An introduction to AtmoTech data

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1 AtmoTech data introduction

I have taken their spreadsheet, coverted it into a series of CSV files and then converted them in pandas dataframes and then saved them as pickle files so that anyone can quickly and easily get the data in Python.

The Python script: - Each CSV file represents a room in the building. - Imports the CSV files into a Pandas DataFrame. - Converts the time-stamps to DateTime and assigns them to the index of the DatFrame. - Removes the NaTs and duplicates from the index. - Saves the each room as a Pickle file.

I have pushed all of this (including the CSV and Pickle files) to a GitHub repository and so one can easily clone everything and start working. Repo: https://github.com/OliCUoB/UoB_JGI_data_viz_AtmoTech

Here is a quick example of how one may do that. There are multiple different rooms which form a building (see Excel spreadsheet for more information). Each room will be treated as a seperate data frame.

```
In [1]: # import libraries
        import pandas as pd
        import matplotlib.pyplot as plt
        # create plost inline
        %matplotlib inline
```

```
In [2]: # create a dictionary to hold each data frame (one for each room)
        file_names = ['brake_test_area.pkl', 'entrance.pkl', 'parked_vehicles.pkl', 'pits.pkl
        dict_of_dfs = {name[:-4]: pd.io.pickle.read_pickle(name) for name in file_names}
        print('dict_of_dfs.keys() = ', dict_of_dfs.keys())
        print('dict_of_dfs[\'brake_test_area\'].describe = ', dict_of_dfs['brake_test_area'].des
        # uncomment below if you want to see a description of all the rooms

        #for name in file_names:
        #    print(name + ': ')
        #    print(dict_of_dfs[name[:-4]].describe())
```

```
dict_of_dfs.keys() =  dict_keys(['workshop', 'brake_test_area', 'pits', 'entrance', 'parked_vehi
dict_of_dfs['brake_test_area'].describe =         PM2.5_nom  PM10_nom  humidity_percent    pm10_
count     8957.0    8957.0       8957.000000  8957.000000  8957.000000
mean        40.0      25.0         40.652216    18.189864    18.184531
std          0.0       0.0          4.902648    34.061608    26.359766
```

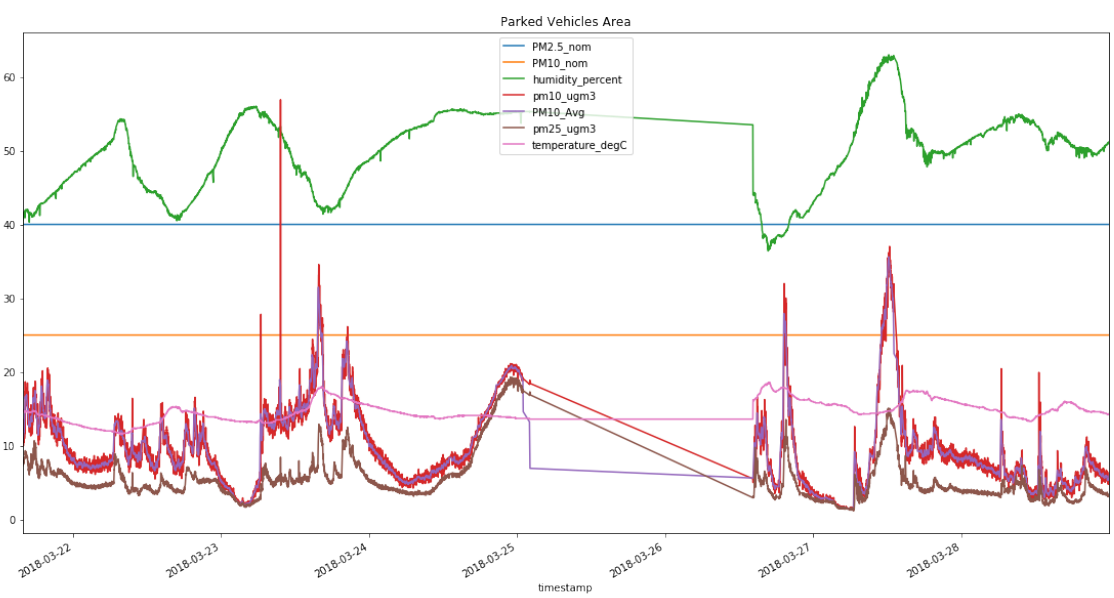
min	40.0	25.0	30.100000	0.723334	0.902833
25%	40.0	25.0	36.400000	7.570002	7.720500
50%	40.0	25.0	41.300000	11.858330	11.939096
75%	40.0	25.0	44.400000	19.153330	19.434163
max	40.0	25.0	53.000000	1095.627000	463.322003

	pm25_ugm3	PM2.5_Avg	temperature_degC
count	8957.000000	8957.000000	8957.000000
mean	6.474399	6.470088	15.388199
std	12.467993	8.663832	1.594050
min	0.713334	0.846000	11.200000
25%	3.251666	3.251499	14.300000
50%	4.531668	4.569000	15.300000
75%	7.143332	7.189834	16.500000
max	734.236500	197.778727	20.200000

In [3]:
```
# Uncomment below to visualise the data in each room
#for name in dict_of_dfs.keys():
#    dict_of_dfs[name].plot(title = name)
```

In [4]:
```
# Parked vehicles looks the craziest so lets take a closer look
plt.rcParams['figure.figsize'] = [19, 10]
dict_of_dfs['parked_vehicles'].plot(title = 'Parked Vehicles Area')
```

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e5558ab38>

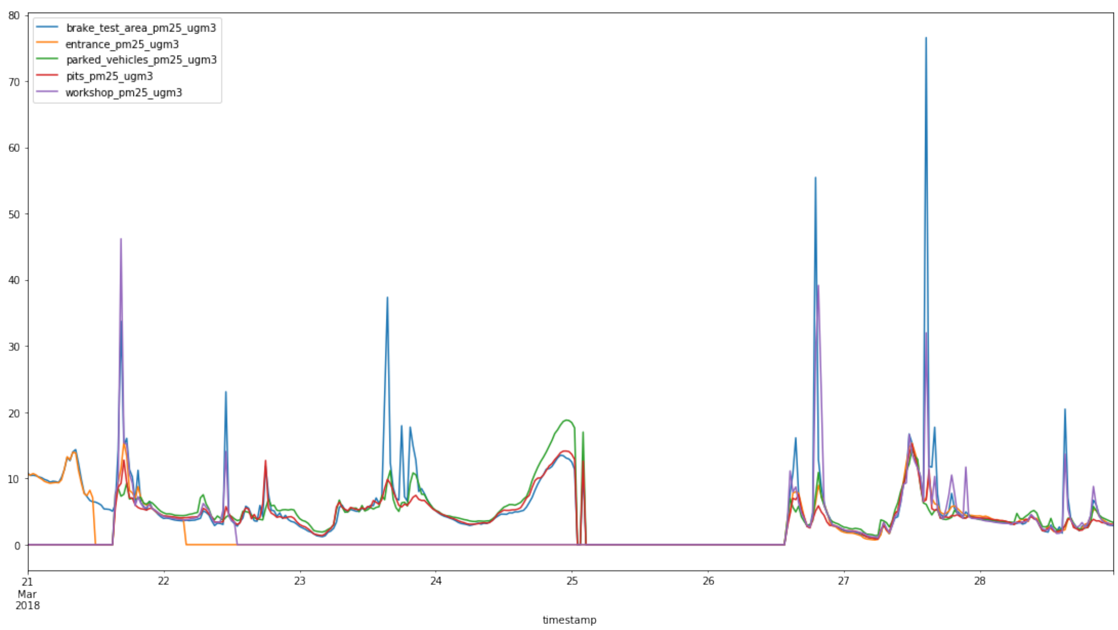


Here we can see that PM10 and PM2.5 are very correlated (and their corresponding moving averages). Notice also that temperature is correlated but it is unclear of the effect of humidity (if any).

```
In [5]: # let's look at the PM2.5 levels for each room
        # there's lots of different time stamps so we resample by 5 minute intervals taking the
        #fig = plt.figure()
        #ax = plt.subplot(111)
        #for name in dict_of_dfs.keys():
        #     print('dict_of_dfs[name].shape = ', dict_of_dfs[name].shape)
        #     dict_of_dfs[name]['pm25_ugm3'].plot(ax=ax)
        dict_of_dfs_resamp = {name[:-4] + '_pm25_ugm3': dict_of_dfs[name[:-4]]['pm25_ugm3'].resa
```

```
In [6]: # put all data into one data frame
        df_dict = {name[:-4] + '_pm25_ugm3': dict_of_dfs[name[:-4]]['pm25_ugm3'] for name in fil
        pm25 = pd.DataFrame(dict_of_dfs_resamp)
        pm25_filled = pm25.fillna(value=0)
        pm25_filled.shape
        pm25_filled.plot()
        #pm25_filled
```

```
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e5540a978>
```



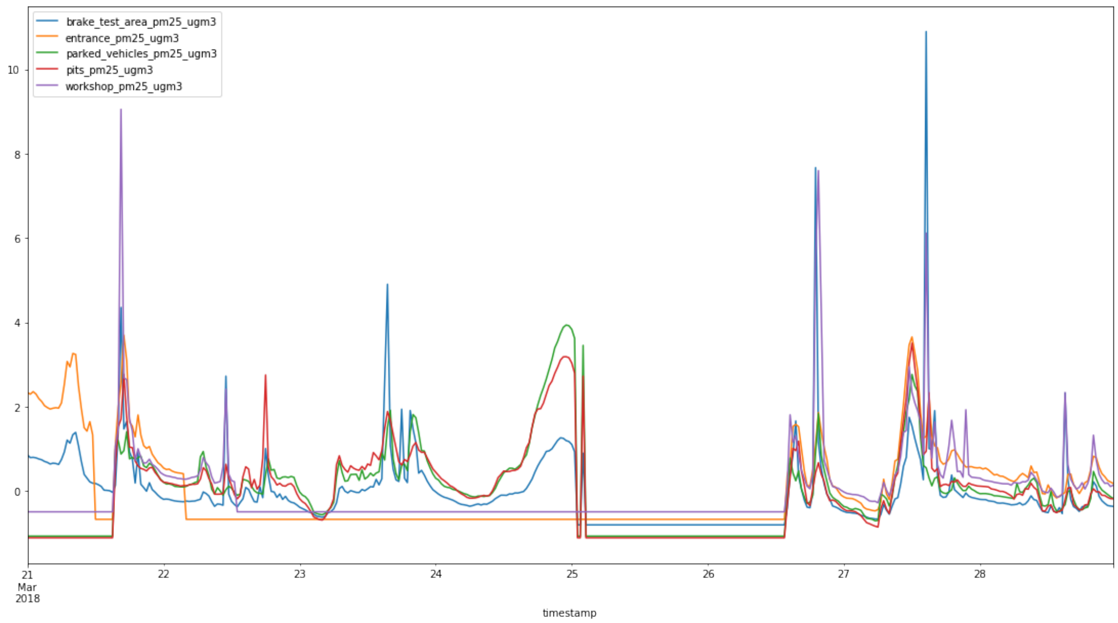
We cannot see what's going on here because the scales are so varied and so here we standardise the data using scikit learn.

```
In [7]: # Fill nans with last known number
        #pm25.fillna(method='pad')
```

```
In [8]: # import libraries
        from sklearn.preprocessing import StandardScaler
        # Standardise the data and plot
```

```
pm25_stand = StandardScaler().fit_transform(pm25_filled)
# this returns a numpy array and so convert back to pandas
pm25_stand = pd.DataFrame(pm25_stand, columns = pm25_filled.columns, index = pm25_filled
pm25_stand.plot()
```

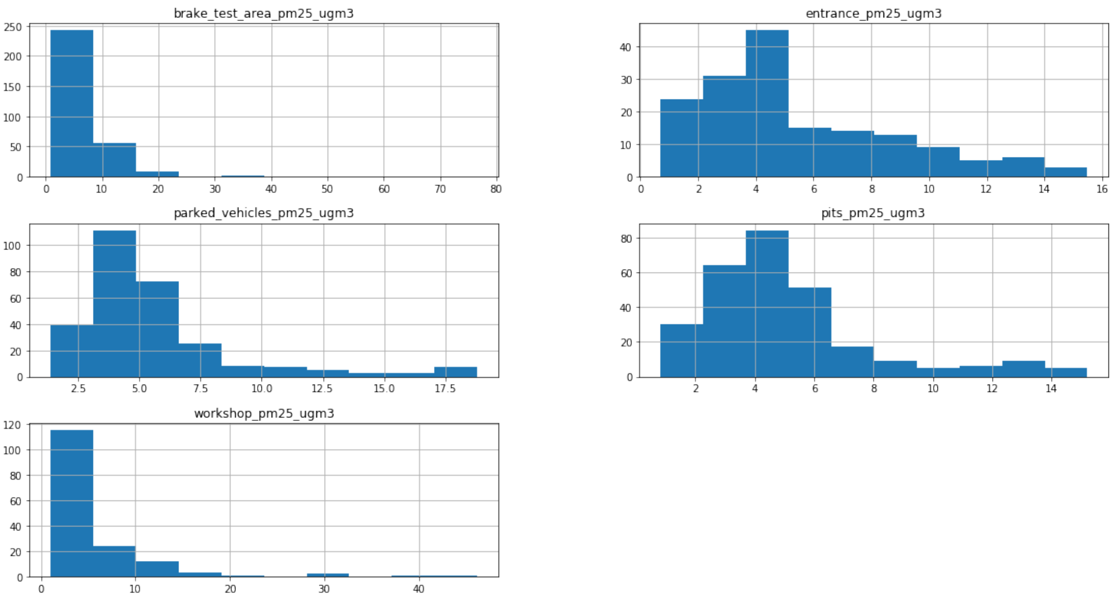
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e39498a90>



We can see that there's some periods of missing data but it's not too bad. All the rooms are strongly correlated (unsurprisingly). However, brake_test_area and workshop peak much higher than elsewhere.

In [9]:
```
pm25.hist()
```

Out[9]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f8e38f6f5c0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f8e38eb5780>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f8e38e818d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f8e38e442b0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f8e38e115c0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f8e38dd50f0>]], dtype=object
```


brake_test_area_pm25_ugm3
0 50 100 150 200 250
0 10 20 30 40 50 60 70 80
entrance_pm25_ugm3
0 10 20 30 40
0 2 4 6 8 10 12 14 16
parked_vehicles_pm25_ugm3
0 20 40 60 80 100
2.5 5.0 7.5 10.0 12.5 15.0 17.5
pits_pm25_ugm3
0 20 40 60 80
2 4 6 8 10 12 14
workshop_pm25_ugm3
0 20 40 60 80 100 120
0 10 20 30 40