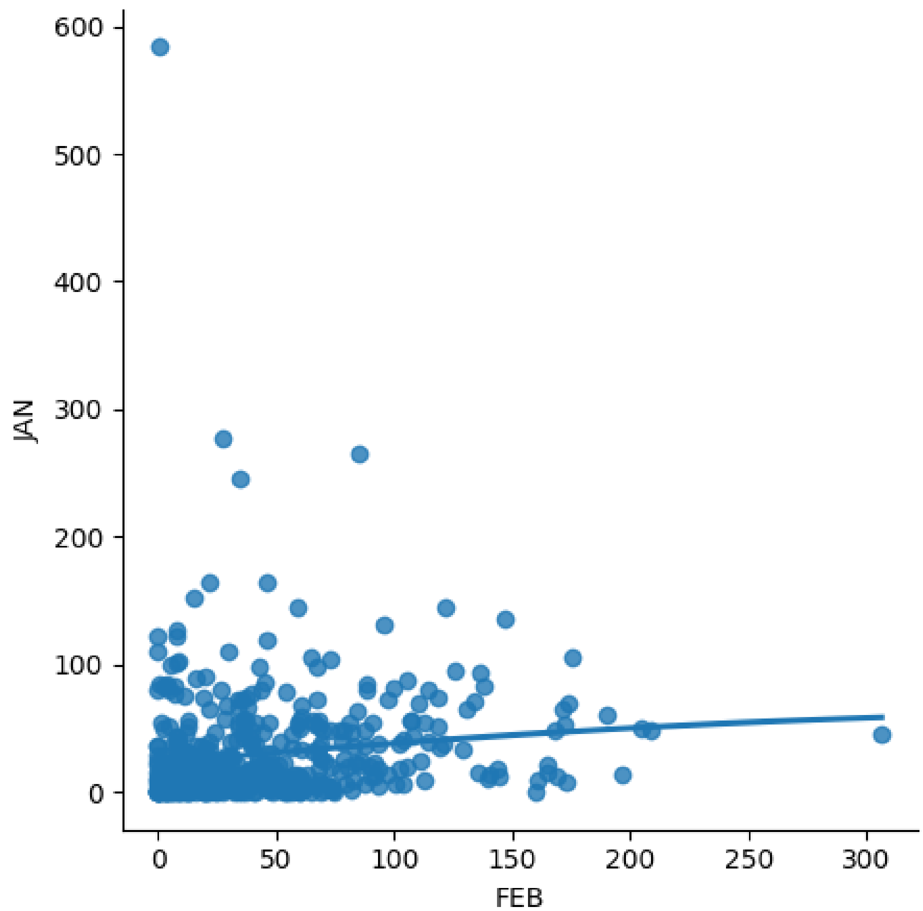
[25]:
```
predictions=reg.predict(X_test)
```

[26]:
```
plt.scatter(y_test,predictions)
```

[26]: <matplotlib.collections.PathCollection at 0x7efc0260e1d0>



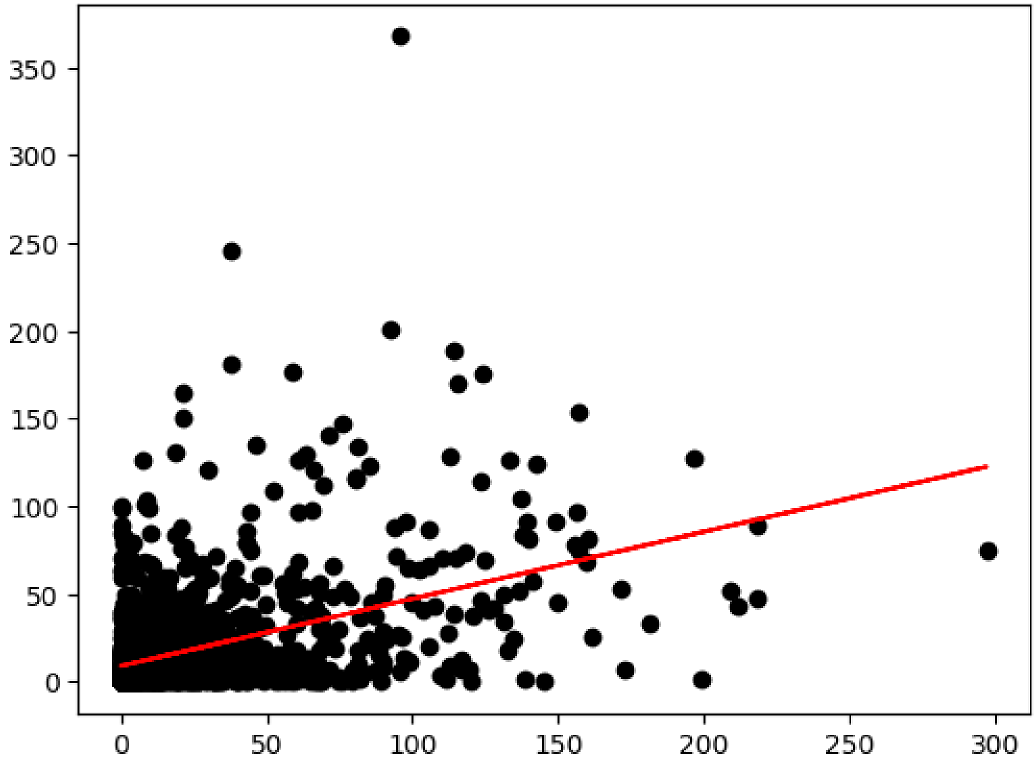
[27]:
```
df500=df[:][:500]
sns.lmplot(x="FEB",y="JAN",order=2,ci=None,data=df500)
plt.show()
```



