

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

In [2]: df = pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs_per_year\
df
```

Out[2]:

	date	BEN	CO	EBE	MXV	NMHC	NO_2	NOx	OXY	O_3	PM
0	2003-03-01 01:00:00	NaN	1.72	NaN	NaN	NaN	73.900002	316.299988	NaN	10.550000	55.2099
1	2003-03-01 01:00:00	NaN	1.45	NaN	NaN	0.26	72.110001	250.000000	0.73	6.720000	52.3899
2	2003-03-01 01:00:00	NaN	1.57	NaN	NaN	NaN	80.559998	224.199997	NaN	21.049999	63.2400
3	2003-03-01 01:00:00	NaN	2.45	NaN	NaN	NaN	78.370003	450.399994	NaN	4.220000	67.8399
4	2003-03-01 01:00:00	NaN	3.26	NaN	NaN	NaN	96.250000	479.100006	NaN	8.460000	95.7799
...	...	...	...	...	...	...	...	...	...	...	...
243979	2003-10-01 00:00:00	0.20	0.16	2.01	3.17	0.02	31.799999	32.299999	1.68	34.049999	7.3800
243980	2003-10-01 00:00:00	0.32	0.08	0.36	0.72	NaN	10.450000	14.760000	1.00	34.610001	7.4000
243981	2003-10-01 00:00:00	NaN	NaN	NaN	NaN	0.07	34.639999	50.810001	NaN	32.160000	16.8300
243982	2003-10-01 00:00:00	NaN	NaN	NaN	NaN	0.07	32.580002	41.020000	NaN	NaN	13.5700
243983	2003-10-01 00:00:00	1.00	0.29	2.15	6.41	0.07	37.150002	56.849998	2.28	21.480000	12.3500

243984 rows × 16 columns

```
In [3]: df1 = df.fillna(0)
df1
```

Out[3]:

	date	BEN	CO	EBE	MXV	NMHC	NO_2	NOx	OXY	O_3	PM
0	2003-03-01 01:00:00	0.00	1.72	0.00	0.00	0.00	73.900002	316.299988	0.00	10.550000	55.2099
1	2003-03-01 01:00:00	0.00	1.45	0.00	0.00	0.26	72.110001	250.000000	0.73	6.720000	52.3899
2	2003-03-01 01:00:00	0.00	1.57	0.00	0.00	0.00	80.559998	224.199997	0.00	21.049999	63.2400
3	2003-03-01 01:00:00	0.00	2.45	0.00	0.00	0.00	78.370003	450.399994	0.00	4.220000	67.8399
4	2003-03-01 01:00:00	0.00	3.26	0.00	0.00	0.00	96.250000	479.100006	0.00	8.460000	95.7799
...	...	...	...	...	...	...	...	...	...	...	...
243979	2003-10-01 00:00:00	0.20	0.16	2.01	3.17	0.02	31.799999	32.299999	1.68	34.049999	7.3800
243980	2003-10-01 00:00:00	0.32	0.08	0.36	0.72	0.00	10.450000	14.760000	1.00	34.610001	7.4000
243981	2003-10-01 00:00:00	0.00	0.00	0.00	0.00	0.07	34.639999	50.810001	0.00	32.160000	16.8300
243982	2003-10-01 00:00:00	0.00	0.00	0.00	0.00	0.07	32.580002	41.020000	0.00	0.000000	13.5700
243983	2003-10-01 00:00:00	1.00	0.29	2.15	6.41	0.07	37.150002	56.849998	2.28	21.480000	12.3500

243984 rows × 16 columns



