Problem statement

To predict How Best the DataFits,To Predict the accuracy of the Rainfall based on the given features

In [3]:

```
#Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [5]:

```
#Reading data
df=pd.read_csv(r"C:\Users\papu\Desktop\jhanavi\rainfall in india 1901-2015
df
```

Out[5]:

	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
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
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
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
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
...	...	...	...	...	...	...	...	...	...	...	...	...
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4

4116 rows × 19 columns

2) Data cleaning and preprocessing

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

Out[6]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV
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
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
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
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
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

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

Out[7]:

	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	
4111	LAKSHADWEEP	2011	5.1	2.8	3.1	85.9	107.2	153.6	350.2	254.0	255.2	117.4	1
4112	LAKSHADWEEP	2012	19.2	0.1	1.6	76.8	21.2	327.0	231.5	381.2	179.8	145.9	
4113	LAKSHADWEEP	2013	26.2	34.4	37.5	5.3	88.3	426.2	296.4	154.4	180.0	72.8	
4114	LAKSHADWEEP	2014	53.2	16.1	4.4	14.9	57.4	244.1	116.1	466.1	132.2	169.2	
4115	LAKSHADWEEP	2015	2.2	0.5	3.7	87.1	133.1	296.6	257.5	146.4	160.4	165.4	2

In [8]:

```
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          4112 non-null   float64
 3   FEB          4113 non-null   float64
 4   MAR          4110 non-null   float64
 5   APR          4112 non-null   float64
 6   MAY          4113 non-null   float64
 7   JUN          4111 non-null   float64
 8   JUL          4109 non-null   float64
 9   AUG          4112 non-null   float64
 10  SEP          4110 non-null   float64
 11  OCT          4109 non-null   float64
 12  NOV          4105 non-null   float64
 13  DEC          4106 non-null   float64
 14  ANNUAL       4090 non-null   float64
 15  Jan-Feb      4110 non-null   float64
 16  Mar-May      4107 non-null   float64
 17  Jun-Sep      4106 non-null   float64
 18  Oct-Dec      4103 non-null   float64
dtypes: float64(17), int64(1), object(1)
memory usage: 611.1+ KB
```

In [9]:

```
df.describe()
```

Out[9]:

	YEAR	JAN	FEB	MAR	APR	MAY	JU
count	4116.000000	4112.000000	4113.000000	4110.000000	4112.000000	4113.000000	4111.0000
mean	1958.218659	18.957320	21.805325	27.359197	43.127432	85.745417	230.2344
std	33.140898	33.585371	35.909488	46.959424	67.831168	123.234904	234.7107
min	1901.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.4000
25%	1930.000000	0.600000	0.600000	1.000000	3.000000	8.600000	70.3500
50%	1958.000000	6.000000	6.700000	7.800000	15.700000	36.600000	138.7000
75%	1987.000000	22.200000	26.800000	31.300000	49.950000	97.200000	305.1500
max	2015.000000	583.700000	403.500000	605.600000	595.100000	1168.600000	1609.9000

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
SUBDIVISION     0
YEAR            0
JAN             4
FEB             3
MAR             6
APR             4
MAY             3
JUN             5
JUL             7
AUG             4
SEP             6
OCT             7
NOV            11
DEC            10
ANNUAL         26
Jan-Feb         6
Mar-May         9
Jun-Sep        10
Oct-Dec        13
dtype: int64
```

