mk 3/08/2023

Out[4]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	
0	2013- 11-01 01:00:00	NaN	0.6	NaN	NaN	135.0	74.0	NaN	NaN	NaN	7.0	NaN	NaN	2
1	2013- 11-01 01:00:00	1.5	0.5	1.3	NaN	71.0	83.0	2.0	23.0	16.0	12.0	NaN	8.3	2
2	2013- 11-01 01:00:00	3.9	NaN	2.8	NaN	49.0	70.0	NaN	NaN	NaN	NaN	NaN	9.0	2
3	2013- 11-01 01:00:00	NaN	0.5	NaN	NaN	82.0	87.0	3.0	NaN	NaN	NaN	NaN	NaN	2
4	2013- 11-01 01:00:00	NaN	NaN	NaN	NaN	242.0	111.0	2.0	NaN	NaN	12.0	NaN	NaN	2
209875	2013- 03-01 00:00:00	NaN	0.4	NaN	NaN	8.0	39.0	52.0	NaN	NaN	NaN	NaN	NaN	2
209876	2013- 03-01 00:00:00	NaN	0.4	NaN	NaN	1.0	11.0	NaN	6.0	NaN	2.0	NaN	NaN	2
209877	2013- 03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	4.0	75.0	NaN	NaN	NaN	NaN	NaN	2
209878	2013- 03-01 00:00:00	NaN	NaN	NaN	NaN	2.0	11.0	52.0	NaN	NaN	NaN	NaN	NaN	2
209879	2013- 03-01 00:00:00	NaN	NaN	NaN	NaN	1.0	10.0	75.0	3.0	NaN	NaN	NaN	NaN	2

209880 rows × 14 columns

```
In [5]: 1 a.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209880 entries, 0 to 209879
Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
π	COTUMIT	Non-Nail Counc	Deype
0	date	209880 non-null	object
1	BEN	50462 non-null	float64
2	CO	87018 non-null	float64
3	EBE	50463 non-null	float64
4	NMHC	25935 non-null	float64
5	NO	209108 non-null	float64
6	NO_2	209108 non-null	float64
7	0_3	121858 non-null	float64
8	PM10	104339 non-null	float64
9	PM25	51980 non-null	float64
10	SO_2	86970 non-null	float64
11	TCH	25935 non-null	float64
12	TOL	50317 non-null	float64
13	station	209880 non-null	int64

dtypes: float64(12), int64(1), object(1)

memory usage: 22.4+ MB

In [6]: 1 b=a.fillna(value=104)
2 b

Out[6]:

		date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	Т
	0	2013- 11-01 01:00:00	104.0	0.6	104.0	104.0	135.0	74.0	104.0	104.0	104.0	7.0	104.0	10
	1	2013- 11-01 01:00:00	1.5	0.5	1.3	104.0	71.0	83.0	2.0	23.0	16.0	12.0	104.0	
	2	2013- 11-01 01:00:00	3.9	104.0	2.8	104.0	49.0	70.0	104.0	104.0	104.0	104.0	104.0	
	3	2013- 11-01 01:00:00	104.0	0.5	104.0	104.0	82.0	87.0	3.0	104.0	104.0	104.0	104.0	10
	4	2013- 11-01 01:00:00	104.0	104.0	104.0	104.0	242.0	111.0	2.0	104.0	104.0	12.0	104.0	10
;	209875	2013- 03-01 00:00:00	104.0	0.4	104.0	104.0	8.0	39.0	52.0	104.0	104.0	104.0	104.0	10
:	209876	2013- 03-01 00:00:00	104.0	0.4	104.0	104.0	1.0	11.0	104.0	6.0	104.0	2.0	104.0	10
:	209877	2013- 03-01 00:00:00	104.0	104.0	104.0	104.0	2.0	4.0	75.0	104.0	104.0	104.0	104.0	10
;	209878	2013- 03-01 00:00:00	104.0	104.0	104.0	104.0	2.0	11.0	52.0	104.0	104.0	104.0	104.0	10
:	209879	2013- 03-01 00:00:00	104.0	104.0	104.0	104.0	1.0	10.0	75.0	3.0	104.0	104.0	104.0	10

209880 rows × 14 columns

In [8]: 1 c=b.head(10000) 2 c

Out[8]:

	date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOI
0	2013- 11-01 01:00:00	104.0	0.6	104.0	104.0	135.0	74.0	104.0	104.0	104.0	7.0	104.0	104.(
1	2013- 11-01 01:00:00	1.5	0.5	1.3	104.0	71.0	83.0	2.0	23.0	16.0	12.0	104.0	3.8
2	2013- 11-01 01:00:00	3.9	104.0	2.8	104.0	49.0	70.0	104.0	104.0	104.0	104.0	104.0	9.(
3	2013- 11-01 01:00:00	104.0	0.5	104.0	104.0	82.0	87.0	3.0	104.0	104.0	104.0	104.0	104.(
4	2013- 11-01 01:00:00	104.0	104.0	104.0	104.0	242.0	111.0	2.0	104.0	104.0	12.0	104.0	104.(
9995	2013- 11-18 09:00:00	104.0	0.7	104.0	104.0	93.0	57.0	4.0	104.0	104.0	104.0	104.0	104.(
9996	2013- 11-18 09:00:00	104.0	104.0	104.0	104.0	138.0	69.0	104.0	23.0	104.0	6.0	104.0	104.(
9997	2013- 11-18 09:00:00	104.0	104.0	104.0	104.0	168.0	64.0	104.0	22.0	15.0	104.0	104.0	104.(
9998	2013- 11-18 09:00:00	104.0	104.0	104.0	104.0	110.0	89.0	104.0	22.0	16.0	104.0	104.0	104.(
9999	2013- 11-18 09:00:00	104.0	104.0	104.0	104.0	53.0	42.0	2.0	104.0	104.0	104.0	104.0	104.(

10000 rows × 14 columns

localhost:8888/notebooks/Project-1.ipynb

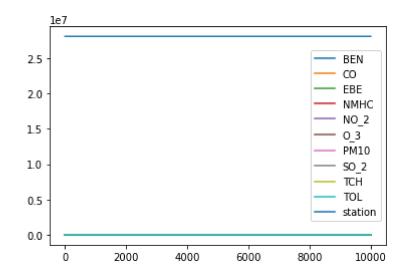
Out[9]:

	BEN	СО	EBE	NMHC	NO_2	O_3	PM10	SO_2	TCH	TOL	station
0	104.0	0.6	104.0	104.0	74.0	104.0	104.0	7.0	104.0	104.0	28079004
1	1.5	0.5	1.3	104.0	83.0	2.0	23.0	12.0	104.0	8.3	28079008
2	3.9	104.0	2.8	104.0	70.0	104.0	104.0	104.0	104.0	9.0	28079011
3	104.0	0.5	104.0	104.0	87.0	3.0	104.0	104.0	104.0	104.0	28079016
4	104.0	104.0	104.0	104.0	111.0	2.0	104.0	12.0	104.0	104.0	28079017
9995	104.0	0.7	104.0	104.0	57.0	4.0	104.0	104.0	104.0	104.0	28079039
9996	104.0	104.0	104.0	104.0	69.0	104.0	23.0	6.0	104.0	104.0	28079040
9997	104.0	104.0	104.0	104.0	64.0	104.0	22.0	104.0	104.0	104.0	28079047
9998	104.0	104.0	104.0	104.0	89.0	104.0	22.0	104.0	104.0	104.0	28079048
9999	104.0	104.0	104.0	104.0	42.0	2.0	104.0	104.0	104.0	104.0	28079049

10000 rows × 11 columns

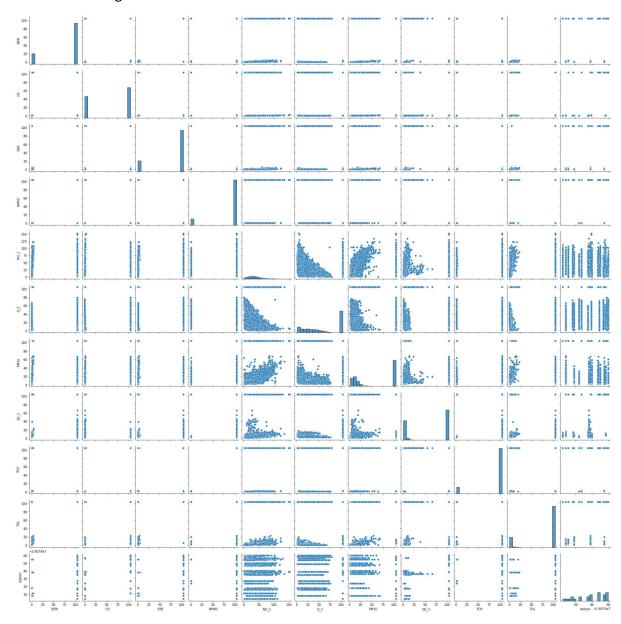
```
In [10]: 1 d.plot.line()
```

Out[10]: <AxesSubplot:>



```
In [11]: 1 sns.pairplot(d)
```

Out[11]: <seaborn.axisgrid.PairGrid at 0x1f70ad5bd90>



```
In [13]: 1    from sklearn.model_selection import train_test_split
2    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

Out[14]: LinearRegression()

```
In [47]:
           1 lr.fit(x_train,y_train)
Out[47]: LinearRegression()
In [15]:
              print(lr.intercept_)
          1.2479844840821386
In [16]:
              coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[16]:
                 Co-efficient
            BEN
                   -0.000969
             CO
                   0.000221
            EBE
                   0.000703
          NMHC
                   0.987915
           NO_2
                   0.000508
In [17]:
              prediction=lr.predict(x_test)
              plt.scatter(y_test,prediction)
Out[17]: <matplotlib.collections.PathCollection at 0x1f714444850>
           100
            80
            60
            40
            20
                       20
                               40
                                        60
                                                80
                                                        100
In [18]:
              print(lr.score(x_test,y_test))
          0.9999953135331272
In [48]:
              print(lr.score(x_train,y_train))
          0.9999954606932426
              from sklearn.linear_model import Ridge,Lasso
In [19]:
```

In [25]: 1 a1=b.head(7000) 2 a1

Out[25]:

	date	BEN	со	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOI
0	2013- 11-01 01:00:00	104.0	0.6	104.0	104.0	135.0	74.0	104.0	104.0	104.0	7.0	104.0	104.(
1	2013- 11-01 01:00:00	1.5	0.5	1.3	104.0	71.0	83.0	2.0	23.0	16.0	12.0	104.0	8.(
2	2013- 11-01 01:00:00	3.9	104.0	2.8	104.0	49.0	70.0	104.0	104.0	104.0	104.0	104.0	9.(
3	2013- 11-01 01:00:00	104.0	0.5	104.0	104.0	82.0	87.0	3.0	104.0	104.0	104.0	104.0	104.(
4	2013- 11-01 01:00:00	104.0	104.0	104.0	104.0	242.0	111.0	2.0	104.0	104.0	12.0	104.0	104.(
6995	2013- 11-13 04:00:00	104.0	0.2	104.0	104.0	1.0	8.0	40.0	104.0	104.0	104.0	104.0	104.(
6996	2013- 11-13 04:00:00	104.0	104.0	104.0	104.0	1.0	5.0	104.0	3.0	104.0	1.0	104.0	104.(
6997	2013- 11-13 04:00:00	104.0	104.0	104.0	104.0	1.0	6.0	104.0	3.0	2.0	104.0	104.0	104.(
6998	2013- 11-13 04:00:00	104.0	104.0	104.0	104.0	1.0	9.0	104.0	5.0	1.0	104.0	104.0	104.(
6999	2013- 11-13 04:00:00	104.0	104.0	104.0	104.0	1.0	9.0	43.0	104.0	104.0	104.0	104.0	104.(

7000 rows × 14 columns

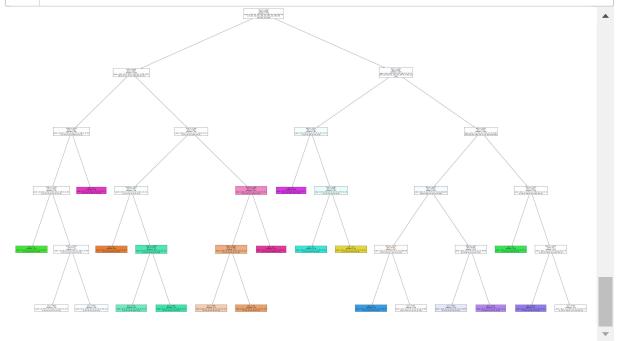
In [28]: 1 h=StandardScaler().fit_transform(f)

```
In [29]:
              logr=LogisticRegression(max iter=10000)
             logr.fit(h,g)
Out[29]: LogisticRegression(max_iter=10000)
In [30]:
              from sklearn.model selection import train test split
              h_train,h_test,g_train,g_test=train_test_split(h,g,test_size=0.3)
In [31]:
             i=[[10,20,30,40,50,60,11,22,33,44,55]]
In [32]:
              prediction=logr.predict(i)
              print(prediction)
         [28079050]
In [33]:
             logr.classes_
Out[33]: array([28079004, 28079008, 28079011, 28079016, 28079017, 28079018,
                28079024, 28079027, 28079035, 28079036, 28079038, 28079039,
                28079040, 28079047, 28079048, 28079049, 28079050, 28079054,
                28079055, 28079056, 28079057, 28079058, 28079059, 28079060],
               dtype=int64)
In [34]:
             logr.predict proba(i)[0][0]
Out[34]: 0.0
In [35]:
             logr.predict proba(i)[0][1]
Out[35]: 0.0
In [36]:
             logr.score(h_test,g_test)
Out[36]: 0.9576190476190476
In [37]:
           1 from sklearn.linear model import ElasticNet
             en=ElasticNet()
           2
              en.fit(x_train,y_train)
Out[37]: ElasticNet()
In [38]:
              print(en.coef_)
         [-0.
                        0.
                                   -0.
                                                0.98701057 0.
                                                                       ]
              print(en.intercept_)
In [39]:
         1.3400191911879489
```

```
In [40]:
             prediction=en.predict(x test)
             print(en.score(x_test,y_test))
         0.9999944213935371
In [41]:
             from sklearn.ensemble import RandomForestClassifier
             rfc=RandomForestClassifier()
           3 rfc.fit(h_train,g_train)
Out[41]: RandomForestClassifier()
In [42]:
             parameters={'max_depth':[1,2,3,4,5],
              'min_samples_leaf':[5,10,15,20,25],
           2
           3
             'n_estimators':[10,20,30,40,50]
             }
In [43]:
           1 from sklearn.model_selection import GridSearchCV
           2 | grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring=
           3 grid_search.fit(h_train,g_train)
Out[43]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
                      param_grid={'max_depth': [1, 2, 3, 4, 5],
                                   'min samples leaf': [5, 10, 15, 20, 25],
                                   'n estimators': [10, 20, 30, 40, 50]},
                      scoring='accuracy')
In [44]:
             grid_search.best_score_
Out[44]: 0.9985714285714286
In [45]:
           1 rfc_best=grid_search.best_estimator_
```

In [46]:

- 1 from sklearn.tree import plot_tree
- plt.figure(figsize=(80,50))
- 3 plot_tree(rfc_best.estimators_[2],filled=True)



Conclusion

Linear Regression=0.9999954606932426

Ridge Regression=0.9999189899159493

Lasso Regression=0.9999189899159493

ElasticNet Regression=0.9999944213935371

Logistic Regression=0.9576190476190476

Random Forest=0.9985714285714286

In []: 1 | Linear Regression is suitable in this dataset