Univariate + Multivariate Time Series Analysis + Forecasting

```
import numpy as np
import pandas as pd
import seaborn as sb
from sklearn.impute import SimpleImputer
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams['figure.figsize'] = (15, 5)
import seaborn as sn
import statsmodels.api as sm
import math
from statsmodels.tsa.stattools import kpss, adfuller
from pmdarima import auto_arima
from statsmodels.tsa.vector_ar.var_model import VAR
```

Understanding Data + Imputing for NO_2

```
df = pd.read_csv ('./AirQualityUCI.csv', sep = ';', na_values = -200)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9471 entries, 0 to 9470
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           9357 non-null   object
 1   Time           9357 non-null   object
 2   CO(GT)         7765 non-null   object
 3   PT08.S1(CO)    8991 non-null   float64
 4   NMHC(GT)       914 non-null    float64
 5   C6H6(GT)       9357 non-null   object
 6   PT08.S2(NMHC)  8991 non-null   float64
 7   NOx(GT)        7718 non-null   float64
 8   PT08.S3(NOx)   8991 non-null   float64
 9   NO2(GT)        7715 non-null   float64
 10  PT08.S4(NO2)   8991 non-null   float64
 11  PT08.S5(O3)    8991 non-null   float64
 12  T              8991 non-null   object
 13  RH             8991 non-null   object
 14  AH             8991 non-null   object
 15  Unnamed: 15    0 non-null      float64
 16  Unnamed: 16    0 non-null      float64
dtypes: float64(10), object(7)
memory usage: 1.2+ MB
```

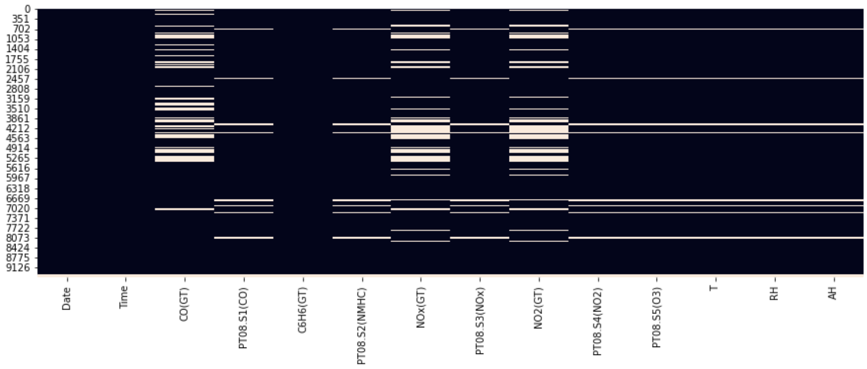
```
# pip list --outdated --format=freeze | grep -v '^\-e' | cut -d = -f 1  | xargs -n1 pip install -U
```

Completing Univariate Analysis First on NO2(GT) (already float)

Date and Time are objects, need to combine them first and then convert them into date-time objects

```
sb.heatmap(df.isnull(), cbar = False);
# Conclusions
# - Remove the last 2 columns and NMHC (GT) [for multivariate analysis done later]
# - Imputing the data for NO2 since this is time series forecasting and ACF won't work properly if simply removed
```

```
df = df.drop (['Unnamed: 15', 'Unnamed: 16', 'NMHC(GT)'], axis = 1)
sb.heatmap(df.isnull(), cbar = False);
```




```
df['TimeStamp'] = pd.to_datetime(df['Date'] + ' ' + df['Time'], format = '%d/%m/%Y %H.%M.%S')

timestamp = df['TimeStamp']
no2_level = df['NO2(GT)']
```

```
df.head()
```

	Date	Time	CO(GT)	PT08.S1(CO)	C6H6(GT)	PT08.S2(NMHC)	NOx(GT)	PT08.S3(NOx)	NO2(GT)	PT08.S4(NO2)	PT08.S5(O3
0	10/03/2004	18.00.00	2,6	1360.0	11,9	1046.0	166.0	1056.0	113.0	1692.0	1268
1	10/03/2004	19.00.00	2	1292.0	9,4	955.0	103.0	1174.0	92.0	1559.0	972
2	10/03/2004	20.00.00	2,2	1402.0	9,0	939.0	131.0	1140.0	114.0	1555.0	1074

```
df.describe()
# NO2 varies a lot min(2) to max(340)
```

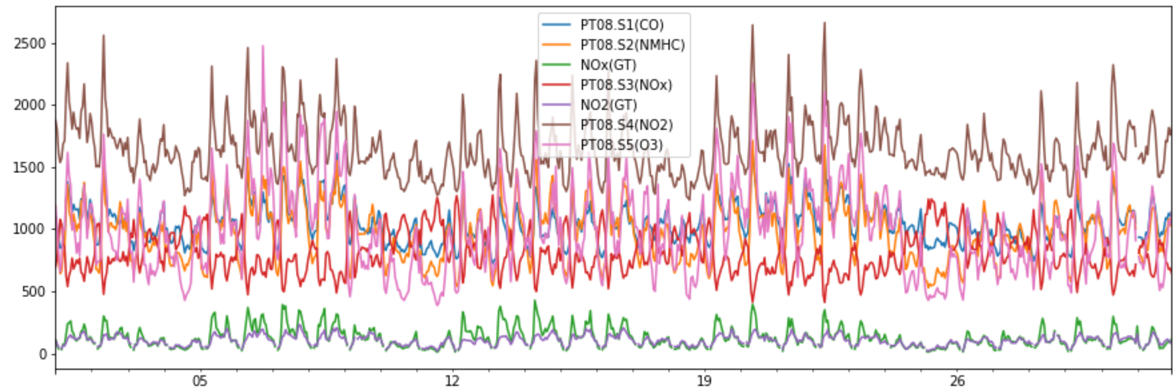
	PT08.S1(CO)	PT08.S2(NMHC)	NOx(GT)	PT08.S3(NOx)	NO2(GT)	PT08.S4(NO2)	PT08.S5(O3)
count	8991.000000	8991.000000	7718.000000	8991.000000	7715.000000	8991.000000	8991.000000
mean	1099.833166	939.153376	246.896735	835.493605	113.091251	1456.264598	1022.906128
std	217.080037	266.831429	212.979168	256.817320	48.370108	346.206794	398.484288
min	647.000000	383.000000	2.000000	322.000000	2.000000	551.000000	221.000000
25%	937.000000	734.500000	98.000000	658.000000	78.000000	1227.000000	731.500000
50%	1063.000000	909.000000	180.000000	806.000000	109.000000	1463.000000	963.000000
75%	1231.000000	1116.000000	326.000000	969.500000	142.000000	1674.000000	1273.500000
max	2040.000000	2214.000000	1479.000000	2683.000000	340.000000	2775.000000	2523.000000

```
df = df[df['TimeStamp'].notna()]
```

```
df['index_col'] = df.index
df = df.set_index('TimeStamp')
```

Analyzing for July 2004 to see a pattern

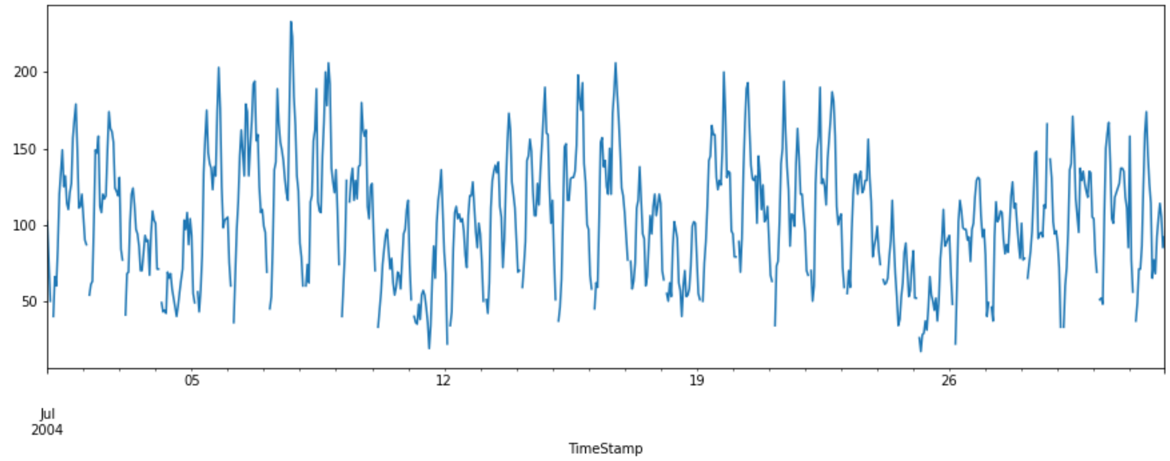
```
levels_2004_July = df.drop(['index_col'], axis = 1).loc['2004-07']
levels_2004_July.plot();
```



Shows that concentrations of different gases are definitely correlated, some that don't make sense in the first go (such as NO2 and O3).

Looking at only NO_2

```
no2_levels_2004_July = df.loc['2004-07']['NO2(GT)']
no2_levels_2004_July.plot(figsize = (15,5));
```

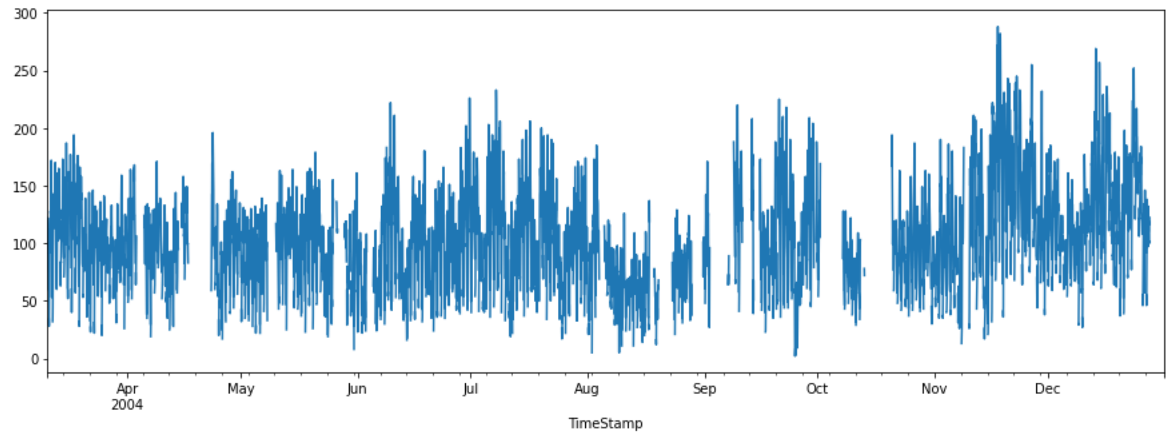


Within a day, the NO2 level peaks and then returns back to a value close to ~50

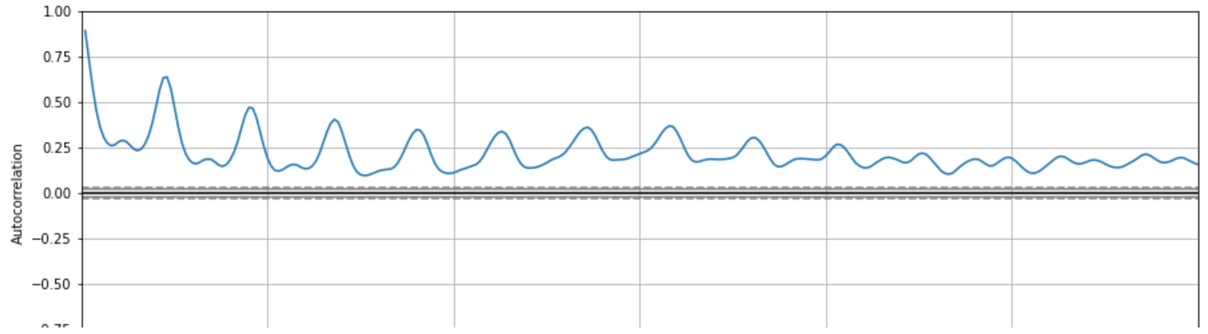
NO2 levels go down during the weekends (Example: 10-11th July, 17-18th July 2004)

Overall there is a weekly cyclic nature

```
no2_levels_2004 = df.loc['2004']['NO2(GT)']
no2_levels_2004.plot(figsize = (15,5));
```




```
# Correlation for NO2 data with different lag values (this was used for imputing)
df_no_na = df.dropna()
ax = pd.plotting.autocorrelation_plot(df_no_na['NO2(GT)'])
ax.set_xlim([0, 300]);
```



For NO_2 levels, there is a repeating trend at a lag of every 24, 48,.. hours -> Highly seasonal time series

But the data needs to be imputed. Possible strategies for imputing values for NO2:

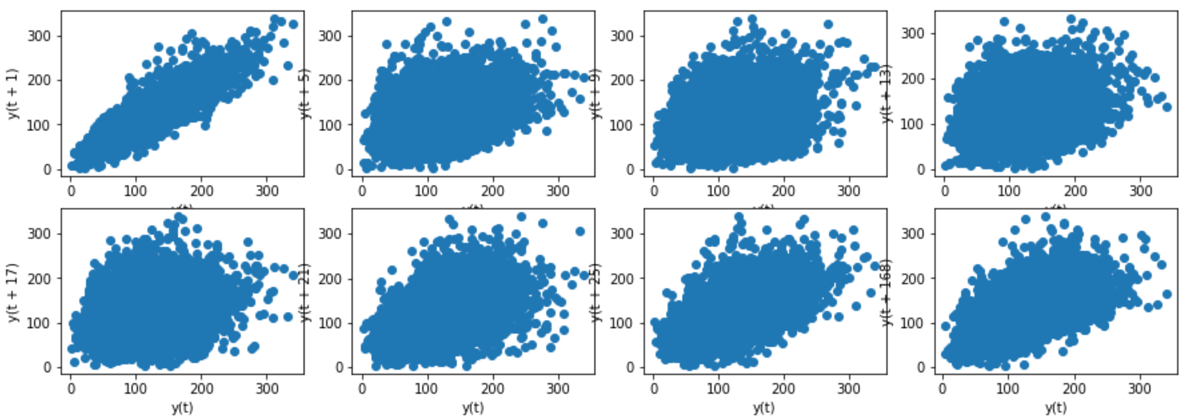
- Remove those records where values are missing [Can't do this since it will break the series]
- Impute with:
    - this day's last hour concentration (lag = 1)
    - the last day's concentration for the same hour (lag = 24)
    - last week same day, same hour concentration

      Last strategy for imputing looks good, from the July concentration graph above. But it is possible that the data is unavailable for that specific hour, so taking an average of multiple values to be on the safer side. So check the last week, or the week before that and so on; until a value is found. Since 24 hour lag seems to be the best, followed by 48 hour lag and so on..

```
lst = list(range(1, 26, 4)) + [24*7] # list for lagplots
lst, len(lst)
```

```
([1, 5, 9, 13, 17, 21, 25, 168], 8)
```

```
# Checking for lag 1 through 24 hours and for 1 week

fig, ax = plt.subplots(nrows = 2, ncols = 4, figsize = (15,5))
for n,lag in enumerate(lst):
    ax = plt.subplot(2, 4, n + 1)
    pd.plotting.lag_plot(df['NO2(GT)'], lag = lag)
```




```
# sm.tsa.acf(df['NO2(GT)'].dropna().to_list(), nlags = 100, fft = False)
```

Observations:

- 24 hour lag doesn't seem to be good correlation
- 1 hour is good, but would fail multiple times because there are too many consecutive nans
- 1 week lag is not bad
- Trying a combination of these to fill in as many nans as possible

```
df_imputed = df[['NO2(GT)']]
```

```
k = df[['NO2(GT)']]
for i in range(30):
    k[f'NO2_shifted_{i}'] = df[['NO2(GT)']].shift(periods = i*24)
```

```
k = k.reset_index()
# df.index - pd.offsets.DateOffset(days = 7)
```

```
/Users/utkarshtripathi/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3: 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-v
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
def helper (row, value):
    index = row['index_col']
    val = np.nan

    for i in range(30):
        if math.isnan(k.loc[index][f'NO2_shifted_{i}']):
            continue
        else:
            val = k.loc[index][f'NO2_shifted_{i}']
            break

    # IF still nan, try taking the interpolation
    if math.isnan(value):
        avg = (k.loc[index-1]['NO2(GT)'] + k.loc[index+1]['NO2(GT)'])/2
        return avg
    else:
        return value
```

```
# k['NO2_shifted_1'].head(25)
```

```
# Try to fill with previous week same hour data as much as possible
df['imputed_NO2'] = df.apply (lambda row: helper(row, row['NO2(GT)']), axis = 1)

# NA values was decreased, but not by the number I was expecting it to
# Better to take those months that have lower NaNs available [this is still hourly analysis]

# df['imputed_NO2'] = df['imputed_NO2'].fillna(method='ffill')
# df['imputed_NO2'] = df['imputed_NO2'].rolling(window = 24, min_periods = 1).mean()
df['imputed_NO2'].isna().sum()
```

```
1322
```

Stationarity Check & quick ARIMA

```
# no2_levels_2004_July = df.loc['2004']['imputed_NO2']
# no2_levels_2004_July.plot(figsize = (15,5));
```

```
lst = []
def return_lowNA (r1, r2, string):
    for i in range(r1,r2):
        if df.loc[string + f'{i}']['imputed_NO2'].isna().sum() < 50:
            lst.append (string + f'{i}')

return_lowNA (4,  10, '2004-0')
return_lowNA (10, 13, '2004-')
return_lowNA (1,   5, '2005-0')

print(lst)
```

```
['2004-06', '2004-07', '2004-11', '2005-01', '2005-02', '2005-03', '2005-04']
```

```
dfx = pd.concat([df.loc[month]['NO2(GT)'] for month in lst])
```

```
dfx
```

```
TimeStamp
2004-06-01 00:00:00     45.0
2004-06-01 01:00:00     23.0
2004-06-01 02:00:00     26.0
2004-06-01 03:00:00      NaN
2004-06-01 04:00:00     24.0
                       ...
2005-04-04 10:00:00    190.0
2005-04-04 11:00:00    179.0
2005-04-04 12:00:00    175.0
2005-04-04 13:00:00    156.0
```

```
2005-04-04 14:00:00    168.0
Name: NO2(GT), Length: 4431, dtype: float64
```

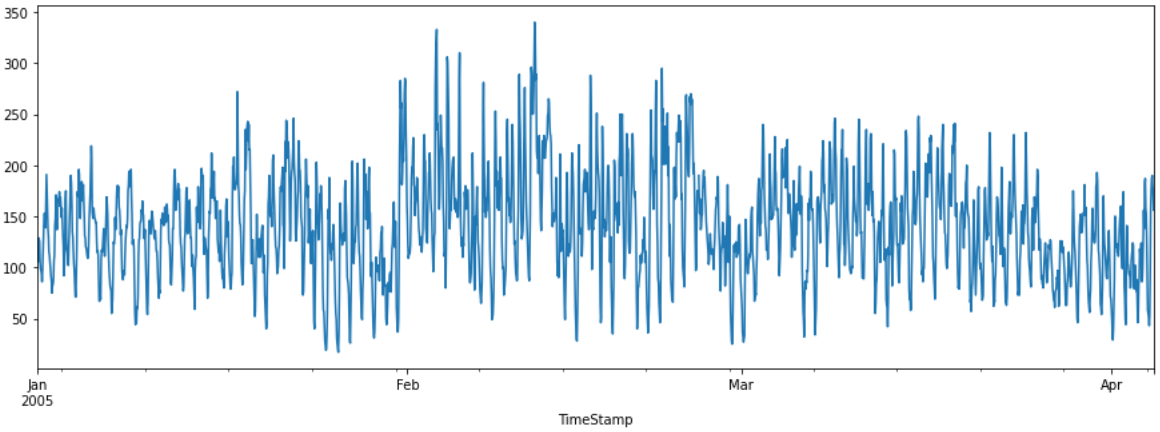
```
dfx = dfx.reset_index()['NO2(GT)']
dfx = dfx.interpolate(limit_direction = "both")
```

```
p1 = kpss(dfx, 'ct')[1] # ct passed if a distinctly visible trend avaialable
print(p1) # less than 0.05 implies non-stationarity
```

```
0.01
/Users/utkarshtripathi/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/stattools.py:2019: InterpolationWarning:
look-up table. The actual p-value is smaller than the p-value returned.

  warn_msg.format(direction="smaller"), InterpolationWarning
```

```
df.loc['2005']['imputed_NO2'].plot()
```

```
<AxesSubplot:xlabel='TimeStamp'>
```



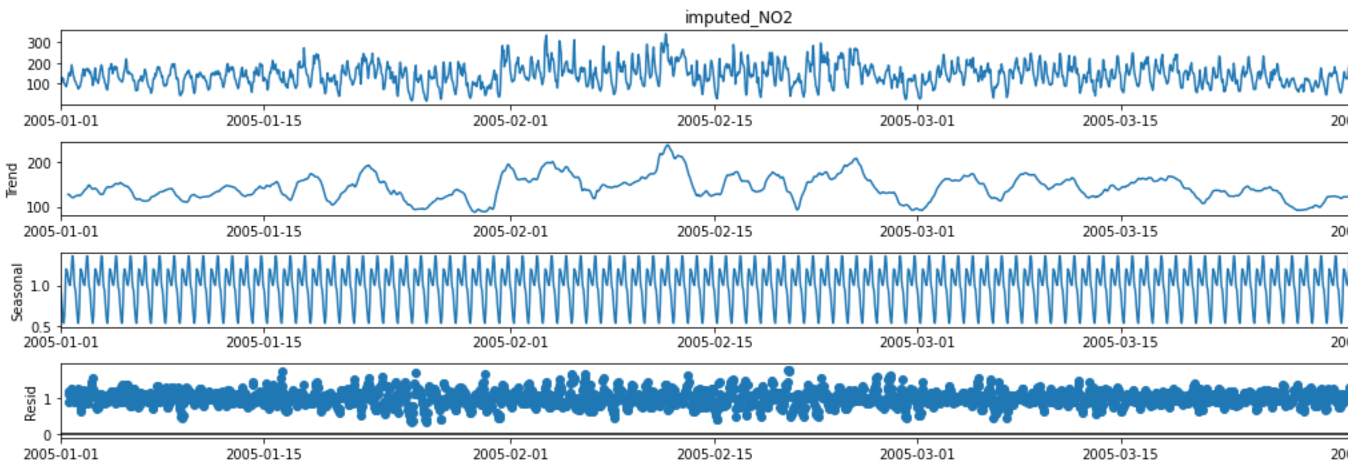

```
df_2005 = df.loc['2005']['imputed_NO2'].interpolate(limit_direction = "both") # for just those 3 NaNs remaining
```

```
from statsmodels.tsa.stattools import kpss, acf
p1 = kpss(df_2005, 'c')[1] # ct passed if a distinctly visible trend avaialable
print(p1) # less than 0.05 implies non-stationarity

# p2 = adfuller(df_2005)
# print(p1, p2)
```

```
0.025261656555949398
```

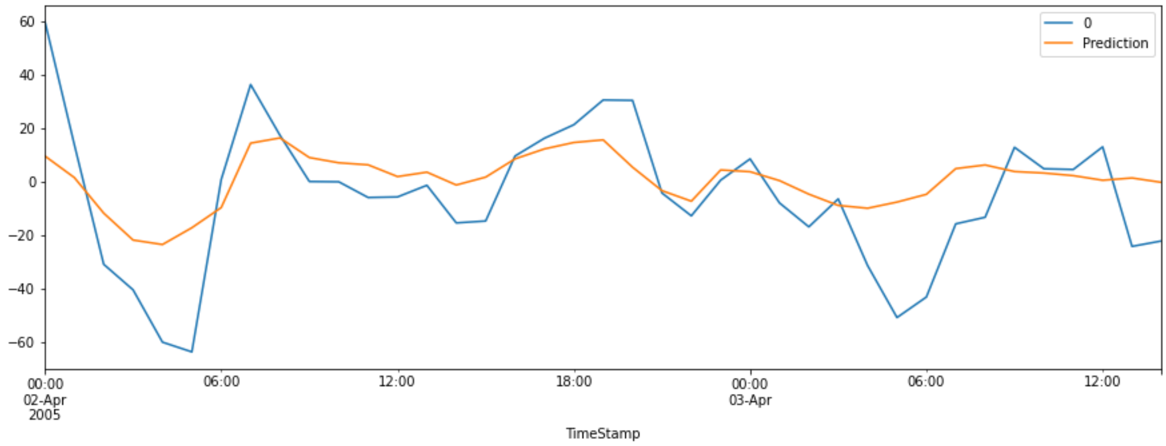
```
# roly-moly (rolling sorry PJ) stats shows it's not faily constant for daily data, but there is no trend as such
#  so will do ARIMA first then AR, ARMA, MA etc. ADFuller test shows it's stationary. It's a borderline case :(

# df_2005.rolling(window = 24).mean().plot()
# df_2005.rolling(window = 24).std().plot()
```

```
decomposed = sm.tsa.seasonal_decompose(df_2005, model = 'additive')
df_2005_ = decomposed.observed - decomposed.trend
decomposed.plot();
```



```
(df_2005_[12:-12]).isna().sum()
df_2005_ = df_2005_[12:-12] # for arima, we dont need to feed in the non-stationary data (isnt that great)


train = df_2005_.loc['2005-01-01':'2005-04-01']
test  = df_2005_.loc['2005-04-02':]


forecast = model.fit(train)
forecast = model.predict(n_periods = len(test))


forecast_X = pd.DataFrame(forecast, index = test.index, columns = ['Next_vals'])


pd.concat([test, forecast_X],axis=1).plot()
```

```
<AxesSubplot:xlabel='TimeStamp'>
```



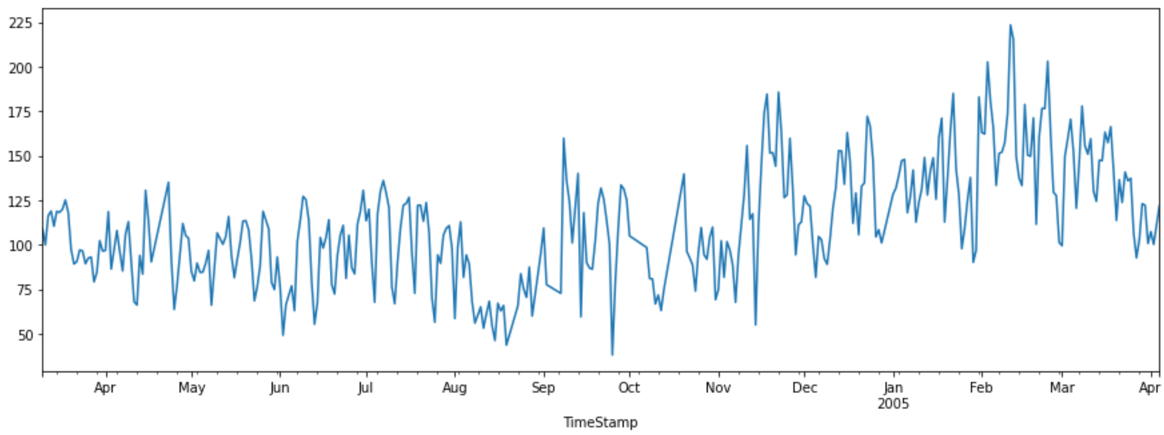
:)

```
# model = pm.auto_arima(df_2005_, m=12, seasonal = True, test = 'adf',error_action='ignore',\
#                       stepwise = False, trace = True)
```

Modeling for Daily

```
df_ = df.resample('D').mean() # take a mean for daily data
print (df_['NO2(GT)'].isna().sum())
df_2 = df_['NO2(GT)'].interpolate(limit_direction = "both")
df_2.plot()
```

```
34
<AxesSubplot:xlabel='TimeStamp'>
```

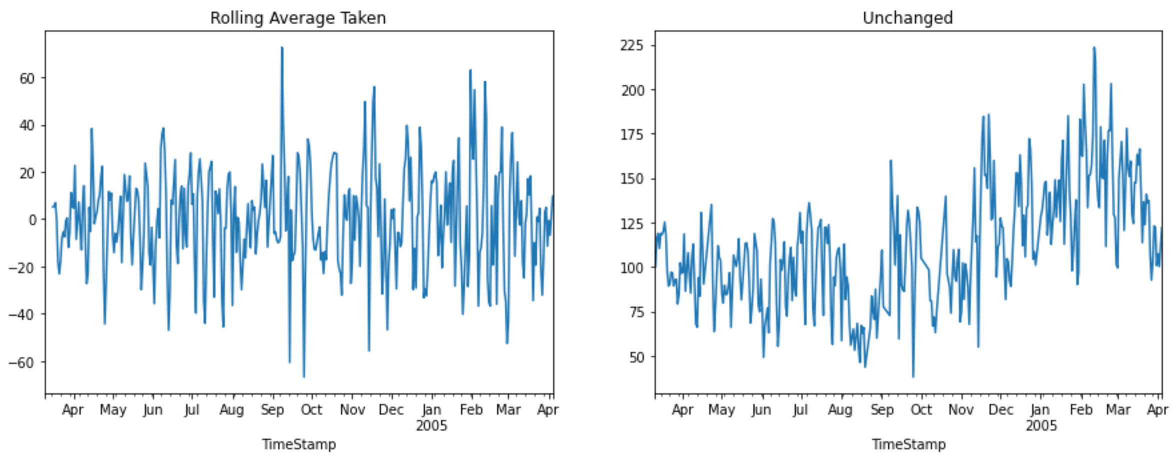



```
p1 = kpss(df_2, 'ct')[1] # ct passed if a distinctly visible trend avaialable
print(p1) # < 0.05 implies non-stationarity

dftest = adfuller(df_2, autolag = 'AIC')
print (dftest[1]) # >0.05 implies non stationarity
```

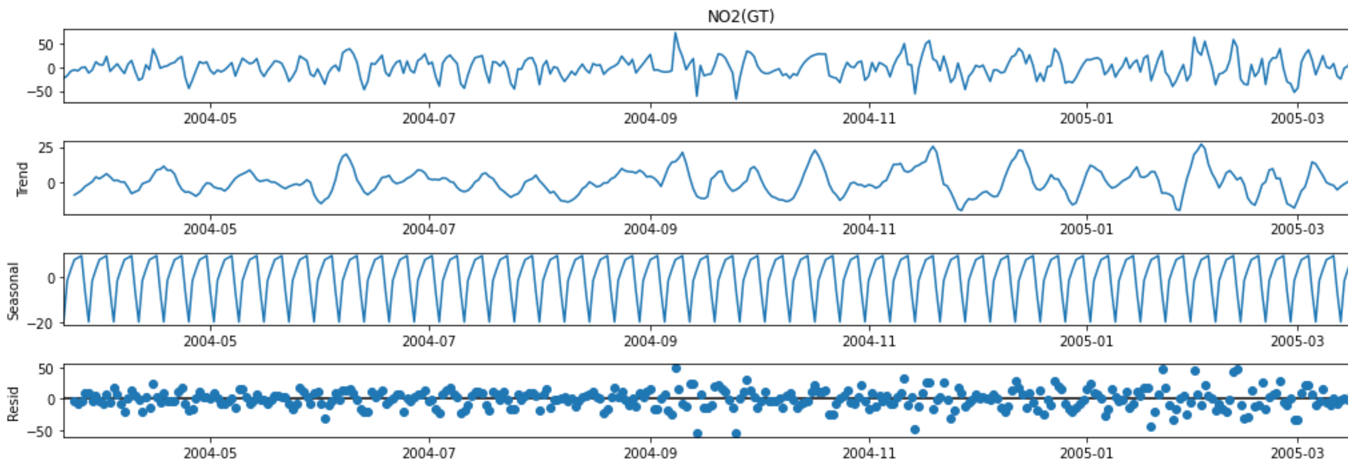
```
0.01
0.17921936347881295
/Users/utkarshtripathi/opt/anaconda3/lib/python3.7/site-packages/statsmodels/tsa/stattools.py:2019: InterpolationWarning:
look-up table. The actual p-value is smaller than the p-value returned.
```

```
    warn_msg.format(direction="smaller"), InterpolationWarning
```

```
# Removing Trend
rolling_mean = df_2.rolling(window = 7).mean()
df_2_noTrend = df_2 - rolling_mean

plt.subplot(121)
df_2_noTrend.plot(title="Rolling Average Taken");
plt.subplot(122)
df_2.plot(title="Unchanged");
```




```
df_2_noTrend = df_2_noTrend['2004-03-21':]
decomposed = sm.tsa.seasonal_decompose(df_2_noTrend, model = 'additive')
# df_2_ = decomposed.observed - decomposed.trend
decomposed.plot();
```




```
dftest = adfuller(df_2_noTrend, autolag = 'AIC')
print (dftest[1]) # >0.05 implies non stationarity
```

```
    1.091756720911131e-09
```

```
# performing arima on this
model = pm.auto_arima(df_2_noTrend, m=7, seasonal = True, test = 'adf',error_action='ignore',\
                      stepwise = False, trace = True)
```

Show hidden output

```
df_2_noTrend
```

```
    TimeStamp
    2004-03-21   -23.192547
    2004-03-22   -17.813665
    2004-03-23    -8.310559
    2004-03-24    -5.440994
    2004-03-25    -7.540373
                    ...
    2005-03-31   -11.476190
    2005-04-01    -0.571429
    2005-04-02    -6.827381
    2005-04-03     1.482143
```

```
2005-04-04     9.648810
Freq: D, Name: NO2(GT), Length: 380, dtype: float64
```

```
train = df_2_noTrend.loc['2004-03-21':'2005-03-20']
test  = df_2_noTrend.loc['2005-03-21':]
```

```
len(train), len(test)
```

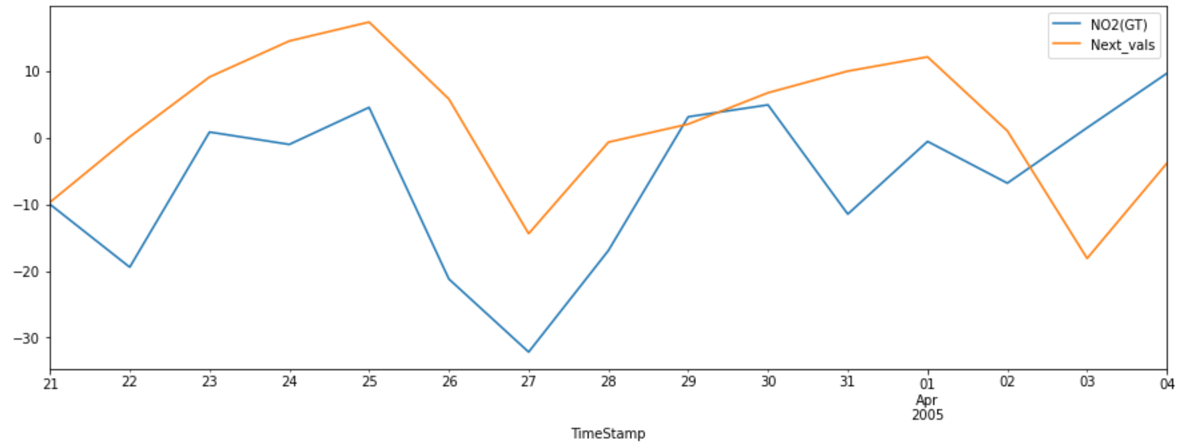
```
(365, 15)
```

```
forecast = model.fit(train)
forecast = model.predict(n_periods = len(test))
```

```
forecast_X = pd.DataFrame(forecast, index = test.index, columns = ['Next_vals'])
```

```
pd.concat([test, forecast_X], axis=1).plot()
```

```
<AxesSubplot:xlabel='TimeStamp'>
```



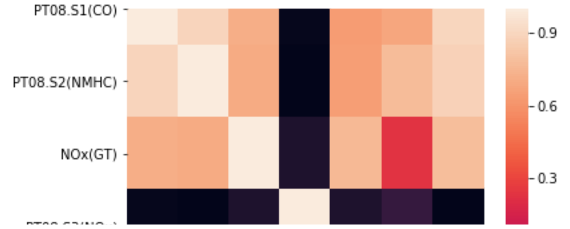
Multivariate Analyzzizz

Correlation Matrix

```
df['NO2(GT)']
```

```
TimeStamp
2004-03-10 18:00:00    113.0
2004-03-10 19:00:00     92.0
2004-03-10 20:00:00    114.0
2004-03-10 21:00:00    122.0
2004-03-10 22:00:00    116.0
                        ...
NaT                       NaN
NaT                       NaN
NaT                       NaN
NaT                       NaN
NaT                       NaN
Name: NO2(GT), Length: 9471, dtype: float64
```

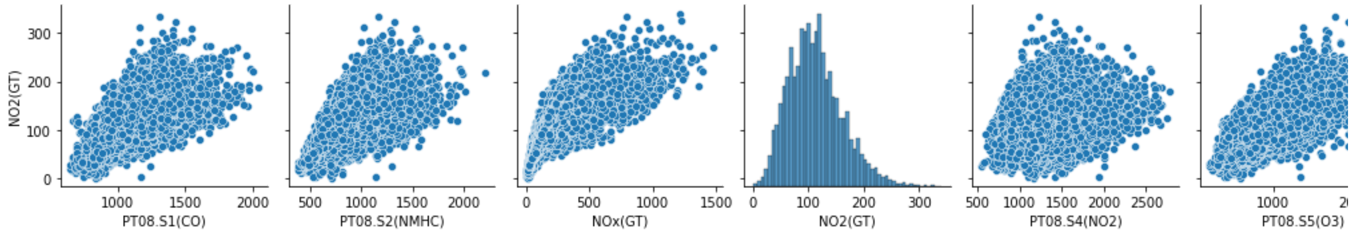
```
corrMatrix = df.corr()
fig, ax = plt.subplots(figsize = (6,6))
sn.heatmap(corrMatrix, annot = False);
```



Observations: Since we are interested in predicting NO_2, all except NOx, tungsten oxide look good predictors (not taking temperature, relative humidity etc for now)


```
x_vars = ['PT08.S1(CO)', 'PT08.S2(NMHC)', 'NOx(GT)', 'NO2(GT)', 'PT08.S4(NO2)', 'PT08.S5(O3)']
```


```
sn.pairplot (df[x_vars], y_vars = ['NO2(GT)']);
```




```
df_multi = df.resample('D').mean()
```

```
df_multi
```

	PT08.S1(CO)	PT08.S2(NMHC)	NOx(GT)	PT08.S3(NOx)	NO2(GT)	PT08.S4(NO2)	PT08.S5(O3)	index_col	imputed_NO
TimeStamp									
2004-03-10	1316.500000	912.333333	132.000000	1167.333333	108.833333	1545.500000	1096.000000	2.5	108.83333
2004-03-11	1244.166667	851.958333	144.391304	1277.250000	99.869565	1522.833333	885.250000	17.5	97.66666
2004-03-12	1281.666667	1008.291667	173.727273	1101.875000	116.272727	1627.291667	1084.375000	41.5	114.62500
2004-03-13	1330.666667	992.833333	184.434783	993.208333	118.869565	1595.791667	1245.916667	65.5	117.35416
2004-03-14	1361.125000	943.916667	146.608696	1001.291667	110.391304	1602.375000	1234.208333	89.5	109.66666
...	...	...	...	...	...	...	...	...	.
2005-03-31	1008.125000	749.416667	185.083333	795.666667	100.708333	1176.541667	763.833333	9257.5	100.70833
2005-04-01	903.291667	663.000000	161.833333	946.875000	107.333333	943.250000	523.958333	9281.5	107.33333
2005-04-02	890.958333	616.291667	142.375000	991.750000	100.166667	864.333333	481.750000	9305.5	100.16666
2005-04-03	981.375000	714.708333	167.666667	856.166667	111.125000	985.166667	717.083333	9329.5	111.12500
2005-04-04	1090.533333	862.266667	263.333333	745.266667	122.000000	1195.066667	995.266667	9349.0	122.00000

391 rows × 9 columns

```
df_multi.isna().sum()
```

```
PT08.S1(CO)       8
PT08.S2(NMHC)     8
NOx(GT)          34
PT08.S3(NOx)      8
NO2(GT)          34
PT08.S4(NO2)      8
PT08.S5(O3)       8
index_col         0
imputed_NO2      34
dtype: int64
```

```
df_multi = df_multi.interpolate(limit_direction = "both")
```

```
for i, col in enumerate(x_vars):
    print(col, adfuller(df_multi[col])[1]) # <0.05 implies stationarity
```

```
PT08.S1(CO) 8.30828998149498e-17
PT08.S2(NMHC) 0.0015732324845519293
NOx(GT) 0.3568268381846265
NO2(GT) 0.17921936347881295
```

```
PT08.S4(NO2) 0.3657985143254272
PT08.S5(O3) 0.0003992170933603379
```

Need to make NOx, NO2, tungsten oxide data series stationary

```
df_multi_stationary = df_multi.diff().dropna()
```

```
for i, col in enumerate(x_vars):
    print(col, adfuller(df_multi_stationary[col])[1]) # <0.05 implies stationarity
```

```
PT08.S1(CO) 1.8237226910900484e-11
PT08.S2(NMHC) 3.370591060929868e-10
NOx(GT) 4.960123831236301e-11
NO2(GT) 3.6068503137062234e-09
PT08.S4(NO2) 3.3357168159110093e-09
PT08.S5(O3) 2.7415013882869992e-11
```

Transformed variables look good to go

```
df_multi_stationary = df_multi.drop(['index_col', 'imputed_NO2'], axis = 1)
```

```
df_multi_stationary
```

	PT08.S1(CO)	**PT08.S2(NMHC)**	**NOx(GT)**	**PT08.S3(NOx)**	**NO2(GT)**	**PT08.S4(NO2)**	**PT08.S5(O3)**
TimeStamp							
2004-03-10	1316.500000	912.333333	132.000000	1167.333333	108.833333	1545.500000	1096.000000
2004-03-11	1244.166667	851.958333	144.391304	1277.250000	99.869565	1522.833333	885.250000
2004-03-12	1281.666667	1008.291667	173.727273	1101.875000	116.272727	1627.291667	1084.375000
2004-03-13	1330.666667	992.833333	184.434783	993.208333	118.869565	1595.791667	1245.916667
2004-03-14	1361.125000	943.916667	146.608696	1001.291667	110.391304	1602.375000	1234.208333
...	...	...	...	...	...	...	...
2005-03-31	1008.125000	749.416667	185.083333	795.666667	100.708333	1176.541667	763.833333
2005-04-01	903.291667	663.000000	161.833333	946.875000	107.333333	943.250000	523.958333
2005-04-02	890.958333	616.291667	142.375000	991.750000	100.166667	864.333333	481.750000
2005-04-03	981.375000	714.708333	167.666667	856.166667	111.125000	985.166667	717.083333
2005-04-04	1090.533333	862.266667	263.333333	745.266667	122.000000	1195.066667	995.266667

391 rows × 7 columns

```
# Source for this function:
# https://stackoverflow.com/questions/58005681/is-it-possible-to-run-a-vector-autoregression-analysis-on-a-large-gdp-data-with

dataset = df_multi_stationary
maxlag=12
test = 'ssr-chi2test'
def grangers_causality_matrix(data, variables, test = 'ssr_chi2test', verbose=False):
    dataset = pd.DataFrame(np.zeros((len(variables), len(variables))), columns=variables, index=variables)
    for c in dataset.columns:
        for r in dataset.index:
            test_result = grangercausalitytests(data[[r,c]], maxlag=maxlag, verbose=False)
            p_values = [round(test_result[i+1][0][test][1],4) for i in range(maxlag)]
            if verbose: print(f'Y = {r}, X = {c}, P Values = {p_values}')
            min_p_value = np.min(p_values)
            dataset.loc[r,c] = min_p_value

    dataset.columns = [var + '_x' for var in variables]
    dataset.index = [var + '_y' for var in variables]
    return dataset

grangers_causality_matrix(dataset, variables = dataset.columns)
```

	PT08.S1(CO)_x	PT08.S2(NMHC)_x	NOx(GT)_x	PT08.S3(NOx)_x	NO2(GT)_x	PT08.S4(NO2)_x	PT08.S5(O3)_x
PT08.S1(CO)_y	1.0000	0.0000	0.0037	0.0036	0.0003	0.0001	0.0000
PT08.S2(NMHC)_y	0.0004	1.0000	0.1505	0.0009	0.0338	0.0072	0.0001
PT08.S3(NOx)_y	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000

Looking at the NO2(GT)-y row: PT08.S1(CO), PT08.S2(NMHC), PT08.S3(NOx), PT08.S4(NO2), PT08.S5(O3) can be taken as features.

```
# df_multi_ = df_multi_stationary[['PT08.S1(CO)','PT08.S2(NMHC)','PT08.S5(O3)', 'NO2(GT)', 'PT08.S3(NOx)']]
df_multi_ = df_multi[['PT08.S1(CO)','PT08.S2(NMHC)','PT08.S5(O3)', 'NO2(GT)', 'PT08.S3(NOx)']]
# taking non-stationary data is easier (there is a nice parameter that enforces stionarity)
# otherwise retransform the transformed data into original for comparison

df_train  = df_multi_[:-10]
df_test   = df_multi_[-10:]

model = VAR(df_train)
model.select_order(10).summary()
```

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	43.70	43.76	9.554e+18	43.72
1	39.59	39.91*	1.560e+17	39.71*
2	39.55	40.13	1.507e+17	39.78
3	39.47	40.31	1.382e+17	39.80
4	39.51	40.62	1.450e+17	39.95
5	39.55	40.92	1.501e+17	40.09
6	39.54	41.18	1.492e+17	40.19
7	39.47	41.37	1.388e+17	40.22
8	39.36*	41.53	1.252e+17*	40.22
9	39.39	41.82	1.288e+17	40.35
10	39.45	42.14	1.366e+17	40.52

Should try 1 and 8 lags

```
var_model = sm.tsa.VARMAX (df_train, enforce_stationarity = True)
modelFit = var_model.fit (disp=False)
trainingSize = len(df_train)
model_predictions = modelFit.get_prediction (start = trainingSize, end = trainingSize + 5).predicted_mean
```

```
/Users/utkarshtripathi/opt/anaconda3/lib/python3.7/site-packages/statsmodels/base/model.py:606: ConvergenceWarning: Maxin
  ConvergenceWarning)
```

```
model_predictions['NO2(GT)']
```

```
2005-03-26    121.700914
2005-03-27    114.828126
Freq: D, Name: NO2(GT), dtype: float64
```

```
df_multi['2005-03-26':'2005-03-27']['NO2(GT)']
```

```
TimeStamp
2005-03-26    106.541667
2005-03-27     92.583333
Freq: D, Name: NO2(GT), dtype: float64
```

```
# list (df_multi['2005-03-26':'2005-04-15'].index)
# pd.DatetimeIndex ['2005-03-26':'2005-04-15']
```

```
x = list (df_multi['2005-03-26':'2005-03-31'].index)
plt.plot (x, model_predictions['NO2(GT)'], x, df_multi['2005-03-26':'2005-03-31']['NO2(GT)'])
```

```
[<matplotlib.lines.Line2D at 0x7fc017e886d0>,
 <matplotlib.lines.Line2D at 0x7fc018494290>]
```

Approach 2

```
lag = 8 # for creating the equation
ret = model.fit(lag)
# ret.summary() # creates equations for all

input_data = df_train.values[-lag:]

pred = ret.forecast(y = input_data, steps = 10)
pred = (pd.DataFrame(pred, index = df_test.index))
pred
```

	0	1	2	3	4
TimeStamp					
2005-03-26	1193.144342	879.338299	1033.029544	115.328066	699.952999
2005-03-27	1131.017946	830.711632	945.650321	105.454243	758.647108
2005-03-28	1167.425444	914.607167	1048.220435	119.074566	721.081722
2005-03-29	1181.721465	938.522693	1099.964894	121.406158	730.186917
2005-03-30	1163.541391	934.532336	1093.682526	121.659631	726.371623
2005-03-31	1153.358861	902.903036	1053.729150	118.619798	745.214044
2005-04-01	1154.155471	914.310214	1065.862065	121.117370	750.659696
2005-04-02	1118.325620	855.300204	980.995680	113.607098	809.717148
2005-04-03	1112.063990	848.998221	961.360294	111.087358	812.077818
2005-04-04	1137.547174	901.932949	1027.344685	117.236633	775.158061

```
df_test
```

	PT08.S1(CO)	PT08.S2(NMHC)	PT08.S5(O3)	NO2(GT)	PT08.S3(NOx)
TimeStamp					
2005-03-26	1216.541667	910.541667	1185.875000	106.541667	590.041667
2005-03-27	1106.333333	723.166667	884.750000	92.583333	726.041667
2005-03-28	1079.666667	745.166667	829.583333	103.041667	748.125000
2005-03-29	1163.333333	943.416667	1133.333333	123.000000	632.083333
2005-03-30	1106.000000	908.791667	1067.416667	122.125000	665.833333
2005-03-31	1008.125000	749.416667	763.833333	100.708333	795.666667
2005-04-01	903.291667	663.000000	523.958333	107.333333	946.875000
2005-04-02	890.958333	616.291667	481.750000	100.166667	991.750000
2005-04-03	981.375000	714.708333	717.083333	111.125000	856.166667
2005-04-04	1090.533333	862.266667	995.266667	122.000000	745.266667

```
x = list (df_test['2005-03-26':'2005-04-04'].index)
plt.plot (x, pred[3], x, df_test['2005-03-26':'2005-04-04']['NO2(GT)'])
```

```
[<matplotlib.lines.Line2D at 0x7fc019ab2d90>,
 <matplotlib.lines.Line2D at 0x7fc0182e6750>]
```