In [11]:
```
df.fillna(method="ffill",inplace=True)
```

In [12]:
```
df.isnull().sum()
```

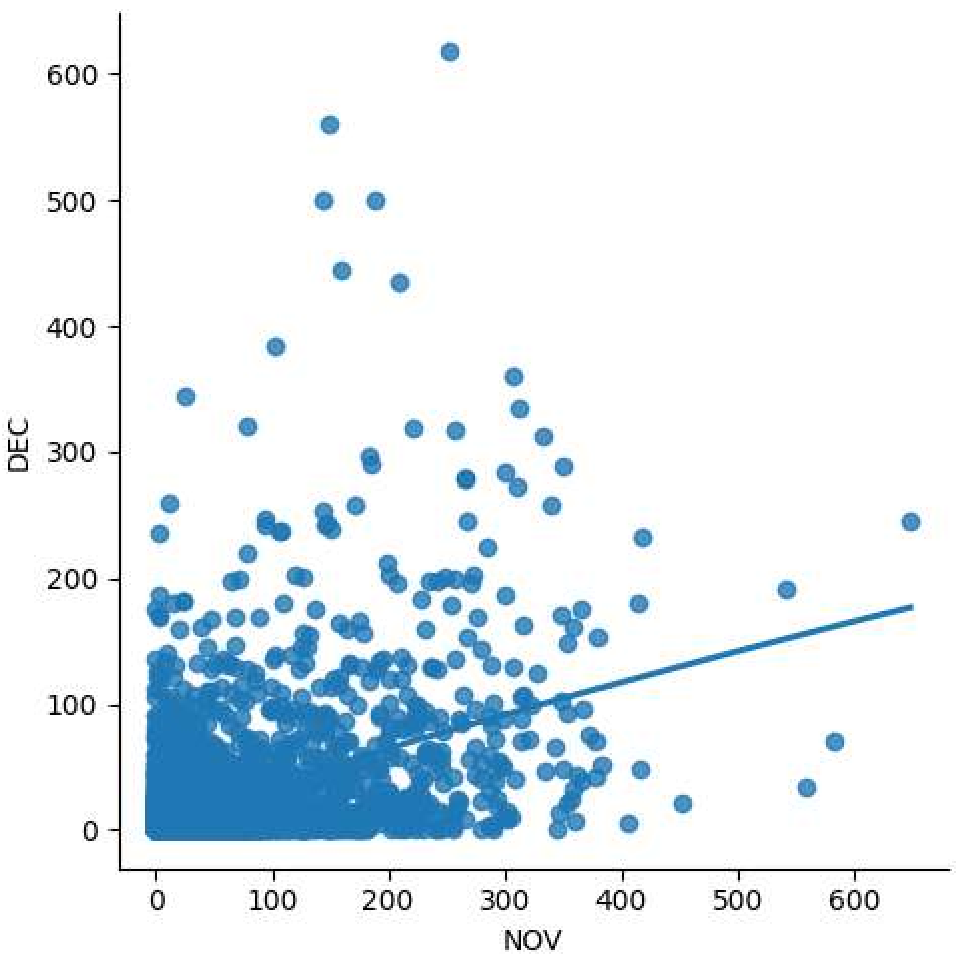
Out[12]:
```
SUBDIVISION    0
YEAR           0
JAN            0
FEB            0
MAR            0
APR            0
MAY            0
JUN            0
JUL            0
AUG            0
SEP            0
OCT            0
NOV            0
DEC            0
ANNUAL         0
Jan-Feb        0
Mar-May        0
Jun-Sep        0
Oct-Dec        0
dtype: int64
```

In [13]:
```
df['YEAR'].value_counts()
```

Out[13]:
```
YEAR
1963    36
2002    36
1976    36
1975    36
1974    36
        ..
1915    35
1918    35
1954    35
1955    35
1909    34
Name: count, Length: 115, dtype: int64
```