[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)
```

[28]: LinearRegression()

[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()
```



[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: 0.18612218989321283

RIDGE MODEL:-

[31]:
```
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

[75]:
```
features= df.columns[0:5]
target= df.columns[-5]
```

[76]:
```
x=np.array(df['JAN']).reshape(-1,1)
y=np.array(df['FEB']).reshape(-1,2)
```

[77]:
```
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)
```

[78]:
```
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)
```

[79]:
```
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))
```

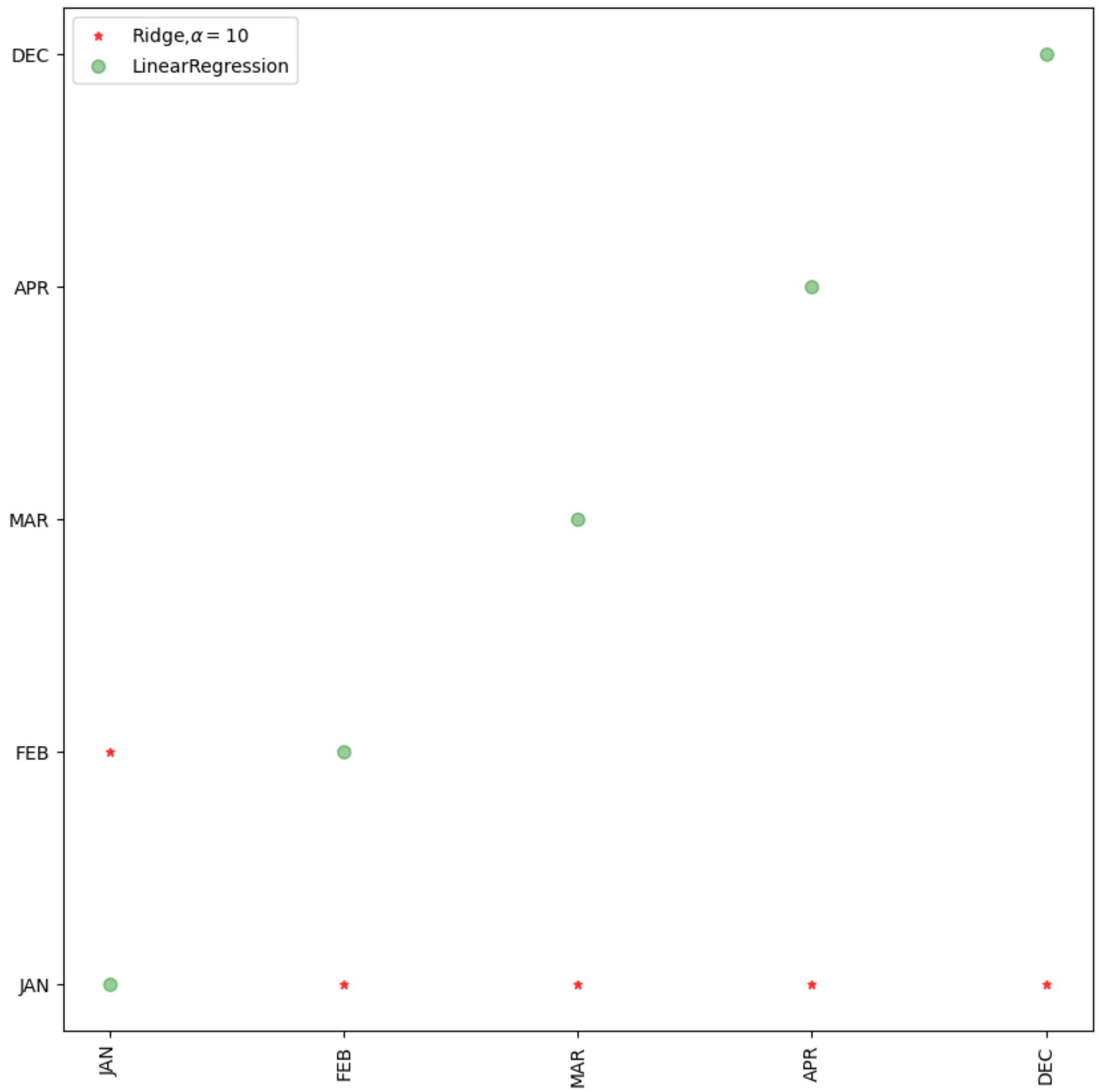
```