```
In [4]: df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243984 entries, 0 to 243983
Data columns (total 16 columns):
#   Column      Non-Null Count  Dtype
---  -
0   date        243984 non-null  object
1   BEN         243984 non-null  float64
2   CO          243984 non-null  float64
3   EBE         243984 non-null  float64
4   MXY         243984 non-null  float64
5   NMHC        243984 non-null  float64
6   NO_2        243984 non-null  float64
7   NOx         243984 non-null  float64
8   OXY         243984 non-null  float64
9   O_3         243984 non-null  float64
10  PM10        243984 non-null  float64
11  PXY         243984 non-null  float64
12  SO_2        243984 non-null  float64
13  TCH         243984 non-null  float64
14  TOL         243984 non-null  float64
15  station     243984 non-null  int64
dtypes: float64(14), int64(1), object(1)
memory usage: 29.8+ MB
```

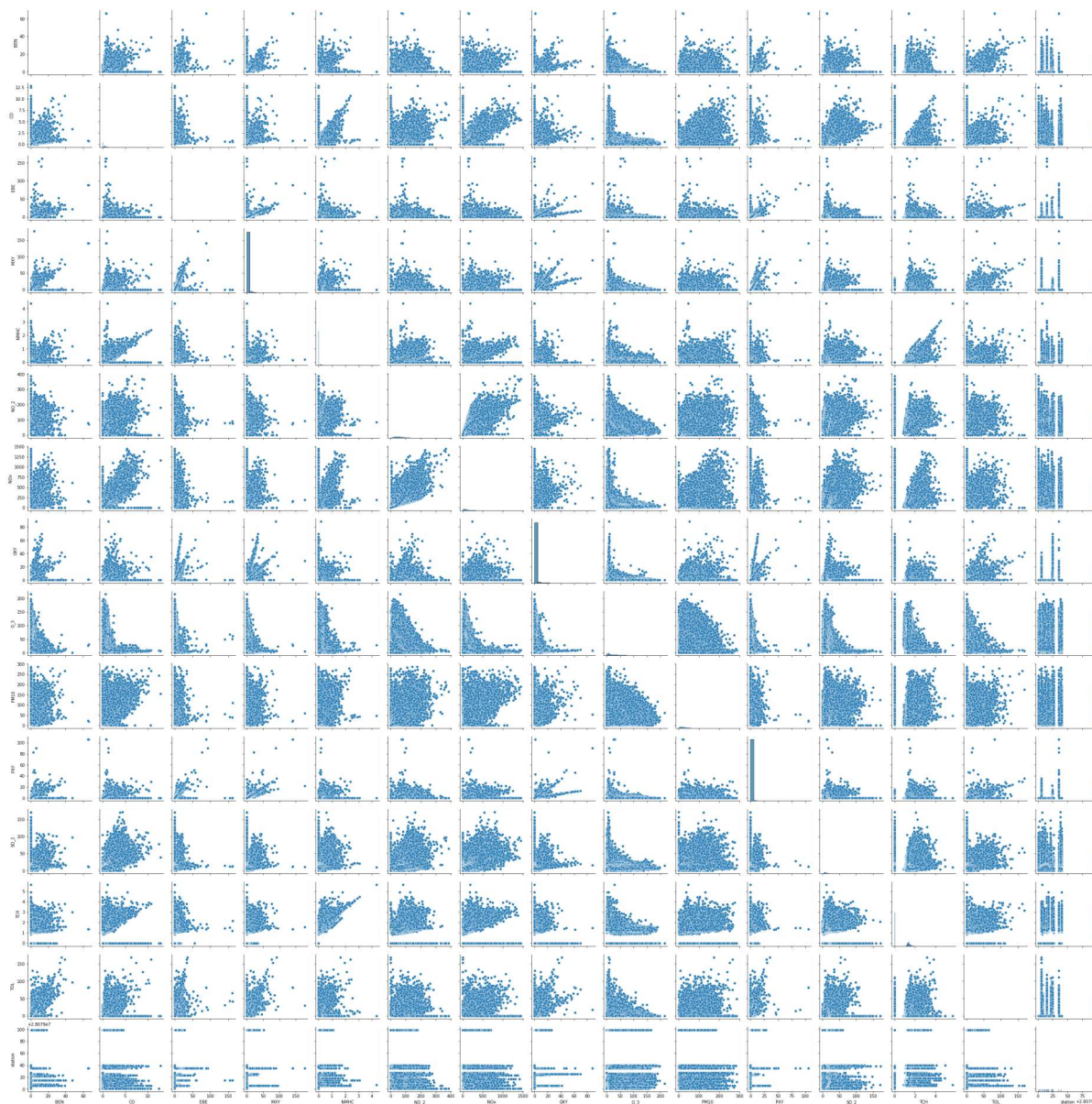
```
In [5]: df1.columns
```

```
Out[5]: Index(['date', 'BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
              'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station'],
              dtype='object')
```

```
In [6]: df2 = df1[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
                  'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station']]
```

