ProjetFinal

June 24, 2020

1 Introduction

Le but de ce projet est de travailler avec un ensemble de donné contenant des informations liées aux taux de pollutions dans le temps et les données météorologique dans certaines stations se trouvant à Beijing et à Londre. A l'aide de cela, nous devons être capable de prédire le taux de concentration de PM2.5, PM10 et 03 pour 35 stations à Beijing et 13 stations à Londre (PM2.5 et PM10). Dans un premier temps, nous allons mettre dans la forme désiré nos données tout en interpollant les champs manquants afin de permettre une prédiction par heure sur le taux de concentration des polluants dans les différentes stations. Ensuite nous présenterons nos models et les résultats obtenus.

2 Beijing

On veut donc pouvoir être capable de prédire la qualité de l'air à Beijing, pour cela nous voulons estimer la concentration des polluants PM2.5, PM10 et 03 pour 35 stations se trouvant à des lieux différents.

Pour cela nous avons à notre disposition 7 fichiers contenant des informations liées à la météo et à la qualité de l'air des différentes stations de Beijing. Dans un premier temps, il est nécessaire d'analyser et de comprendre ces donnés afin de détérminer les informations que nous voulons utiliser pour construire notre modèle.

Aprés avoir compris ces fichiers, nous avons jugé inutile de prendre en considération les fichiers "beijing_17_18 meo.csv" et "beijing_201802_201803 me.csv" puisqu'ils contiennent des informations moins exacte que le fichier "Beijing_historical_meo_grid.csv", car celui-ci indique les attributs météorologique à une latitude et longitude donnée à une date précise. Contrairement au deux autres fichiers météo, "Beijing_historical_meo_grid.csv" ne donnent pas des informations liées à des districts de Beijing, ceci est un avantage, car nous ne savons pas quelles stations se trouvent dans quel district alors que nous connaissons leur latitude et longitude avec le fichier "Beijing AirQuality Stations.xlsx". De plus, nous prendrons les données contenues dans les fichiers "beijing_17_18_aq.csv" et "beijing_201802_201803_aq.csv" afin d'obtenir le taux de concentration des polluants à des temps donnés pour chaque station.

Pour pouvoir rendre ces données utilisables par nos futurs modèles, il est indispensable d'effetuer un traitement de ces données afin de les transformer dans la forme voulue.

2.1 Traitement des donées

Initialement, nous allons charger les fichiers nécessaires sous la forme de dataframe à l'aide de la librairie pandas, nous permettant de plus facillement manier les données.

[12]:
```
import pandas as pd
import numpy as np


# S'assure que panda affiche toutes les colonnes
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 200)

# Fonction permettant de lire un fichier csv pour retourner la dataframe␣
↪correspondante.
def get_dataframe(filename):
    df = pd.read_csv(filename)
    return df

# Fonction permettant d'obtenir les éléments présents dans une liste qui ne sont␣
↪pas dans une autre.
def diff(first, second):
    second = set(second)
    return [item for item in first if item not in second]

# Si on a déjà les données en mémoire, on les supprime.
if 'aq1' in globals():
  del aq1
if 'aq2' in globals():
  del aq2
if 'meo' in globals():
  del meo
if 'aq_stations' in globals():
  del aq_stations


aq1 = get_dataframe('./final_project_data/beijing_17_18_aq.csv')␣
↪#stationId,utc_time,PM2.5,PM10,NO2,CO,O3,SO2
aq2 = get_dataframe('./final_project_data/beijing_201802_201803_aq.csv')␣
↪#stationId,utc_time,PM2.5,PM10,NO2,CO,O3,SO2
meo = get_dataframe('./final_project_data/Beijing_historical_meo_grid.csv')␣
↪#stationName, longitude, latitue, utc_time, temperature, pressure, humidity,␣
↪wind_direction, wind_speed/kph

aq_stations = get_dataframe('./final_project_data/Beijing_AirQuality_Stations_en.
↪csv') #Some undefined value du to the conversion to csv (it was a xlsx file)
```

```
                                                                      #-> #"Unnamed:␣
↪1": longitude, "Unnamed: 2": latitude, 'Pollutant Species': stationName



#Nettoie Beijing_AirQuality_Station_en.csv
aq_stations = aq_stations.iloc[11:,]
aq_stations = aq_stations.drop("Unnamed: 3", axis=1)
aq_stations.dropna(subset = ["Unnamed: 2"], inplace=True) #Delete row which␣
↪contains Nan
aq_stations = aq_stations.rename(columns={"Pollutant Species": "StationName"})
aq_stations = aq_stations.rename(columns={"Unnamed: 1": "Longitude"})
aq_stations = aq_stations.rename(columns={"Unnamed: 2": "Latitude"})
print("Pollutions par station jusqu'au 31 janvier 2018: ")
print(aq1)
print("Pollutions par station jusqu'au 31 mars 2018: ")
print(aq2)
print("Données météorologique compléte du 1.1.17 au 27.3.18: ")
print(meo)
print("Nom des stations avec leur latitude et longitude: ")
print(aq_stations)
```

```
Pollutions par station jusqu'au 31 janvier 2018:
                stationId             utc_time  PM2.5   PM10    NO2   CO   O3  SO2
0        aotizhongxin_aq  2017-01-01 14:00:00  453.0  467.0  156.0  7.2  3.0  9.0
1        aotizhongxin_aq  2017-01-01 15:00:00  417.0  443.0  143.0  6.8  2.0  8.0
2        aotizhongxin_aq  2017-01-01 16:00:00  395.0  467.0  141.0  6.9  3.0  8.0
3        aotizhongxin_aq  2017-01-01 17:00:00  420.0  484.0  139.0  7.4  3.0  9.0
4        aotizhongxin_aq  2017-01-01 18:00:00  453.0  520.0  157.0  7.6  4.0  9.0
...                  ...                  ...    ...    ...    ...  ...  ...  ...
311005      zhiwuyuan_aq  2018-01-31 11:00:00    NaN    NaN    NaN  NaN  NaN  NaN
311006      zhiwuyuan_aq  2018-01-31 12:00:00    NaN    NaN    NaN  NaN  NaN  NaN
311007      zhiwuyuan_aq  2018-01-31 13:00:00    NaN    NaN    NaN  NaN  NaN  NaN
311008      zhiwuyuan_aq  2018-01-31 14:00:00    NaN    NaN    NaN  NaN  NaN  NaN
311009      zhiwuyuan_aq  2018-01-31 15:00:00    NaN    NaN    NaN  NaN  NaN  NaN

[311010 rows x 8 columns]
Pollutions par station jusqu'au 31 mars 2018:
               stationId             utc_time  PM2.5  PM10   NO2   CO   O3   SO2
0        aotizhongxin_aq  2018-01-31 16:00:00   49.0  82.0  90.0  0.9  6.0  10.0
1        aotizhongxin_aq  2018-01-31 17:00:00   47.0  80.0  90.0  0.9  5.0  10.0
2        aotizhongxin_aq  2018-01-31 18:00:00   46.0  91.0  91.0  1.3  5.0  28.0
3        aotizhongxin_aq  2018-01-31 19:00:00   60.0  95.0  85.0  2.0  6.0  38.0
4        aotizhongxin_aq  2018-01-31 20:00:00   52.0  91.0  81.0  1.9  5.0  30.0
...                  ...                  ...    ...   ...   ...  ...  ...   ...
49415       zhiwuyuan_aq  2018-03-31 11:00:00    NaN   NaN   NaN  NaN  NaN   NaN
49416       zhiwuyuan_aq  2018-03-31 12:00:00    NaN   NaN   NaN  NaN  NaN   NaN
```

```
49417     zhiwuyuan_aq  2018-03-31 13:00:00    NaN   NaN   NaN  NaN  NaN   NaN
49418     zhiwuyuan_aq  2018-03-31 14:00:00    NaN   NaN   NaN  NaN  NaN   NaN
49419     zhiwuyuan_aq  2018-03-31 15:00:00    NaN   NaN   NaN  NaN  NaN   NaN

[49420 rows x 8 columns]
Données météorologique compléte du 1.1.17 au 27.3.18:
              stationName  longitude  latitude             utc_time  temperature
pressure  humidity  wind_direction  wind_speed/kph
0        beijing_grid_000      115.0      39.0  2017-01-01 00:00:00        -5.47
984.73     76.60          53.71           3.53
1        beijing_grid_001      115.0      39.1  2017-01-01 00:00:00        -5.53
979.33     75.40          43.59           3.11
2        beijing_grid_002      115.0      39.2  2017-01-01 00:00:00        -5.70
963.14     71.80           0.97           2.75
3        beijing_grid_003      115.0      39.3  2017-01-01 00:00:00        -5.88
946.94     68.20         327.65           3.84
4        beijing_grid_004      115.0      39.4  2017-01-01 00:00:00        -5.34
928.80     58.81         317.85           6.14
...                   ...        ...       ...                  ...          ...
...       ...            ...             ...
7034701  beijing_grid_646      118.0      40.6  2018-03-27 05:00:00        21.64
943.63     27.87         196.62          14.79
7034702  beijing_grid_647      118.0      40.7  2018-03-27 05:00:00        22.58
948.03     24.92         197.92          15.80
7034703  beijing_grid_648      118.0      40.8  2018-03-27 05:00:00        22.64
945.85     23.57         206.12          16.94
7034704  beijing_grid_649      118.0      40.9  2018-03-27 05:00:00        22.71
943.67     22.23         213.17          18.38
7034705  beijing_grid_650      118.0      41.0  2018-03-27 05:00:00        22.73
942.95     21.78         215.27          18.91

[7034706 rows x 9 columns]
Nom des stations avec leur latitude et longitude:
          StationName Longitude Latitude
11          dongsi_aq   116.417   39.929
12         tiantan_aq   116.407   39.886
13        guanyuan_aq   116.339   39.929
14   wanshouxigong_aq   116.352   39.878
15    aotizhongxin_aq   116.397   39.982
16    nongzhanguan_aq   116.461   39.937
17          wanliu_aq   116.287   39.987
18      beibuxinqu_aq   116.174    40.09
19       zhiwuyuan_aq   116.207   40.002
20  fengtaihuayuan_aq   116.279   39.863
21         yungang_aq   116.146   39.824
22         gucheng_aq   116.184   39.914
25        fangshan_aq   116.136   39.742
26          daxing_aq   116.404   39.718
```

```
27        yizhuang_aq   116.506   39.795
28        tongzhou_aq   116.663   39.886
29          shunyi_aq   116.655   40.127
30        pingchang_aq   116.23   40.217
31       mentougou_aq   116.106   39.937
32          pinggu_aq     117.1   40.143
33         huairou_aq   116.628   40.328
34           miyun_aq   116.832    40.37
35          yanqin_aq   115.972   40.453
38        dingling_aq    116.22   40.292
39        badaling_aq   115.988   40.365
40     miyunshuiku_aq   116.911   40.499
41       donggaocun_aq   117.12     40.1
42      yongledian_aq   116.783   39.712
43            yufa_aq     116.3    39.52
44         liulihe_aq       116    39.58
47         qianmen_aq   116.395   39.899
48  yongdingmennei_aq   116.394   39.876
49     xizhimenbei_aq   116.349   39.954
50      nansanhuan_aq   116.368   39.856
51       dongsihuan_aq   116.483   39.939
```

On remarque que des valeurs sont manquantes et que les intervalles de temps observés ne coicident pas avec le but de notre travail puique nous voulons des données de "training" jusqu'au 20 mars 2018 et des données de test pour le 21 et 22 mars 2018.

C'est donc pour cela que nous avons définis deux fonctions: la première nous permet de couper nos tableaux de données selon leur date (daterange) et la deuxième nous permettra de rendre notre courbe de donnée plus lisse (extrapolate) pour ensuite interpoler de façon linéaire leur valeur.

[13]:
```
from datetime import timedelta, date, datetime

#Fonction de prendre les valeurs dans un intervale de temps
def daterange(date1, date2):
    for m in range(int ((date2 - date1).days)+1):
        for n in range(24):
            yield date1 + timedelta(days=m,hours=n)


# Extrapolation
from scipy.optimize import curve_fit

# Function to curve fit to the data
def func(x, a, b, c, d):
    return a * (x ** 3) + b * (x ** 2) + c * x + d

def extrapolate(df, stringCols, verbose=False):
```

```
    dfStrings = df[stringCols]
    df = df.drop(stringCols, axis=1)

    # Parametre initial
    guess = (0.5, 0.5, 0.5, 0.5)

    # Crée une copie sans Nan pour effectue l'extrapolation
    fit_df = df.dropna()

    # stocke les parametres de nos fonctions pour chaque colonne
    col_params = {}


    for col in fit_df.columns:
        x = fit_df.index.astype(float).values
        y = fit_df[col].values
        params = curve_fit(func, x, y, guess)
        col_params[col] = params[0]

    # Extrapole chaque colonne
    for col in df.columns:
        x = df[pd.isnull(df[col])].index.astype(float).values
        df[col][x] = func(x, *col_params[col])

    if verbose:
        for col in col_params:
            print ('f_{}(x) = {:0.3e} x^3 + {:0.3e} x^2 + {:0.4f} x + {:0.4f}'.
 ↪format(col, *col_params[col]))

    for col in stringCols:
        df[col] = dfStrings[col]
    return df
```

On veut maintenant mettre ensemble nos deux dataframes qui contiennent les informations liées à la polution, pour ensuite extraire la partie qui nous intéresse de tel sorte qu'elle soit complète.

[14]:
```
# On met ensemble nos données
aq = aq1.append(aq2)

# On prend la partie qui nous interrese (date)
start_dt = datetime(2017, 1, 1, 0, 0, 0)
end_dt = datetime(2018, 3, 22, 23, 0, 0)
ran = daterange(start_dt, end_dt)
times = [r.strftime("%Y-%m-%d %H:%M:%S") for r in ran] #Définis l'intervalle de␣
 ↪date désirées

#Tout les utc_times ne sont pas présent, on veut donc les ajouters
```

```python
missing_aq = []
for id in aq.stationId.unique():
    dates_id = aq[aq.stationId == id].utc_time
    missing_dates_id = diff(times, dates_id)
    for date in missing_dates_id:
        missing_aq.append({'utc_time': date, 'stationId': id})

aq = aq.append(missing_aq, ignore_index=True)


# On garde l'intervalle définis
aq = aq.loc[(aq.utc_time >= times[0]) & (aq.utc_time <= times[-1])]

# On trie pour mettre les données dans l'odre
aq = aq.sort_values(['utc_time', 'stationId'])

#On interpole les champs manquants et on effectue l'extrapolation
for station in aq['stationId'].unique():
    aq.loc[aq.stationId == station] = extrapolate(aq.loc[aq.stationId ==␣
 ↪station].interpolate(method='linear'),['utc_time','stationId'])

print(aq)
```

```
                stationId            utc_time       PM2.5        PM10
NO2        CO          O3         SO2
360430    aotizhongxin_aq  2017-01-01 00:00:00   69.932996   97.089615
40.204503  0.956157  132.961799  10.619530
361229        badaling_aq  2017-01-01 00:00:00   71.784150  101.539151
69.454298  1.110830   82.189375   7.142756
362028      beibuxinqu_aq  2017-01-01 00:00:00   69.446673  118.312223
40.530284  1.089999  104.412977   6.030658
362827          daxing_aq  2017-01-01 00:00:00   73.119710  129.766365
39.252133  0.838183  126.362099  11.570621
363626        dingling_aq  2017-01-01 00:00:00   59.427071   86.238030
28.695780  0.681447  129.550561   4.997298
...                   ...                 ...         ...         ...
...          ...         ...         ...
357245  yongdingmennei_aq  2018-03-22 23:00:00  164.000000  168.000000
103.000000  1.900000    2.000000  11.000000
357989      yongledian_aq  2018-03-22 23:00:00  161.000000  199.000000
100.000000  2.300000    3.000000   7.000000
358733            yufa_aq  2018-03-22 23:00:00  156.000000  186.000000
81.000000  1.200000    2.000000   6.000000
359477         yungang_aq  2018-03-22 23:00:00  129.000000  166.000000
100.000000  1.400000    3.000000   7.000000
360221       zhiwuyuan_aq  2018-03-22 23:00:00    9.000000   21.000000
27.000000  0.400000   28.000000   2.000000
```

```
[381115 rows x 8 columns]
```

[15]:

```
# On veut maintenant ajouter les latitudes et longitude au station␣
↪correspondante.

longitude = aq_stations["Longitude"]
latitude = aq_stations["Latitude"]
stationName = aq_stations["StationName"]
aq_stations = aq_stations.sort_values(['StationName'])

# Selon la valeur de la station, on récupere la latitude et la longitude␣
↪correspondante se trouvant dans choices.
conditions = [(aq["stationId"] == aq_stations.StationName.
↪iloc[0]),(aq["stationId"] == aq_stations.StationName.iloc[1]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[2]),(aq["stationId"] == aq_stations.StationName.iloc[3]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[4]),(aq["stationId"] == aq_stations.StationName.iloc[5]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[6]),(aq["stationId"] == aq_stations.StationName.iloc[7]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[8]),(aq["stationId"] == aq_stations.StationName.iloc[9]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[10]),(aq["stationId"] == aq_stations.StationName.iloc[11]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[12]),(aq["stationId"] == aq_stations.StationName.iloc[13]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[14]),(aq["stationId"] == aq_stations.StationName.iloc[15]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[16]),(aq["stationId"] == aq_stations.StationName.iloc[17]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[18]),(aq["stationId"] == aq_stations.StationName.iloc[19]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[20]),(aq["stationId"] == aq_stations.StationName.iloc[21]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[22]),(aq["stationId"] == aq_stations.StationName.iloc[23]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[24]),(aq["stationId"] == aq_stations.StationName.iloc[25]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[26]),(aq["stationId"] == aq_stations.StationName.iloc[27]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[28]),(aq["stationId"] == aq_stations.StationName.iloc[29]),
              (aq["stationId"] == aq_stations.StationName.
↪iloc[30]),(aq["stationId"] == aq_stations.StationName.iloc[31]),
```

```
            (aq["stationId"] == aq_stations.StationName.
↪iloc[32]),(aq["stationId"] == aq_stations.StationName.iloc[33]),
            (aq["stationId"] == aq_stations.StationName.iloc[34])]

choices = aq_stations['Latitude']
aq['Latitude'] = np.select(conditions,choices,default=1)
choices = aq_stations['Longitude']
aq['Longitude'] = np.select(conditions,choices,default=1)

print(aq)
```

```
               stationId            utc_time      PM2.5       PM10
NO2        CO          O3        SO2 Latitude Longitude
360430    aotizhongxin_aq  2017-01-01 00:00:00   69.932996   97.089615
40.204503  0.956157  132.961799  10.619530   39.982   116.397
361229        badaling_aq  2017-01-01 00:00:00   71.784150  101.539151
69.454298  1.110830   82.189375   7.142756   40.365   115.988
362028      beibuxinqu_aq  2017-01-01 00:00:00   69.446673  118.312223
40.530284  1.089999  104.412977   6.030658    40.09   116.174
362827          daxing_aq  2017-01-01 00:00:00   73.119710  129.766365
39.252133  0.838183  126.362099  11.570621   39.718   116.404
363626        dingling_aq  2017-01-01 00:00:00   59.427071   86.238030
28.695780  0.681447  129.550561   4.997298   40.292    116.22
...                   ...                  ...         ...         ...
...        ...        ...        ...       ...       ...
357245  yongdingmennei_aq  2018-03-22 23:00:00  164.000000  168.000000
103.000000  1.900000   2.000000  11.000000   39.876    116.394
357989      yongledian_aq  2018-03-22 23:00:00  161.000000  199.000000
100.000000  2.300000   3.000000   7.000000   39.712    116.783
358733            yufa_aq  2018-03-22 23:00:00  156.000000  186.000000
81.000000  1.200000   2.000000   6.000000    39.52     116.3
359477         yungang_aq  2018-03-22 23:00:00  129.000000  166.000000
100.000000  1.400000   3.000000   7.000000   39.824    116.146
360221       zhiwuyuan_aq  2018-03-22 23:00:00    9.000000   21.000000
27.000000  0.400000   28.000000   2.000000   40.002   116.207

[381115 rows x 10 columns]
```

Maintenant nous voulons calculer l'aproximation la plus proche de la latitude et longitude des stations se trouvant dans le fichier météo après l'avoir coupé selon la date désirée.

[16]:
```
from functools import partial

# Calcule la valeur la plus proche pour une pair de valeur dans une liste de␣
↪duplet
def nearestValue(liste,value):
  dist=lambda s,d: (s[0]-d[0])**2+(s[1]-d[1])**2
  return min(liste, key=partial(dist, value))
```

```python
# On prend la partie qui nous interrese (d)
start_dt = datetime(2017, 1, 1, 0, 0, 0)
end_dt = datetime(2018, 3, 22, 23, 0, 0)
ran = daterange(start_dt, end_dt)
times = [r.strftime("%Y-%m-%d %H:%M:%S") for r in ran]

meo = meo.loc[(meo.utc_time >= times[0]) & (meo.utc_time <= times[-1])]

# Maintenant on veux trouver la latitude et la longitude la plus proche de meo␣
↪dans aq pour récuperer les donnés météo correspondant
A = meo["longitude"]
B = meo["latitude"]
C = zip(A, B)
C = list(C)

#On récupere toute les valeurs de longitude et latitude
D = aq_stations["Longitude"]
E = aq_stations["Latitude"]
F = list(zip(D,E))

allValue = [nearestValue(C,[float(element[0]),float(element[1])]) for element in␣
↪F] # Contient la latitude et longitude la plus proche

print(allValue)
print(meo)
```

```
[(116.4, 40.0), (116.0, 40.4), (116.2, 40.1), (116.4, 39.7), (116.2, 40.3),
(117.1, 40.1), (116.4, 39.9), (116.5, 39.9), (116.1, 39.7), (116.3, 39.9),
(116.3, 39.9), (116.2, 39.9), (116.6, 40.3), (116.0, 39.6), (116.1, 39.9),
(116.8, 40.4), (116.9, 40.5), (116.4, 39.9), (116.5, 39.9), (116.2, 40.2),
(117.1, 40.1), (116.4, 39.9), (116.7, 40.1), (116.4, 39.9), (116.7, 39.9),
(116.3, 40.0), (116.4, 39.9), (116.3, 40.0), (116.0, 40.5), (116.5, 39.8),
(116.4, 39.9), (116.8, 39.7), (116.3, 39.5), (116.1, 39.8), (116.2, 40.0)]
              stationName  longitude  latitude             utc_time  temperature
pressure  humidity  wind_direction  wind_speed/kph
0        beijing_grid_000      115.0      39.0  2017-01-01 00:00:00        -5.47
984.73     76.60           53.71            3.53
1        beijing_grid_001      115.0      39.1  2017-01-01 00:00:00        -5.53
979.33     75.40           43.59            3.11
2        beijing_grid_002      115.0      39.2  2017-01-01 00:00:00        -5.70
963.14     71.80            0.97            2.75
3        beijing_grid_003      115.0      39.3  2017-01-01 00:00:00        -5.88
946.94     68.20          327.65            3.84
4        beijing_grid_004      115.0      39.4  2017-01-01 00:00:00        -5.34
928.80     58.81          317.85            6.14
...                   ...        ...       ...                  ...          ...
```

```
...       ...              ...             ...
6968299  beijing_grid_646      118.0      40.6  2018-03-22 23:00:00         5.48
950.88     46.63           271.90          1.55
6968300  beijing_grid_647      118.0      40.7  2018-03-22 23:00:00         5.74
955.91     46.10           264.08          1.70
6968301  beijing_grid_648      118.0      40.8  2018-03-22 23:00:00         5.53
953.85     45.90           310.06          1.53
6968302  beijing_grid_649      118.0      40.9  2018-03-22 23:00:00         5.32
951.78     45.70           343.14          2.24
6968303  beijing_grid_650      118.0      41.0  2018-03-22 23:00:00         5.24
951.10     45.63           349.34          2.57

[6968304 rows x 9 columns]
```

Désormais, nous voulons insérer dans nos données les attributs du fichier météorologique qui nous interesse. Pour cela, nous sélectionons les parties de aq contenant les stations à la latitude et longitude exacte et nous la concatenons à un tableau de la même taille contenant les données météorologiques à une position approximée. En faisant cela, nous avons remarqué des duplications dans nos utc_times, car nos tableaux n'étaient pas de la même taille. Par conséquent, nous les enlevons avant d'effectuer cette opération.

[17]:
```
#On enleve les duplications et stocke dans aq_concat2

# On index par utc_time afin d'enlever les duplications dans l'index
if not aq.index.name == 'utc_time':
  aq = aq.set_index(['utc_time'])

#Contient la premiere station sans duplication
aq_concat = aq[aq.stationId == aq.stationId.unique()[0]]
stations = aq.stationId.unique()[1:]
aq_concat = aq_concat.loc[~aq_concat.index.duplicated(keep='first')]

#Nous ajoutons chaque station sans duplication au tableau définis précédemment
for i in range(1,35):
  aq_concat2 = aq[aq.stationId == aq.stationId.unique()[i]]
  aq_concat = aq_concat.append(aq_concat2.loc[~aq_concat2.index.
 ↪duplicated(keep='first')])

aq = aq_concat # On stocke dans aq

#On stocke l'index contenant nos utc-times
times = aq.index

# Clean l'index
aq_stations = aq_stations.reset_index(drop=True)

# On déclare nos deux premiers tableaux pour effectuer l'opèration désirée
```

```python
# On selectionne les parties à l'aide de deux booléeans donnés par la latitude␣
↪et longitude.
stationBool = aq['Longitude'] == "116.397"
stationBool2 = aq['Latitude'] == "39.982"
station1 = aq[stationBool & stationBool2]

meoBool = meo['longitude'] == 116.4
meoBool2 = meo['latitude'] == 40.0
meo1 = meo[meoBool & meoBool2]

# Clean Index pour effectuer la concaténation
station1 = station1.reset_index(drop=True)
meo1 = meo1.reset_index(drop=True)
# On concatene les attributs qui nous interrese.
station1 = pd.concat([station1,␣
↪meo1[["temperature",'pressure','humidity','wind_direction','wind_speed/
↪kph']]], axis=1)

# On fait la même chose pour chaque autre station
for i in range(1,35):
  stationBool = aq['Longitude'] == str(aq_stations['Longitude'][i])
  stationBool2 = aq['Latitude'] == str(aq_stations['Latitude'][i])
  stationPart = aq[stationBool & stationBool2]
  meoBool = meo['longitude'] == allValue[i][0]
  meoBool2 = meo['latitude'] == allValue[i][1]
  meoPart = meo[meoBool & meoBool2]
  stationPart = stationPart.reset_index(drop=True)
  meoPart = meoPart.reset_index(drop=True)
  station1 = station1.append(pd.concat([stationPart,␣
↪meoPart[["temperature",'pressure','humidity','wind_direction','wind_speed/
↪kph']]], axis=1))

# Clean l'index
station1 = station1.reset_index(drop=True)
# On stocke le résultat dans aq.
aq = station1
print(aq)
```

```
              stationId      PM2.5       PM10        NO2        CO          O3
SO2 Latitude Longitude  temperature  pressure  humidity  wind_direction
wind_speed/kph
0       aotizhongxin_aq  69.932996  97.089615  40.204503  0.956157  132.961799
10.619530   39.982   116.397         -5.96   1019.95     68.60           132.90
4.51
1       aotizhongxin_aq  69.932406  97.089357  40.204104  0.956148  132.963853
10.619316   39.982   116.397         -3.36   1019.82     58.43           141.39
4.17
```

```
2       aotizhongxin_aq  69.931817  97.089099  40.203705  0.956140  132.965906
10.619101   39.982   116.397         -0.77    1019.69     48.27          151.13
3.93
3       aotizhongxin_aq  69.931227  97.088841  40.203307  0.956131  132.967960
10.618887   39.982   116.397          1.82    1019.55     38.10          161.75
3.82
4       aotizhongxin_aq  69.930637  97.088583  40.202908  0.956122  132.970013
10.618672   39.982   116.397          2.97    1018.86     35.65          155.45
4.50
...                  ...        ...        ...        ...       ...         ...
...       ...       ...          ...       ...       ...              ...
...
374635     zhiwuyuan_aq   9.000000  21.000000  27.000000  0.400000   28.000000
2.000000   40.002   116.207         9.59     990.56     35.67          29.54
1.71
374636     zhiwuyuan_aq   9.000000  21.000000  27.000000  0.400000   28.000000
2.000000   40.002   116.207         9.16     990.62     36.31          37.28
2.71
374637     zhiwuyuan_aq   9.000000  21.000000  27.000000  0.400000   28.000000
2.000000   40.002   116.207         8.72     990.68     36.96          40.83
3.72
374638     zhiwuyuan_aq   9.000000  21.000000  27.000000  0.400000   28.000000
2.000000   40.002   116.207         9.15     991.19     36.04          36.18
3.69
374639     zhiwuyuan_aq   9.000000  21.000000  27.000000  0.400000   28.000000
2.000000   40.002   116.207         9.58     991.70     35.12          31.50
3.69

[374640 rows x 14 columns]
```

[18]:
```
# On remet utc_time pour ordonner les données.
aq.insert(0, 'utc_time', times)

#Convertion en numérique
aq["Latitude"] = pd.to_numeric(aq["Latitude"])
aq["Longitude"] = pd.to_numeric(aq["Longitude"])

#On ordonne
aq = aq.sort_values(['utc_time', 'stationId'])

#On enleve le station_id
aq = aq.drop(['stationId'], axis=1)

# Clean Index
aq = aq.reset_index(drop=True)

print(aq)
```

```
                   utc_time       PM2.5        PM10         NO2        CO
O3         SO2  Latitude  Longitude  temperature  pressure  humidity
wind_direction  wind_speed/kph
0       2017-01-01 00:00:00   69.932996   97.089615   40.204503  0.956157
132.961799  10.619530    39.982    116.397         -5.96   1019.95     68.60
132.90            4.51
1       2017-01-01 00:00:00   71.784150  101.539151   69.454298  1.110830
82.189375   7.142756    40.365    115.988         -6.29    946.71     72.23
306.26            7.32
2       2017-01-01 00:00:00   69.446673  118.312223   40.530284  1.089999
104.412977   6.030658    40.090    116.174         -6.10    999.06     72.34
338.39            0.69
3       2017-01-01 00:00:00   73.119710  129.766365   39.252133  0.838183
126.362099  11.570621    39.718    116.404         -5.59   1022.43     78.05
107.16            3.98
4       2017-01-01 00:00:00   59.427071   86.238030   28.695780  0.681447
129.550561   4.997298    40.292    116.220         -6.52    978.46     75.38
320.99            4.29
...                     ...         ...         ...         ...        ...
...        ...        ...         ...          ...        ...       ...
...              ...
374635  2018-03-22 23:00:00  164.000000  168.000000  103.000000  1.900000
2.000000  11.000000    39.876    116.394          9.46   1008.14     36.89
55.70            4.21
374636  2018-03-22 23:00:00  161.000000  199.000000  100.000000  2.300000
3.000000   7.000000    39.712    116.783          9.73   1012.04     39.70
181.73            1.94
374637  2018-03-22 23:00:00  156.000000  186.000000   81.000000  1.200000
2.000000   6.000000    39.520    116.300          9.95   1010.59     41.87
181.65            1.40
374638  2018-03-22 23:00:00  129.000000  166.000000  100.000000  1.400000
3.000000   7.000000    39.824    116.146          9.99    994.18     36.78
26.07            4.07
374639  2018-03-22 23:00:00    9.000000   21.000000   27.000000  0.400000
28.000000   2.000000    40.002    116.207          9.58    991.70     35.12
31.50            3.69

[374640 rows x 14 columns]
```

Nous pouvons maintenant définir nos données d'entrainement et nos données de test en effectuant un tri sur leur date.

[19]:
```python
if not aq.index.name == 'utc_time':
    aq = aq.set_index(['utc_time'])
x_train = aq[aq.index < '2018-03-21']
x_test = aq[aq.index > '2018-03-21']
Y = aq[['PM2.5', 'PM10', 'O3']] # On selectionne uniquement les trois attributs␣
 ↪à prédire
```

```python
y_train = Y[aq.index < '2018-03-21']
y_test = Y[aq.index > '2018-03-21']

print(x_test)
print(x_train)
print(y_train)
print(y_test)
```

```
                     PM2.5   PM10    NO2   CO    O3    SO2  Latitude  Longitude
temperature  pressure  humidity  wind_direction  wind_speed/kph
utc_time
2018-03-21 00:00:00   55.0   93.0   72.0  1.0   2.0   5.0    39.982    116.397
4.63   1018.13     19.57          114.55             1.89
2018-03-21 00:00:00   42.0   70.0   86.0  0.4   2.0   8.0    40.365    115.988
1.26    946.15     22.80           78.44             2.73
2018-03-21 00:00:00   52.0  108.0   73.0  1.0   2.0   3.0    40.090    116.174
3.90    997.29     21.65           68.13             2.29
2018-03-21 00:00:00   39.0   79.0   59.0  1.4  16.0  18.0    39.718    116.404
3.99   1020.92     19.97          230.54             7.50
2018-03-21 00:00:00   31.0   43.0   39.0  0.7  17.0   2.0    40.292    116.220
2.69    976.66     22.11           57.81             3.15
...                    ...    ...    ...  ...   ...   ...       ...        ...
...         ...       ...            ...             ...
2018-03-22 23:00:00  164.0  168.0  103.0  1.9   2.0  11.0    39.876    116.394
9.46   1008.14     36.89           55.70             4.21
2018-03-22 23:00:00  161.0  199.0  100.0  2.3   3.0   7.0    39.712    116.783
9.73   1012.04     39.70          181.73             1.94
2018-03-22 23:00:00  156.0  186.0   81.0  1.2   2.0   6.0    39.520    116.300
9.95   1010.59     41.87          181.65             1.40
2018-03-22 23:00:00  129.0  166.0  100.0  1.4   3.0   7.0    39.824    116.146
9.99    994.18     36.78           26.07             4.07
2018-03-22 23:00:00    9.0   21.0   27.0  0.4  28.0   2.0    40.002    116.207
9.58    991.70     35.12           31.50             3.69

[1680 rows x 13 columns]
                         PM2.5        PM10        NO2        CO          O3
SO2  Latitude  Longitude  temperature  pressure  humidity  wind_direction
wind_speed/kph
utc_time
2017-01-01 00:00:00  69.932996   97.089615  40.204503  0.956157  132.961799
10.619530    39.982    116.397        -5.96   1019.95     68.60           132.90
4.51
2017-01-01 00:00:00  71.784150  101.539151  69.454298  1.110830   82.189375
7.142756    40.365    115.988        -6.29    946.71     72.23           306.26
7.32
2017-01-01 00:00:00  69.446673  118.312223  40.530284  1.089999  104.412977
6.030658    40.090    116.174        -6.10    999.06     72.34           338.39
```

```
0.69
2017-01-01 00:00:00  73.119710  129.766365  39.252133  0.838183  126.362099
11.570621    39.718    116.404        -5.59   1022.43     78.05          107.16
3.98
2017-01-01 00:00:00  59.427071   86.238030  28.695780  0.681447  129.550561
4.997298    40.292    116.220        -6.52    978.46     75.38          320.99
4.29
...                        ...         ...        ...       ...         ...
...       ...        ...          ...       ...       ...             ...
...
2018-03-20 23:00:00  48.000000   65.000000  75.000000  0.800000    6.000000
10.000000    39.876    116.394         4.06   1019.19     20.03          196.03
3.14
2018-03-20 23:00:00  52.000000   88.000000  82.000000  0.900000    3.000000
2.000000    39.712    116.783         2.88   1023.53     21.52          230.52
8.39
2018-03-20 23:00:00  33.000000   68.000000  30.000000  0.600000   50.000000
17.000000    39.520    116.300         2.76   1022.22     21.74          229.41
10.85
2018-03-20 23:00:00  63.000000   95.000000  67.000000  1.100000    2.000000
5.000000    39.824    116.146         3.65   1004.84     22.51          235.43
3.74
2018-03-20 23:00:00   9.000000   21.000000  27.000000  0.400000   28.000000
2.000000    40.002    116.207         3.84   1002.04     22.19          112.62
1.08

[372960 rows x 13 columns]
                         PM2.5        PM10          O3
utc_time
2017-01-01 00:00:00  69.932996   97.089615  132.961799
2017-01-01 00:00:00  71.784150  101.539151   82.189375
2017-01-01 00:00:00  69.446673  118.312223  104.412977
2017-01-01 00:00:00  73.119710  129.766365  126.362099
2017-01-01 00:00:00  59.427071   86.238030  129.550561
...                        ...         ...         ...
2018-03-20 23:00:00  48.000000   65.000000    6.000000
2018-03-20 23:00:00  52.000000   88.000000    3.000000
2018-03-20 23:00:00  33.000000   68.000000   50.000000
2018-03-20 23:00:00  63.000000   95.000000    2.000000
2018-03-20 23:00:00   9.000000   21.000000   28.000000

[372960 rows x 3 columns]
                     PM2.5   PM10    O3
utc_time
2018-03-21 00:00:00   55.0   93.0   2.0
2018-03-21 00:00:00   42.0   70.0   2.0
2018-03-21 00:00:00   52.0  108.0   2.0
2018-03-21 00:00:00   39.0   79.0  16.0
```

```
2018-03-21 00:00:00   31.0   43.0  17.0
...                    ...    ...   ...
2018-03-22 23:00:00  164.0  168.0   2.0
2018-03-22 23:00:00  161.0  199.0   3.0
2018-03-22 23:00:00  156.0  186.0   2.0
2018-03-22 23:00:00  129.0  166.0   3.0
2018-03-22 23:00:00    9.0   21.0  28.0

[1680 rows x 3 columns]
```

La conversion en numpy facilite l'ordonnement de nos données, puisque nous voulons maintenant pour chaque utc_time obtenir une ligne contenant les informations des 35 stations. Ensuite nous supprimons la dernière ligne de X et la première ligne de Y pour pouvoir prédire les conditions météorologiques à l'heure qui suit.

[20]:
```
# Convertie en numpy pour pouvoir effectuer le reshape désiré.
nbXattribut = 13
nbYattribut = 3
nbrStation = 35
def reshape(frame, nbStation):
  return frame.to_numpy().reshape(int(frame.shape[0]/nbStation),nbStation*frame.
 ↪shape[1])

x_train = reshape(x_train,nbrStation)
x_test = reshape(x_test,nbrStation)
y_train = reshape(y_train,nbrStation)
y_test = reshape(y_test,nbrStation)

print("verify size of x_train: ")
print(len(x_train[0]))
print(nbrStation * nbXattribut)
print("")
print("verify size of x_train: ")
print(len(x_train[0]))
print(nbrStation * nbXattribut)
print("")

print("verify size of y_train: ")
print(len(y_train[0]))
print(nbrStation * nbYattribut)
print("")

print("verify size of y_test: ")
print(len(y_test[0]))
print(nbrStation * nbYattribut)
print("")
```

```
# Delete first row of y and last of x , Because we want y to have the value of␣
↪the next hours

x_train = np.delete(x_train,-1,0)
x_test = np.delete(x_test,-1,0)

y_train = np.delete(y_train,0,0)
y_test = np.delete(y_test,0,0)
```

```
verify size of x_train:
455
455

verify size of x_train:
455
455

verify size of y_train:
105
105

verify size of y_test:
105
105
```

2.2 Modèles

Nous pouvons désormais définir nos modèles à l'aide de la librarie sklearn, mais avant cela nous définissons une fonction nous permettant d'afficher les résultats et les plots obtenus.

[21]:
```
# Plots
import matplotlib.pyplot as plt

def plot_model_prediction(mod):
    # fait la prédiction
    prediction = mod.predict(x_test)

    # Evalue la précision du model
    from sklearn.metrics import mean_absolute_error, median_absolute_error
    print("Test")
    print("The Explained Variance: %.2f" % mod.score(x_test, y_test))
    print("The Mean Absolute Error: %.2f " % mean_absolute_error(y_test,␣
↪prediction))
    print("The Median Absolute Error: %.2f " % median_absolute_error(y_test,␣
↪prediction))
```

```
    print("Train")
    pred_train = mod.predict(x_train)
    print("The Explained Variance: %.2f" % mod.score(x_train, y_train))
    print("The Mean Absolute Error: %.2f " % mean_absolute_error(y_train,␣
↪pred_train))
    print("The Median Absolute Error: %.2f " % median_absolute_error(y_train,␣
↪pred_train))


    y_prediction = np.copy(y_test)
    y_prediction[:] = prediction

    fig=plt.figure(figsize=(13, 13), dpi= 80, facecolor='w', edgecolor='k')
    plt.plot(y_test)
    plt.show()

    fig=plt.figure(figsize=(13, 13), dpi= 80, facecolor='w', edgecolor='k')
    plt.plot(y_prediction)
    plt.show()
```

2.2.1 Régression linéaire

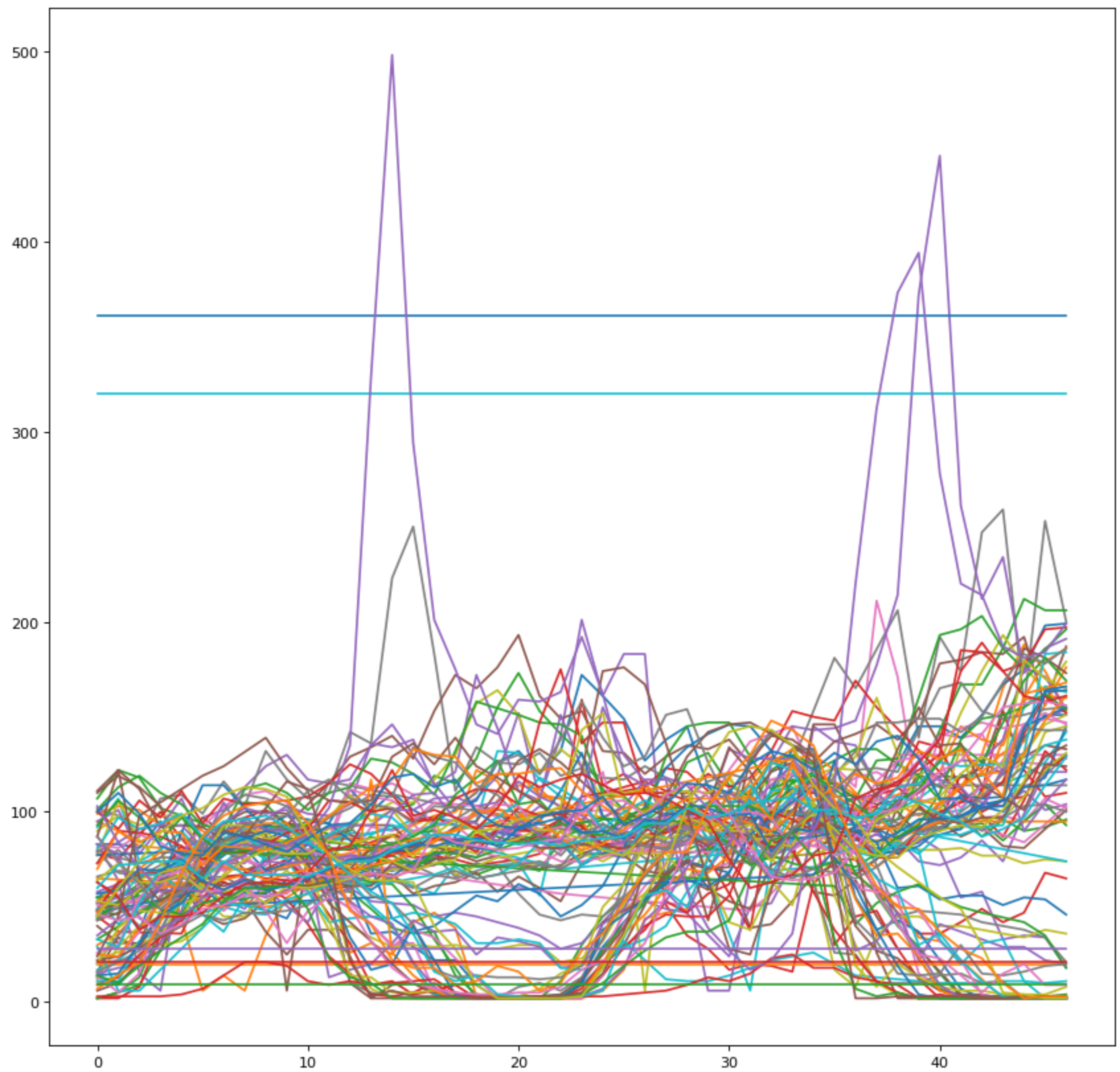
[22]:
```
from sklearn.linear_model import LinearRegression

regr = LinearRegression()
regr.fit(x_train, y_train)

plot_model_prediction(regr)
```

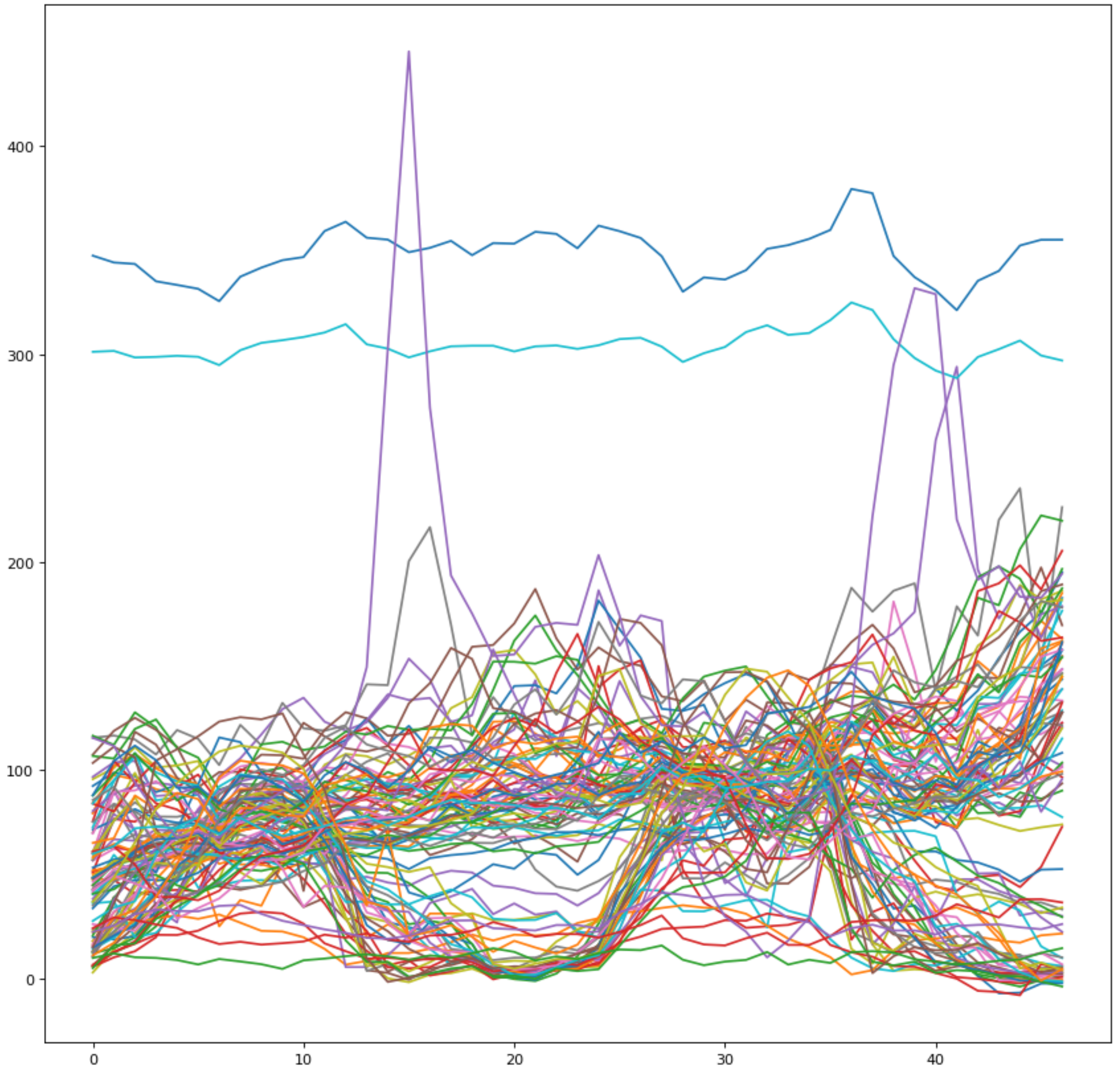
```
Test
The Explained Variance: 0.79
The Mean Absolute Error: 8.92
The Median Absolute Error: 7.01
Train
The Explained Variance: 0.94
The Mean Absolute Error: 9.14
```

```
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
```

```
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
```

```
The Median Absolute Error: 5.91
```



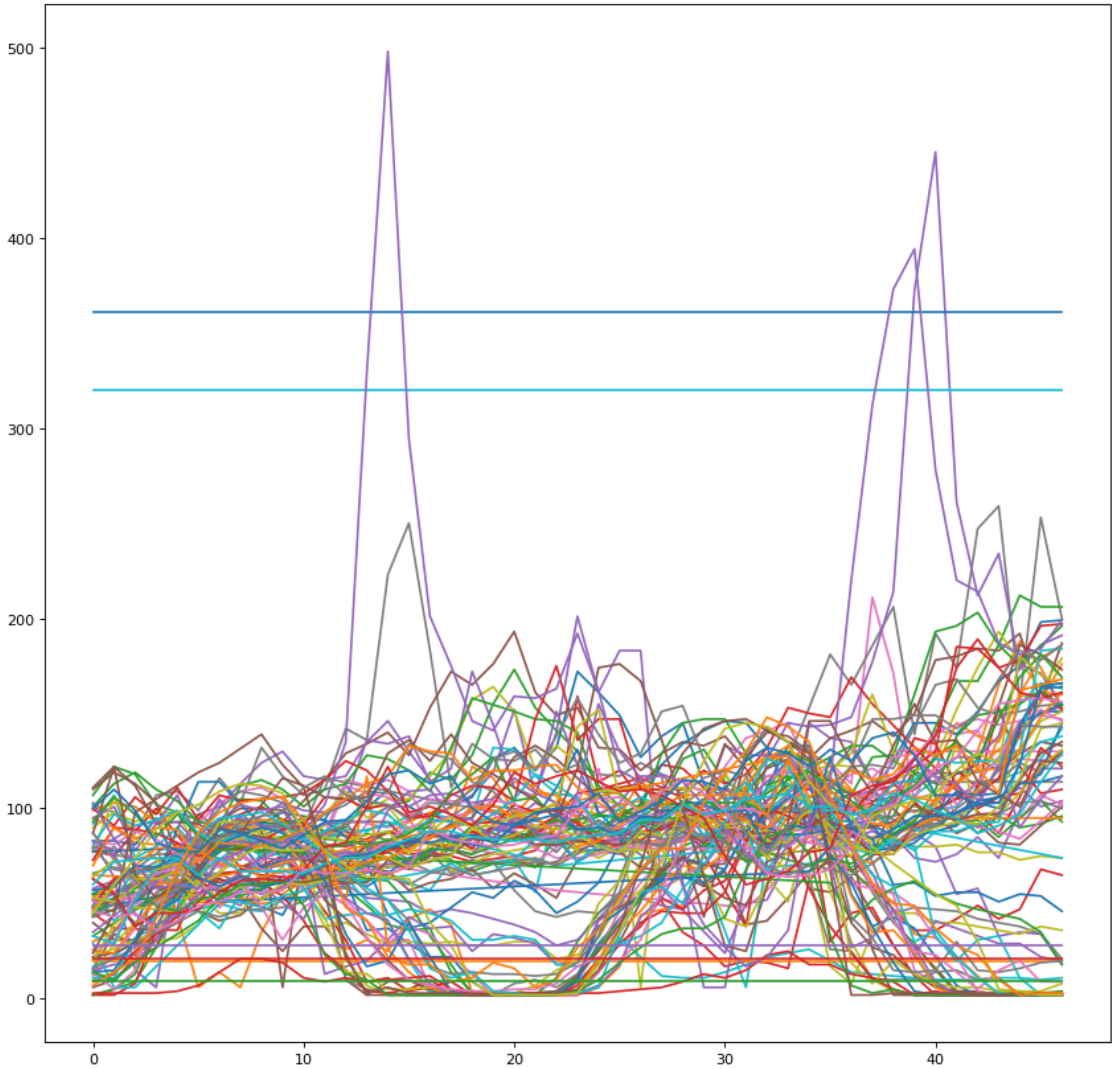


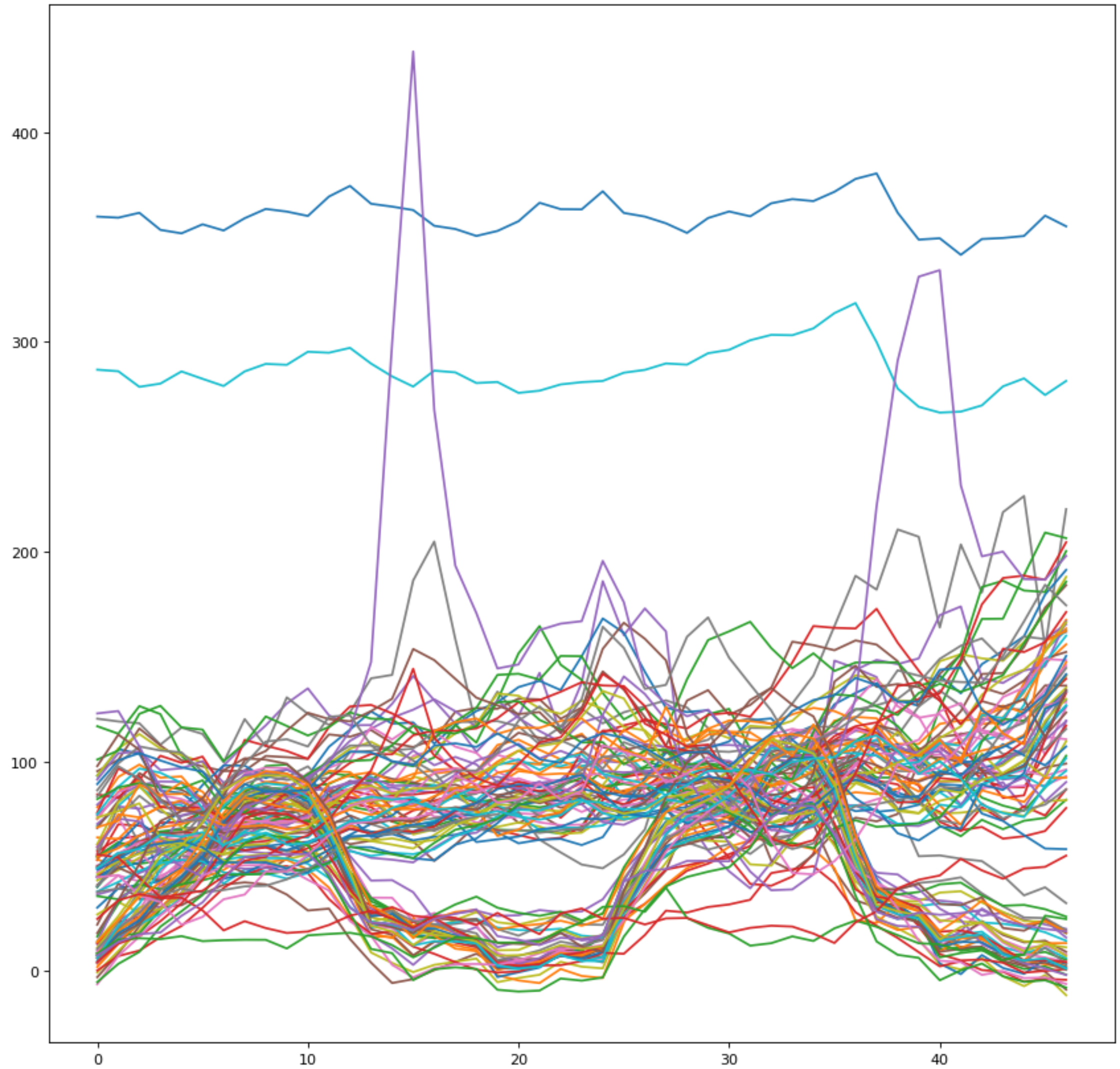
2.2.2 MLP regressor

[23]:
```
from sklearn.neural_network import MLPRegressor

regr_2 = MLPRegressor(random_state=1, max_iter=1000)
regr_2.fit(x_train, y_train)

plot_model_prediction(regr_2)
```

```
Test
The Explained Variance: 0.65
The Mean Absolute Error: 12.90
The Median Absolute Error: 10.52
Train
```

```
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)

The Explained Variance: 0.91
The Mean Absolute Error: 12.86
The Median Absolute Error: 8.80
```


500
400
300
200
100
0
0
10
20
30
40

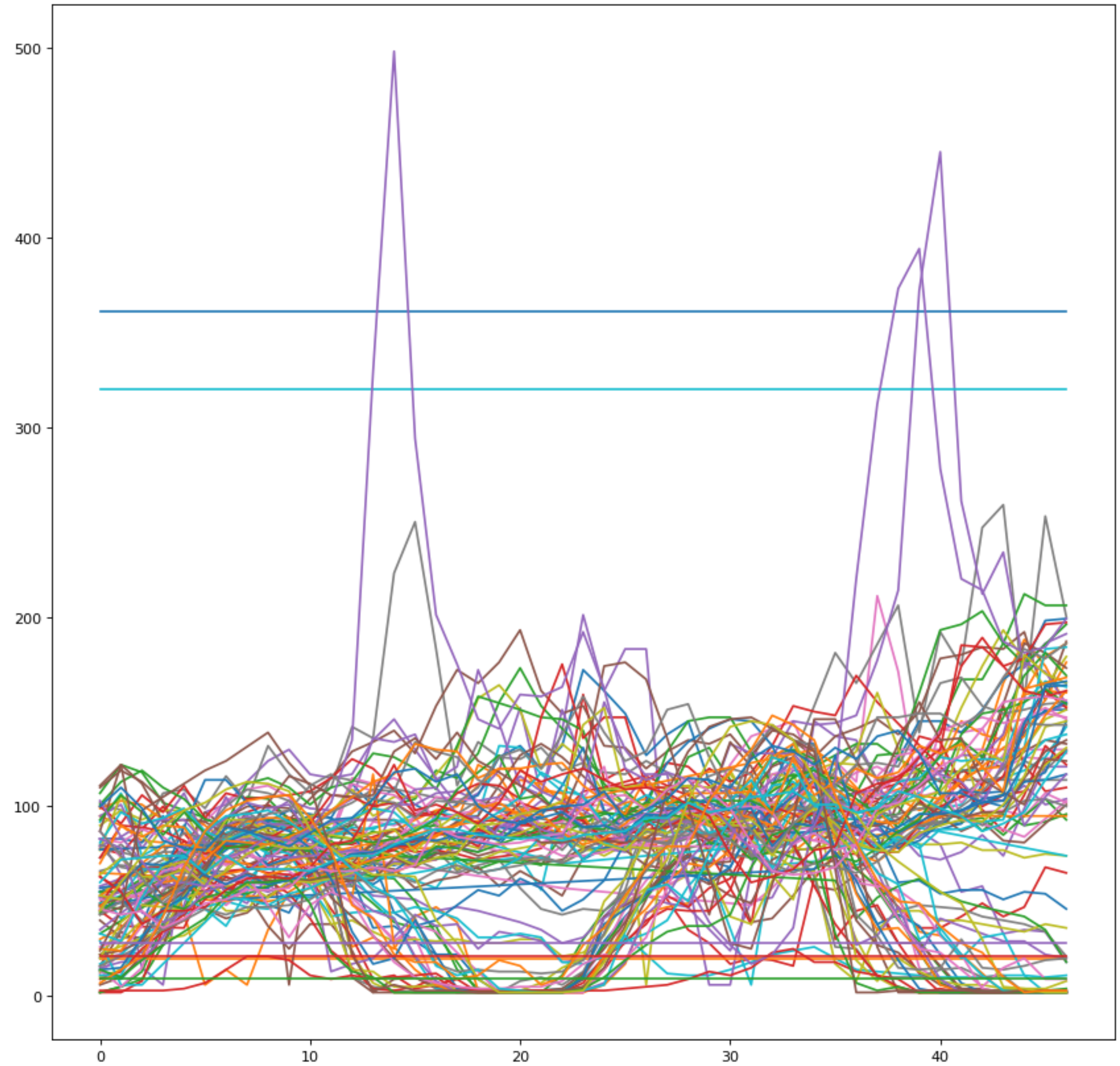


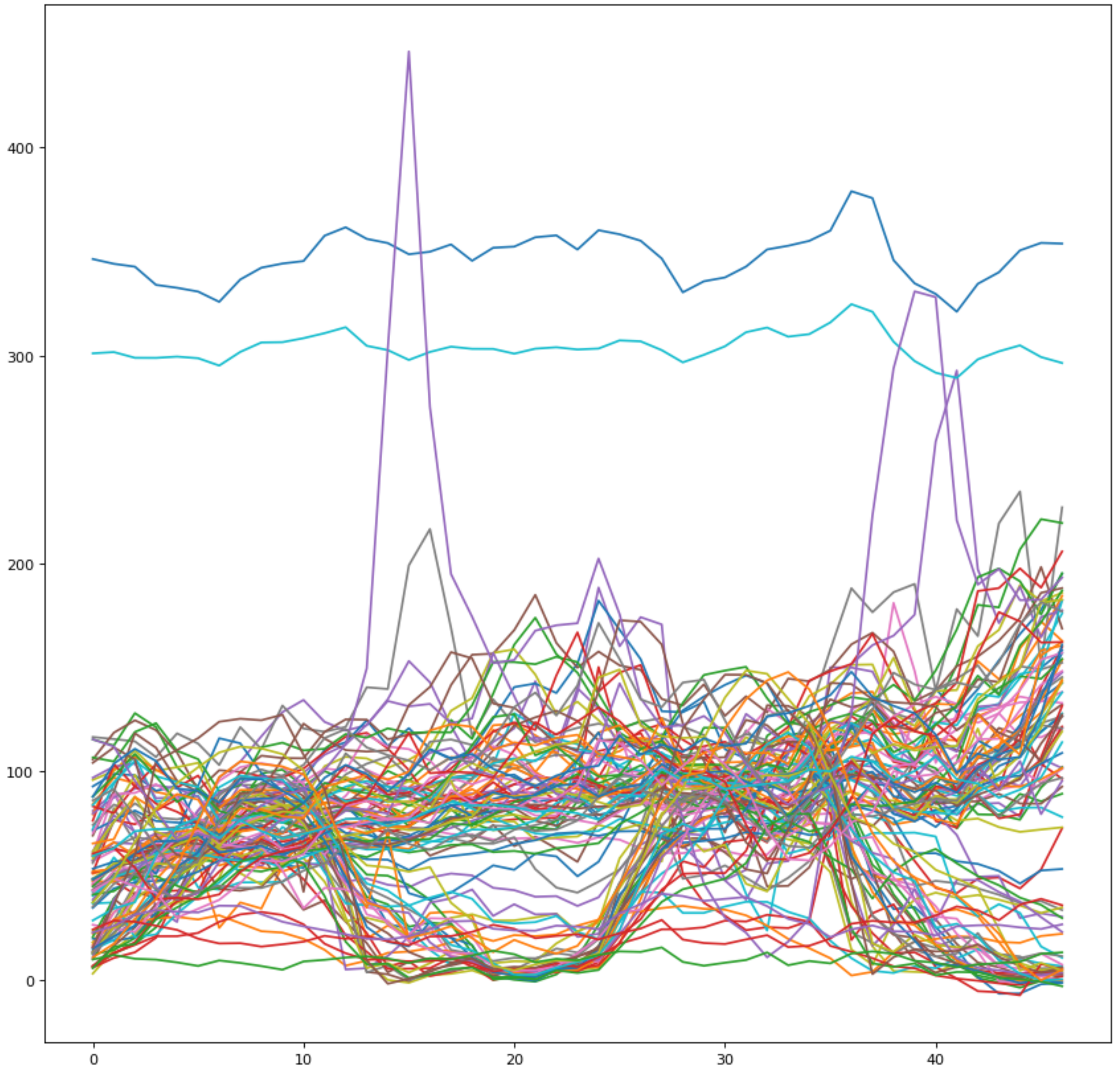
2.2.3 MultiOutput Regressor

[24]:
```
import numpy as np
from sklearn.datasets import load_linnerud
from sklearn.multioutput import MultiOutputRegressor
from sklearn.linear_model import Ridge
regr_3 = MultiOutputRegressor(Ridge(random_state=123)).fit(x_train, y_train)

plot_model_prediction(regr_3)
```

```
Test
The Explained Variance: 0.71
The Mean Absolute Error: 8.91
The Median Absolute Error: 6.94
```

```
Train
The Explained Variance: 0.95
The Mean Absolute Error: 9.13
The Median Absolute Error: 5.88
```





2.3 Cross validation

[25]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn import metrics
# Compute score
scoresRegr = cross_val_score(regr, x_train, y_train)
scoresRegr2 = cross_val_score(regr_2, x_train, y_train)
scoresRegr3 = cross_val_score(regr_3, x_train, y_train)
```

```
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
```

```
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
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'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
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'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
```

```
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
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multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
```

2.4 Statistical signifcant test

[26]:
```
# Between linear and MLPRegressor
from scipy.stats import pearsonr
# If p > 0.05: H0 Rejected
stat, p = pearsonr(scoresRegr, scoresRegr2)
print(p)
print(stat)
```

```
0.13131295375568075
0.765626052506868
```

[27]:
```
# Between linear and MultiOutputRegressor
from scipy.stats import pearsonr
# If p > 0.05: H0 Rejected
stat, p = pearsonr(scoresRegr, scoresRegr3)
print(p)
print(stat)
```

```
0.116735818664728
```

```
0.7837327298732639
```

[28]:
```
# Between MultiOutputRegressor and MLPRegressor
from scipy.stats import pearsonr
# If p > 0.05: H0 Rejected
stat, p = pearsonr(scoresRegr3, scoresRegr2)
print(p)
print(stat)
```

```
0.5417798444663433
0.3683966046778729
```

3 Traitement des données de Londres

3.1 Affichage des données

Dans cette partie nous allons travailler avec les données de Londres. Pour cela nous utilisons trois fichiers:

1. London_historical_meo_grid.csv qui contient des données météo
2. London_AirQuality_Stations.csv qui contient les données géorgraphiques des stations de mesure
3. London_historical_aqi_forecast_stations_20180331.csv qui contient les valeurs des différentes particules

Nous commencons donc par lire les fichiers et afficher les données qu'ils contiennent.

[29]:
```
import pandas as pd

pd.set_option('display.max_columns', None)
pd.set_option('display.width', 200)

meo = pd.read_csv('final_project_data/London_historical_meo_grid.csv',␣
 ↪encoding='utf-8-sig', sep='\s*,\s*', engine='python')
location = pd.read_csv('final_project_data/London_AirQuality_Stations.csv')
location.sort_values('need_prediction',ascending=True, inplace=False,␣
 ↪kind='quicksort', na_position='last', ignore_index=False)
pollution = pd.read_csv('final_project_data/
 ↪London_historical_aqi_forecast_stations_20180331.csv')


print("=========================Pollution ================")
print(pollution)

print("=========================meteo ================")
print(meo)
print('Min:', meo.utc_time.min())
print('Max:', meo.utc_time.max())
```

```python
print("=============== Location ========")
print(location)
```

```
========================Pollution ================
        Unnamed: 0 MeasurementDateGMT station_id  PM2.5 (ug/m3)  PM10 (ug/m3)
NO2 (ug/m3)
0                0      2017/1/1 0:00        CD1            40.0          44.4
36.6
1                1      2017/1/1 1:00        CD1            31.6          34.4
46.2
2                2      2017/1/1 2:00        CD1            24.7          28.1
38.3
3                3      2017/1/1 3:00        CD1            21.2          24.5
32.8
4                4      2017/1/1 4:00        CD1            24.9          23.0
28.1
...            ...                ...        ...             ...           ...
...
141656       10892    2018/3/30 20:00        TH4             3.5          11.2
44.3
141657       10893    2018/3/30 21:00        TH4             4.7          12.3
52.8
141658       10894    2018/3/30 22:00        TH4             5.4          14.0
54.7
141659       10895    2018/3/30 23:00        TH4             8.9          16.5
47.0
141660       10896     2018/3/31 0:00        TH4             NaN           NaN
NaN

[141661 rows x 6 columns]
========================meteo ================
             stationName  longitude  latitude            utc_time  temperature
pressure  humidity  wind_direction  wind_speed/kph
0        london_grid_000       -2.0      50.5  2017-01-01 00:00:00         9.36
1024.81     77.90          250.88          23.74
1        london_grid_001       -2.0      50.6  2017-01-01 00:00:00         9.09
1024.25     78.96          249.86          21.81
2        london_grid_002       -2.0      50.7  2017-01-01 00:00:00         8.30
1022.55     82.13          245.35          16.08
3        london_grid_003       -2.0      50.8  2017-01-01 00:00:00         7.50
1020.86     85.30          235.98          10.55
4        london_grid_004       -2.0      50.9  2017-01-01 00:00:00         6.92
1015.89     88.51          228.21          10.97
...                  ...        ...       ...                 ...          ...
...          ...             ...             ...
9303961  london_grid_856        2.0      52.1  2018-03-27 05:00:00         7.06
```

```
1011.21     85.77          189.56           27.38
9303962  london_grid_857        2.0      52.2  2018-03-27 05:00:00         7.03
1011.11     85.88          189.88           26.71
9303963  london_grid_858        2.0      52.3  2018-03-27 05:00:00         6.91
1011.01     85.91          189.05           25.75
9303964  london_grid_859        2.0      52.4  2018-03-27 05:00:00         6.79
1010.92     85.94          188.15           24.79
9303965  london_grid_860        2.0      52.5  2018-03-27 05:00:00         6.74
1010.89     85.95          187.84           24.47

[9303966 rows x 9 columns]
Min: 2017-01-01 00:00:00
Max: 2018-03-27 05:00:00
=============== Location ========
   Unnamed: 0 api_data need_prediction  historical_data   Latitude  Longitude
SiteType                                  SiteName
0         BX9     True             NaN             True  51.465983   0.184877
Suburban                 Bexley - Slade Green FDMS
1         BX1     True             NaN             True  51.465983   0.184877
Suburban                      Bexley - Slade Green
2         BL0     True            True             True  51.522287  -0.125848
Urban Background                       Camden - Bloomsbury
3         CD9     True            True             True  51.527707  -0.129053
Roadside                      Camden - Euston Road
4         CD1     True            True             True  51.544219  -0.175284
Kerbside                    Camden - Swiss Cottage
5         CT2     True             NaN             True  51.514525  -0.104516
Kerbside        City of London - Farringdon Street
6         CT3     True             NaN             True  51.513847  -0.077766
Urban Background     City of London - Sir John Cass School
7         CR8      NaN             NaN             True  51.410039  -0.127523
Urban Background                 Croydon - Norbury Manor
8         GN0     True            True             True  51.490532   0.074003
Roadside            Greenwich - A206 Burrage Grove
9         GR4     True            True             True  51.452580   0.070766
Suburban                        Greenwich - Eltham
10        GN3     True            True             True  51.486957   0.095111
Roadside         Greenwich - Plumstead High Street
11        GR9     True            True             True  51.456357   0.040725
Roadside              Greenwich - Westhorne Avenue
12        GB0      NaN             NaN             True  51.456300   0.085606
Roadside    Greenwich and Bexley - Falconwood FDMS
13        HR1      NaN             NaN             True  51.617327  -0.298775
Urban Background                         Harrow - Stanmore
14        HV1     True            True             True  51.520787   0.205461
Roadside                        Havering - Rainham
15        LH0      NaN             NaN             True  51.488780  -0.441627
Urban Background                 Hillingdon - Harlington
```

```
16         KC1      NaN             NaN             True  51.521047  -0.213492
Urban Background        Kensington and Chelsea - North Ken
17         KF1      True            True            True  51.521047  -0.213492
Urban Background  Kensington and Chelsea - North Ken FIDAS
18         LW2      True            True            True  51.474954  -0.039641
Roadside                       Lewisham - New Cross
19         RB7      True            NaN             True  51.569484   0.082907
Urban Background                    Redbridge - Ley Street
20         TD5      True            NaN             True  51.425256  -0.345608
Suburban         Richmond Upon Thames - Bushy Park
21         ST5      True            True            True  51.389287  -0.141662
Industrial            Sutton - Beddington Lane north
22         TH4      True            True            True  51.515046  -0.008418
Roadside                  Tower Hamlets - Blackwall
23         MY7      True            True            True  51.522540  -0.154590
Kerbside        Westminster - Marylebone Road FDMS
```

On voit que dans le fichiers de pollution les valeurs sont données par rapport aux stations_id. Dans le fichiers météo les valeurs sont données par rapport aux coordonées de latitude et de longitude. Nous allons donc devoir faire le liens entre les données de pollution et les données métorologiques afin de pouvoir faire travailler des algorithmes dessus.

3.2 Liaison de la météo et de la pollution

Nous commençons par supprimer toutes les stations qui ne sont pas nécessaire dans notre dataFrame location. Toutes les stations supprimées sont celles dont nous n'avons la prédiction n'est pas demandée.

Nous supprimons également toutes les colonnes qui ne sont pas nécessaires pour notre travail. Nous gardons donc que les id des stations avec leurs coordonées géographique.

[30]:
```
try:
  location = location[location.need_prediction == True]
except:
  pass


if location.shape[1] != 3:
  location = location.drop('api_data', 1)
  location = location.drop('need_prediction', 1)
  location = location.drop('historical_data', 1)
  location = location.drop('SiteType', 1)
  location = location.drop('SiteName', 1)




print(location)
```

```
   Unnamed: 0   Latitude  Longitude
2          BL0  51.522287  -0.125848
3          CD9  51.527707  -0.129053
4          CD1  51.544219  -0.175284
8          GN0  51.490532   0.074003
9          GR4  51.452580   0.070766
10         GN3  51.486957   0.095111
11         GR9  51.456357   0.040725
14         HV1  51.520787   0.205461
17         KF1  51.521047  -0.213492
18         LW2  51.474954  -0.039641
21         ST5  51.389287  -0.141662
22         TH4  51.515046  -0.008418
23         MY7  51.522540  -0.154590
```

Maintenant que la dataFrame location est nettoyée, nous pouvons commencer avec le reste. Nous copions tout d'abord polution dans une variable globale aq qui nous permettera d'ajouter des éléments sans toucher à la dataFrame originale.

Nous trions ensuite aq par les station_id et l'affichons

[31]:
```
aq = pollution.copy()
location = location.reset_index(drop=True)

aq = aq.sort_values(['station_id'])
print(aq)
```

```
        Unnamed: 0 MeasurementDateGMT station_id  PM2.5 (ug/m3)  PM10 (ug/m3)
NO2 (ug/m3)
16344         5447    2017/8/15 23:00        BL0            8.3           16.3
77.5
14534         3637     2017/6/1 13:00        BL0            8.5           12.1
13.6
14533         3636     2017/6/1 12:00        BL0            9.7           12.0
18.1
14532         3635     2017/6/1 11:00        BL0            7.9           12.2
18.1
14531         3634     2017/6/1 10:00        BL0            5.2           15.3
18.4
...            ...                ...        ...            ...            ...
...
134398        3634     2017/6/1 10:00        TH4            4.9           19.2
46.8
134399        3635     2017/6/1 11:00        TH4            4.5           18.3
50.0
134400        3636     2017/6/1 12:00        TH4            5.9           19.9
47.1
134392        3628      2017/6/1 4:00        TH4           10.1           23.2
47.3
```

```
141660       10896     2018/3/31 0:00        TH4            NaN           NaN
NaN

[141661 rows x 6 columns]
```

Nous remarquons que les dates de aq et location ne sont malheureusement pas sous le même format. De plus nous voyons également qu'elles ne correspondent pas aux dates voulues. Pour cela nous allons utiliser deux fonctions que nous avons écrite:

1. getMeoTime(time): Cette fonction prends en argument la date de la prise de mesure dans la dataFrame aq et la traduit pour avoir la même forme de date que meo. Nous itérons donc sur les éléments de "*MeasurementDateGMT*", les traduisons et les remettons à leurs place. Ainsi toutes les dates auront le même format.
2. daterange(date1,date2): Cette fonction nous permet de prendre les données uniquement dans les dates voulues.

[32]:
```
from datetime import timedelta, date, datetime
#2017-01-01 00:00:00
def getMeoTime(time):
  try:
    r = datetime.strptime(time+":00",'%Y/%m/%d %H:%M:%S').strftime('%Y-%m-%d %H:
↪%M:%S')
    return r
  except:
    return time

def daterange(date1, date2):
    for m in range(int ((date2 - date1).days)+1):
        for n in range(24):
            yield date1 + timedelta(days=m,hours=n)

# On prend la partie qui nous interrese
for x in range(aq.shape[0]):
  #print(aq.at[x,'MeasurementDateGMT'])
  aq.at[x,'MeasurementDateGMT']= getMeoTime(aq.at[x,'MeasurementDateGMT'])
aq = aq.sort_values(['MeasurementDateGMT'])
start_dt = datetime(2017, 1, 1, 0, 0, 0)
end_dt = datetime(2018, 3, 22, 23, 0, 0)
ran = daterange(start_dt, end_dt)
times = [r.strftime("%Y-%m-%d %H:%M:%S") for r in ran]

aq = aq.loc[(aq.MeasurementDateGMT >= times[0]) & (aq.MeasurementDateGMT <=␣
↪times[-1])]
meo = meo.loc[(meo.utc_time >= times[0]) & (meo.utc_time <= times[-1])]
aq = aq.sort_values(['station_id','MeasurementDateGMT'])
aq = aq.reset_index(drop=True)
meo = meo.reset_index(drop=True)
print(aq)
```

```python
print(meo)
```

```
       Unnamed: 0   MeasurementDateGMT station_id  PM2.5 (ug/m3)  PM10 (ug/m3)
NO2 (ug/m3)
0               0  2017-01-01 00:00:00        BL0           30.8          31.6
10.8
1               1  2017-01-01 01:00:00        BL0           22.9          34.6
17.3
2               2  2017-01-01 02:00:00        BL0           18.4          25.2
14.2
3               3  2017-01-01 03:00:00        BL0           19.5          24.0
14.8
4               4  2017-01-01 04:00:00        BL0           22.1          26.7
16.7
...           ...                  ...        ...            ...           ...
...
139147      10699  2018-03-22 19:00:00        TH4            9.6          16.3
47.1
139148      10700  2018-03-22 20:00:00        TH4           10.6          10.4
41.6
139149      10701  2018-03-22 21:00:00        TH4            9.9          12.5
38.1
139150      10702  2018-03-22 22:00:00        TH4            6.7          18.4
61.0
139151      10703  2018-03-22 23:00:00        TH4            6.2          13.2
50.0

[139152 rows x 6 columns]
             stationName  longitude  latitude            utc_time  temperature
pressure  humidity  wind_direction  wind_speed/kph
0        london_grid_000       -2.0      50.5  2017-01-01 00:00:00         9.36
1024.81     77.90          250.88           23.74
1        london_grid_001       -2.0      50.6  2017-01-01 00:00:00         9.09
1024.25     78.96          249.86           21.81
2        london_grid_002       -2.0      50.7  2017-01-01 00:00:00         8.30
1022.55     82.13          245.35           16.08
3        london_grid_003       -2.0      50.8  2017-01-01 00:00:00         7.50
1020.86     85.30          235.98           10.55
4        london_grid_004       -2.0      50.9  2017-01-01 00:00:00         6.92
1015.89     88.51          228.21           10.97
...                  ...        ...       ...                 ...          ...
...       ...             ...               ...
9216139  london_grid_856        2.0      52.1  2018-03-22 23:00:00         7.14
1011.51     77.65          238.95           26.70
9216140  london_grid_857        2.0      52.2  2018-03-22 23:00:00         7.07
1011.33     77.93          237.09           25.65
9216141  london_grid_858        2.0      52.3  2018-03-22 23:00:00         6.97
```

```
1011.16     78.26          235.45          24.75
9216142  london_grid_859        2.0      52.4  2018-03-22 23:00:00         6.86
1011.00     78.59          233.69          23.87
9216143  london_grid_860        2.0      52.5  2018-03-22 23:00:00         6.82
1010.95     78.70          233.07          23.58

[9216144 rows x 9 columns]
```

Dans la dataFrame aq il manque également les coordonmées des stations. Nous allons donc ajouter les coordonées qui correspondent en fonction de leur nom en utisant la dataFrame location. Pour cela nous utilisons la fonction numpy select qui nous permet de choisir la longitude en fonction du nom de la station. Par exemple, pour la latitude on choisit la sation qui correspond à la position true dans choice. On fait pareil longitude et affichons la nouvelle version d'aq.

[33]:
```python
import numpy as np

conditions = [(aq["station_id"] == location.at[0,'Unnamed:␣
↪0']),(aq["station_id"] == location.at[1,'Unnamed: 0']),
              (aq["station_id"] == location.at[2,'Unnamed:␣
↪0']),(aq["station_id"] == location.at[3,'Unnamed: 0']),
              (aq["station_id"] == location.at[4,'Unnamed:␣
↪0']),(aq["station_id"] == location.at[5,'Unnamed: 0']),
              (aq["station_id"] == location.at[6,'Unnamed:␣
↪0']),(aq["station_id"] == location.at[7,'Unnamed: 0']),
              (aq["station_id"] == location.at[8,'Unnamed:␣
↪0']),(aq["station_id"] == location.at[9,'Unnamed: 0']),
              (aq["station_id"] == location.at[10,'Unnamed:␣
↪0']),(aq["station_id"] == location.at[11,'Unnamed: 0']),
              (aq["station_id"] == location.at[12,'Unnamed: 0'])]
choices = location['Latitude']
aq['Latitude'] = np.select(conditions,choices,default=1)
choices = location['Longitude']
aq['Longitude'] = np.select(conditions,choices,default=1)
try:
  aq = aq.drop('Unnamed: 0', 1)
except:
  pass
print(aq)
```

```
         MeasurementDateGMT station_id  PM2.5 (ug/m3)  PM10 (ug/m3)  NO2 (ug/m3)
Latitude  Longitude
0        2017-01-01 00:00:00        BL0           30.8          31.6         10.8
51.522287  -0.125848
1        2017-01-01 01:00:00        BL0           22.9          34.6         17.3
51.522287  -0.125848
2        2017-01-01 02:00:00        BL0           18.4          25.2         14.2
51.522287  -0.125848
3        2017-01-01 03:00:00        BL0           19.5          24.0         14.8
```

```
51.522287  -0.125848
4       2017-01-01 04:00:00        BL0          22.1          26.7          16.7
51.522287  -0.125848
...                     ...        ...           ...           ...           ...
...         ...
139147  2018-03-22 19:00:00        TH4           9.6          16.3          47.1
51.515046  -0.008418
139148  2018-03-22 20:00:00        TH4          10.6          10.4          41.6
51.515046  -0.008418
139149  2018-03-22 21:00:00        TH4           9.9          12.5          38.1
51.515046  -0.008418
139150  2018-03-22 22:00:00        TH4           6.7          18.4          61.0
51.515046  -0.008418
139151  2018-03-22 23:00:00        TH4           6.2          13.2          50.0
51.515046  -0.008418

[139152 rows x 7 columns]
```

Maintenant que nous avons la bonne forme dans aq il faut qu'on trouve un moyen pour faire correspondre chaque station de mesure de pollution à une station de mesure de la météo. Pour cela, nous allons chercher les valeurs qui correspondent le plus dans les coordonées de manière à avoir la météo qu'il faisait à la station de mesure. Pour cela, nous créons la fonction nearestValue. Cette fonction nous permet de trouver les valeurs les plus proches dans deux listes. Nous créons donc une variable allValue qui nous permettera donc de savoir quelle lagitude et longitutde prendre.

[34]:
```
from functools import partial

# Calcule la valeur la plus proche pour une pair de valeur dans une liste de␣
↪duplet
def nearestValue(liste,value):
  dist=lambda s,d: (s[0]-d[0])**2+(s[1]-d[1])**2
  return min(liste, key=partial(dist, value))

# Maintenant on veux trouver la latitude et la longitude la plus proche de meo␣
↪dans aq pour récuperer les donnés météo correspondant
A = meo["longitude"]
B = meo["latitude"]
C = list(zip(A, B))


#On récupere toute les valeurs de longitude et latitude
D = location["Longitude"]
E = location["Latitude"]
F = list(zip(D,E))

allValue = [nearestValue(C,[float(element[0]),float(element[1])]) for element in␣
↪F]
```

On va maintenant essayer d'avoir la météo dans aq. Pour cela nous commencons par supprimer tous les éventuels doublons.

[35]:
```
if not aq.index.name == 'MeasurementDateGMT':
    aq = aq.set_index(['MeasurementDateGMT'])

aq_concat = aq[aq.station_id == aq.station_id.unique()[0]]

stations = aq.station_id.unique()[1:]
aq_concat = aq_concat.loc[~aq_concat.index.duplicated(keep='first')]



for i in range(1,13):
  aq_concat2 = aq[aq.station_id == aq.station_id.unique()[i]]
  aq_concat = aq_concat.append(aq_concat2.loc[~aq_concat2.index.
 ↪duplicated(keep='first')])
times = aq_concat.index
aq = aq_concat # On enleve les duplciation dans aq
location = location.reset_index(drop=True)
```

Nous allons à présent ajouter les éléments de la météo dans aq. Pour cela, nous créons une variable intermédiaire appelée station1. Dans cette dataFrame nous ajoutons les valeur de aq et nous ajoutons les valeurs contenues dans météo pour les coordonées les plus proches à l'aide de la variable allValue qui contient les paire de valeur de coordonées les plus proches. Nous copions ensuite la variable intermédiare dans aq de manière à pouvoir continuer à travailler avec.

[36]:
```
stationBool = aq['Longitude'] == location['Longitude'][0]
stationBool2 = aq['Latitude'] == location['Latitude'][0]
station1 = aq[stationBool & stationBool2]
meoBool = meo['longitude'] == allValue[0][0]
meoBool2 = meo['latitude'] == allValue[0][1]
meo1 = meo[meoBool & meoBool2]

station1 = station1.reset_index(drop=True)

meo1 = meo1.reset_index(drop=True)
station1 = pd.concat([station1,␣
 ↪meo1[["temperature",'pressure','humidity','wind_direction','wind_speed/
 ↪kph']]], axis=1)


for i in range(1,13):
  stationBool = aq['Longitude'] == location['Longitude'][i]
  stationBool2 = aq['Latitude'] == location['Latitude'][i]
  stationPart = aq[stationBool & stationBool2]
  meoBool = meo['longitude'] == allValue[i][0]
  meoBool2 = meo['latitude'] == allValue[i][1]
```

```
    meoPart = meo[meoBool & meoBool2]
    stationPart = stationPart.reset_index(drop=True)

    meoPart = meoPart.reset_index(drop=True)
    station1 = station1.append(pd.concat([stationPart,␣
 ↪meoPart[["temperature",'pressure','humidity','wind_direction','wind_speed/
 ↪kph']]], axis=1))

station1 = station1.reset_index(drop=True)

aq = station1.copy()
print(aq)
```

```
       station_id  PM2.5 (ug/m3)  PM10 (ug/m3)  NO2 (ug/m3)   Latitude
Longitude  temperature  pressure  humidity  wind_direction  wind_speed/kph
0             BL0           30.8          31.6         10.8  51.522287
-0.125848        5.80   1019.93     91.38         221.79           15.57
1             BL0           22.9          34.6         17.3  51.522287
-0.125848        5.84   1018.73     89.96         220.34           16.49
2             BL0           18.4          25.2         14.2  51.522287
-0.125848        5.89   1017.53     88.54         219.03           17.41
3             BL0           19.5          24.0         14.8  51.522287
-0.125848        5.93   1016.33     87.12         217.86           18.35
4             BL0           22.1          26.7         16.7  51.522287
-0.125848        6.12   1015.38     87.54         216.18           18.78
...           ...            ...           ...          ...        ...
...          ...        ...       ...             ...            ...
139147        MY7            NaN           NaN          NaN  51.522540
-0.154590        7.47   1010.65     64.17         243.47           17.38
139148        MY7            NaN           NaN          NaN  51.522540
-0.154590        7.23   1010.07     65.13         236.05           17.38
139149        MY7            NaN           NaN          NaN  51.522540
-0.154590        6.98   1009.50     66.09         228.75           17.67
139150        MY7            NaN           NaN          NaN  51.522540
-0.154590        6.73   1008.32     69.13         220.19           18.01
139151        MY7            NaN           NaN          NaN  51.522540
-0.154590        6.49   1007.14     72.17         212.11           18.73

[139152 rows x 11 columns]
```

Comme nous avons perdu la date, nous la remetons manuellement depuis une sauvegarde faite plus haut.

[37]:
```
try:
    aq.insert(0, 'utc_time', times)
except:
    pass
aq = aq.sort_values(['utc_time','station_id'])
```

```python
aq = aq.reset_index(drop=True)
print(aq)
```

```
                    utc_time station_id  PM2.5 (ug/m3)  PM10 (ug/m3)  NO2 (ug/m3)
Latitude  Longitude  temperature  pressure  humidity  wind_direction
wind_speed/kph
0       2017-01-01 00:00:00        BL0          30.8          31.6         10.8
51.522287  -0.125848         5.80   1019.93     91.38          221.79
15.57
1       2017-01-01 00:00:00        CD1          40.0          44.4         36.6
51.544219  -0.175284         5.91   1019.61     90.76          221.29
15.91
2       2017-01-01 00:00:00        CD9          28.7          32.3         90.6
51.527707  -0.129053         5.80   1019.93     91.38          221.79
15.57
3       2017-01-01 00:00:00        GN0          50.7          63.3         24.7
51.490532   0.074003         5.61   1020.16     92.41          223.73
15.04
4       2017-01-01 00:00:00        GN3          59.6          47.5         18.4
51.486957   0.095111         5.61   1020.16     92.41          223.73
15.04
...                     ...        ...           ...           ...          ...
...        ...          ...        ...       ...            ...            ...
139147  2018-03-22 23:00:00        KF1           6.4          10.2          NaN
51.521047  -0.213492         6.49   1007.14     72.17          212.11
18.73
139148  2018-03-22 23:00:00        LW2           9.7           NaN          NaN
51.474954  -0.039641         6.49   1007.66     71.23          215.59
17.60
139149  2018-03-22 23:00:00        MY7           NaN           NaN          NaN
51.522540  -0.154590         6.49   1007.14     72.17          212.11
18.73
139150  2018-03-22 23:00:00        ST5           7.0          11.0         28.4
51.389287  -0.141662         6.02   1003.41     75.70          213.74
18.32
139151  2018-03-22 23:00:00        TH4           6.2          13.2         50.0
51.515046  -0.008418         6.49   1007.66     71.23          215.59
17.60

[139152 rows x 12 columns]
```

3.3 Nettoyage et séparation des données

Comme nous voyons qu'il y a des donneées incomplètes, nous appliquons une interpolation directement sur la dataFrame afin d'avoir des donnèes complètes.

[38]:
```
print("before inter",aq.isnull().sum().sum())
aq = aq.interpolate(method="linear")
print("After",aq.isnull().sum().sum())
```

```
before inter 58176
After 0
```

On va maintenant séparer nos données en train et data. Toutes les données avant le 21 mars sont données en train et nous gardons les données du 21 et 22 mars pour le test

[39]:
```
aq = aq = aq.sort_values(['utc_time', 'station_id'])
if not aq.index.name == 'utc_time':
    aq = aq.set_index(['utc_time'])
x_trainDF = aq[aq.index < '2018-03-21']
x_testDF = aq[aq.index > '2018-03-21']
Y = aq[['PM2.5 (ug/m3)', 'PM10 (ug/m3)']]
y_trainDF = Y[aq.index < '2018-03-21']
y_testDF = Y[aq.index > '2018-03-21']
```

Nous obtenons donc les dataFrame suivantes:

[40]:
```
print(x_testDF)
print(x_trainDF)
print(y_trainDF)
print(y_testDF)
```

```
                    station_id  PM2.5 (ug/m3)  PM10 (ug/m3)  NO2 (ug/m3)
Latitude  Longitude  temperature  pressure  humidity  wind_direction
wind_speed/kph
utc_time
2018-03-21 00:00:00        BL0           8.40     21.400000         49.5
51.522287  -0.125848         2.44   1028.91     76.29           345.80
6.25
2018-03-21 00:00:00        CD1          11.10     26.600000         63.5
51.544219  -0.175284         2.45   1028.77     76.08           344.03
6.11
2018-03-21 00:00:00        CD9           9.00     26.100000         69.0
51.527707  -0.129053         2.44   1028.91     76.29           345.80
6.25
2018-03-21 00:00:00        GN0          12.50     25.900000         71.1
51.490532   0.074003         2.30   1028.89     77.49           347.47
6.79
2018-03-21 00:00:00        GN3          10.80     25.000000         82.9
51.486957   0.095111         2.30   1028.89     77.49           347.47
6.79
...                        ...            ...           ...          ...
...        ...          ...       ...       ...              ...            ...
2018-03-22 23:00:00        KF1           6.40     10.200000         25.1
51.521047  -0.213492         6.49   1007.14     72.17           212.11
```

```
18.73
2018-03-22 23:00:00        LW2          9.70    10.466667          26.2
51.474954  -0.039641         6.49   1007.66     71.23          215.59
17.60
2018-03-22 23:00:00        MY7          8.35    10.733333          27.3
51.522540  -0.154590         6.49   1007.14     72.17          212.11
18.73
2018-03-22 23:00:00        ST5          7.00    11.000000          28.4
51.389287  -0.141662         6.02   1003.41     75.70          213.74
18.32
2018-03-22 23:00:00        TH4          6.20    13.200000          50.0
51.515046  -0.008418         6.49   1007.66     71.23          215.59
17.60

[624 rows x 11 columns]
                   station_id  PM2.5 (ug/m3)  PM10 (ug/m3)  NO2 (ug/m3)
Latitude  Longitude  temperature  pressure  humidity  wind_direction
wind_speed/kph
utc_time
2017-01-01 00:00:00        BL0          30.8          31.6         10.80
51.522287  -0.125848         5.80   1019.93     91.38          221.79
15.57
2017-01-01 00:00:00        CD1          40.0          44.4         36.60
51.544219  -0.175284         5.91   1019.61     90.76          221.29
15.91
2017-01-01 00:00:00        CD9          28.7          32.3         90.60
51.527707  -0.129053         5.80   1019.93     91.38          221.79
15.57
2017-01-01 00:00:00        GN0          50.7          63.3         24.70
51.490532   0.074003         5.61   1020.16     92.41          223.73
15.04
2017-01-01 00:00:00        GN3          59.6          47.5         18.40
51.486957   0.095111         5.61   1020.16     92.41          223.73
15.04
...                        ...            ...           ...           ...
...        ...          ...       ...       ...              ...            ...
2018-03-20 23:00:00        KF1           8.6          16.5         51.35
51.521047  -0.213492         2.87   1028.61     73.35          353.77
6.57
2018-03-20 23:00:00        LW2          11.9          29.4         44.30
51.474954  -0.039641         2.85   1028.88     73.43          355.98
7.04
2018-03-20 23:00:00        MY7           7.0          20.5         37.25
51.522540  -0.154590         2.87   1028.61     73.35          353.77
6.57
2018-03-20 23:00:00        ST5           7.0          16.0         30.20
51.389287  -0.141662         1.63   1024.31     79.40          353.20
7.32
```

```
2018-03-20 23:00:00        TH4           13.4          36.0         85.20
51.515046  -0.008418          2.85    1028.88     73.43           355.98
7.04

[138528 rows x 11 columns]
                     PM2.5 (ug/m3)  PM10 (ug/m3)
utc_time
2017-01-01 00:00:00           30.8          31.6
2017-01-01 00:00:00           40.0          44.4
2017-01-01 00:00:00           28.7          32.3
2017-01-01 00:00:00           50.7          63.3
2017-01-01 00:00:00           59.6          47.5
...                            ...           ...
2018-03-20 23:00:00            8.6          16.5
2018-03-20 23:00:00           11.9          29.4
2018-03-20 23:00:00            7.0          20.5
2018-03-20 23:00:00            7.0          16.0
2018-03-20 23:00:00           13.4          36.0

[138528 rows x 2 columns]
                     PM2.5 (ug/m3)  PM10 (ug/m3)
utc_time
2018-03-21 00:00:00           8.40     21.400000
2018-03-21 00:00:00          11.10     26.600000
2018-03-21 00:00:00           9.00     26.100000
2018-03-21 00:00:00          12.50     25.900000
2018-03-21 00:00:00          10.80     25.000000
...                            ...           ...
2018-03-22 23:00:00           6.40     10.200000
2018-03-22 23:00:00           9.70     10.466667
2018-03-22 23:00:00           8.35     10.733333
2018-03-22 23:00:00           7.00     11.000000
2018-03-22 23:00:00           6.20     13.200000

[624 rows x 2 columns]
```

Nous allons maintenant mettre toutes les données sur une seule ligne par heure afin d'avoir une prédiction par heure. Pour celà, nous faisons une reshape des dataFrame de manière à ce que pour chaque heure nous ayons toutes les données sur une seule ligne.

Ensuite nous supprimons le dernier éléments des x et le premier des y de manière à ce que les y ait une heure d'avance sur les x. Ainsi le but est de prédire le taux de pollution à une heure précise en fonction de l'heure d'avant.

[41]:
```python
import numpy as np
def reshape(frame, nbStation=13):
  return frame.to_numpy().reshape(int(frame.shape[0]/nbStation),nbStation*frame.
 ↪shape[1])
```

```
try:
  x_trainDF = x_trainDF.drop(['station_id',],axis=1)
except:
  pass
try:
  x_testDF = x_testDF.drop(['station_id'],axis=1)
except:
  pass

x_train = reshape(x_trainDF)
x_test = reshape(x_testDF)
y_test = reshape(y_testDF)
y_train = reshape(y_trainDF)

x_train = np.delete(x_train,-1,0)
x_test = np.delete(x_test,-1,0)
y_train = np.delete(y_train,0,0)
y_test = np.delete(y_test,0,0)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(10655, 130)
(47, 130)
(10655, 26)
(47, 26)
```

3.4 Modèle

Dans cette partie nous allons comparer plusieurs modèles et utiliseront la fonction suivante pour analyser leur résultats

[42]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, median_absolute_error,␣
↪accuracy_score
def plot_model_prediction(mod):

    prediction = mod.predict(x_test)

    print("Test")
    print("The Explained Variance: %.2f" % mod.score(x_test, y_test))
    print("The Mean Absolute Error: %.2f " % mean_absolute_error(y_test,␣
↪prediction))
    print("The Median Absolute Error: %.2f" % median_absolute_error(y_test,␣
↪prediction))
```

```
    print("Train")
    pred_train = mod.predict(x_train)
    print("The Explained Variance: %.2f" % mod.score(X_train, y_train))
    print("The Mean Absolute Error: %.2f " % mean_absolute_error(y_train,␣
↪pred_train))
    print("The Median Absolute Error: %.2f" % median_absolute_error(y_train,␣
↪pred_train))

    y_prediction = np.copy(y_test)
    y_prediction[:] = prediction

    fig=plt.figure(figsize=(13, 13), dpi= 80, facecolor='w', edgecolor='k')
    plt.plot(y_test)
    plt.show()

    fig=plt.figure(figsize=(13, 13), dpi= 80, facecolor='w', edgecolor='k')
    plt.plot(y_prediction)
    plt.show()
```

3.4.1 Régression linéaire

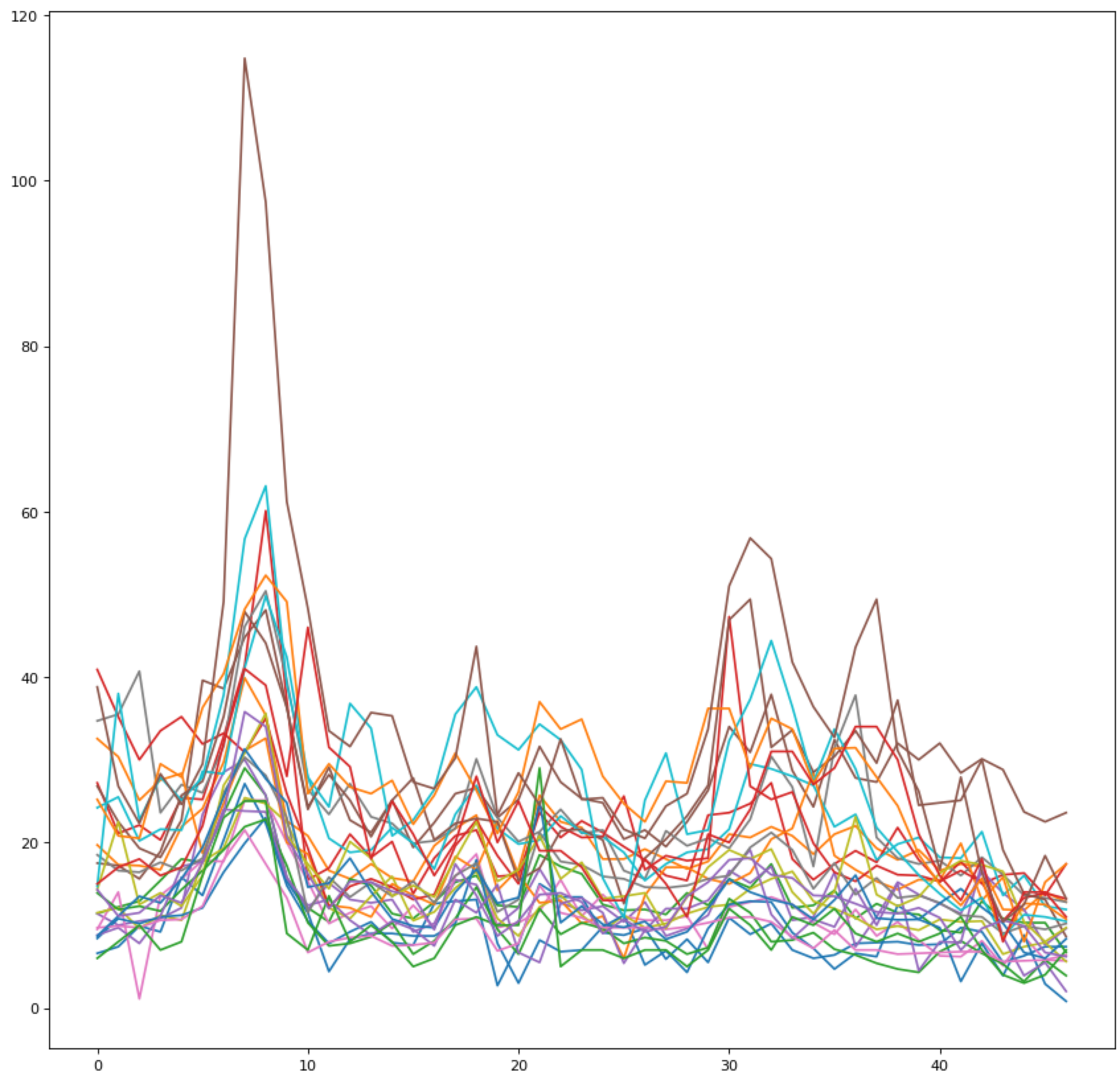
Le principe de la régression est de classfier en faisant une regréssion linéaire entre les différentes catégories

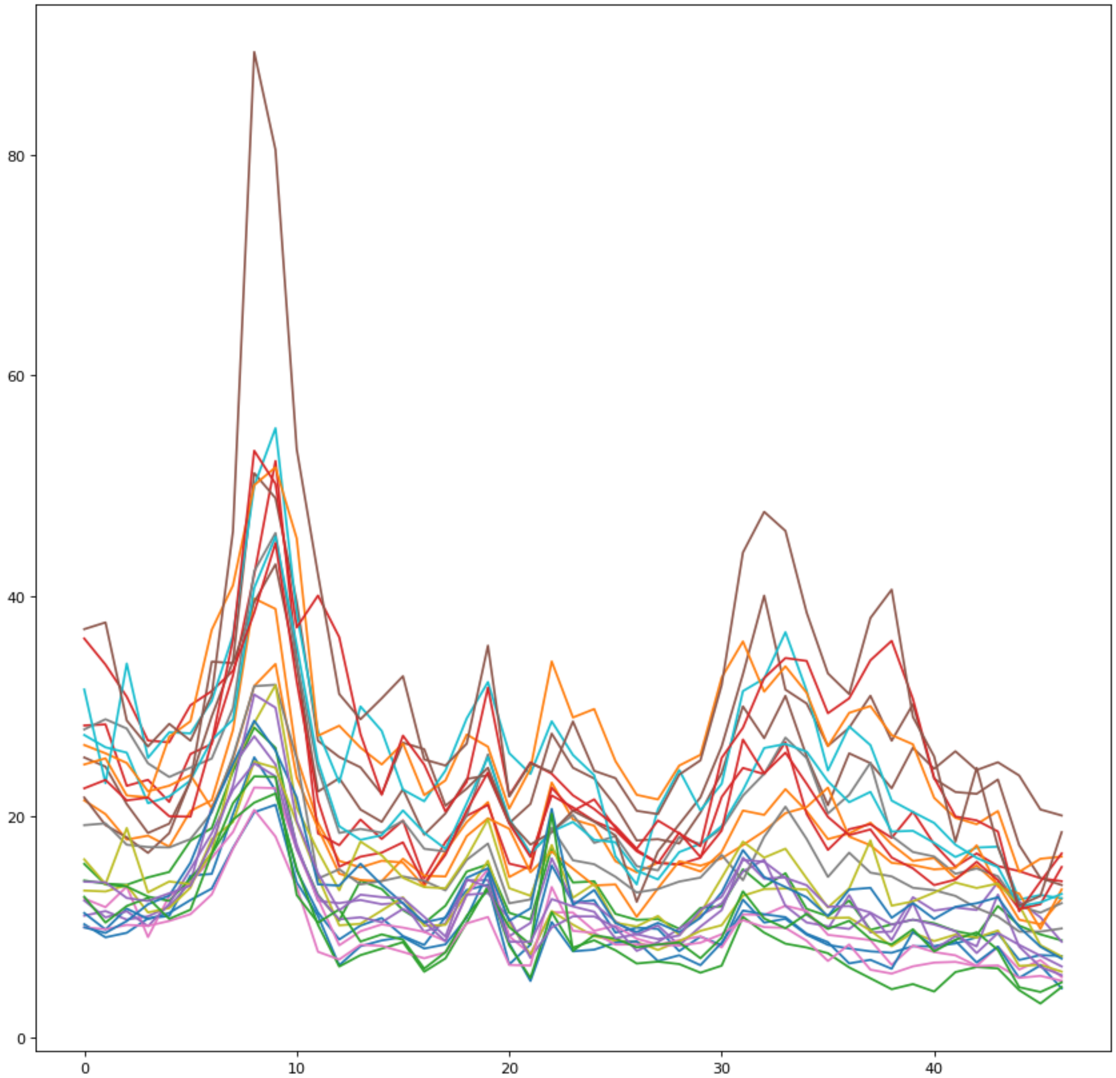
[43]:
```
from sklearn.linear_model import LinearRegression

regr = LinearRegression()
X_train = x_train
regr.fit(X_train, y_train)

plot_model_prediction(regr)
```

```
Test
The Explained Variance: 0.48
The Mean Absolute Error: 3.50
The Median Absolute Error: 2.66
Train
The Explained Variance: 0.85
The Mean Absolute Error: 2.90
The Median Absolute Error: 2.08
```

```
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
```

```
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
```





Nous voyons qu'à priori ce modèle semble relativement bien fonctionner avec une erreur moyenne de 3.5 lors des tests.

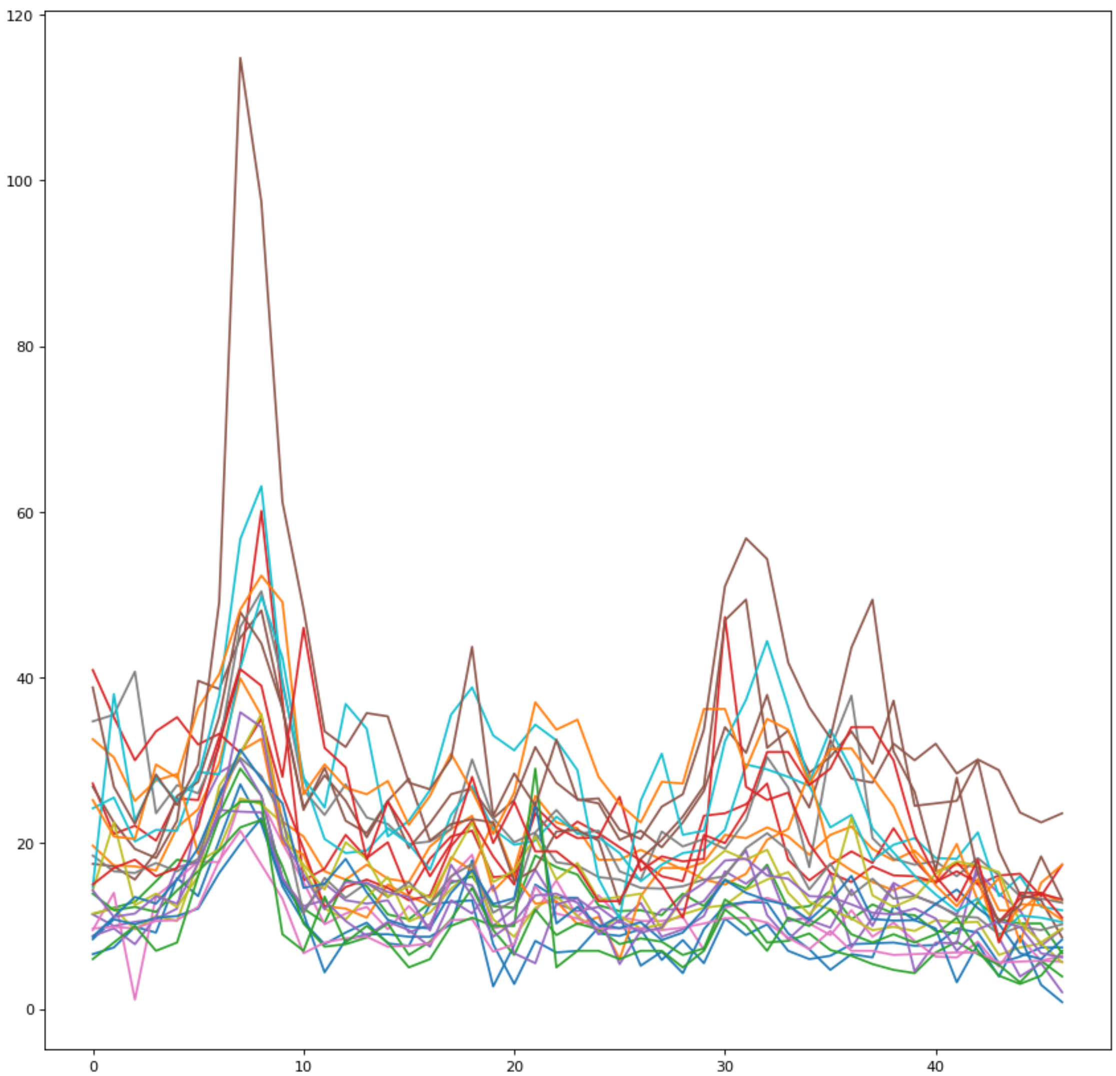
3.4.2 Neural network MLPRegressor

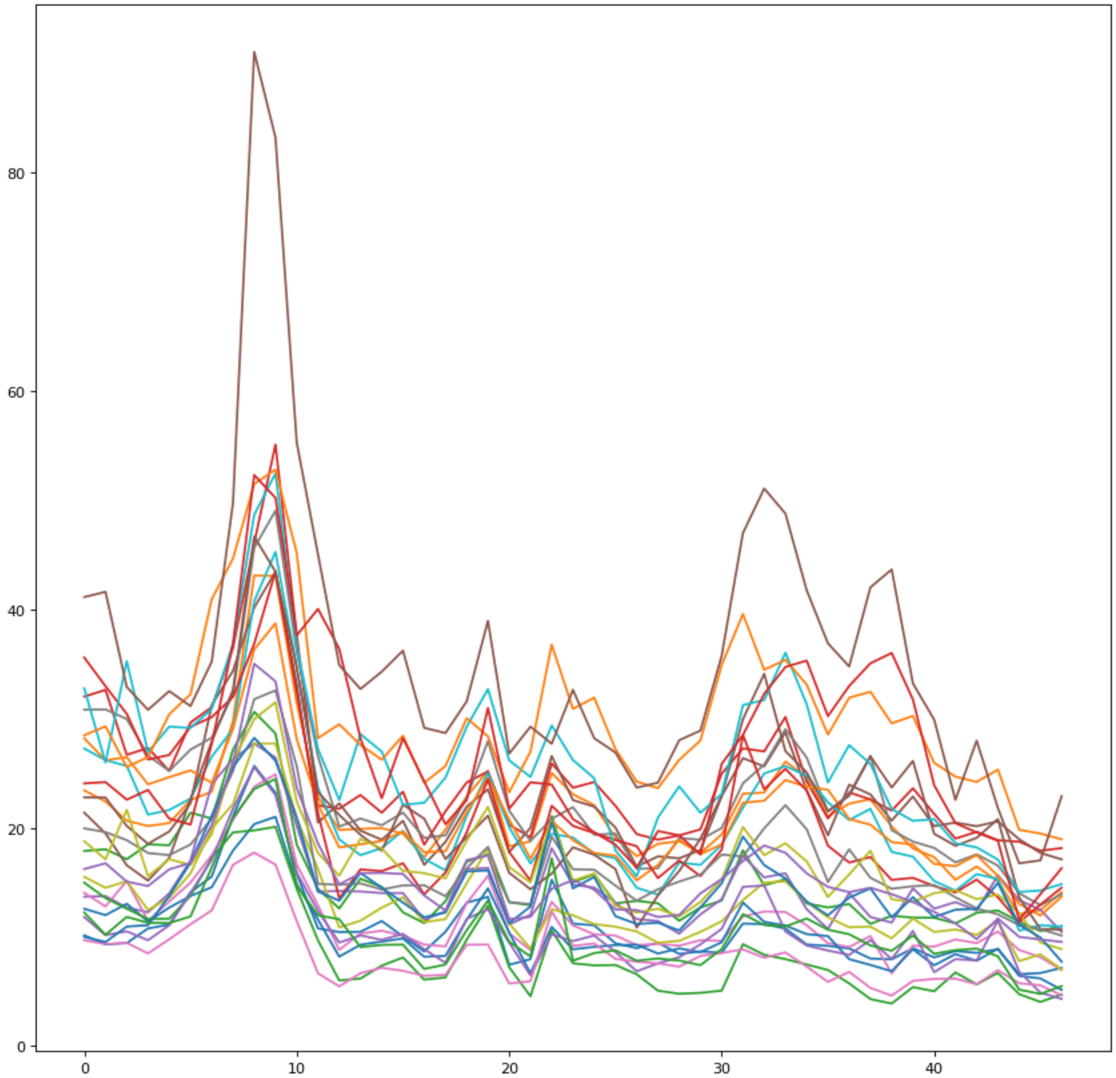
C'est modèle qui utilise un perceptron à plusieurs étage et qui cherche à optimiser le MSE

[44]:
```
from sklearn.neural_network import MLPRegressor

regr_2 = MLPRegressor(random_state=1, max_iter=1000) # Vary hidden nodes
regr_2.fit(X_train, y_train)

plot_model_prediction(regr_2)
```

```
Test
The Explained Variance: 0.44
The Mean Absolute Error: 3.77
The Median Absolute Error: 3.02
Train
The Explained Variance: 0.82
The Mean Absolute Error: 3.39
The Median Absolute Error: 2.64
```

```
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
```


120
100
80
60
40
20
0
0
10
20
30
40



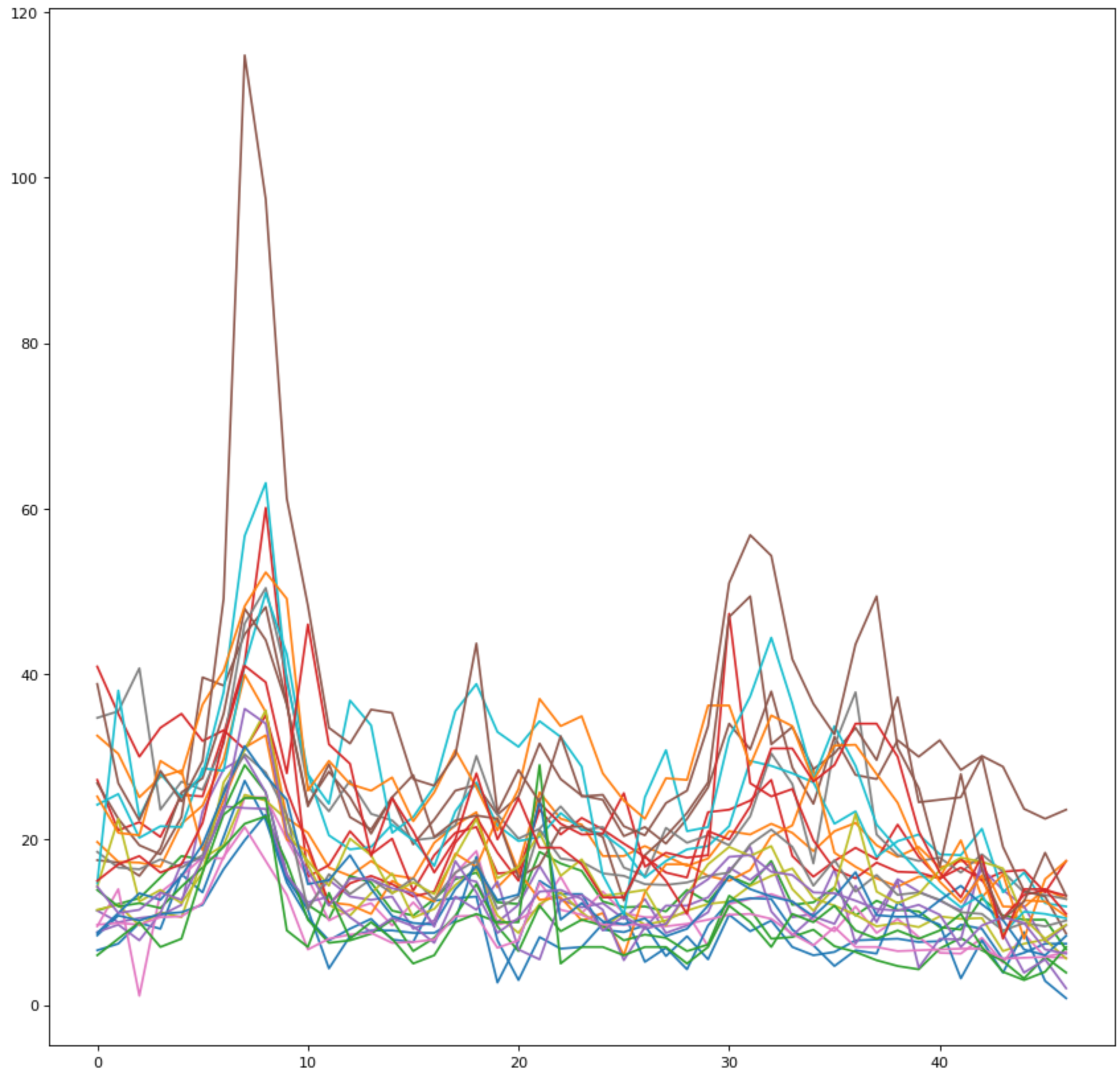
Nous voyons qu'avec une erreure moyenne de 3.77 lors du test, ce modèle est assez performant.

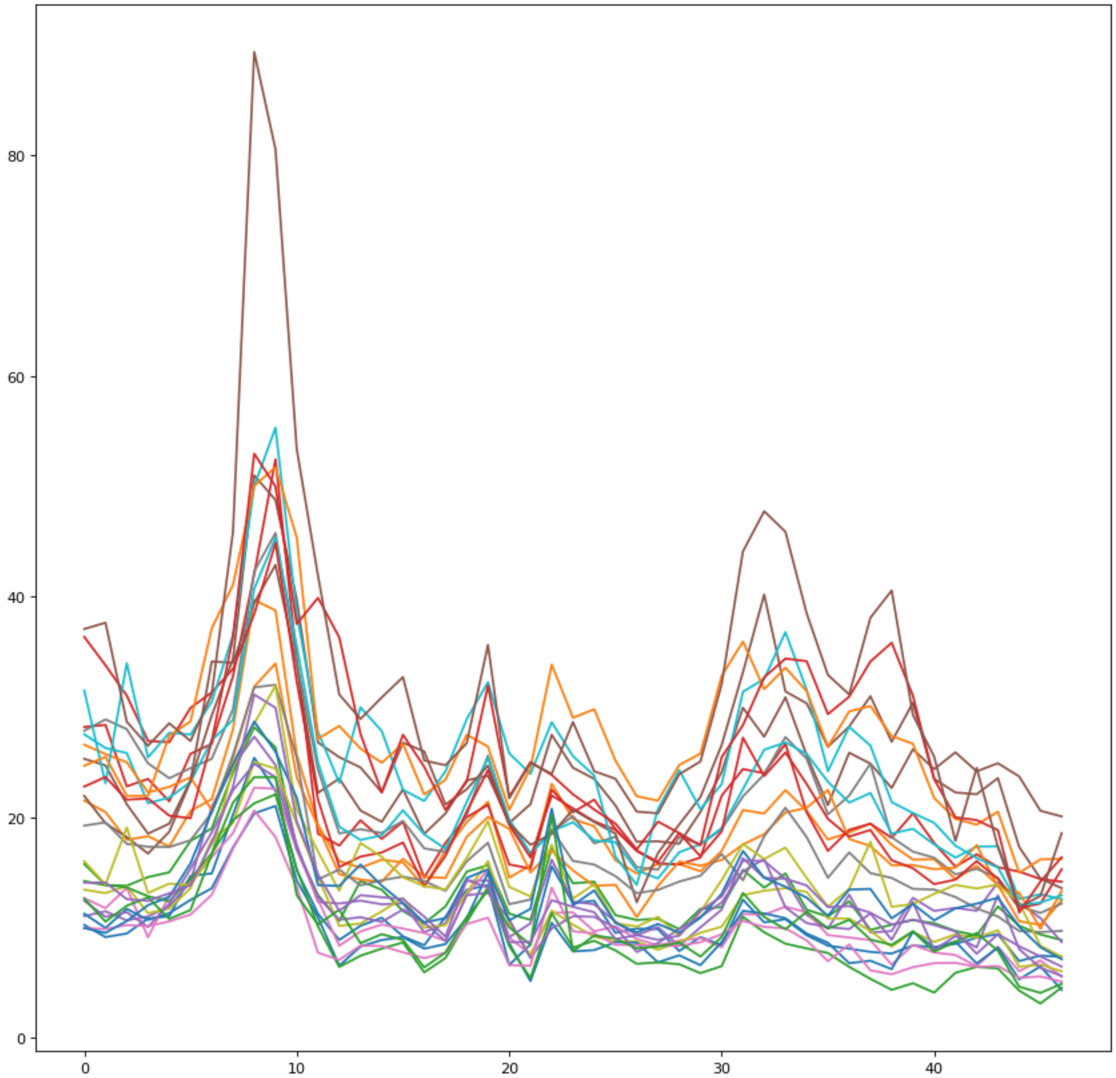
3.4.3 Ridge regression (MultiOutputRegressor)

C'est une regression mutlti cible. Cette stratégie consite à fitter un regresseur par cible. C'est une stratégie pour étendre des régresseurs qui ne supportent pas plusieurs cibles comme c'est le cas ici (On cherche à estimer plus d'un paramètre)

[45]:
```
from sklearn.multioutput import MultiOutputRegressor
from sklearn.linear_model import Ridge
regr_3 = MultiOutputRegressor(Ridge(random_state=123)).fit(x_train, y_train)

plot_model_prediction(regr_3)
```

```
Test
The Explained Variance: 0.46
The Mean Absolute Error: 3.50
The Median Absolute Error: 2.67
Train
The Explained Variance: 0.86
The Mean Absolute Error: 2.90
The Median Absolute Error: 2.08
```





3.5 Cross validation et statistical significant tests

Nous commencons par effectuer la cross-validation. Ceci consiste à séparer notre ensemble de données en plusieurs paire d'ensemble [test,train]. De cette manière on peut mesurer l'efficacité d'un modèle sur plusieurs ensembles de test train.

[46]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn import metrics

scoresRegr = cross_val_score(regr, x_train, y_train)
scoresRegr2 = cross_val_score(regr_2, x_train, y_train)
scoresRegr3 = cross_val_score(regr_3, x_train, y_train)

print("Score regression linéaire",scoresRegr)
```

```python
print("Score regression MlPregressor",scoresRegr2)
print("Score regression Ridge regression",scoresRegr3)
```

```
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
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  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
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multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
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'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
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'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
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'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
The default value of multioutput (not exposed in score method) will change from
'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
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```

```
please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
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  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
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'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
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'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
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'variance_weighted' to 'uniform_average' in 0.23 to keep consistent with
'metrics.r2_score'. To specify the default value manually and avoid the warning,
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'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
C:\Users\mathi\anaconda3\lib\site-packages\sklearn\base.py:434: FutureWarning:
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  "multioutput='uniform_average').", FutureWarning)
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please either call 'metrics.r2_score' directly or make a custom scorer with
'metrics.make_scorer' (the built-in scorer 'r2' uses
multioutput='uniform_average').
  "multioutput='uniform_average').", FutureWarning)
```

```
Score regression linéaire [0.89872761 0.61239018 0.69088577 0.77132658 0.8453092
]
Score regression MlPregressor [0.88401098 0.60798505 0.62874834 0.74654544
0.81524443]
Score regression Ridge regression [0.90261816 0.72034877 0.71494993 0.8166383
0.85396259]
```

On voit que la cross validation permet de voir que les modèles n'ont pas les mêmes performances en fonction des des données de test et d'entraînement. Par exemple, la régression linéaire à un score de 90% sur le premier ensemble contre seulement de 60 % sur le deuxième.

[47]:
```
#between linear and MLPRegressor
from scipy.stats import pearsonr
stat, p = pearsonr(scoresRegr, scoresRegr2)
print(p)
```

```
0.002675103606793419
```

[48]:
```
# between linear and MultiOutputRegressor
from scipy.stats import pearsonr
stat, p = pearsonr(scoresRegr, scoresRegr3)
print(p)
```

```
0.00884277675965391
```

[49]:
```
#between MultiOutputRegressor and MLPRegressor
from scipy.stats import pearsonr
stat, p = pearsonr(scoresRegr3, scoresRegr2)
print(p)
```

```
0.00043310498335152615
```

4 Conclusion

En conclusion dans ce travail nous avons travaillés avec deux ensembles de données: Bejing et Londre. Nous avons manipulé ces données afin d'avoir les données voulue dans la forme voulue afin d'appliques des modèles de prédictions. Pour chacunes des données nous avons comparé trois modèles différents. Nous allons maintenant analyser le résultat. Après avoir travaillé sur les données de Bejing et Londres de manières à les rendres utilisables, nous avons utiliser trois modèles différents:

1. Régression linéaire
2. MLPregressor
3. MultiOutPut Regressor.

Nous remarquons que les multiOutPut regressor est le plus performant pour les données de Bejing.

Dans le cas de Londres le modèle le plus performant sont la regréssion linéaire et le multiOutPut regressor.

Cependant, dans le cas de Londres les modèles sont semblables aux résutats des significant tests. Cela peut être due à une mauvaise interpolation des données manquantes.