 Ridge Model:

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

[80]:
```
lr=LinearRegression()
```

[81]:
```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.
 ↪7,linestyle='none',marker="*",markersize=5,color='red',label=r'Ridge,$\alpha=10$',zorder=7)
plt.plot(features,alpha=0.
 ↪4,linestyle='none',marker='o',markersize=7,color="green",label='LinearRegression')
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```



LASSO MODEL:-

[82]:
```
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))
```

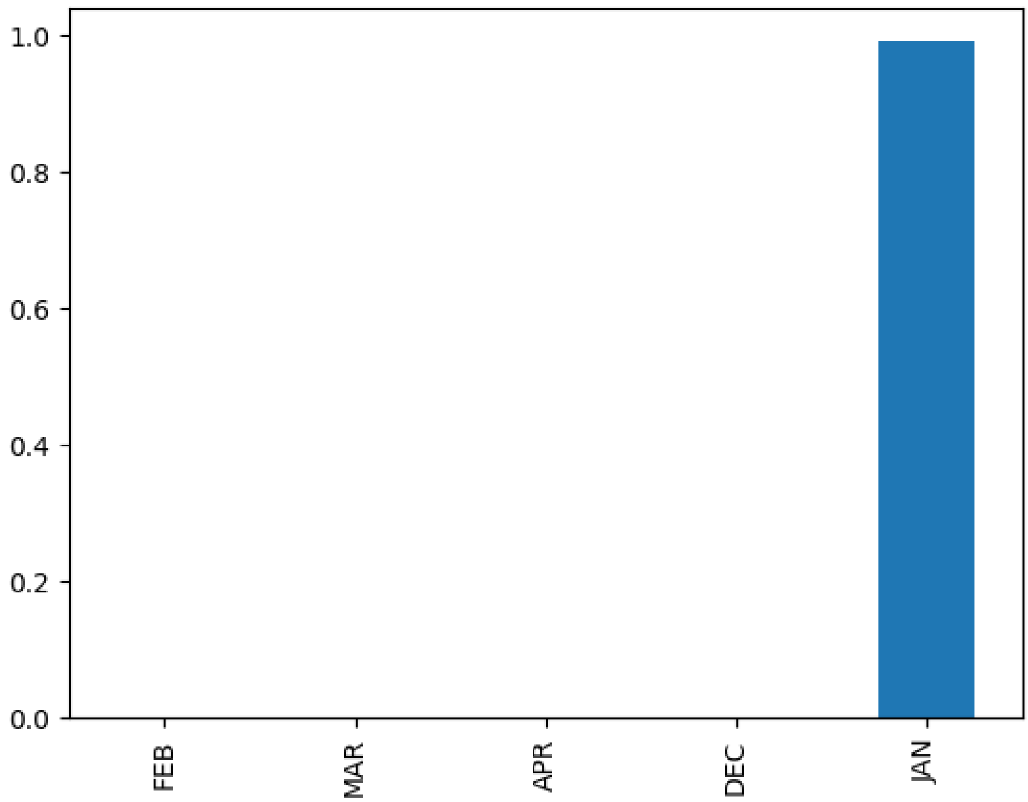
```
 Lasso Model:

The train score for ls model is 0.9999207747038827
```

The test score for ls model is0.9999206791315255

[83]:
```
pd.Series(lasso.coef_,features).sort_values(ascending=True).plot(kind="bar")
```

[83]: <Axes: >

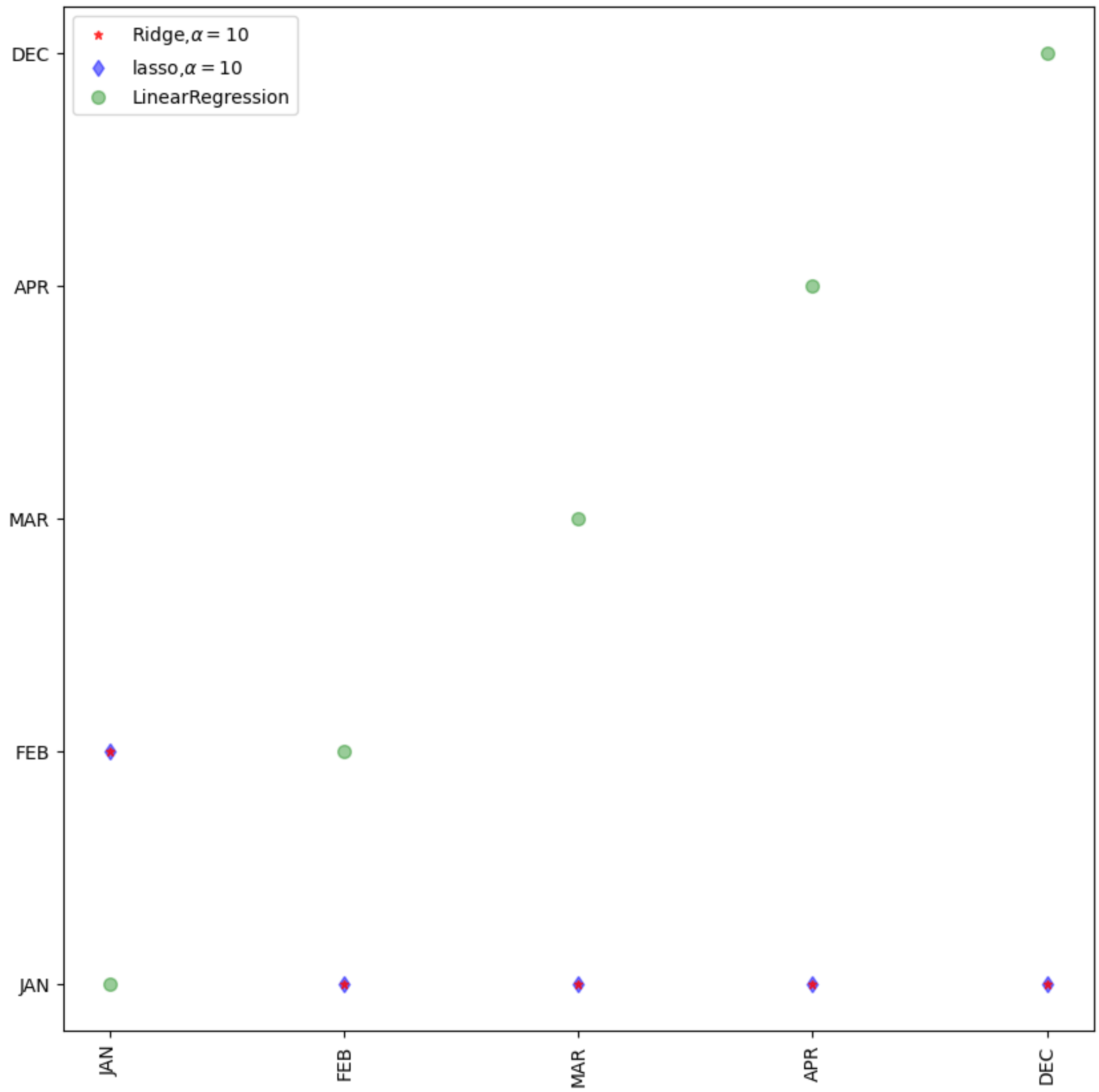


[84]:
```
from sklearn.linear_model import LassoCV
lasso_cv=LassoCV(alphas=[0.0001,0.001,0.01,1,10],random_state=0).
 ↪fit(x_train,y_train)
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999921
0.9999999999999921
```

[85]:
```
plt.figure(figsize= (10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.
 ↪7,linestyle='none',marker="*",markersize=5,color='red',label=r'Ridge,$\alpha=10$',zorder=7)
plt.plot(lasso_cv.coef_,alpha=0.
 ↪5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso,$\alpha=10$')
```

```
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:-

[86]:
```
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]
0.016258606966612632
0.9999992160905338
```

[88]:
```
y_pred_elastic =eln.predict(x_train)
mean_squared_error=np.mean((y_pred_elastic - y_train)**2)
print(mean_squared_error)
```

```
0.0008816302333951295
```

#***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