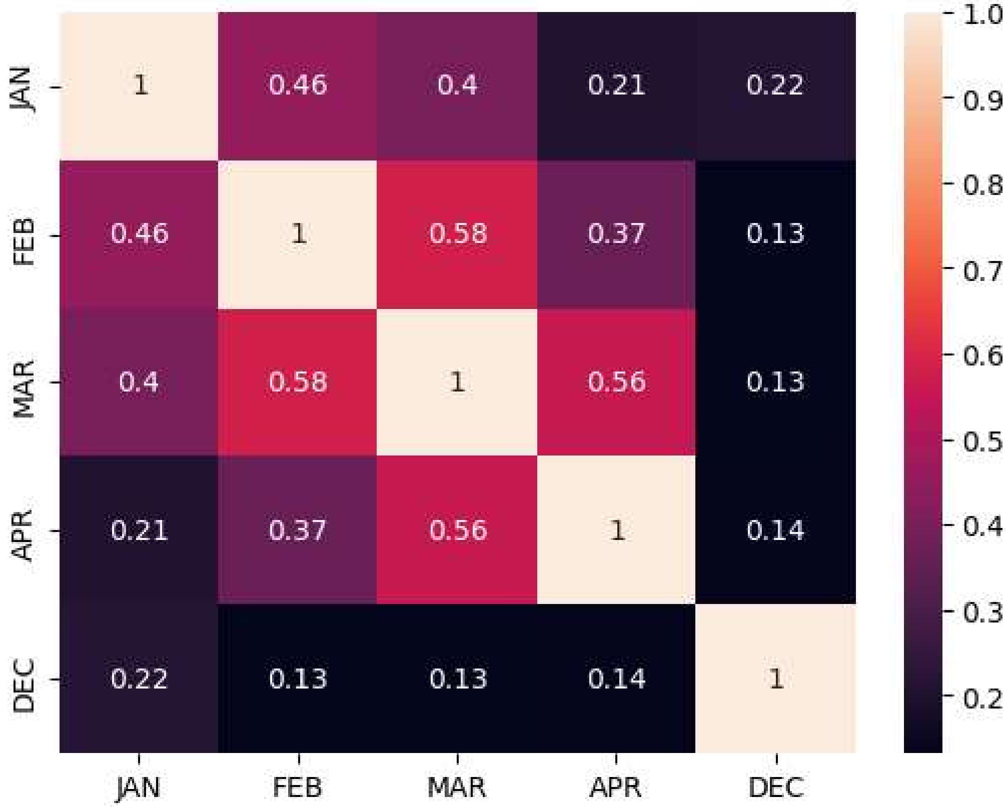
3) Exploratory Data Analysis

In [14]:
```
sns.lmplot(x='NOV',y='DEC',order=2,data=df,ci=None)
plt.show()
```



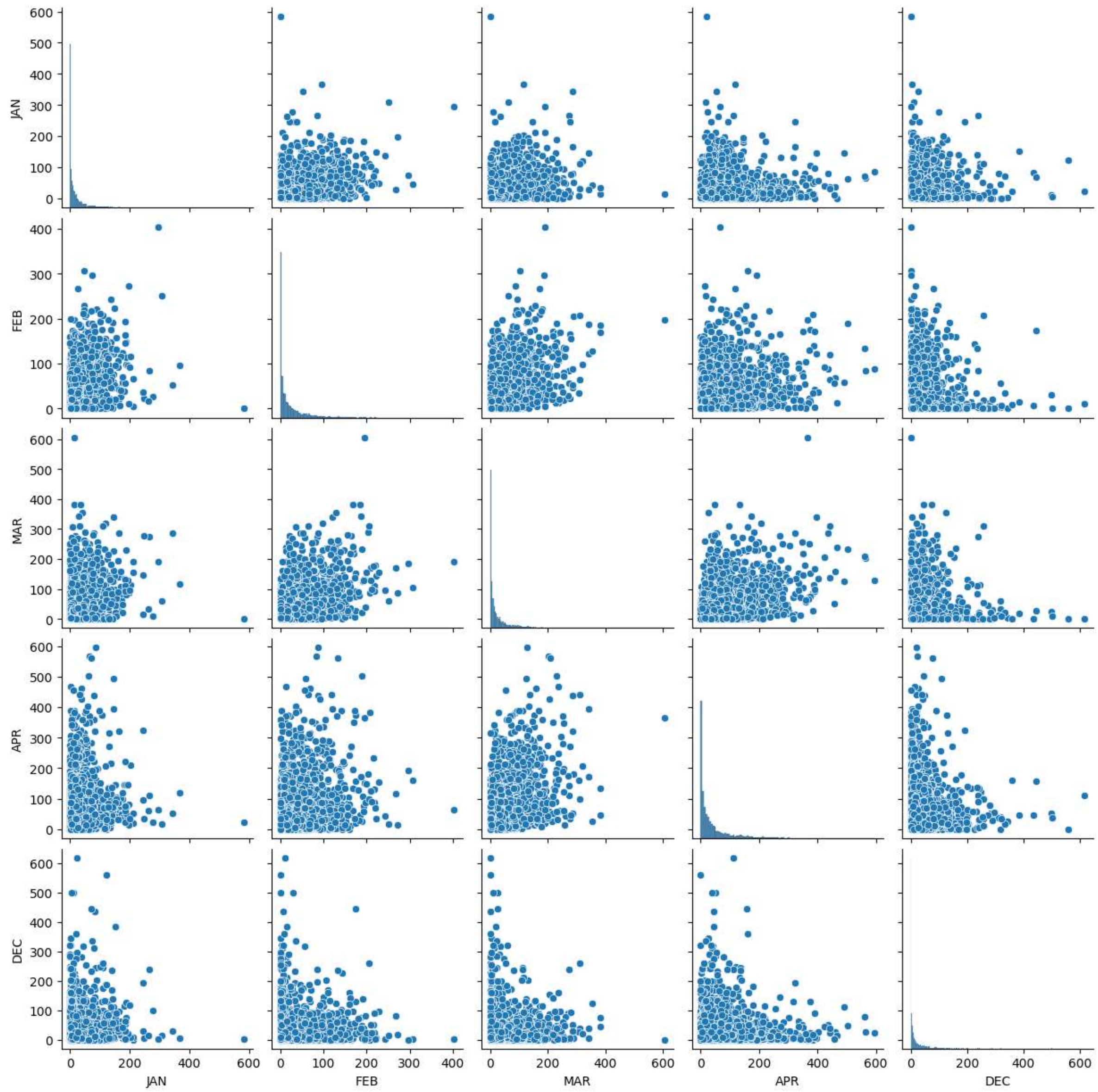
In [15]:

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



In [16]:

```
sns.pairplot(df)
plt.show()
```



4)Training our Model

In [17]:

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

In [18]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30)
```

In [19]:

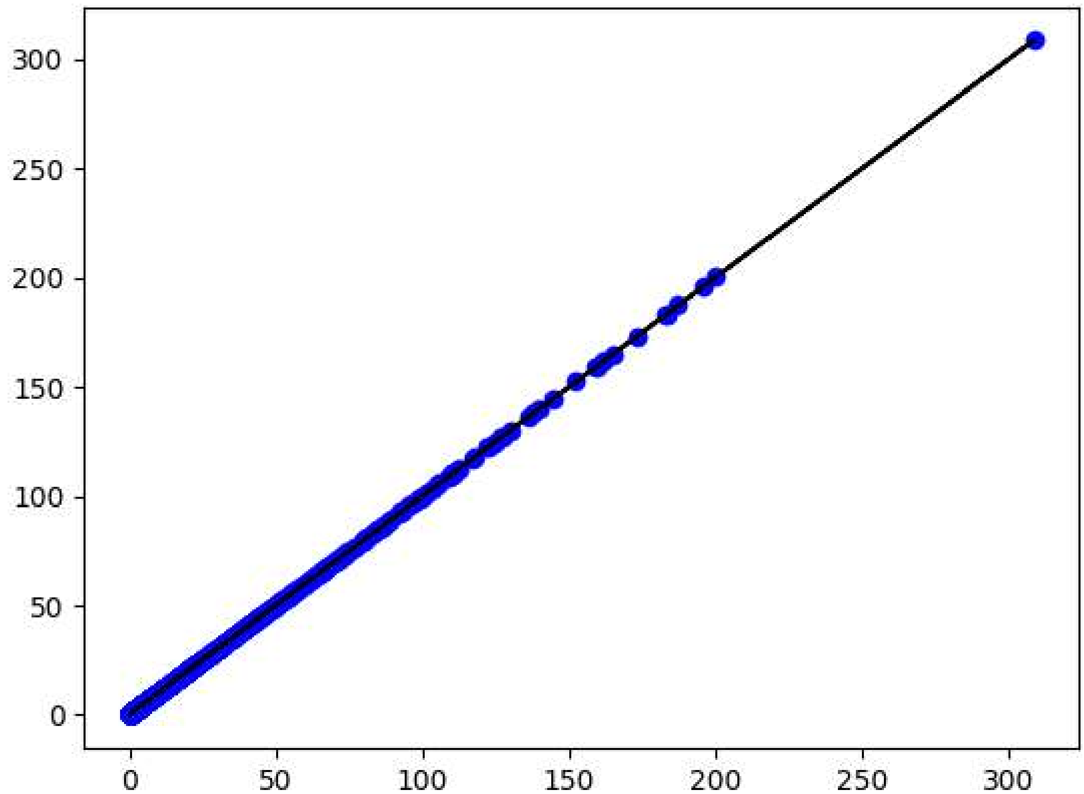
```
lin=LinearRegression()
lin.fit(x_train,y_train)
print(lin.score(x_train,y_train))
```

```
1.0
```

5)Exploring our Results

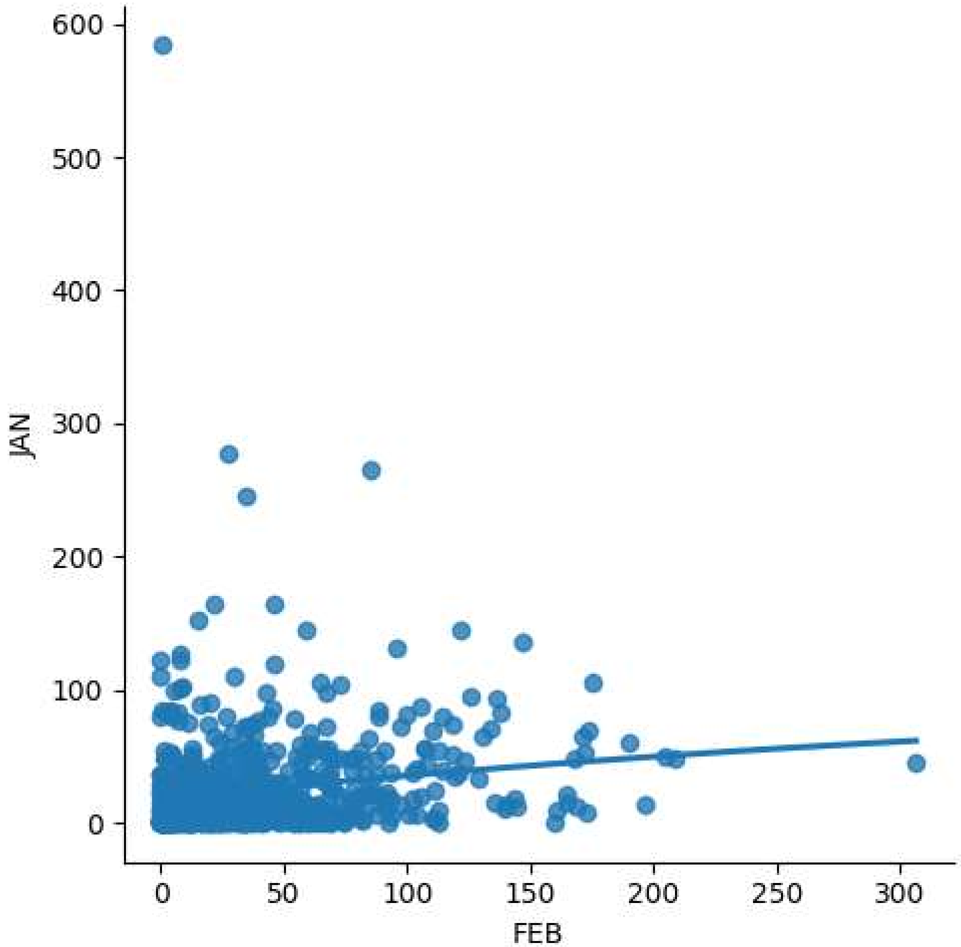
In [20]:
```
y_pred=lin.predict(x_test)
plt.scatter(x_test,y_test,color='blue')
plt.plot(x_test,y_pred,color='black')
plt.show()

```



7)Working with subset of data

In [21]:
```
df700=df[:][:700]
sns.lmplot(x='FEB',y='JAN',order=2,ci=None,data=df700)
plt.show()
```



In [22]:
```
df700.fillna(method='ffill',inplace=True)
```

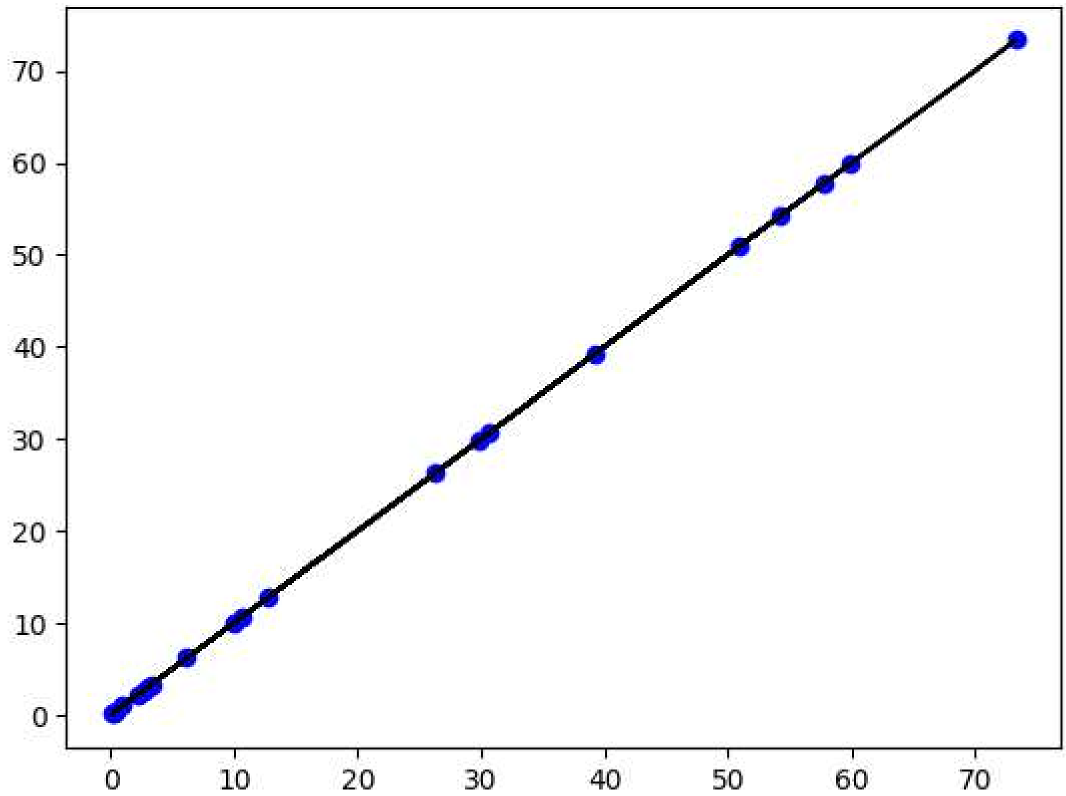
In [23]:
```
x=np.array(df700['FEB']).reshape(-1,1)
y=x=np.array(df700['JAN']).reshape(-1,1)
```

In [24]:
```
df700.dropna(inplace=True)
```

In [25]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.03)
lr=LinearRegression()
lr.fit(x_train,y_train)
print(lr.score(x_test,y_test))
```

```
1.0
```

In [26]:
```
y_pred=lr.predict(x_test)
plt.scatter(x_test,y_test,color='b')
plt.plot(x_test,y_pred,color='k')
plt.show()
```



In [27]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

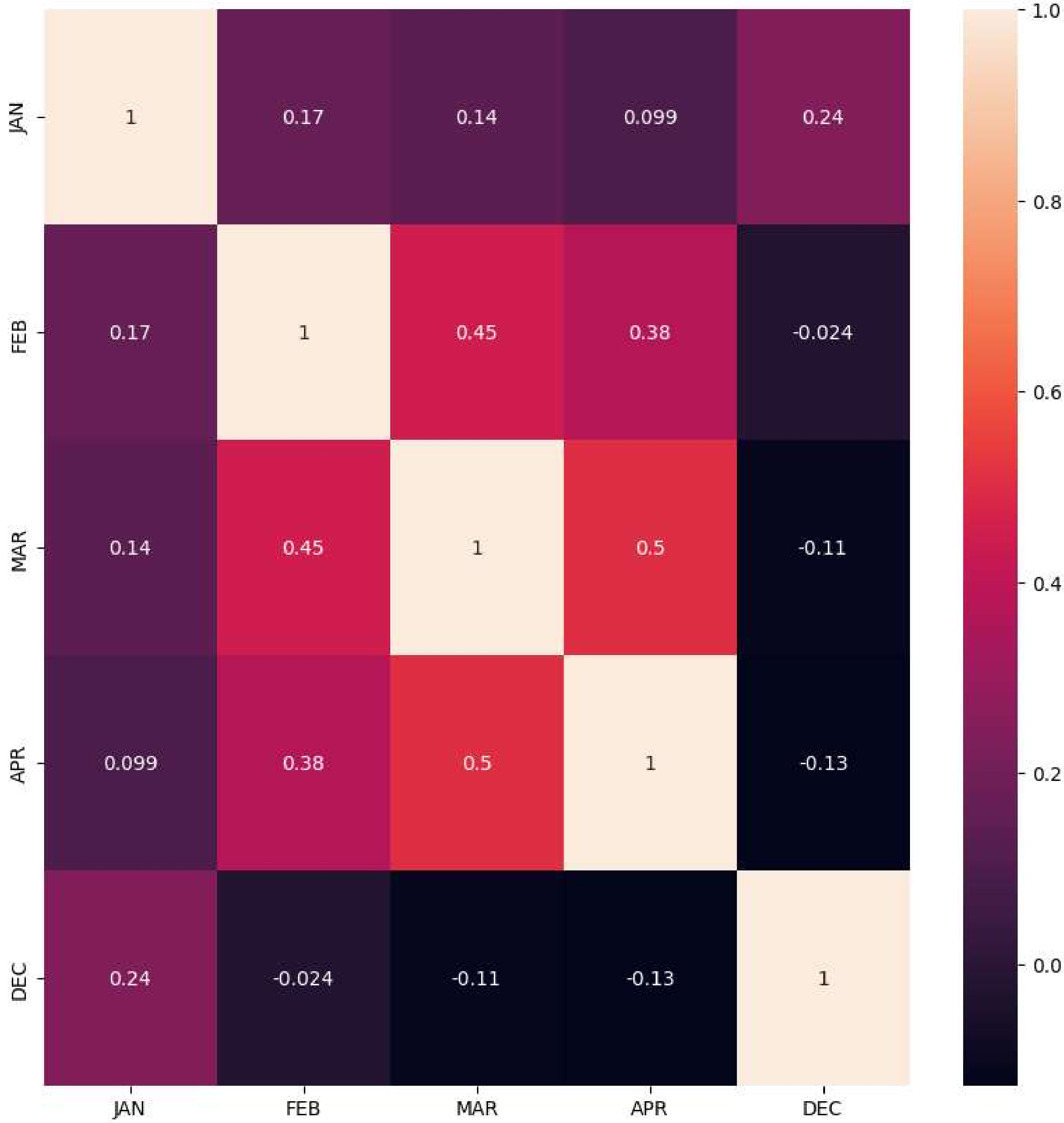
In [28]:
```
lr=LinearRegression()
lr.fit(x_train,y_train)
y_pred=lr.predict(x_test)
r2=r2_score(y_test,y_pred)
print("R2 score:",r2)
```

```
R2 score: 1.0
```

Ridge Regression

In [29]:
```
#Importing Libraries
from sklearn.linear_model import Lasso,Ridge
from sklearn.preprocessing import StandardScaler
```

In [30]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df700.corr(),annot=True)
plt.show()
```



In [31]:
```
features=df.columns[0:5]
target=df.columns[-5]
```

In [32]:
```
x=df[features].values
y=df[target].values
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_s
print("The dimension of X_train is {}".format(x_train.shape))
print("The dimension of X_test is {}".format(x_test.shape))
```

```
The dimension of X_train is (2881, 5)
The dimension of X_test is (1235, 5)
```

In [33]:

```
lr = LinearRegression()
#Fit model
lr.fit(x_train, y_train)
#predict
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 [34]:

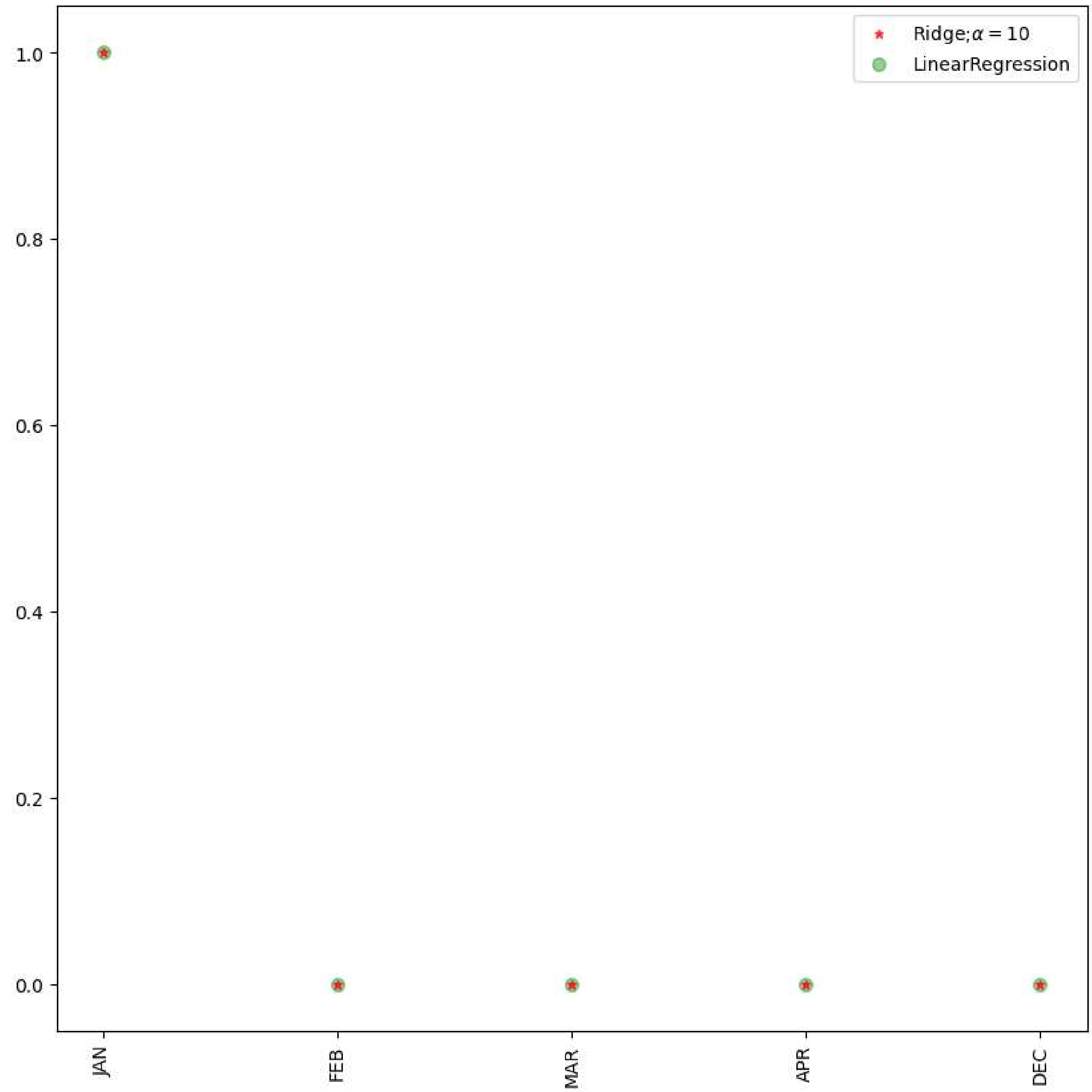
```
ridgeReg = Ridge(alpha=10)
ridgeReg.fit(x_train,y_train)
#train and test scorefor ridge regression
train_score_ridge = ridgeReg.score(x_train, y_train)
test_score_ridge = ridgeReg.score(x_test, y_test)
print("\nRidge Model:\n")
print("The train score for ridge model is {}".format(train_score_ridge))
print("The test score for ridge model is {}".format(test_score_ridge))
```

```
Ridge Model:

The train score for ridge model is 0.9999999999856335
The test score for ridge model is 0.9999999999840021
```

In [38]:

```
plt.figure(figsize=(10,10))
plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker="*",mar
plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker="o",markersi
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Lasso Regression

In [40]:
```python
#Importing libraries
lasso= Lasso(alpha=10)
lasso.fit(x_train,y_train)
#train and test scorefor ridge regression
train_score_ls = lasso.score(x_train, y_train)
test_score_ls= lasso.score(x_test, y_test)
print("\nLasso Model:\n")
print("The train score for lasso model is {}".format(train_score_ls))
print("The test score for lasso model is {}".format(test_score_ls))
```

```
Lasso Model:

The train score for lasso model is 0.9999147271297208
The test score for lasso model is 0.9999147248375002
```

In [41]:
```python
plt.figure(figsize=(10,10))
```

Out[41]:
```
<Figure size 1000x1000 with 0 Axes>

<Figure size 1000x1000 with 0 Axes>
```

In [42]:
```python
from sklearn.linear_model import LassoCV
```

In [43]:
```python
#using the linear cv model
from sklearn.linear_model import RidgeCV
#cross validation
ridge_cv=RidgeCV(alphas =[0.0001,0.001,0.01,0.1,1,10]).fit(x_train,y_trai
#score
print(ridge_cv.score(x_train,y_train))
print(ridge_cv.score(x_test,y_test))
```

```
0.999999999261034
0.9999999993719254
```

In [44]:
```python
#using the linear cv model
from sklearn.linear_model import LassoCV
#cross validation
lasso_cv=LassoCV(alphas =[0.0001,0.001,0.01,0.1,1,10]).fit(x_train,y_trai
#score
print(lasso_cv.score(x_train,y_train))
print(lasso_cv.score(x_test,y_test))
```

```
0.9999999999999915
0.9999999999999915
```

Elastic Regression

In [45]:

```
from sklearn.linear_model import ElasticNet

```

In [46]:

```
el=ElasticNet()
el.fit(x_train,y_train)
print(el.coef_)
print(el.intercept_)
el.score(x,y)
```

```
[9.99044548e-01 1.38835344e-05 4.58897515e-05 0.00000000e+00
 0.00000000e+00]
0.016565679683697711
```

Out[46]:

```
0.9999991435191248
```

In [47]:

```
y_pred_elastic=el.predict(x_train)
```

In [48]:

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

```
0.0009226812593703956
```

conclusion

from the above dataset we have got that rigidRegression is bestfit

In [ ]:

```

```