```
In [7]: sns.pairplot(df2)
```

```
Out[7]: <seaborn.axisgrid.PairGrid at 0x1d8c13962e0>
```

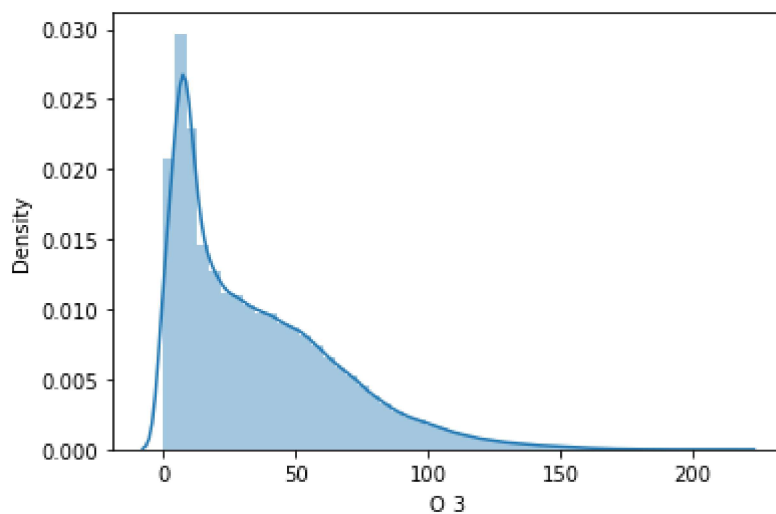


```
In [8]: sns.distplot(df2['O_3'])
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

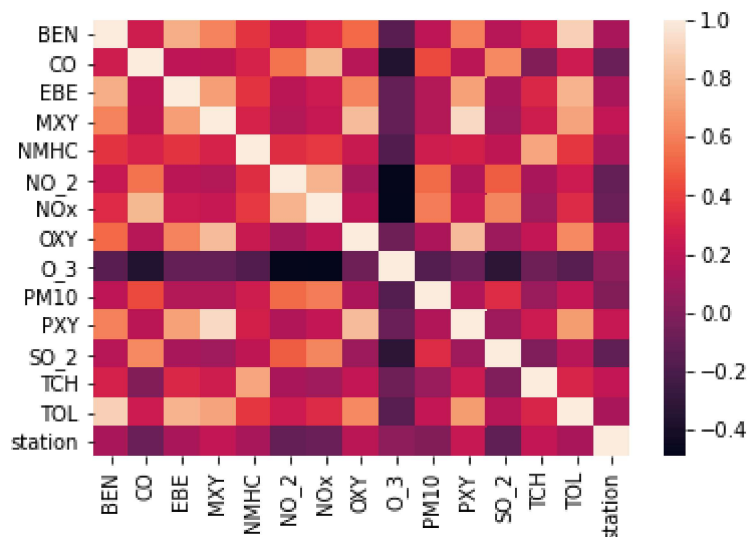
```
warnings.warn(msg, FutureWarning)
```

```
Out[8]: <AxesSubplot:xlabel='O_3', ylabel='Density'>
```



```
In [9]: sns.heatmap(df2.corr())
```

```
Out[9]: <AxesSubplot:>
```



## Linear Regression

```
In [40]: x = df2[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',  
               'PM10', 'PXY', 'SO_2', 'TCH']]  
y = df2['TOL']
```

```
In [41]: from sklearn.model_selection import train_test_split  
  
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30)
```

```
In [42]: from sklearn.linear_model import LinearRegression  
  
lr = LinearRegression()  
lr.fit(x_train,y_train)
```

Out[42]: LinearRegression()

```
In [43]: print(lr.intercept_)  
  
0.05153717878677311
```

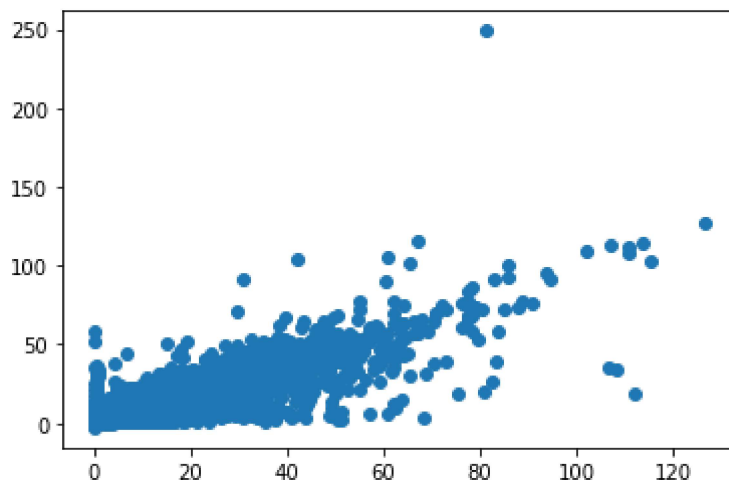
```
In [44]: coeff = pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])  
coeff
```

Out[44]:

	Co-efficient
<b>BEN</b>	2.751783
<b>CO</b>	-0.413755
<b>EBE</b>	0.409060
<b>MXY</b>	0.615866
<b>NMHC</b>	0.462169
<b>NO_2</b>	0.000508
<b>NOx</b>	0.003124
<b>OXY</b>	0.261635
<b>O_3</b>	-0.001993
<b>PM10</b>	0.002020
<b>PXY</b>	-0.517661
<b>SO_2</b>	0.006842
<b>TCH</b>	0.080668

```
In [45]: prediction = lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[45]: <matplotlib.collections.PathCollection at 0x1d8ee99c130>



```
In [46]: print(lr.score(x_test,y_test))
```

0.8588823576390503

```
In [47]: lr.score(x_train,y_train)
```

Out[47]: 0.8522993489926665

## Ridge and Lasso

```
In [48]: from sklearn.linear_model import Ridge,Lasso
```

```
In [49]: rr = Ridge(alpha=10)
rr.fit(x_train,y_train)
rr.score(x_train,y_train)
```

Out[49]: 0.852299345539862

```
In [50]: rr.score(x_test,y_test)
```

Out[50]: 0.8588808675901978

```
In [51]: ls = Lasso(alpha=10)
ls.fit(x_train,y_train)
ls.score(x_train,y_train)
```

Out[51]: 0.3420746807446454

```
In [52]: ls.score(x_test,y_test)
```

Out[52]: 0.3523943809006804

## ElasticNET regression

```
In [53]: from sklearn.linear_model import ElasticNet  
es = ElasticNet()  
es.fit(x_train,y_train)
```

Out[53]: ElasticNet()

```
In [54]: print(es.coef_)
```

```
[ 1.83576883e+00 -0.00000000e+00  6.35732366e-01  6.11793843e-01  
 0.00000000e+00  0.00000000e+00  4.90226757e-03  2.25159780e-02  
-1.24296046e-03  1.78610812e-03  0.00000000e+00  0.00000000e+00  
 0.00000000e+00]
```

```
In [55]: print(es.intercept_)
```

0.08538665806495027

```
In [56]: print(es.score(x_test,y_test))
```

0.8307640903754144

```
In [57]: print(es.score(x_train,y_train))
```

0.827585164995586

## LogisticRegression

```
In [58]: from sklearn.linear_model import LogisticRegression
```

```
In [59]: feature_matrix = df2.iloc[:,0:15]  
target_vector = df2.iloc[:,-1]
```

```
In [60]: feature_matrix.shape
```

Out[60]: (243984, 15)

```
In [61]: from sklearn.preprocessing import StandardScaler
```

```
In [62]: fs = StandardScaler().fit_transform(feature_matrix)
```



```
In [63]: logs = LogisticRegression()  
logs.fit(fs,target_vector)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:  
763: ConvergenceWarning: lbfgs failed to converge (status=1):  
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:  
<https://scikit-learn.org/stable/modules/preprocessing.html> (<https://scikit-learn.org/stable/modules/preprocessing.html>)  
Please also refer to the documentation for alternative solver options:  
[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression) ([https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression))  
n\_iter\_i = \_check\_optimize\_result(

```
Out[63]: LogisticRegression()
```

```
In [64]: observation = [[1.4,1.5,1.6,2.7,2.3,3.3,2.3,4.1,2.3,4.2,1.2,2.1,4.3,6,2.2]]  
prediction = logs.predict(observation)
```

```
In [65]: print(prediction)  
  
[28079035]
```

```
In [66]: logs.classes_
```

```
Out[66]: array([28079001, 28079003, 28079004, 28079006, 28079007, 28079008,  
                28079009, 28079011, 28079012, 28079014, 28079015, 28079016,  
                28079017, 28079018, 28079019, 28079021, 28079022, 28079023,  
                28079024, 28079025, 28079026, 28079027, 28079035, 28079036,  
                28079038, 28079039, 28079040, 28079099], dtype=int64)
```

```
In [67]: from sklearn.model_selection import train_test_split  
  
x_train,x_test,y_train,y_test = train_test_split(feature_matrix,target_vector,t
```

```
In [68]: print(logs.score(x_test,y_test))  
  
0.035807967648505384
```

```
In [69]: print(logs.score(x_train,y_train))  
  
0.035945148371079934
```

## Conclusion

Linear regression is bestfit model

Linear regression is best fit model for dataset madrid\_2001. The score of x\_train,y\_train is 0.8588823576390503 and x\_test and y\_test score is 0.8522993489926665.

In [ ]: