rainfall-regression-1

September 15, 2023

1 Amount of Rainfall Prediction using Regression models

[1]:
```
import pandas as pd
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
df = pd.read_csv("/content/rainfall in india.csv")
df.head()
```

[2]:
```
                 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
```

[3]:
```
df.shape
```

[3]: (3887, 19)

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3887 entries, 0 to 3886
Data columns (total 19 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   SUBDIVISION  3887 non-null   object
 1   YEAR         3887 non-null   int64
 2   JAN          3885 non-null   float64
 3   FEB          3885 non-null   float64
 4   MAR          3883 non-null   float64
 5   APR          3885 non-null   float64
 6   MAY          3886 non-null   float64
 7   JUN          3884 non-null   float64
 8   JUL          3883 non-null   float64
 9   AUG          3885 non-null   float64
 10  SEP          3884 non-null   float64
 11  OCT          3883 non-null   float64
 12  NOV          3882 non-null   float64
 13  DEC          3881 non-null   float64
 14  ANNUAL       3872 non-null   float64
 15  Jan-Feb      3884 non-null   float64
 16  Mar-May      3882 non-null   float64
 17  Jun-Sep      3881 non-null   float64
 18  Oct-Dec      3880 non-null   float64
dtypes: float64(17), int64(1), object(1)
memory usage: 577.1+ KB
```

[5]:
```
df.describe()
```

[5]:

	YEAR	JAN	FEB	MAR	APR	\
count	3887.000000	3885.000000	3885.000000	3883.000000	3885.000000	
mean	1958.221250	18.909833	22.165740	27.454365	41.072252	
std	33.139584	33.790445	36.571112	47.818302	67.812487	
min	1901.000000	0.000000	0.000000	0.000000	0.000000	
25%	1930.000000	0.500000	0.500000	0.900000	2.800000	
50%	1958.000000	5.700000	6.600000	7.300000	14.000000	
75%	1987.000000	22.100000	27.300000	30.700000	45.500000	
max	2015.000000	583.700000	403.500000	605.600000	595.100000	

	MAY	JUN	JUL	AUG	SEP	\
count	3886.000000	3884.000000	3883.000000	3885.000000	3884.000000	
mean	79.227586	214.869902	338.604172	288.736371	196.910247	
std	119.355452	226.145284	266.648228	189.613004	136.400297	
min	0.000000	0.400000	2.400000	0.600000	0.100000	
25%	7.900000	67.300000	171.450000	154.600000	100.375000	
50%	33.000000	130.150000	279.000000	257.400000	172.900000	
75%	83.850000	262.000000	407.750000	376.700000	265.400000	

```
max    1168.600000  1609.900000  2362.800000  1664.600000  1222.000000

               OCT          NOV          DEC       ANNUAL      Jan-Feb  \
count  3883.000000  3882.000000  3881.000000  3872.000000  3884.000000
mean     87.588823    33.837816    17.057228  1361.243285    41.082878
std      93.031482    62.677156    41.071189   885.605666    60.263823
min       0.000000     0.000000     0.000000    62.300000     0.000000
25%      13.000000     0.500000     0.100000   785.025000     3.800000
50%      58.500000     8.000000     2.400000  1086.300000    18.950000
75%     135.700000    36.375000    14.700000  1543.225000    50.500000
max     948.300000   648.900000   617.500000  6331.100000   699.500000

           Mar-May      Jun-Sep      Oct-Dec
count  3882.000000  3881.000000  3880.000000
mean    147.419835  1038.634939   138.315541
std     200.307760   704.438118   153.514971
min       0.000000    57.400000     0.000000
25%      21.825000   558.700000    30.875000
50%      68.650000   861.200000    90.600000
75%     169.750000  1253.200000   190.950000
max    1745.800000  4536.900000  1252.500000
```

[6]:

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

[6]:

```
SUBDIVISION     0
YEAR            0
JAN             2
FEB             2
MAR             4
APR             2
MAY             1
JUN             3
JUL             4
AUG             2
SEP             3
OCT             4
NOV             5
DEC             6
ANNUAL         15
Jan-Feb         3
Mar-May         5
Jun-Sep         6
Oct-Dec         7
dtype: int64
```

[7]:

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

[8]:
```
df.isnull().sum()
```

[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
```

[9]:
```
df.duplicated().sum()
```

[9]:
```
0
```

[10]:
```
df['SUBDIVISION'].value_counts()
```

[10]:
```
EAST RAJASTHAN                        115
WEST MADHYA PRADESH                   115
NORTH INTERIOR KARNATAKA              115
COASTAL KARNATAKA                     115
TAMIL NADU                            115
RAYALSEEMA                            115
TELANGANA                             115
COASTAL ANDHRA PRADESH                115
CHHATTISGARH                          115
VIDARBHA                              115
MATATHWADA                            115
MADHYA MAHARASHTRA                    115
KONKAN & GOA                          115
SAURASHTRA & KUTCH                    115
GUJARAT REGION                        115
EAST MADHYA PRADESH                   115
SOUTH INTERIOR KARNATAKA              115
EAST UTTAR PRADESH                    115
```

```
ASSAM & MEGHALAYA                     115
JAMMU & KASHMIR                       115
HIMACHAL PRADESH                      115
PUNJAB                                115
HARYANA DELHI & CHANDIGARH            115
UTTARAKHAND                           115
WEST UTTAR PRADESH                    115
WEST RAJASTHAN                        115
BIHAR                                 115
JHARKHAND                             115
ORISSA                                115
GANGETIC WEST BENGAL                  115
SUB HIMALAYAN WEST BENGAL & SIKKIM    115
NAGA MANI MIZO TRIPURA                115
ANDAMAN & NICOBAR ISLANDS             110
ARUNACHAL PRADESH                      97
Name: SUBDIVISION, dtype: int64
```

[11]:
```
df.YEAR.unique()
```

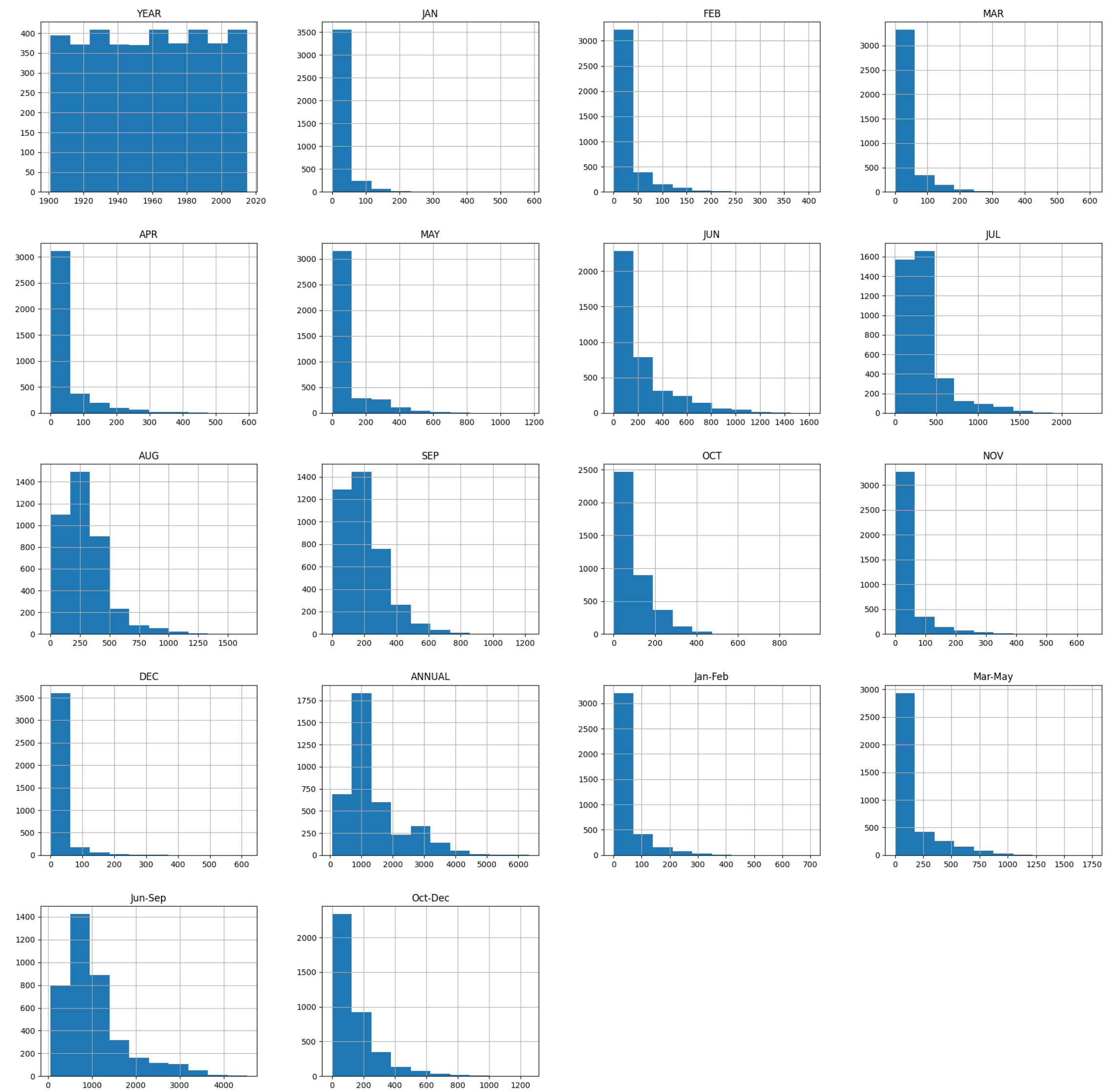
[11]:
```
array([1901, 1902, 1903, 1904, 1905, 1906, 1907, 1908, 1910, 1911, 1912,
       1913, 1914, 1915, 1916, 1917, 1918, 1919, 1920, 1921, 1922, 1923,
       1924, 1925, 1926, 1927, 1928, 1929, 1930, 1931, 1932, 1933, 1934,
       1935, 1936, 1937, 1938, 1939, 1940, 1941, 1942, 1946, 1947, 1949,
       1950, 1951, 1952, 1953, 1954, 1955, 1956, 1957, 1958, 1959, 1960,
       1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970, 1971,
       1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981, 1982,
       1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993,
       1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004,
       2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015,
       1943, 1944, 1945, 1948, 1909])
```

[12]:
```
df.SUBDIVISION.unique()
```

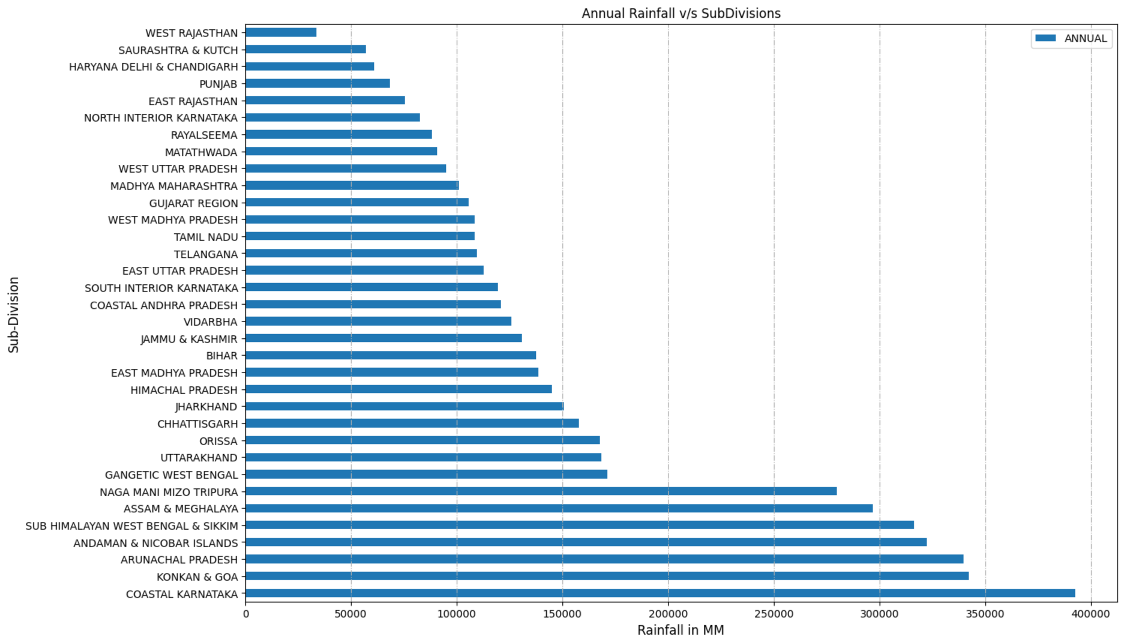
[12]:
```
array(['ANDAMAN & NICOBAR ISLANDS', 'ARUNACHAL PRADESH',
       'ASSAM & MEGHALAYA', 'NAGA MANI MIZO TRIPURA',
       'SUB HIMALAYAN WEST BENGAL & SIKKIM', 'GANGETIC WEST BENGAL',
       'ORISSA', 'JHARKHAND', 'BIHAR', 'EAST UTTAR PRADESH',
       'WEST UTTAR PRADESH', 'UTTARAKHAND', 'HARYANA DELHI & CHANDIGARH',
       'PUNJAB', 'HIMACHAL PRADESH', 'JAMMU & KASHMIR', 'WEST RAJASTHAN',
       'EAST RAJASTHAN', 'WEST MADHYA PRADESH', 'EAST MADHYA PRADESH',
       'GUJARAT REGION', 'SAURASHTRA & KUTCH', 'KONKAN & GOA',
       'MADHYA MAHARASHTRA', 'MATATHWADA', 'VIDARBHA', 'CHHATTISGARH',
       'COASTAL ANDHRA PRADESH', 'TELANGANA', 'RAYALSEEMA', 'TAMIL NADU',
       'COASTAL KARNATAKA', 'NORTH INTERIOR KARNATAKA',
       'SOUTH INTERIOR KARNATAKA'], dtype=object)
```

1.1 Visualizing the dataset

[13]:
```
df.hist(figsize=(24,24));
```

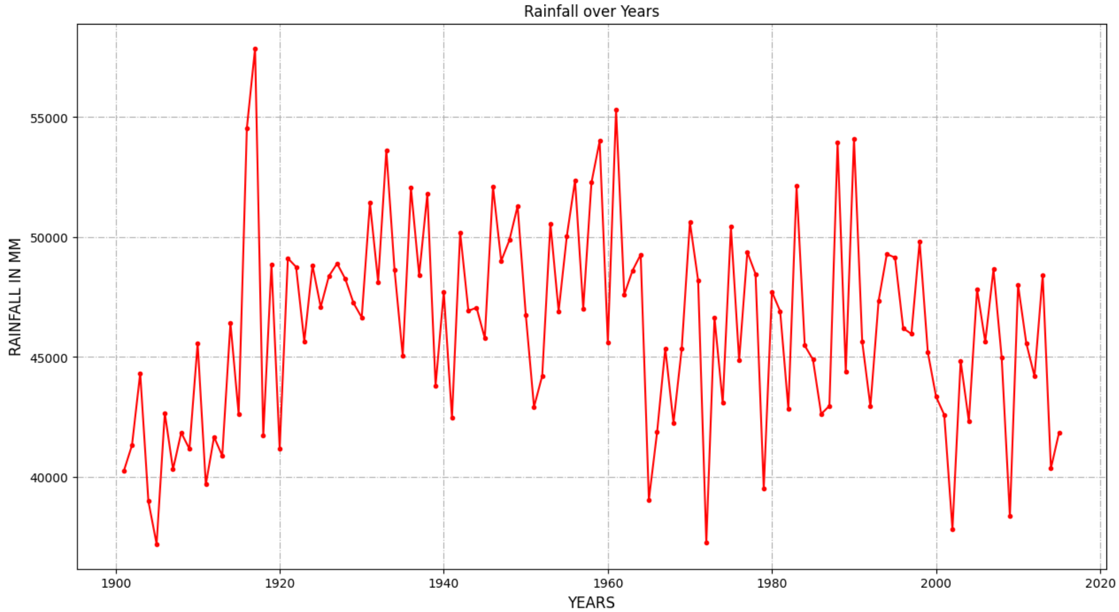


[14]:
```
df[["SUBDIVISION","ANNUAL"]].groupby("SUBDIVISION").sum().
  ↪sort_values(by='ANNUAL',ascending=False).
  ↪plot(kind='barh',stacked=True,figsize=(15,10))
plt.xlabel("Rainfall in MM",size=12)
plt.ylabel("Sub-Division",size=12)
plt.title("Annual Rainfall v/s SubDivisions")
plt.grid(axis="x",linestyle="-.")
plt.show()
```

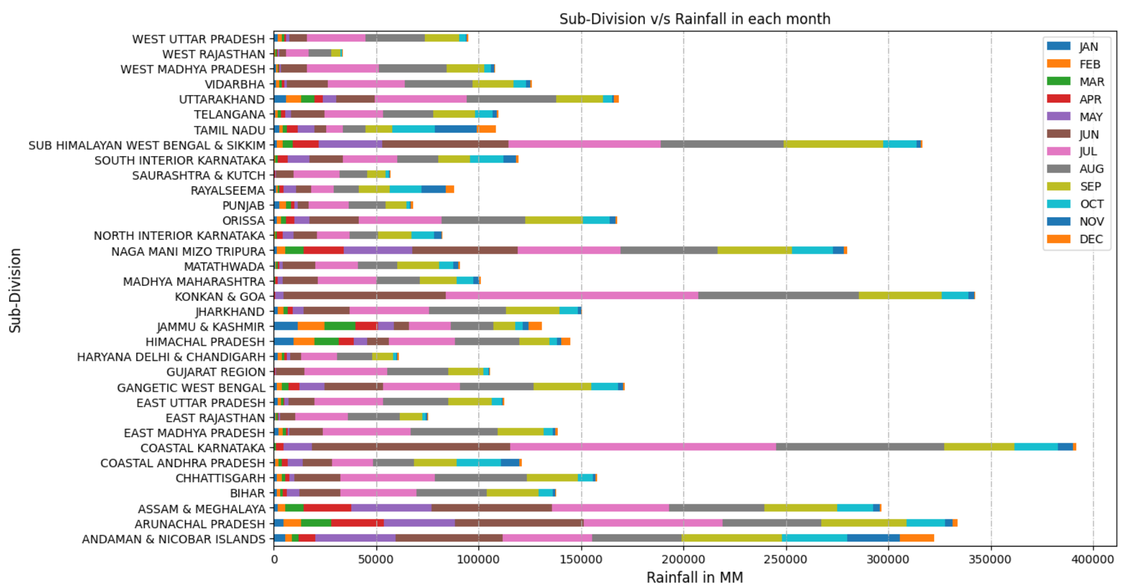


[15]:
```
plt.figure(figsize=(15,8))
df.groupby("YEAR").sum()['ANNUAL'].plot(kind="line",color="r",marker=".")
plt.xlabel("YEARS",size=12)
plt.ylabel("RAINFALL IN MM",size=12)
plt.grid(axis="both",linestyle="-.")
plt.title("Rainfall over Years")
plt.show()
```

```
<ipython-input-15-64cf992d7485>:2: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.sum is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  df.groupby("YEAR").sum()['ANNUAL'].plot(kind="line",color="r",marker=".")
```



[16]:
```
df[['SUBDIVISION', 'JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL',
       'AUG', 'SEP', 'OCT', 'NOV', 'DEC']].groupby("SUBDIVISION").sum().
 ↪plot(kind="barh",stacked=True,figsize=(13,8))
plt.title("Sub-Division v/s Rainfall in each month")
plt.xlabel("Rainfall in MM",size=12)
plt.ylabel("Sub-Division",size=12)
plt.grid(axis="x",linestyle="-.")
plt.show()
```



[17]:
```
df.corr()
```

```
<ipython-input-17-2f6f6606aa2c>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  df.corr()
```

[17]:
```
             YEAR       JAN       FEB       MAR       APR       MAY       JUN  \
YEAR     1.000000 -0.049201 -0.019677  0.022538  0.009234  0.007683 -0.011065
JAN     -0.049201  1.000000  0.466372  0.411304  0.222171  0.141304 -0.029891
FEB     -0.019677  0.466372  1.000000  0.588000  0.381366  0.228551  0.050298
MAR      0.022538  0.411304  0.588000  1.000000  0.571679  0.388697  0.174074
APR      0.009234  0.222171  0.381366  0.571679  1.000000  0.677039  0.445185
MAY      0.007683  0.141304  0.228551  0.388697  0.677039  1.000000  0.566982
JUN     -0.011065 -0.029891  0.050298  0.174074  0.445185  0.566982  1.000000
JUL     -0.013928 -0.043425  0.024944  0.094588  0.248373  0.324280  0.747678
AUG      0.005350  0.021774  0.080199  0.135006  0.250687  0.344440  0.682612
SEP     -0.011926  0.034833  0.084417  0.179542  0.390488  0.520697  0.587302
OCT      0.007738  0.019887  0.010526  0.089758  0.351495  0.518810  0.443441
NOV     -0.017265  0.078232 -0.009754  0.008894  0.128587  0.318825  0.143881
DEC     -0.015863  0.239079  0.152872  0.147616  0.135111  0.250414  0.060478
ANNUAL  -0.008958  0.123506  0.210254  0.337346  0.575650  0.700569  0.889232
Jan-Feb -0.039464  0.843778  0.868263  0.587386  0.355978  0.217881  0.013824
Mar-May  0.012140  0.256634  0.407178  0.663610  0.877374  0.913959  0.529692
Jun-Sep -0.009532 -0.013208  0.063854  0.163197  0.380408  0.498240  0.901179
Oct-Dec -0.006275  0.107926  0.043385  0.097644  0.300292  0.509438  0.341960

              JUL       AUG       SEP       OCT       NOV       DEC    ANNUAL  \
YEAR    -0.013928  0.005350 -0.011926  0.007738 -0.017265 -0.015863 -0.008958
JAN     -0.043425  0.021774  0.034833  0.019887  0.078232  0.239079  0.123506
FEB      0.024944  0.080199  0.084417  0.010526 -0.009754  0.152872  0.210254
MAR      0.094588  0.135006  0.179542  0.089758  0.008894  0.147616  0.337346
APR      0.248373  0.250687  0.390488  0.351495  0.128587  0.135111  0.575650
MAY      0.324280  0.344440  0.520697  0.518810  0.318825  0.250414  0.700569
JUN      0.747678  0.682612  0.587302  0.443441  0.143881  0.060478  0.889232
JUL      1.000000  0.699319  0.521876  0.261734 -0.019678 -0.035075  0.806421
AUG      0.699319  1.000000  0.507431  0.255850  0.001576 -0.001542  0.772839
SEP      0.521876  0.507431  1.000000  0.421982  0.172828  0.128717  0.740307
OCT      0.261734  0.255850  0.421982  1.000000  0.425745  0.273332  0.556727
NOV     -0.019678  0.001576  0.172828  0.425745  1.000000  0.465834  0.247656
DEC     -0.035075 -0.001542  0.128717  0.273332  0.465834  1.000000  0.197774
ANNUAL   0.806421  0.772839  0.740307  0.556727  0.247656  0.197774  1.000000
Jan-Feb -0.009163  0.060993  0.070789  0.017543  0.037971  0.226819  0.196934
Mar-May  0.300626  0.322570  0.484315  0.448405  0.234523  0.228795  0.693827
Jun-Sep  0.907246  0.850627  0.716369  0.392235  0.072689  0.030930  0.941727
```

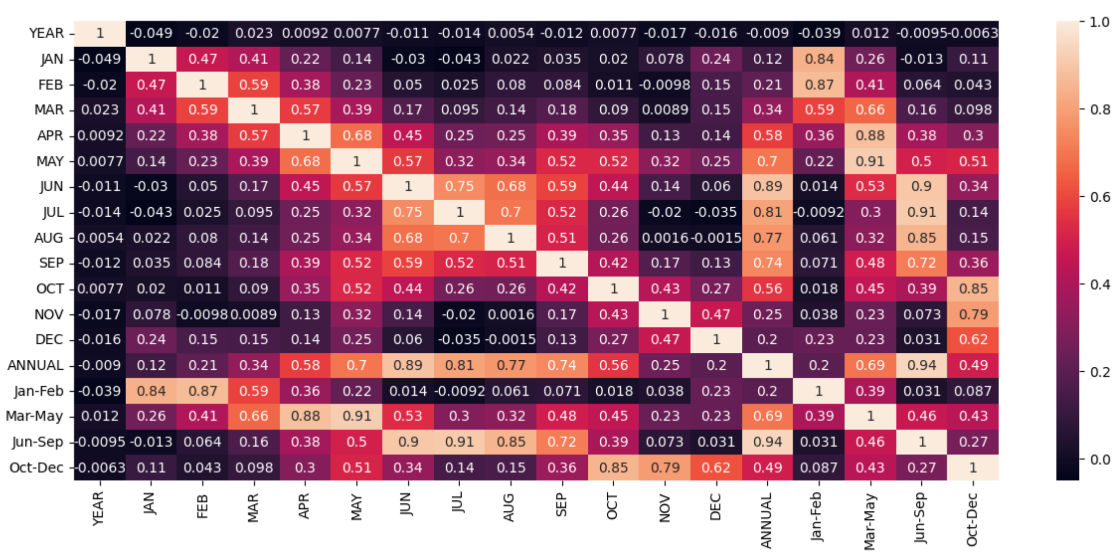
Oct-Dec	0.140230	0.153604	0.359787	0.849799	0.787910	0.621750	0.489474

	Jan-Feb	Mar-May	Jun-Sep	Oct-Dec
YEAR	-0.039464	0.012140	-0.009532	-0.006275
JAN	0.843778	0.256634	-0.013208	0.107926
FEB	0.868263	0.407178	0.063854	0.043385
MAR	0.587386	0.663610	0.163197	0.097644
APR	0.355978	0.877374	0.380408	0.300292
MAY	0.217881	0.913959	0.498240	0.509438
JUN	0.013824	0.529692	0.901179	0.341960
JUL	-0.009163	0.300626	0.907246	0.140230
AUG	0.060993	0.322570	0.850627	0.153604
SEP	0.070789	0.484315	0.716369	0.359787
OCT	0.017543	0.448405	0.392235	0.849799
NOV	0.037971	0.234523	0.072689	0.787910
DEC	0.226819	0.228795	0.030930	0.621750
ANNUAL	0.196934	0.693827	0.941727	0.489474
Jan-Feb	1.000000	0.390941	0.031418	0.086855
Mar-May	0.390941	1.000000	0.464635	0.427005
Jun-Sep	0.031418	0.464635	1.000000	0.274116
Oct-Dec	0.086855	0.427005	0.274116	1.000000

[18]:

```python
plt.figure(figsize=(15,6))
sns.heatmap(df.corr(),annot=True)
plt.show()
```

```
<ipython-input-18-2b948c0c3eb5>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(),annot=True)
```



1.2 Label Encoding:

[19]:
```
from sklearn.preprocessing import LabelEncoder
Encoder=LabelEncoder()
df["SUBDIVISION"] = Encoder.fit_transform(df["SUBDIVISION"])
```

[20]:
```
df.head()
```

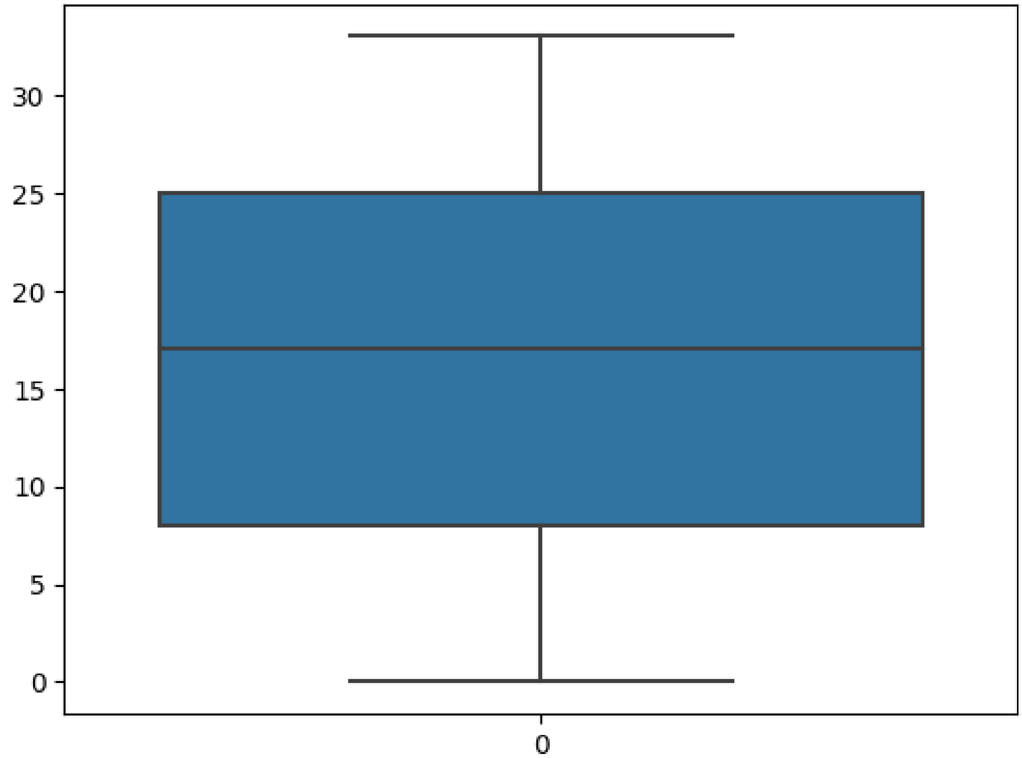
[20]:
```
   SUBDIVISION  YEAR   JAN    FEB   MAR    APR    MAY    JUN    JUL    AUG  \
0            0  1901  49.2   87.1  29.2    2.3  528.8  517.5  365.1  481.1
1            0  1902   0.0  159.8  12.2    0.0  446.1  537.1  228.9  753.7
2            0  1903  12.7  144.0   0.0    1.0  235.1  479.9  728.4  326.7
3            0  1904   9.4   14.7   0.0  202.4  304.5  495.1  502.0  160.1
4            0  1905   1.3    0.0   3.3   26.9  279.5  628.7  368.7  330.5

     SEP    OCT    NOV    DEC  ANNUAL  Jan-Feb  Mar-May  Jun-Sep  Oct-Dec
0  332.6  388.5  558.2   33.6  3373.2    136.3    560.3   1696.3    980.3
1  666.2  197.2  359.0  160.5  3520.7    159.8    458.3   2185.9    716.7
2  339.0  181.2  284.4  225.0  2957.4    156.7    236.1   1874.0    690.6
3  820.4  222.2  308.7   40.1  3079.6     24.1    506.9   1977.6    571.0
4  297.0  260.7   25.4  344.7  2566.7      1.3    309.7   1624.9    630.8
```

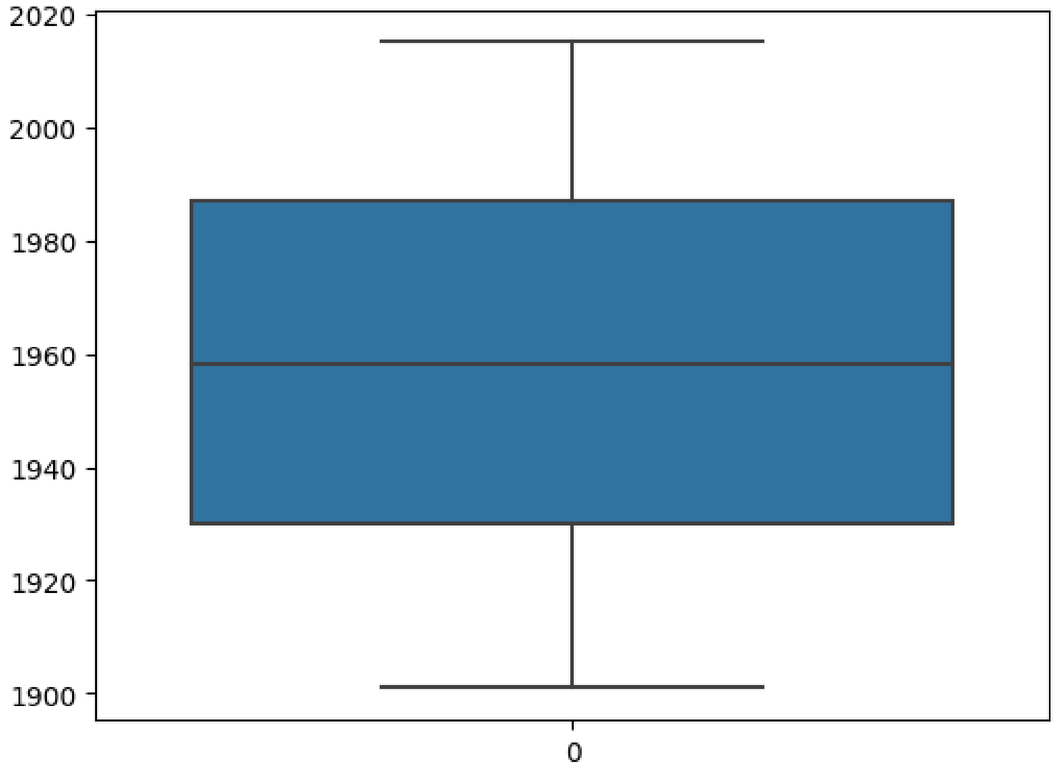
1.3 Removing Outliers:

[21]:
```
#Plotting Boxplot for numerical value to identify whether outliers present or
↪not
for i in df:
  print('Column = ',i)
  sns.boxplot(df[i])
  plt.show()
```

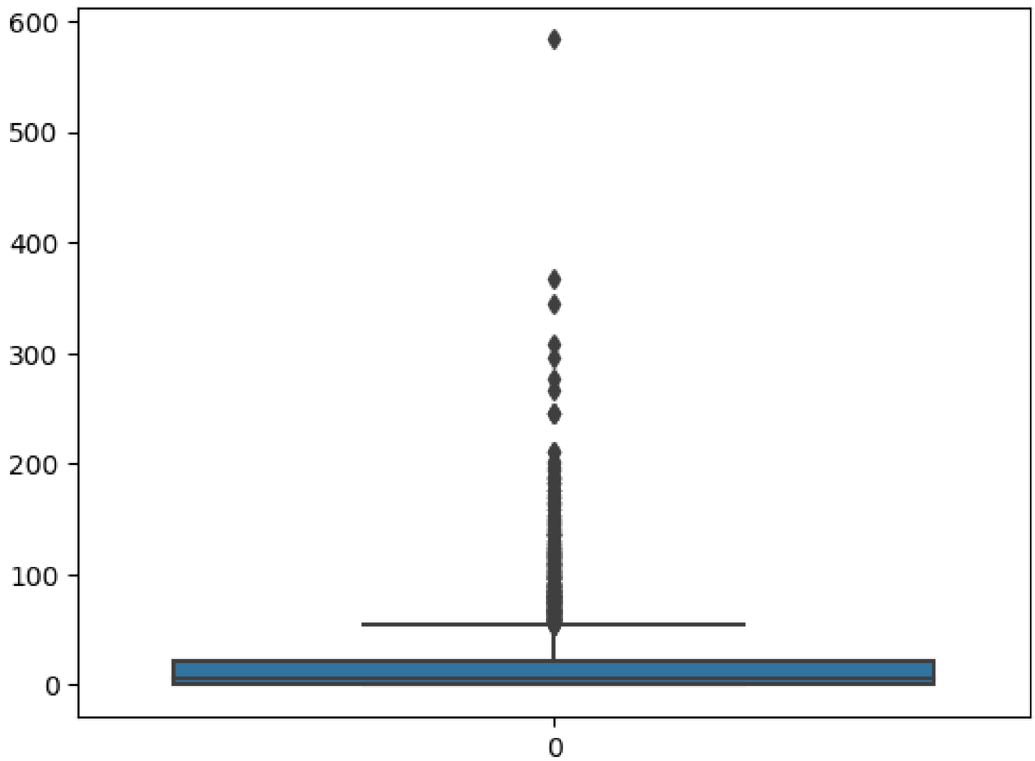
```
Column =  SUBDIVISION
```



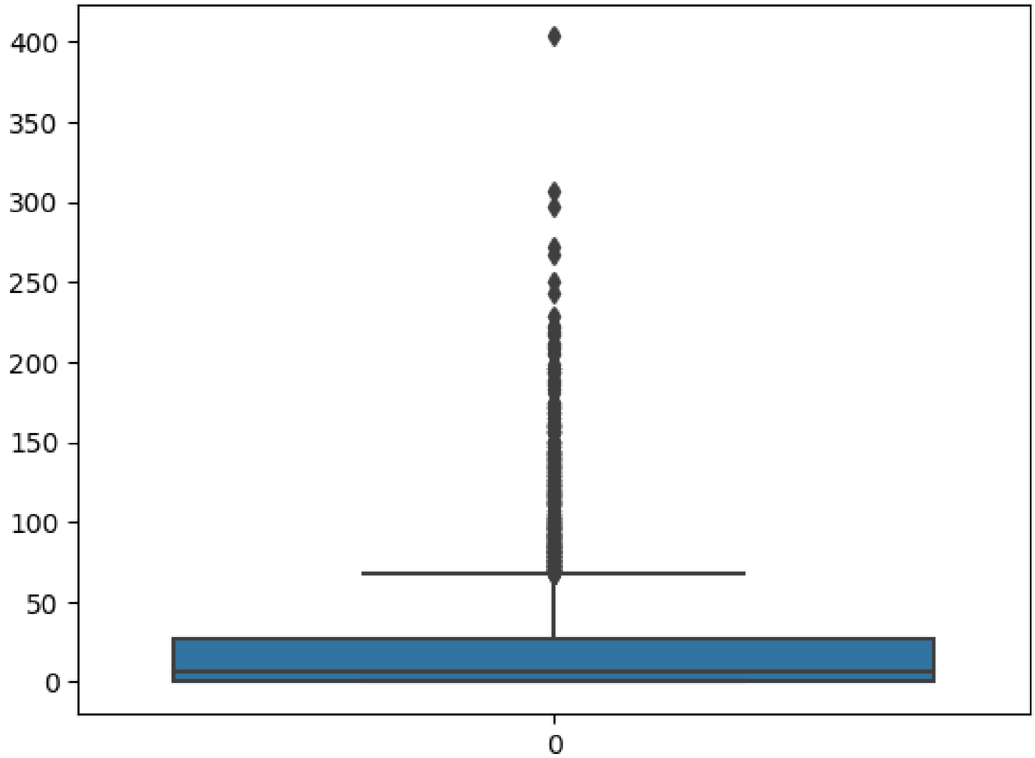

```
Column =  YEAR
```



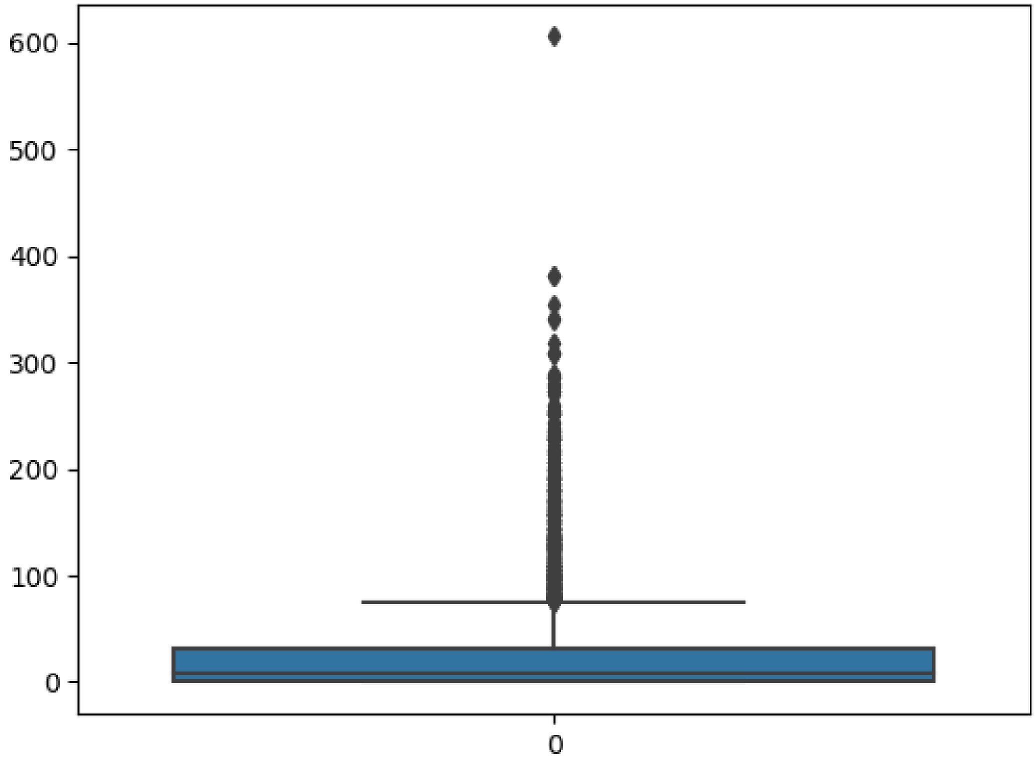

```
Column =  JAN
```



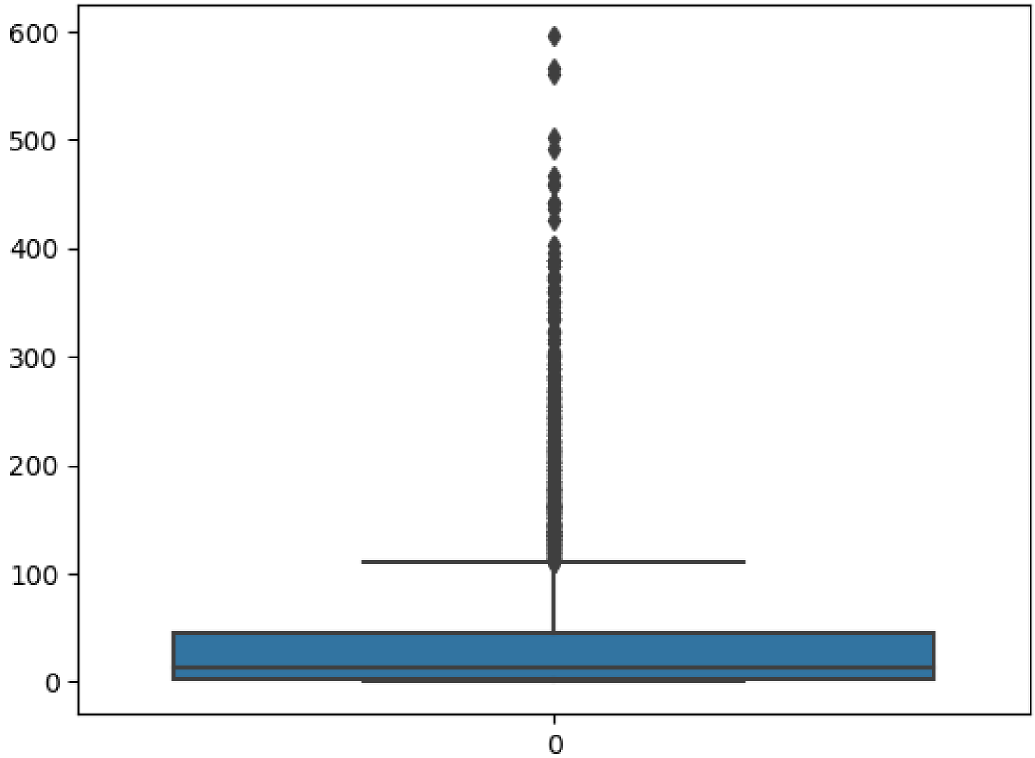
Column = FEB



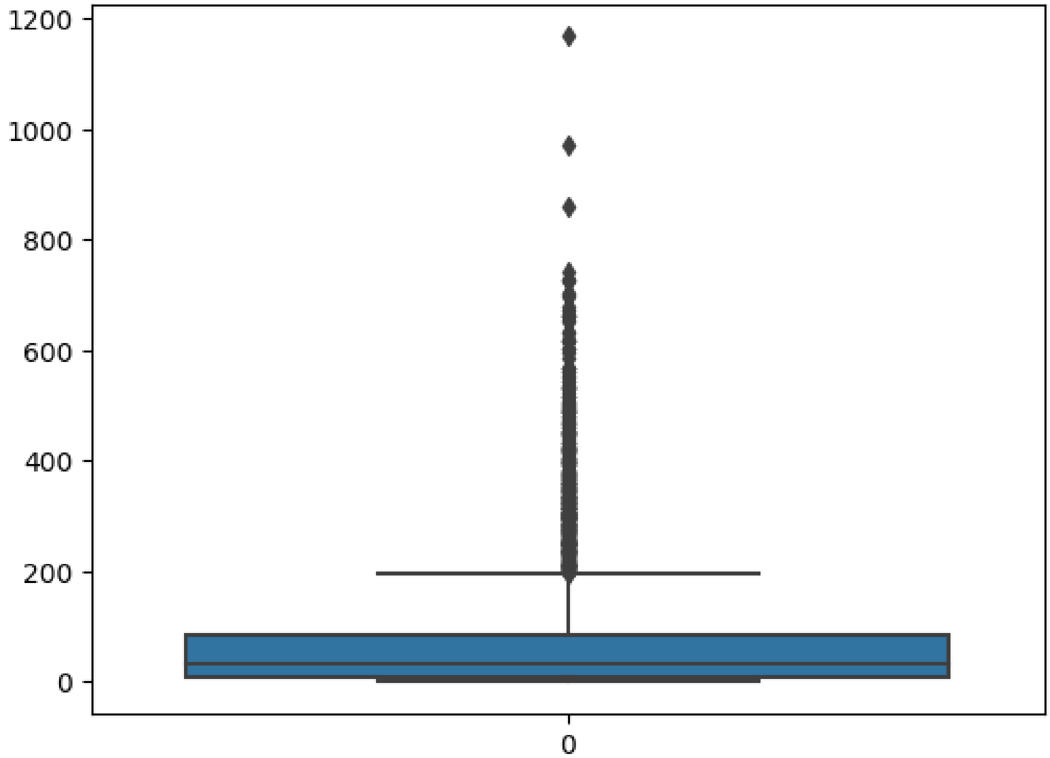
Column = MAR



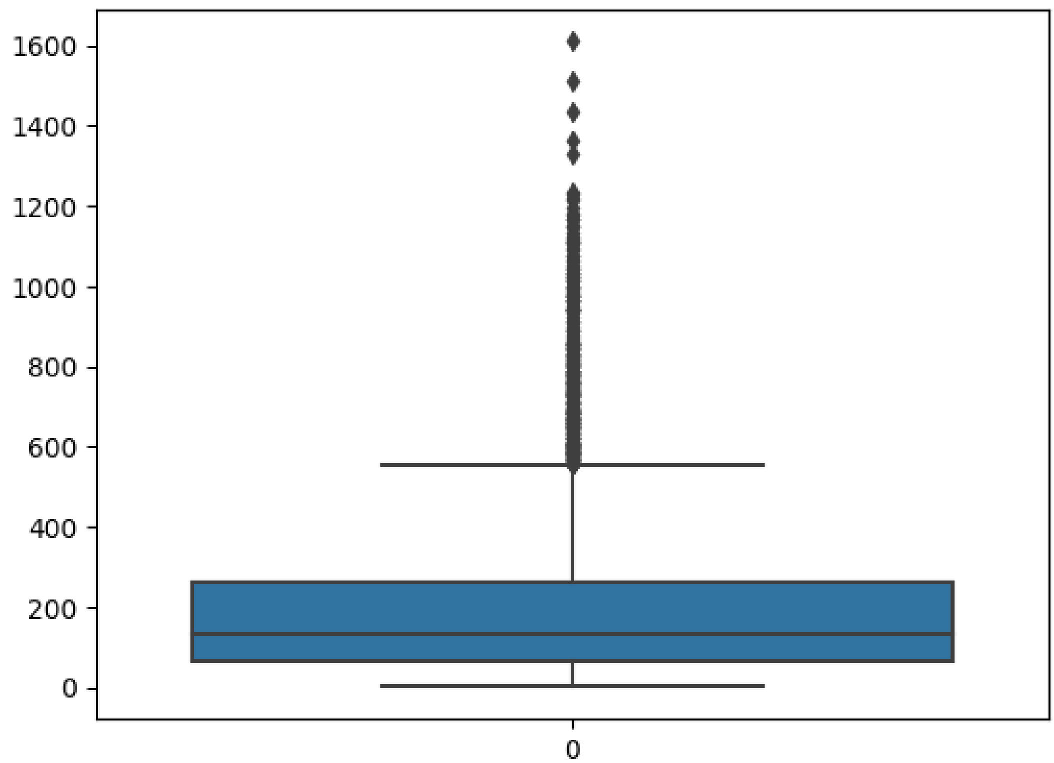

```
Column =  APR
```



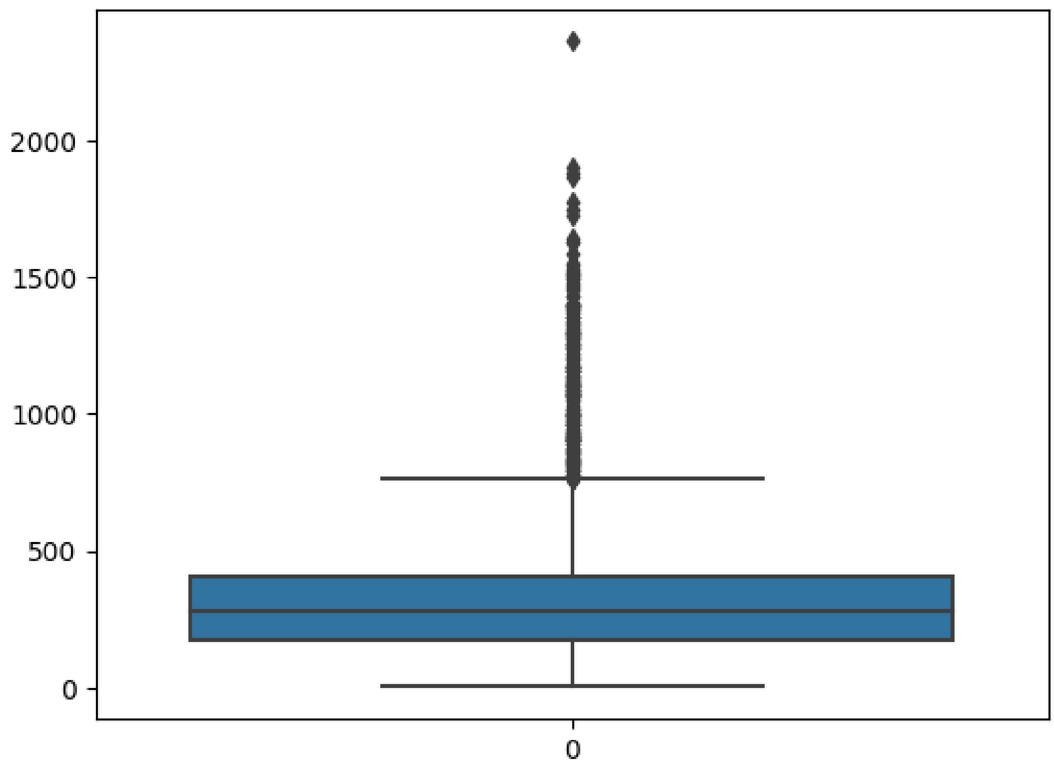
Column = MAY



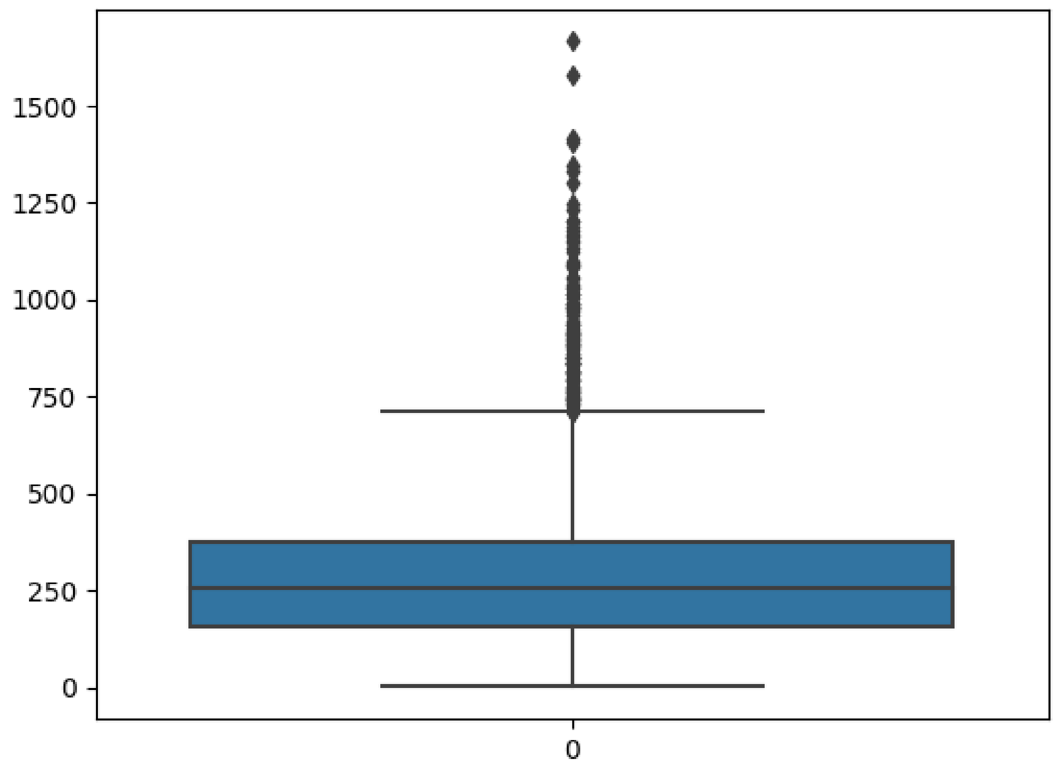
Column = JUN



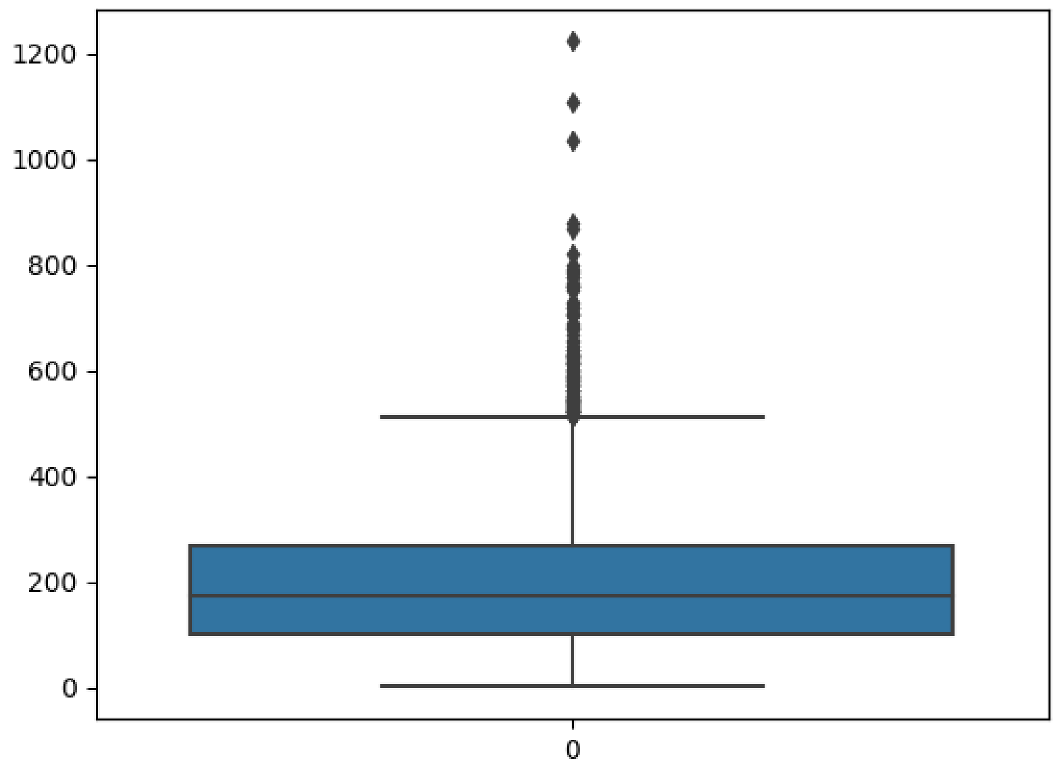

```
Column =  JUL
```



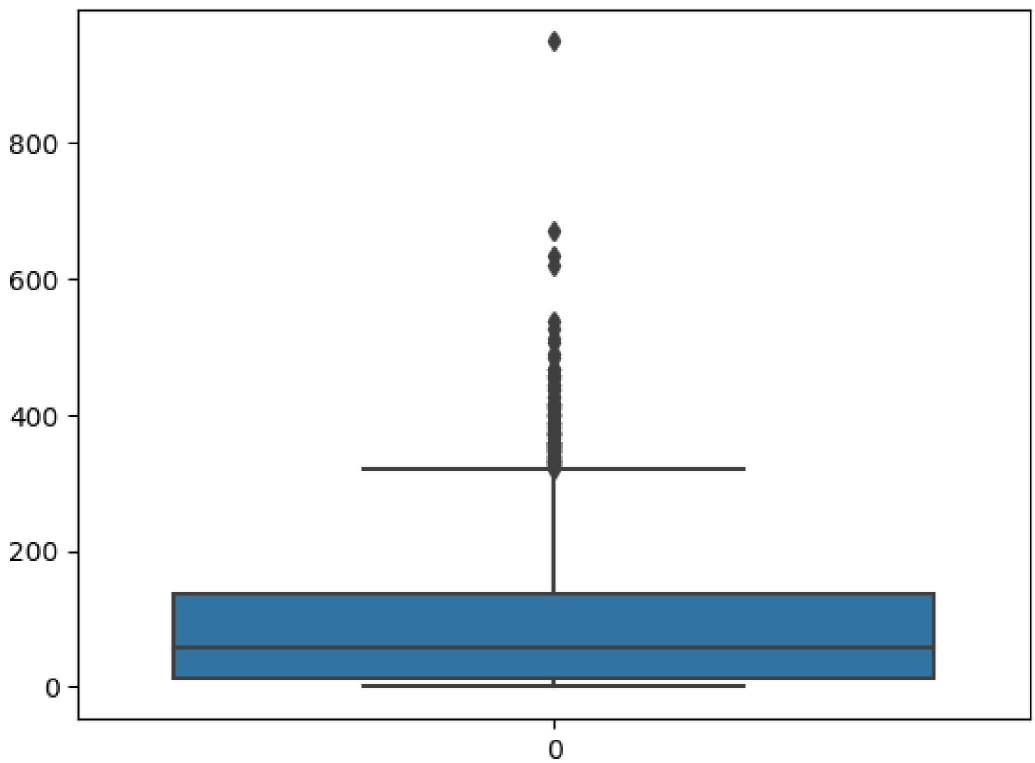

```
Column =  AUG
```



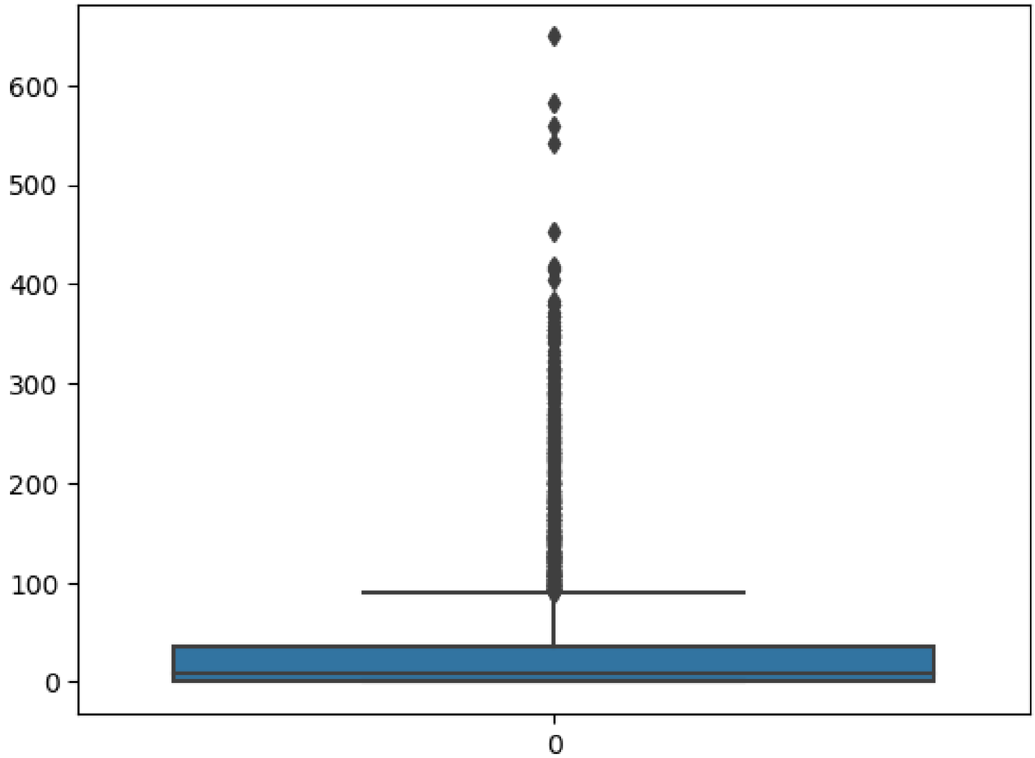

```
Column =  SEP
```



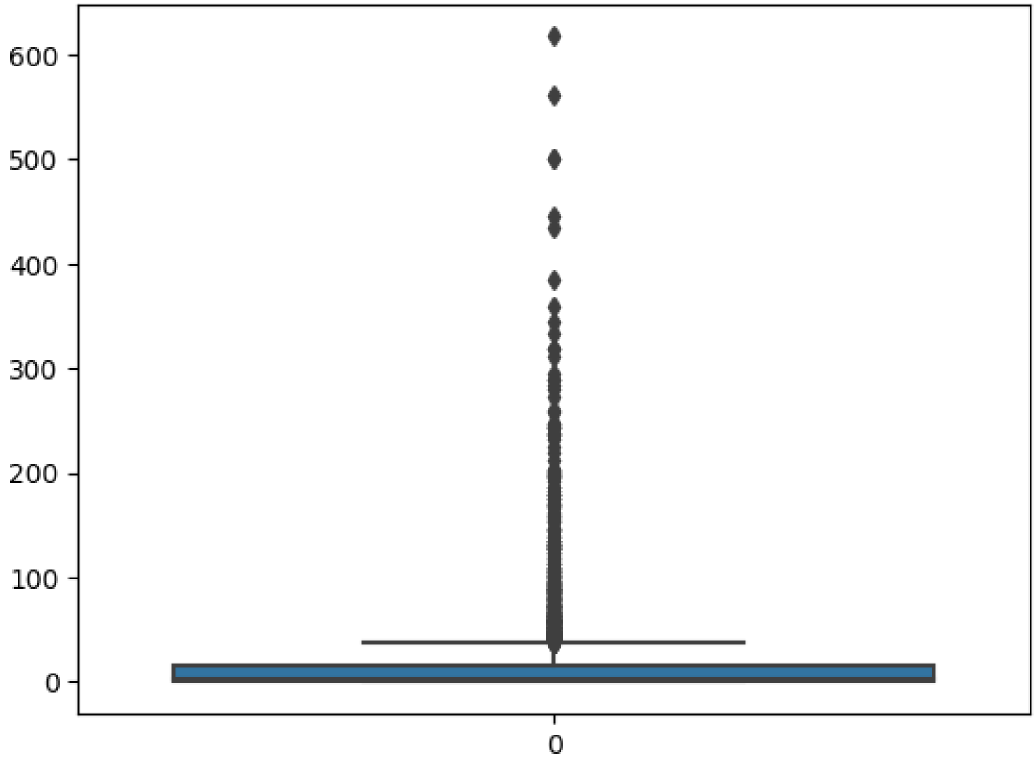
Column = OCT



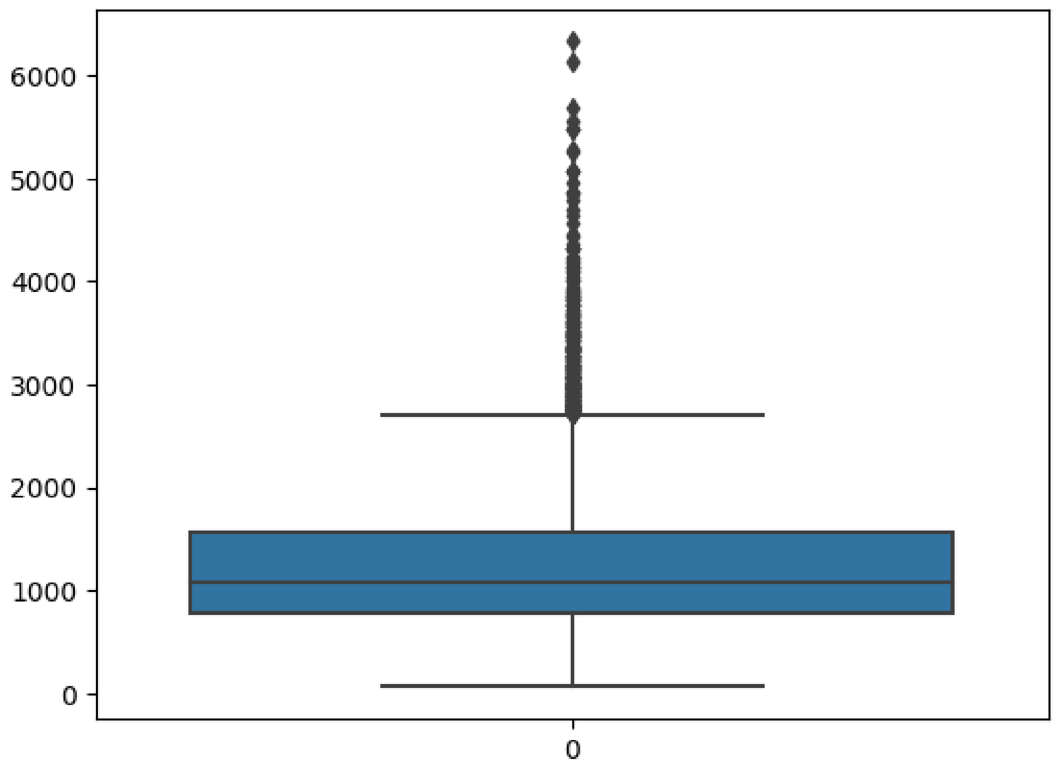
Column = NOV



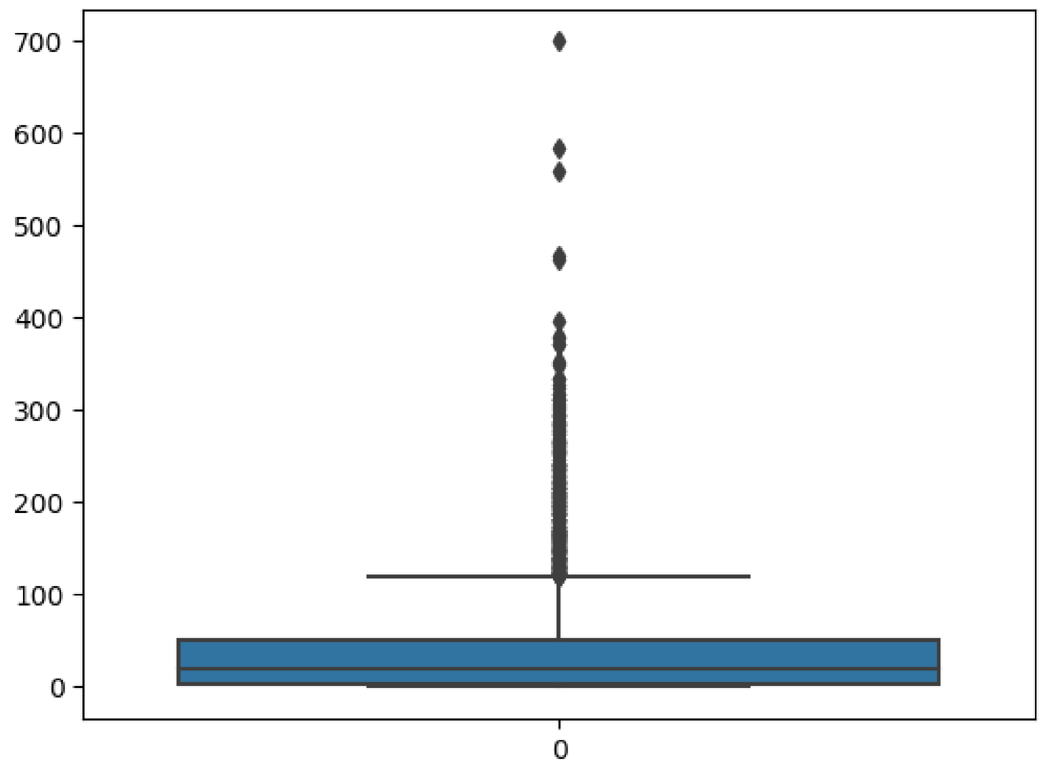

```
Column =  DEC
```



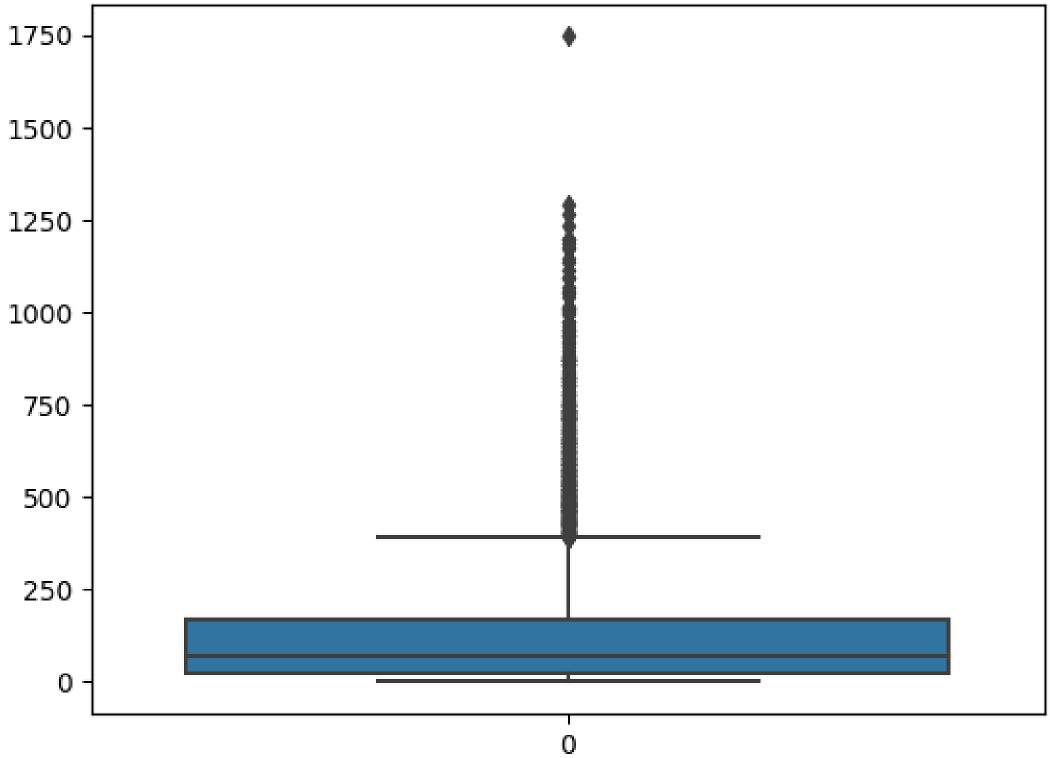
Column = ANNUAL



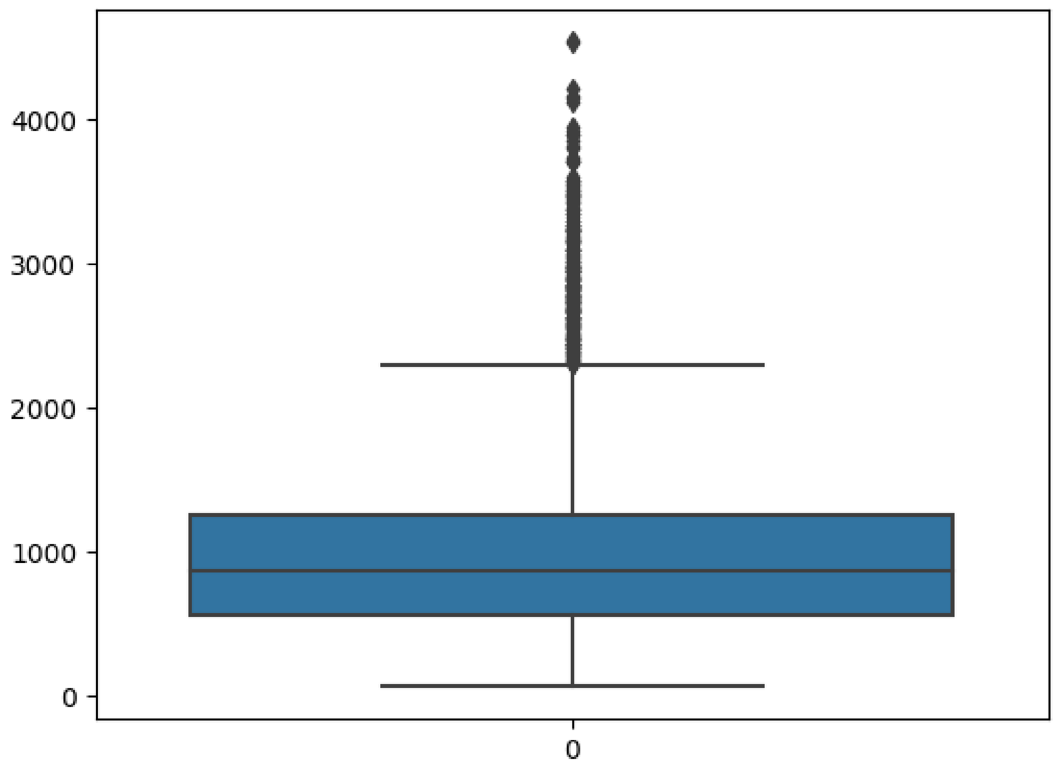

```
Column =  Jan-Feb
```



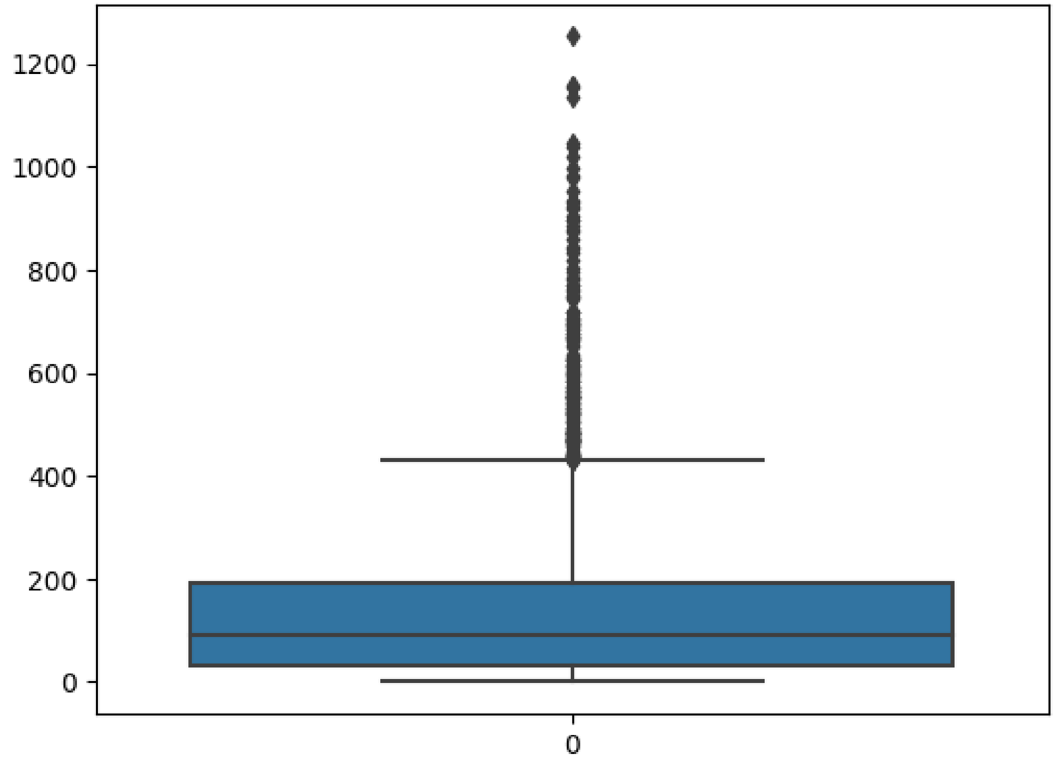
Column = Mar-May




```
Column =  Jun-Sep
```




```
Column =  Oct-Dec
```



[22]:
```
Q1=df['ANNUAL'].quantile(0.25)
Q3=df['ANNUAL'].quantile(0.75)
IQR=Q3-Q1
UL=Q3+1.5*IQR
LL=Q1-1.5*IQR
df=df[(df['ANNUAL']<UL) & (df['ANNUAL']>LL)]
```

[23]:
```
df.shape
```

[23]: (3421, 19)

[24]:
```
from datetime import date
df['NO OFYEAR'] = date.today().year - df['YEAR']
```

```
<ipython-input-24-c6f53b52a45c>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['NO OFYEAR'] = date.today().year - df['YEAR']
```

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

```
[25]:    SUBDIVISION  YEAR   JAN  FEB    MAR    APR    MAY    JUN    JUL    AUG  \
4              0  1905   1.3  0.0    3.3   26.9  279.5  628.7  368.7  330.5
5              0  1906  36.6  0.0    0.0    0.0  556.1  733.3  247.7  320.5
9              0  1911   0.0  8.4    0.0  122.5  327.3  649.0  253.0  187.1
11             0  1913  84.8  0.5    1.3    2.5  190.7  530.0  280.8  205.8
15             0  1917   8.0  3.6  112.0    4.5  295.9  301.1  394.8  437.4

      SEP    OCT    NOV    DEC  ANNUAL  Jan-Feb  Mar-May  Jun-Sep  Oct-Dec  \
4   297.0  260.7   25.4  344.7  2566.7      1.3    309.7   1624.9    630.8
5   164.3  267.8  128.9   79.2  2534.4     36.6    556.1   1465.8    475.9
9   464.5  333.8   94.5  247.1  2687.2      8.4    449.8   1553.6    675.4
11  580.1  288.8  133.0   67.5  2365.8     85.3    194.5   1596.7    489.3
15  471.8  238.1  108.3  236.9  2612.4     11.6    412.4   1605.1    583.3

    NO OFYEAR
4         118
5         117
9         112
11        110
15        106
```

1.4 Splitting the Data for Training Testing.

```
[26]: x=df.drop(columns=['ANNUAL','YEAR'])
      y=df['ANNUAL']
```

```
[27]: x.head()
```

```
[27]:    SUBDIVISION   JAN  FEB    MAR    APR    MAY    JUN    JUL    AUG    SEP  \
4              0   1.3  0.0    3.3   26.9  279.5  628.7  368.7  330.5  297.0
5              0  36.6  0.0    0.0    0.0  556.1  733.3  247.7  320.5  164.3
9              0   0.0  8.4    0.0  122.5  327.3  649.0  253.0  187.1  464.5
11             0  84.8  0.5    1.3    2.5  190.7  530.0  280.8  205.8  580.1
15             0   8.0  3.6  112.0    4.5  295.9  301.1  394.8  437.4  471.8

      OCT    NOV    DEC  Jan-Feb  Mar-May  Jun-Sep  Oct-Dec  NO OFYEAR
4   260.7   25.4  344.7      1.3    309.7   1624.9    630.8        118
5   267.8  128.9   79.2     36.6    556.1   1465.8    475.9        117
9   333.8   94.5  247.1      8.4    449.8   1553.6    675.4        112
11  288.8  133.0   67.5     85.3    194.5   1596.7    489.3        110
15  238.1  108.3  236.9     11.6    412.4   1605.1    583.3        106
```

```
[28]: from sklearn.model_selection import train_test_split
```

[29]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
↪3,random_state=42)
```

[30]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(2394, 18)
(1027, 18)
(2394,)
(1027,)
```

2 Visualizing the results

[31]:
```
import plotly.express as px
```

[32]:
```
fig=px.scatter(df,x=df['SUBDIVISION'],␣
↪y=df['ANNUAL'],trendline='ols',trendline_color_override='red')
fig.show()
results = px.get_trendline_results(fig)
print(results)
```

```
                                        px_fit_results
0  <statsmodels.regression.linear_model.Regressio…
```

[33]:
```
results.px_fit_results.iloc[0].summary()
```

[33]:

Dep. Variable:	y	**R-squared:**	0.092
Model:	OLS	**Adj. R-squared:**	0.092
Method:	Least Squares	**F-statistic:**	347.2
Date:	Fri, 15 Sep 2023	**Prob (F-statistic):**	6.85e-74
Time:	19:20:38	**Log-Likelihood:**	-26196.
No. Observations:	3421	**AIC:**	5.240e+04
Df Residuals:	3419	**BIC:**	5.241e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	1409.8534	18.542	76.037	0.000	1373.500	1446.207
x1	-17.3091	0.929	-18.635	0.000	-19.130	-15.488

Omnibus:	512.921	**Durbin-Watson:**	0.306
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	794.577
Skew:	1.050	**Prob(JB):**	2.88e-173
Kurtosis:	4.080	**Cond. No.**	42.3

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[34]:
```
fig=px.scatter(df,x=df['YEAR'],␣
 ↪y=df['ANNUAL'],trendline='ols',trendline_color_override='red')
fig.show()
results = px.get_trendline_results(fig)
print(results)
```

```
                              px_fit_results
0  <statsmodels.regression.linear_model.Regressio…
```

[35]:
```
fig=px.scatter(df,x=df['AUG'],␣
 ↪y=df['ANNUAL'],trendline='ols',trendline_color_override='red')
fig.show()
results = px.get_trendline_results(fig)
print(results)
```

```
                              px_fit_results
0  <statsmodels.regression.linear_model.Regressio…
```

2.1 Scaling the data

[36]:
```
#Scaling the data
from sklearn.preprocessing import RobustScaler
```

[37]:
```
rs=RobustScaler()
x_train_scl=rs.fit_transform(x_train)
x_test_scl=rs.transform(x_test)
```

[38]:
```
from sklearn.metrics import␣
 ↪mean_squared_error,mean_absolute_percentage_error,r2_score,mean_absolute_error
```

2.2 Fitting Linear Regression

[39]:
```
from sklearn.linear_model import LinearRegression
LR = LinearRegression()
LR_model = LR.fit(x_train_scl,y_train)
LR_model
```

[39]: LinearRegression()

[40]:
```
y_pred = LR_model.predict(x_test_scl)
y_pred_train = LR_model.predict(x_train_scl)
```

[41]:
```
from math import sqrt
```

2.3 Evaluation metrics

[42]:
```
mse=np.sqrt(mean_squared_error(y_test,y_pred))
print('MSE = ',mse)
mape=mean_absolute_percentage_error(y_test,y_pred)
print('MAPE = ',mape)
mae=mean_absolute_error(y_test,y_pred)
print('MAE =',mae)
```

```
MSE =  17.282893269004088
MAPE =  0.0012377277897482222
MAE = 1.4026635120204174
```

[43]:
```
LR_rmse=np.sqrt(mean_squared_error(y_test,y_pred))
print('RMSE = ',LR_rmse)
```

```
RMSE =  17.282893269004088
```

[44]:
```
error=sqrt(mse)
error
```

[44]: 4.157269929774117

[45]:
```
r2_score(y_train,y_pred_train)
```

[45]: 0.9999773369945448

[46]:
```
r2_score(y_test,y_pred)
```

[46]: 0.9990470027134594

2.4 Fitting Decission Tree Regression

[47]:
```
from sklearn.tree import DecisionTreeRegressor
DT = DecisionTreeRegressor()
DT_model = DT.fit(x_train_scl,y_train)
DT_model
```

[47]: DecisionTreeRegressor()

[48]:
```
y_pred = DT_model.predict(x_test_scl)
y_pred_train = DT_model.predict(x_train_scl)
```

[49]:
```
mse=np.sqrt(mean_squared_error(y_test,y_pred))
print('MSE = ',mse)
mape=mean_absolute_percentage_error(y_test,y_pred)
print('MAPE = ',mape)
mae=mean_absolute_error(y_test,y_pred)
```

```
print('MAE =',mae)
```

```
MSE =  99.91395889506
MAPE =  0.063134346421302
MAE = 65.82882181110028
```

[50]:
```
error=sqrt(mse)
error
```

[50]: 9.995697018970713

[51]:
```
r2_score(y_test,y_pred)
```

[51]: 0.9681498778010226

3 Regularization Techniques

###-Ridge Regression:

[52]:
```
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
```

3.1 Tunning

[53]:
```
ridge=Ridge()
parameters={'alpha':[1e-15,1e-10,1e-8,1e-3,1e-2,5,10,20,30,35,40,45,50,55,100]}
ridge_regressor=GridSearchCV(ridge,parameters,scoring='neg_mean_squared_error',cv=5)
ridge_regressor.fit(x_train_scl,y_train)
```

[53]:
```
GridSearchCV(cv=5, estimator=Ridge(),
             param_grid={'alpha': [1e-15, 1e-10, 1e-08, 0.001, 0.01, 5, 10, 20,
                                   30, 35, 40, 45, 50, 55, 100]},
             scoring='neg_mean_squared_error')
```

[54]:
```
print(ridge_regressor.best_params_)
print(ridge_regressor.best_score_)
```

```
{'alpha': 5}
-14.789731607600398
```

[55]:
```
print("Best Parameter for Ridge:",ridge_regressor.best_estimator_)
```

```
Best Parameter for Ridge: Ridge(alpha=5)
```

[56]:
```
ridge=Ridge(alpha=100.0)
```

[57]:
```
ridge_model=ridge.fit(x_train_scl,y_train)
```

[58]:
```
ridge_model
```

[58]: Ridge(alpha=100.0)

[59]:
```
y_pred = ridge_model.predict(x_test_scl)
y_pred_train = ridge_model.predict(x_train_scl)
```

[60]:
```
mse=np.sqrt(mean_squared_error(y_test,y_pred))
print('MSE = ',mse)
mape=mean_absolute_percentage_error(y_test,y_pred)
print('MAPE = ',mape)
mae=mean_absolute_error(y_test,y_pred)
print('MAE =',mae)
```

```
MSE =  20.2976939702703
MAPE =  0.011965520401746576
MAE = 9.32958037824982
```

[61]:
```
error=sqrt(mse)
error
```

[61]: 4.505296213377129

[62]:
```
r2_score(y_train,y_pred_train)
```

[62]: 0.999576292865514

[63]:
```
r2_score(y_test,y_pred)
```

[63]: 0.9986855254898491

###-Lasso Regression:

[64]:
```
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
```

[65]:
```
# create a lasso object
lasso = Lasso(max_iter=10000)
```

[66]:
```
# check for best alpha value using GridSearch
parameter={'alpha':[1e-15,1e-10,1e-8,1e-3,1e-2,1,5,1e1,1e2,1e3,1e4,1e5,1e6,1e7]}
lasso_regressor=GridSearchCV(
    lasso,parameter,
    scoring='neg_mean_squared_error',
    cv=5
    )
```

[67]:
```
lasso_model=lasso_regressor.fit(x_train_scl,y_train)
```

[68]:
```
lasso_model
```

[68]:
```
GridSearchCV(cv=5, estimator=Lasso(max_iter=10000),
             param_grid={'alpha': [1e-15, 1e-10, 1e-08, 0.001, 0.01, 1, 5, 10.0,
                                   100.0, 1000.0, 10000.0, 100000.0, 1000000.0,
                                   10000000.0]},
             scoring='neg_mean_squared_error')
```

3.2 Tunning

[69]:
```
GridSearchCV(cv=5, estimator=Lasso(max_iter=100000),
             param_grid={'alpha': [1e-15, 1e-10, 1e-08, 0.001, 0.01, 1, 5, 10.0,
                                   100.0, 1000.0, 10000.0, 100000.0, 1000000.0,
                                   10000000.0]},
             scoring='neg_mean_squared_error')
```

[69]:
```
GridSearchCV(cv=5, estimator=Lasso(max_iter=100000),
             param_grid={'alpha': [1e-15, 1e-10, 1e-08, 0.001, 0.01, 1, 5, 10.0,
                                   100.0, 1000.0, 10000.0, 100000.0, 1000000.0,
                                   10000000.0]},
             scoring='neg_mean_squared_error')
```

[70]:
```
print("Best Parameter for Lasso:",lasso_regressor.best_estimator_)
```

```
Best Parameter for Lasso: Lasso(alpha=0.01, max_iter=10000)
```

[71]:
```
lasso=Lasso(alpha=100.0,max_iter=100000)

# fit into the object
lasso.fit(x_train_scl,y_train)
```

[71]:
```
Lasso(alpha=100.0, max_iter=100000)
```

[72]:
```
y_pred = lasso.predict(x_test_scl)
y_pred_train = lasso.predict(x_train_scl)
```

[73]:
```
mse=np.sqrt(mean_squared_error(y_test,y_pred))
print('MSE = ',mse)
mape=mean_absolute_percentage_error(y_test,y_pred)
print('MAPE = ',mape)
mae=mean_absolute_error(y_test,y_pred)
print('MAE =',mae)
```

```
MSE =  184.76371805122238
MAPE =  0.205593393948917
MAE = 146.77004671754315
```

[74]:
```
error=sqrt(mse)
error
```

[74]: 13.592781836372655

[75]:
```
r2_score(y_train,y_pred_train)
```

[75]: 0.8877056551602704

[76]:
```
r2_score(y_test,y_pred)
```

[76]: 0.8910838818566653

3.3 Fitting Linear SVR

[77]:
```
from sklearn.svm import LinearSVR
```

[78]:
```
SVR_mod = LinearSVR()
SVR_model = SVR_mod.fit(x_train_scl,y_train)
SVR_model
```

[78]: LinearSVR()

[79]:
```
SVR_y_pred = SVR_model.predict(x_test_scl)
SVR_y_pred_train= SVR_model.predict(x_train_scl)
```

[80]:
```
r2_score(y_test,SVR_y_pred)
```

[80]: 0.9988244456890908

[81]:
```
r2_score(y_train,SVR_y_pred_train)
```

[81]: 0.9999309279515805

4 Fitting Neural Networks

###MLP Regressor

[82]:
```
from sklearn.neural_network import MLPRegressor
```

[83]:
```
NN = MLPRegressor()
NN_model = NN.fit(x_train_scl,y_train)
NN_model
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:686:
ConvergenceWarning:
```

```
Stochastic Optimizer: Maximum iterations (200) reached and the optimization
hasn't converged yet.
```

[83]: MLPRegressor()

[84]:
```
NN_y_pred = NN_model.predict(x_test_scl)
NN_y_pred_train = NN_model.predict(x_train_scl)
```

[85]:
```
r2_score(y_test,NN_y_pred)
```

[85]: 0.6166845881455115

[86]:
```
r2_score(y_train,NN_y_pred_train)
```

[86]: 0.5725644900202689

4.1 Fitting Random Forest Regression

[87]:
```
from sklearn.ensemble import RandomForestRegressor
```

[88]:
```
RF = RandomForestRegressor(max_depth=100, max_features='sqrt',␣
↪min_samples_leaf=4,
                           min_samples_split=10, n_estimators=800)
```

[89]:
```
RF_model=RF.fit(x_train_scl, y_train)
RF_model
```

[89]:
```
RandomForestRegressor(max_depth=100, max_features='sqrt', min_samples_leaf=4,
                      min_samples_split=10, n_estimators=800)
```

[90]:
```
RF_y_pred=RF_model.predict(x_test_scl)
RF_y_pred_train=RF_model.predict(x_train_scl)
```

[91]:
```
mse=np.sqrt(mean_squared_error(y_test,y_pred))
print('MSE = ',mse)
mape=mean_absolute_percentage_error(y_test,y_pred)
print('MAPE = ',mape)
mae=mean_absolute_error(y_test,y_pred)
print('MAE =',mae)
```

```
MSE =  184.76371805122238
MAPE =  0.205593393948917
MAE = 146.77004671754315
```

[92]:
```
error=sqrt(mse)
error
```

[92]: 13.592781836372655

[93]:
```
r2_score(y_test,RF_y_pred)
```

[93]: 0.9809028947052615

[94]:
```
r2_score(y_train,RF_y_pred_train)
```

[94]: 0.9919404483485026

[94]:

4.1.1 Tracking Model Performance

Model Name	R2 score
Decission Tree	96.15
Linear Regression	98.70
Ridge Regression	97.51
Lasso Regression	89.1o
Support Vector Reg	94.90
Neural Network(MLP)	61.66
Random Forest Regression	97.07

R2 scores for each of the models when running on the train/test data split.

[94]: