Global Analysis

February 15, 2023

Air Quality in Catalonia challenge is asking participants to use the data from the Catalan Transparency Portal to analyze the evolution of air pollution in Catalonia over the past three decades and develop algorithms to predict air pollutant concentrations. We provide a global analysis of air quality, build algorithms to predict air pollutant concentrations, and write a final report.

0.1 Import Libraries

First, we import the libraries: matplotlib and seaborn for visualisation; pandas for data wrangling.

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

pd.set_option('display.max_columns', 25)
plt.rcParams["figure.figsize"] = [10, 6]
plt.style.use('fivethirtyeight')
```

0.2 Import Data

Next, we read the csv data and store it as pandas dataframe. We also display the data.

[2]:
```
df = pd.read_csv("9c820e0e5b3a4264aa5058f24a82386d.csv")
df
```

[2]:
```
         CODI EOI                 NOM ESTACIO        DATA  MAGNITUD  \
0        43148003       Tarragona (Bonavista)  25/01/2023        10
1         8137001      Montseny (La Castanya)  25/01/2023        12
2         8124009           Mollet del Vallès  25/01/2023         7
3         8114006                   Martorell  25/01/2023         7
4         8112003                     Manlleu  25/01/2023         8
…               …                           …           …         …
3106369   8125002           Montcada i Reixac  01/01/1991        14
3106370   8019004         Barcelona (Poblenou)  01/01/1991         1
3106371   8101001  L'Hospitalet de Llobregat  01/01/1991         6
3106372   8125002           Montcada i Reixac  01/01/1991         7
3106373   8101001  L'Hospitalet de Llobregat  01/01/1991        14

        CONTAMINANT UNITATS TIPUS ESTACIO AREA URBANA  CODI INE  \
0              PM10   µg/m3    industrial    suburban     43148
```

```
1                NOX   µg/m3    background       rural      8137
2                 NO   µg/m3       traffic    suburban      8124
3                 NO   µg/m3    background    suburban      8114
4                NO2   µg/m3    background    suburban      8112
…              …    …            …       …        …
3106369           O3   µg/m3       traffic    suburban      8125
3106370          SO2   µg/m3    background       urban      8019
3106371           CO   mg/m3    background       urban      8101
3106372           NO   µg/m3       traffic    suburban      8125
3106373           O3   µg/m3    background       urban      8101

                              MUNICIPI  CODI COMARCA        NOM COMARCA  …  \
0                            Tarragona            36         Tarragonès  …
1                             Montseny            41    Vallès Oriental  …
2                    Mollet del Vallès            41    Vallès Oriental  …
3                            Martorell            11     Baix Llobregat  …
4                              Manlleu            24              Osona  …
…                                    …         …                …   …
3106369              Montcada i Reixac            40  Vallès Occidental  …
3106370                      Barcelona            13         Barcelonès  …
3106371  Hospitalet de Llobregat, l'            13         Barcelonès  …
3106372              Montcada i Reixac            40  Vallès Occidental  …
3106373  Hospitalet de Llobregat, l'            13         Barcelonès  …

          17h   18h   19h    20h    21h    22h    23h   24h  ALTITUD  \
0        18.0  24.0  28.0   29.0   39.0   33.0   24.0  20.0       39
1        14.0   9.0   4.0    3.0    3.0    3.0    2.0   2.0      693
2         9.0  26.0  17.0    7.0   16.0   62.0   62.0  58.0       90
3         5.0   2.0   2.0    4.0    7.0    7.0    3.0   1.0       78
4        21.0  22.0  22.0   35.0   38.0   36.0   32.0  28.0      460
…       …    …    …     …     …     …     …    …        …
3106369  22.0  10.0   0.0    0.0    0.0    0.0    0.0   0.0       34
3106370  13.0  13.0  20.0   15.0   16.0   16.0   19.0  16.0        3
3106371   0.6   1.0   1.9    1.5    1.6    1.6    1.1   1.0       29
3106372   9.0  15.0  71.0  157.0  167.0  204.0  136.0  74.0       34
3106373  47.0  18.0   6.0   13.0   11.0    2.0   12.0  12.0       29

           LATITUD  LONGITUD                GEOREFERENCIA
0        41.115910  1.191999   POINT (1.1919986 41.11591)
1        41.779280  2.358002    POINT (2.358002 41.77928)
2        41.549183  2.212098  POINT (2.2120984 41.549183)
3        41.475384  1.921202  POINT (1.9212021 41.475384)
4        42.003307  2.287299  POINT (2.2872992 42.003307)
…              …       …                           …
3106369  41.481972  2.188298   POINT (2.188298 41.481972)
3106370  41.403878  2.204501   POINT (2.204501 41.403878)
3106371  41.370475  2.114999   POINT (2.114999 41.370475)
```

```
3106372  41.481972  2.188298   POINT (2.188298 41.481972)
3106373  41.370475  2.114999   POINT (2.114999 41.370475)

[3106374 rows x 40 columns]
```

Here are the most frequently used Cabin names:

[70]:
```python
df['NOM ESTACIO'].value_counts()
```

[70]:
```
Igualada                             75800
Constantí                            73536
Reus                                 72855
Tarragona (Bonavista)                72287
Vila-seca                            70140
                                     …
Veciana (estació agroalimentària)     2227
Viladecans                            1594
Sant Just Desvern (CEIP Montseny)     1357
Barcelona (Torre Girona)              1343
el Prat de Llobregat (Sant Cosme)       26
Name: NOM ESTACIO, Length: 116, dtype: int64
```

We display the most frequent 5-digit numeric code corresponding to the municipality (the first two digits correspond to the province, and the next three identify the Integer municipality)

[74]:
```python
df['CODI EOI'].value_counts()
```

[74]:
```
8102005     75800
43047001    73536
43123005    72855
43148003    72287
43171001    70140
            …
8297001      2227
8301002      1594
8221004      1357
8019056      1343
8169007        26
Name: CODI EOI, Length: 124, dtype: int64
```

We display the most frequent pollutants:

[75]:
```python
df['MAGNITUD'].value_counts()
```

[75]:
```
8      547242
7      546531
14     486801
1      452854
```

```
12     273300
6      266753
10     170283
65     147623
42      65304
3       57239
44      49797
30      16032
9       11424
11       6872
331      3577
53       3014
58       1728
Name: MAGNITUD, dtype: int64
```

We convert the data column to datetime and display the most frequent dates in the data:

[71]:
```python
df.DATA = pd.to_datetime(df.DATA, format="%d/%m/%Y")

df.DATA.value_counts()
```

[71]:
```
2021-10-25    368
2021-11-01    368
2021-10-11    368
2021-10-12    368
2021-10-13    368
             …
1991-02-23     25
1991-03-25     23
1991-01-01     22
1991-01-04     21
1991-01-08     19
Name: DATA, Length: 11713, dtype: int64
```

We create date features and one hot encode pollutants

[7]:
```python
df['year'] = df.DATA.dt.year
df['month'] = df.DATA.dt.month
df['day'] = df.DATA.dt.day

cols = ['01h', '02h', '03h', '04h', '05h', '06h', '07h', '08h',
       '09h', '10h', '11h', '12h', '13h', '14h', '15h', '16h', '17h', '18h',
       '19h', '20h', '21h', '22h', '23h', '24h']

df['sum_day'] = df[cols].sum(axis=1)

polutant_dummies = pd.get_dummies(df.MAGNITUD)
df = pd.concat([df, polutant_dummies], axis=1)
```

We further group the by pollutants and time:

```
[88]: df_monthly = df.groupby(['year', 'month', "MAGNITUD"])['sum_day'].agg(['mean',␣
      ↪"median", "count"])
```

```
[89]: df_monthly
```

```
[89]:                             mean    median  count
      year month MAGNITUD
      1991 1     1          416.633218   336.00    289
                 3         2640.886364  2179.50     88
                 6           41.639091    33.65    110
                 7         1602.384146  1391.00    164
                 8          955.169697   933.00    165
      …                            …       …     …
      2023 1     12         843.120000   608.00   1600
                 14         967.541224   954.00   1225
                 30          21.459200    16.20    125
                 65          39.072000    33.50    300
                 331        129.180000    96.30     25

      [4016 rows x 3 columns]
```

From The best to worst months of the year in terms of pollution:

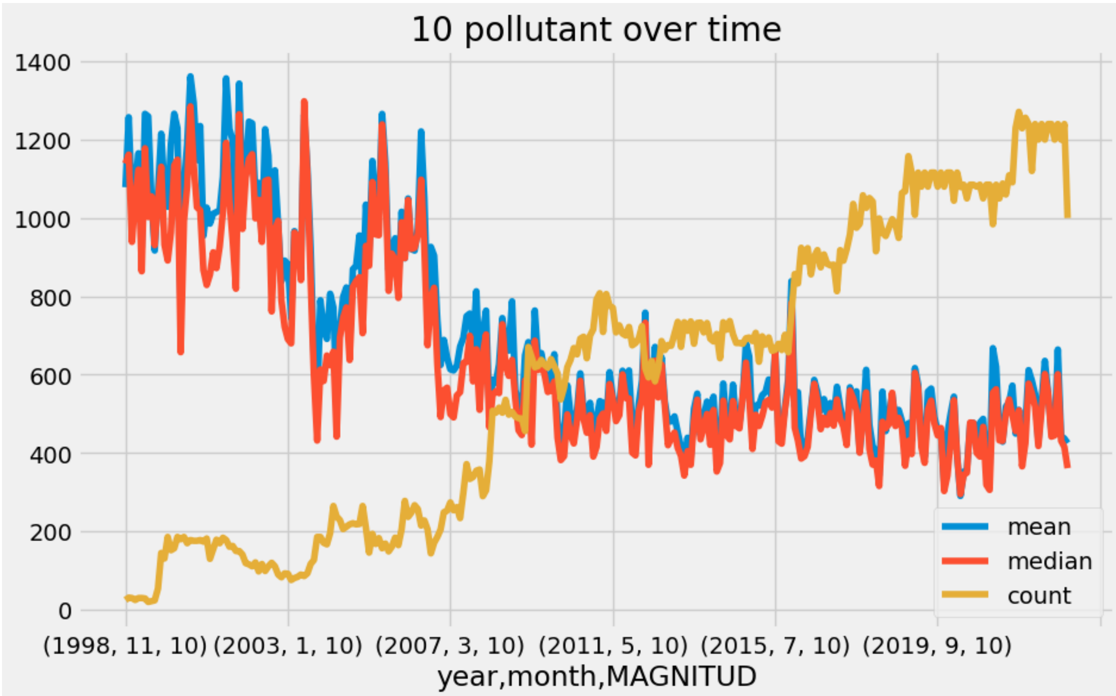
```
[94]: df.groupby(['month'])['sum_day'].agg(['mean', "median", "count"]).reset_index().
      ↪sort_values('mean')
```

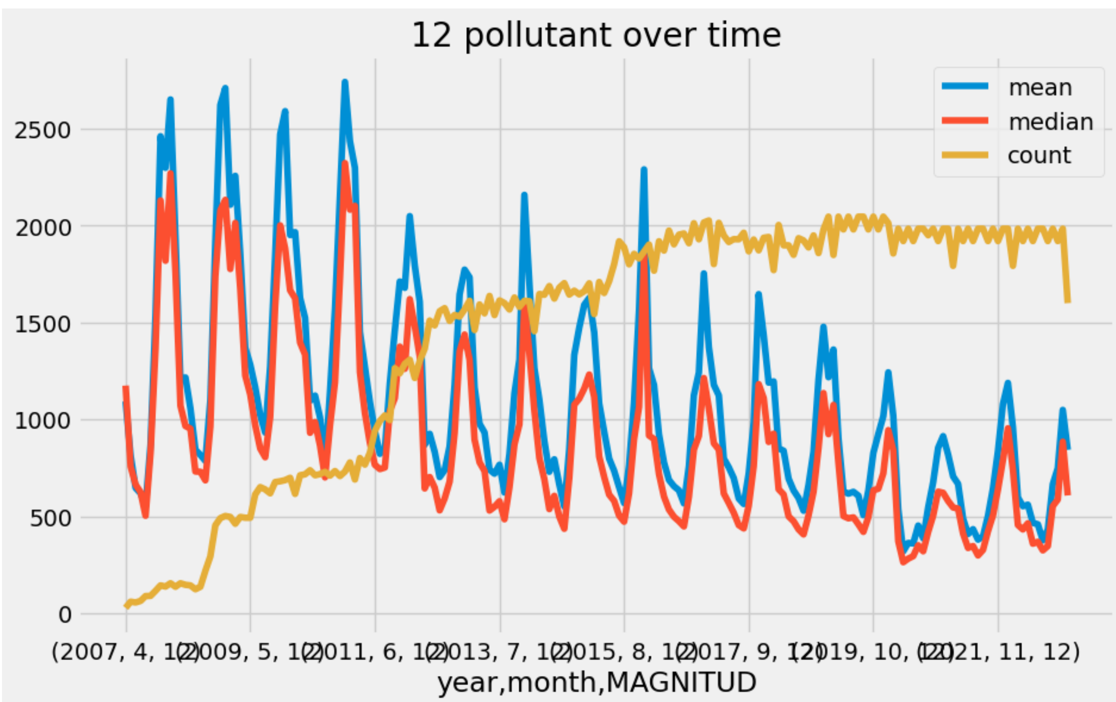
```
[94]:     month        mean  median   count
      7       8  474.698796   232.0  264288
      8       9  502.721422   274.0  255262
      6       7  525.401401   244.0  263708
      5       6  531.070319   253.0  255068
      4       5  532.889356   262.0  261264
      9      10  543.575806   336.0  264994
      3       4  551.074431   279.0  253566
      2       3  591.856147   341.0  260670
      10     11  599.728589   340.0  258701
      0       1  614.346660   348.0  266026
      1       2  621.984413   383.0  236300
      11     12  633.050464   343.0  266527
```

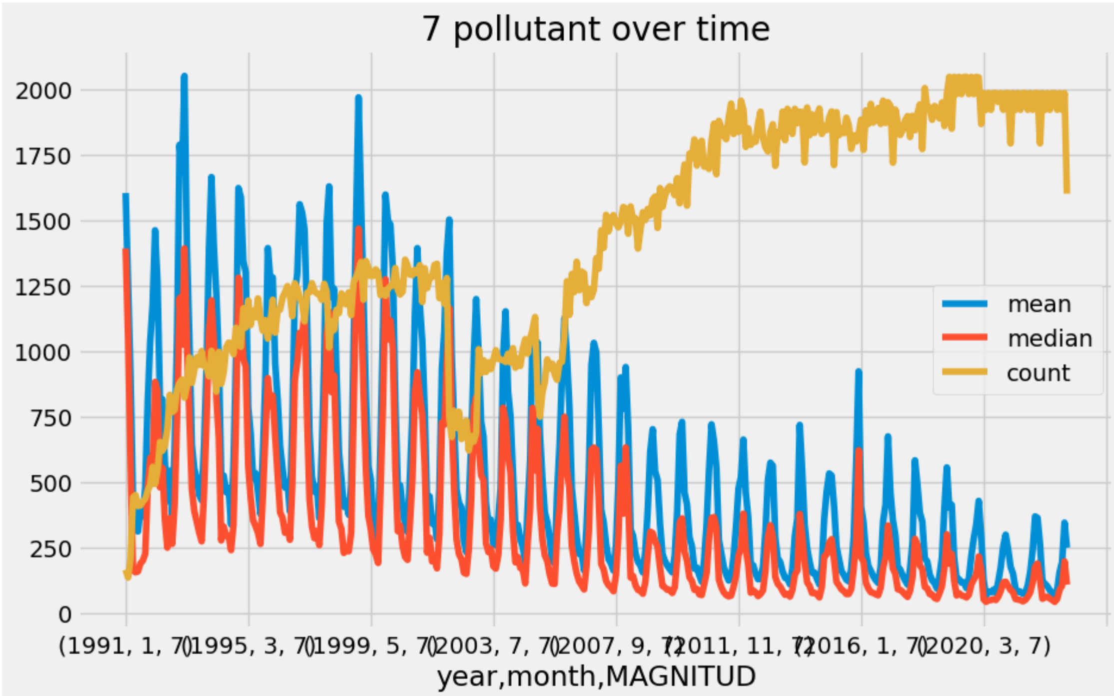
We display the aggregated data:

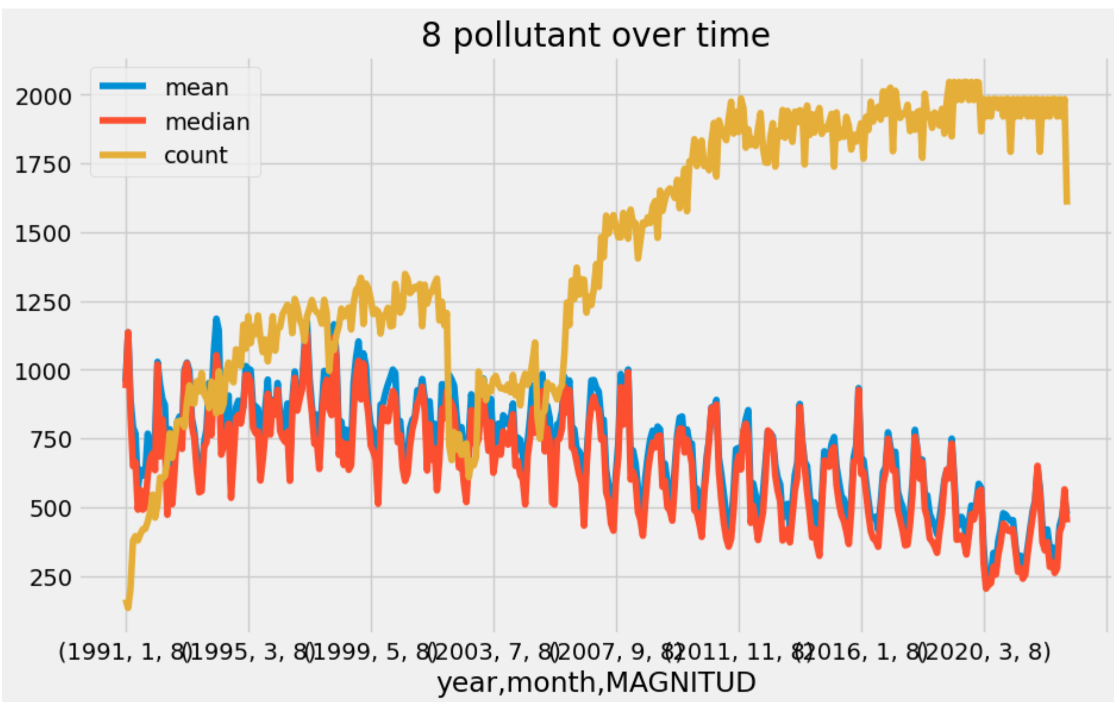
```
[78]: pollutantsIds = df['MAGNITUD'].unique()

      for x in pollutantsIds:
```

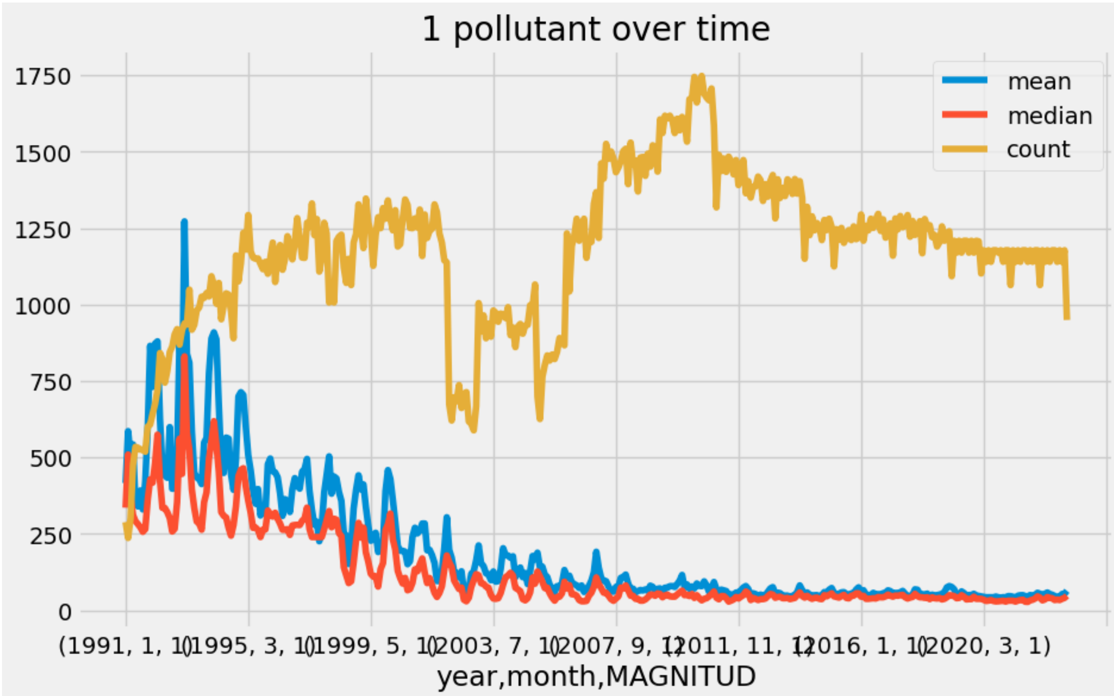
```
    df_monthly.loc[(df_monthly.index.get_level_values('MAGNITUD') == x)].
↪plot(title=f"{x} pollutant over time")
```

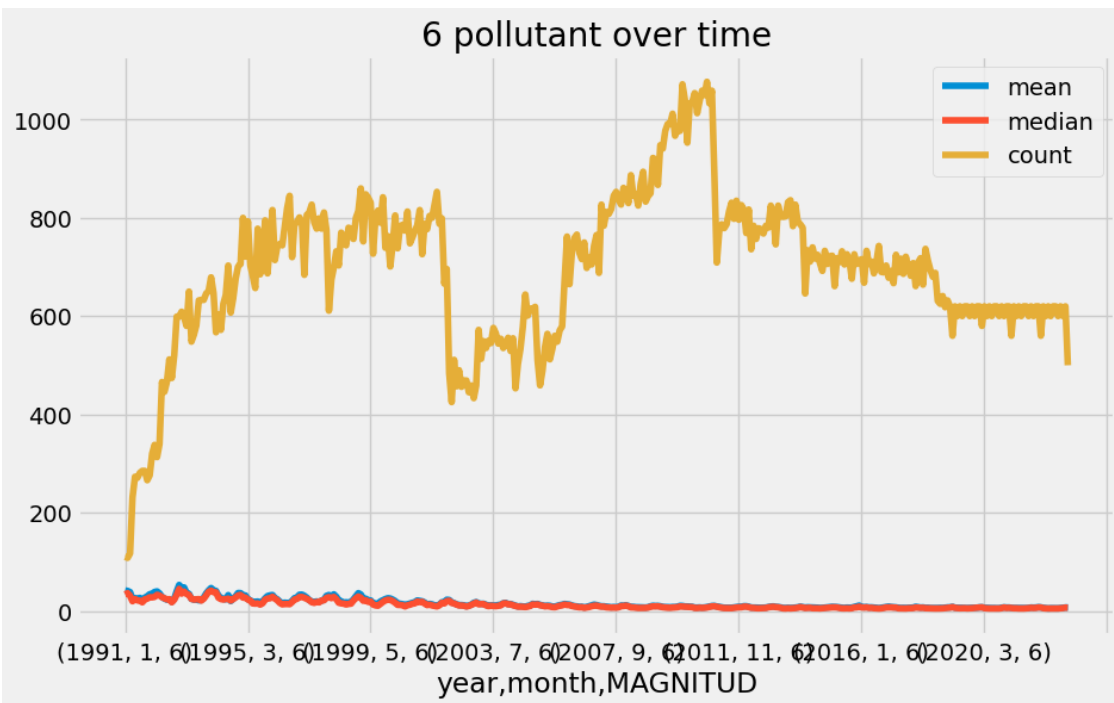


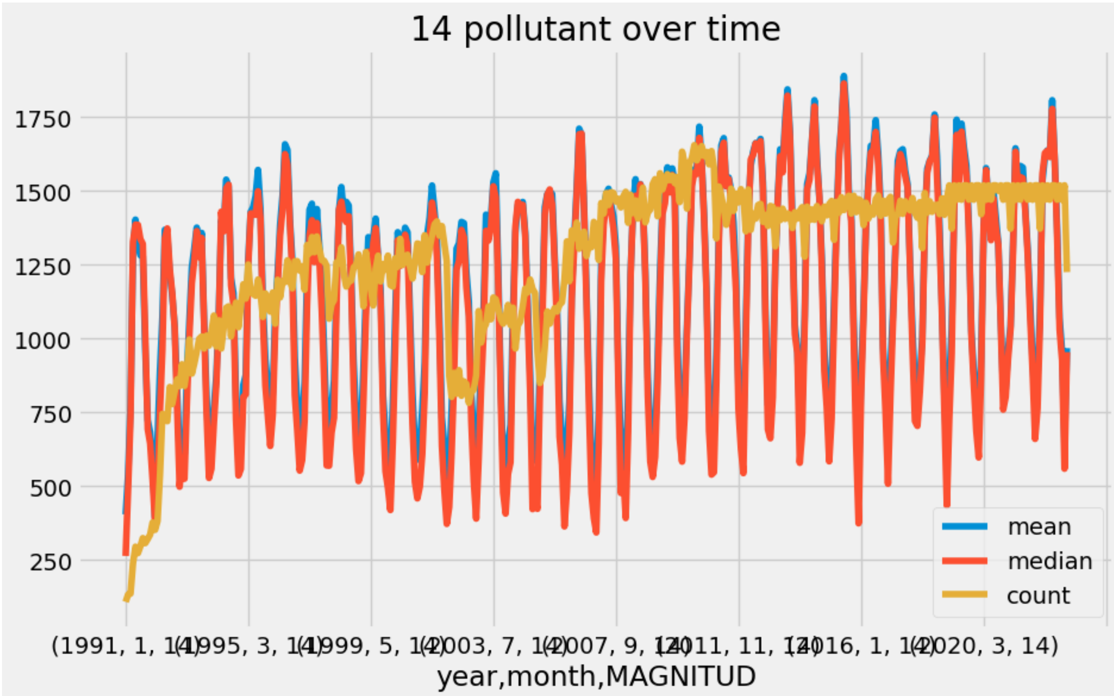


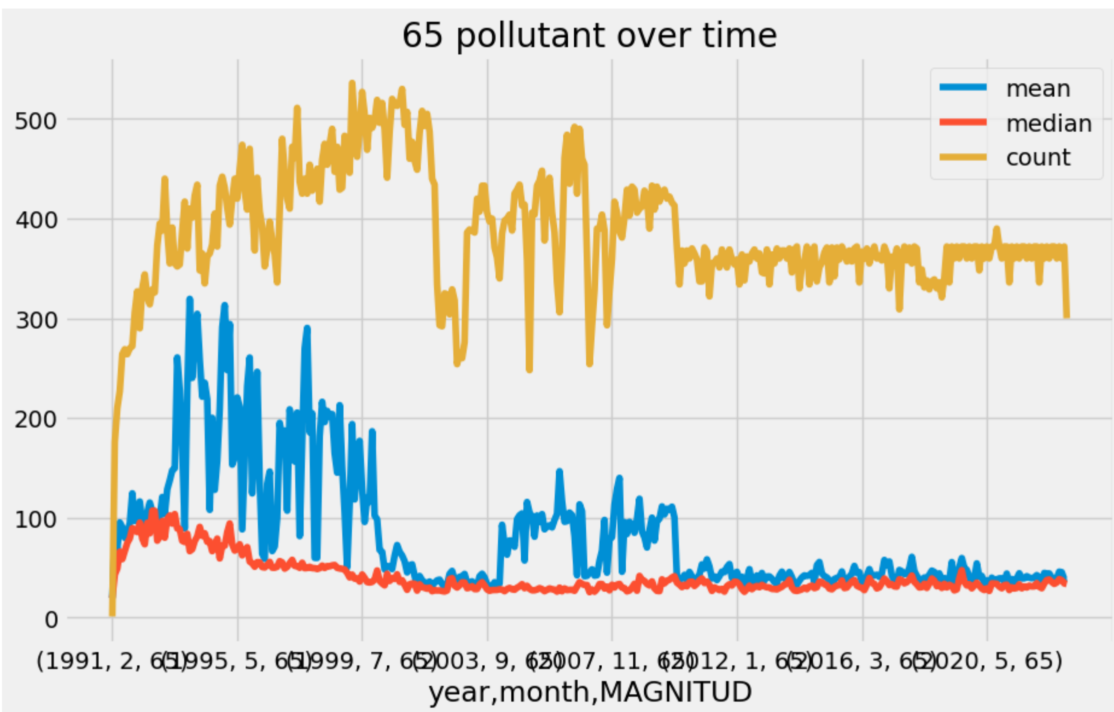

7 pollutant over time
mean
median
count
2000
1750
1500
1250
1000
750
500
250
0
(1991, 1, 7)
(1995, 3, 7)
(1999, 5, 7)
(2003, 7, 7)
(2007, 9, 7)
(2011, 11, 7)
(2016, 1, 7)
(2020, 3, 7)
year,month,MAGNITUD

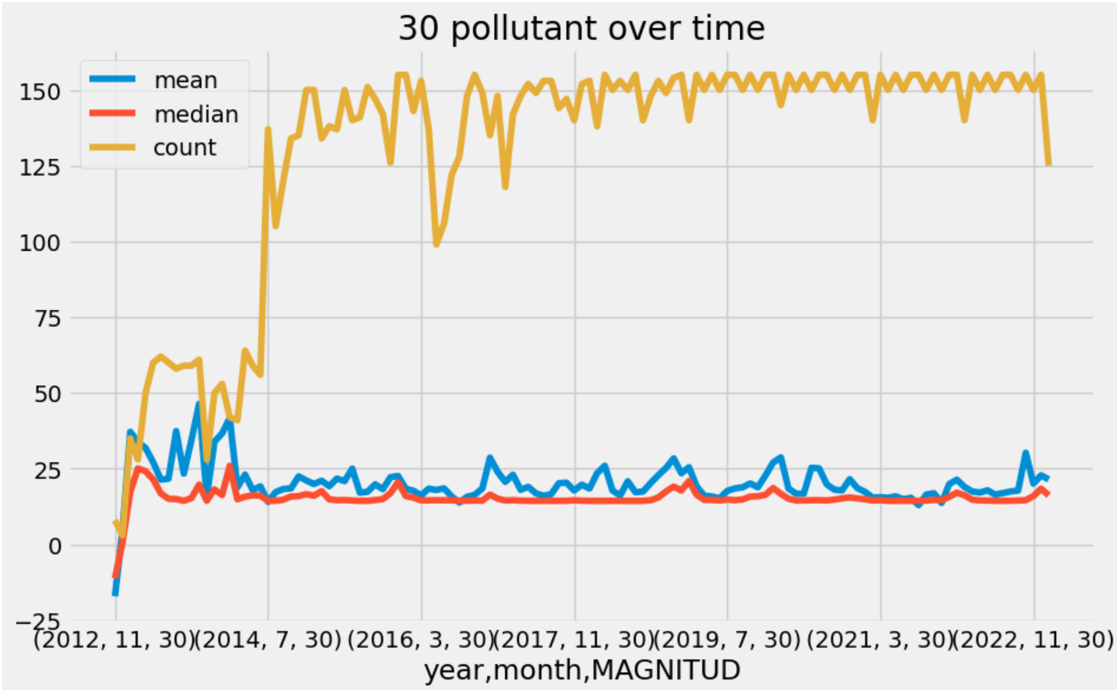

8 pollutant over time
mean
median
count
2000
1750
1500
1250
1000
750
500
250
(1991, 1, 8)
(1995, 3, 8)
(1999, 5, 8)
(2003, 7, 8)
(2007, 9, 8)
(2011, 11, 8)
(2016, 1, 8)
(2020, 3, 8)
year,month,MAGNITUD

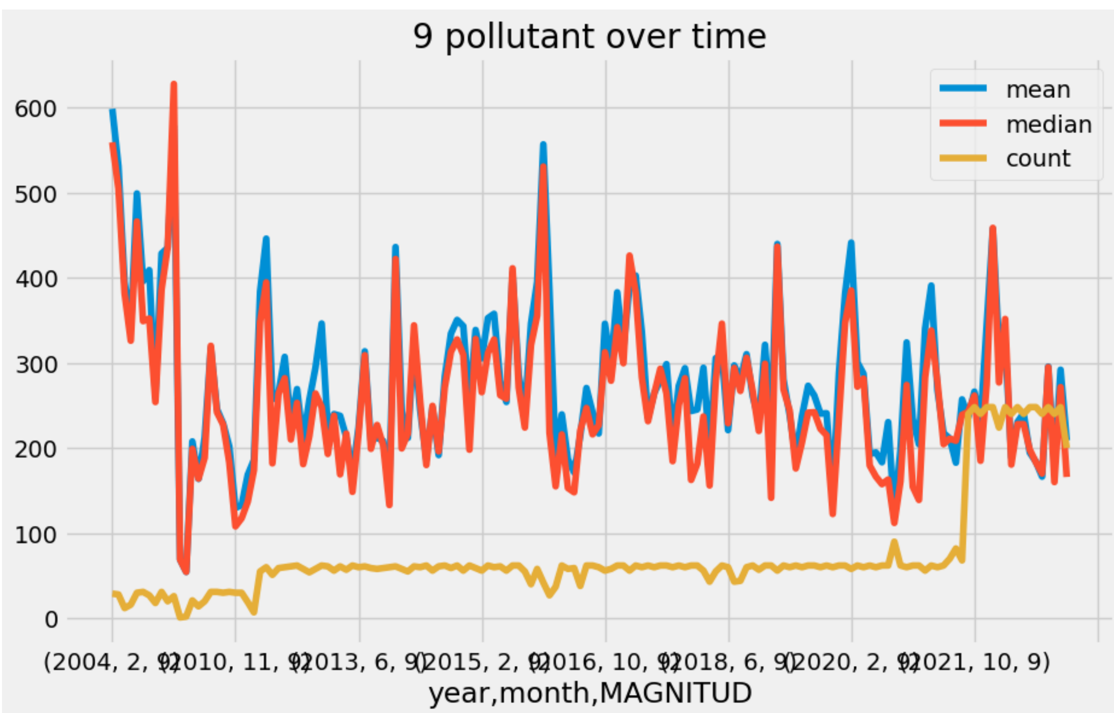

1 pollutant over time
1750
1500
1250
1000
750
500
250
0
mean
median
count
(1991, 1, 1)
(1995, 3, 1)
(1999, 5, 1)
(2003, 7, 1)
(2007, 9, 1)
(2011, 11, 1)
(2016, 1, 1)
(2020, 3, 1)
year,month,MAGNITUD

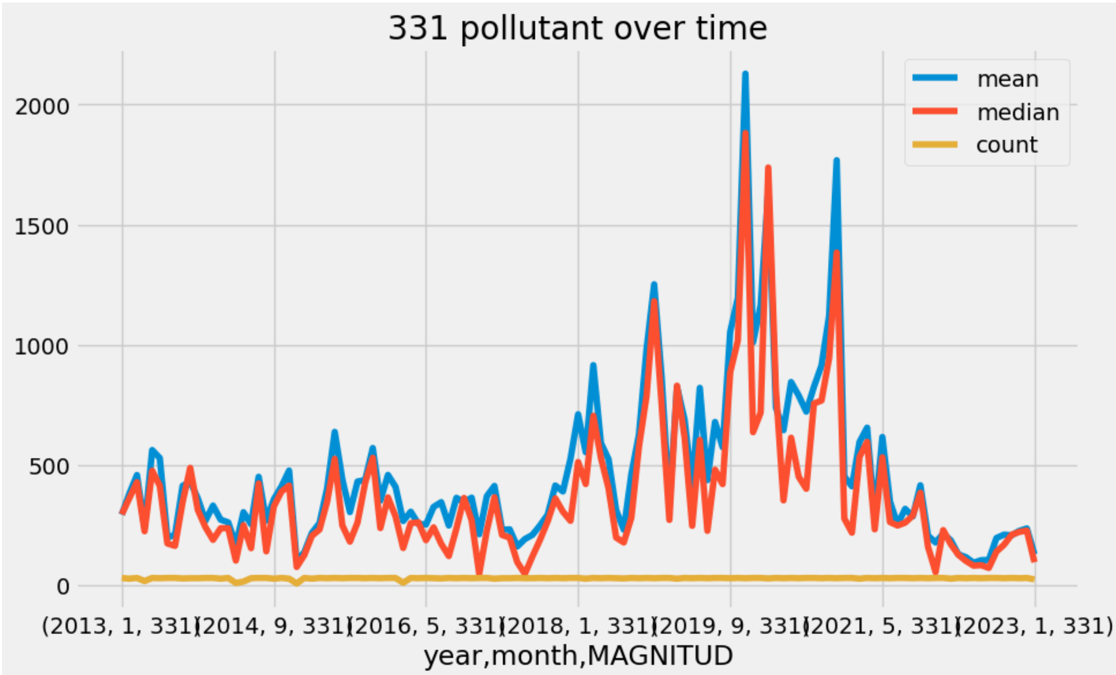

6 pollutant over time
1000
800
600
400
200
0
mean
median
count
(1991, 1, 6)
(1995, 3, 6)
(1999, 5, 6)
(2003, 7, 6)
(2007, 9, 6)
(2011, 11, 6)
(2016, 1, 6)
(2020, 3, 6)
year,month,MAGNITUD

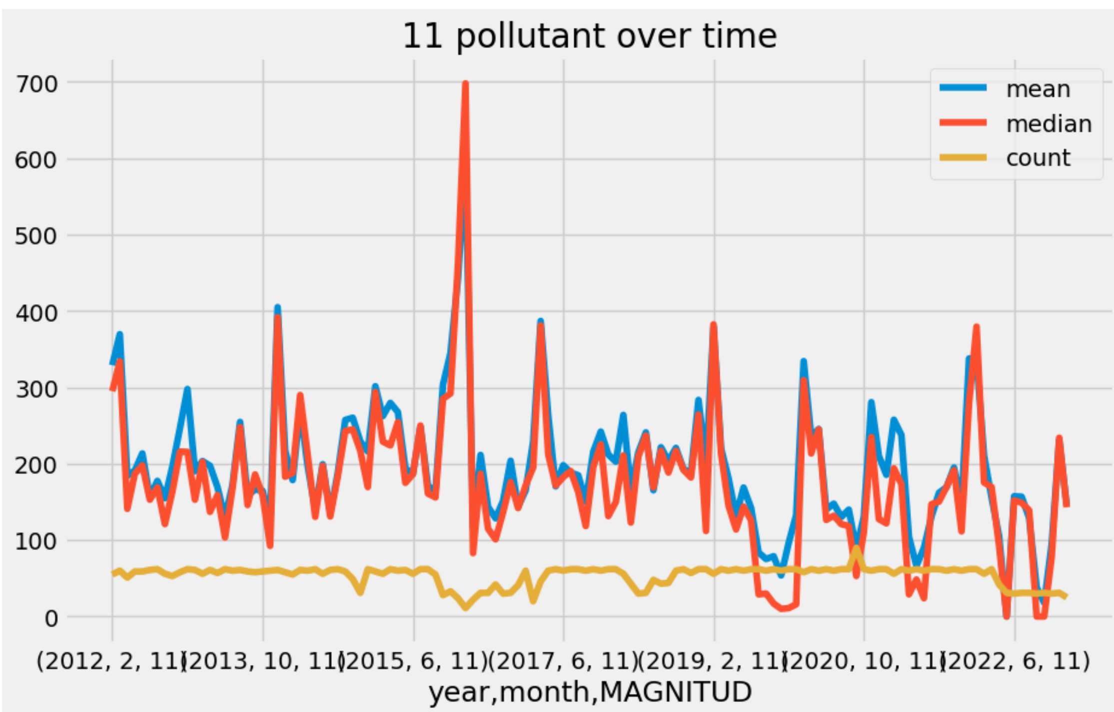

14 pollutant over time
1750
1500
1250
1000
750
500
250
mean
median
count
(1991, 1, 14)
(1995, 3, 14)
(1999, 5, 14)
(2003, 7, 14)
(2007, 9, 14)
(2011, 11, 14)
(2016, 1, 14)
(2020, 3, 14)
year,month,MAGNITUD

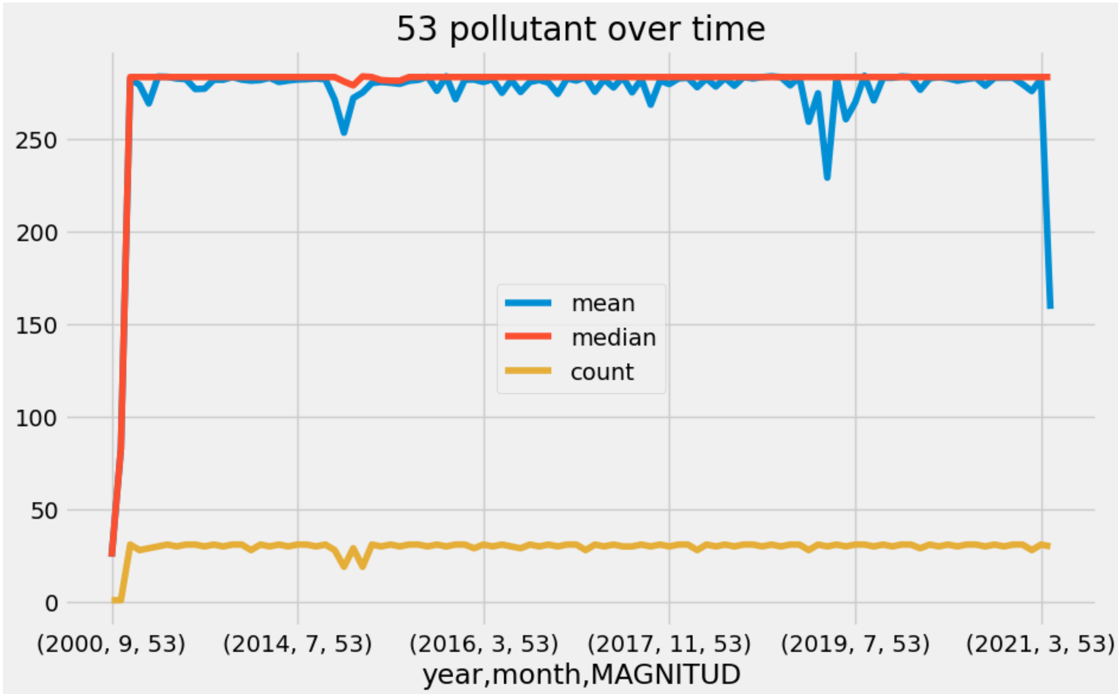

65 pollutant over time
500
400
300
200
100
0
mean
median
count
(1991, 2, 65)
(1995, 5, 65)
(1999, 7, 65)
(2003, 9, 65)
(2007, 11, 65)
(2012, 1, 65)
(2016, 3, 65)
(2020, 5, 65)
year,month,MAGNITUD


30 pollutant over time
mean
median
count
150
125
100
75
50
25
0
−25
(2012, 11, 30)
(2014, 7, 30)
(2016, 3, 30)
(2017, 11, 30)
(2019, 7, 30)
(2021, 3, 30)
(2022, 11, 30)
year,month,MAGNITUD

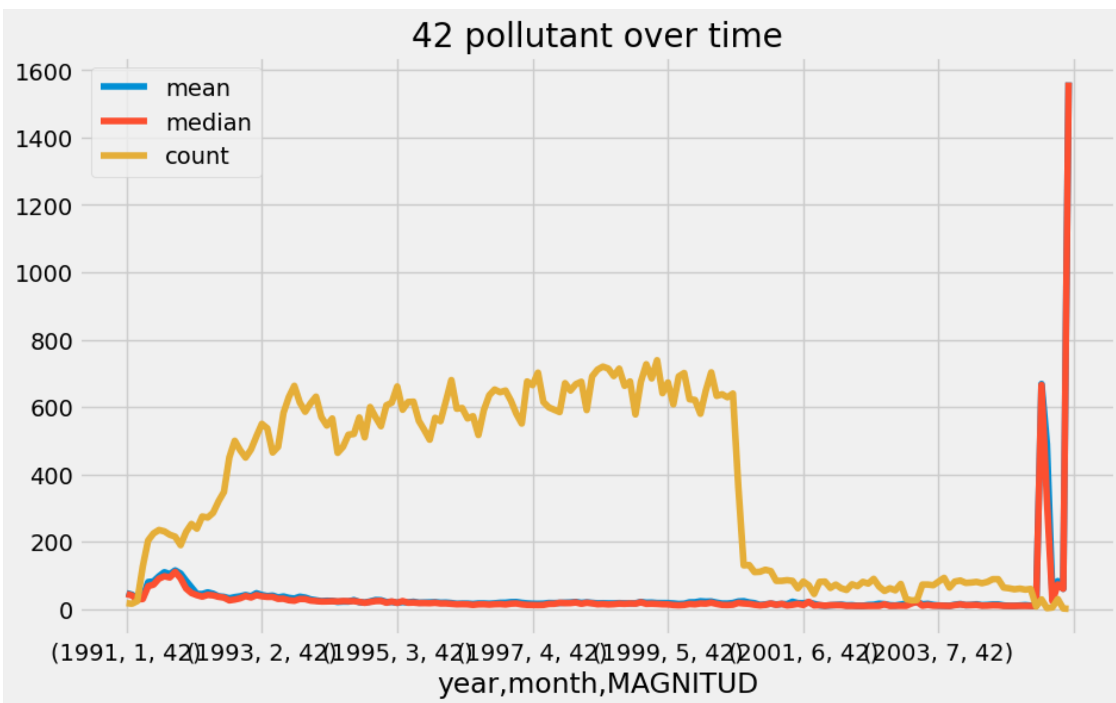

9 pollutant over time
mean
median
count
600
500
400
300
200
100
0
(2004, 2, 9)
(2010, 11, 9)
(2013, 6, 9)
(2015, 2, 9)
(2016, 10, 9)
(2018, 6, 9)
(2020, 2, 9)
(2021, 10, 9)
year,month,MAGNITUD


331 pollutant over time
mean
median
count
2000
1500
1000
500
0
(2013, 1, 331)
(2014, 9, 331)
(2016, 5, 331)
(2018, 1, 331)
(2019, 9, 331)
(2021, 5, 331)
(2023, 1, 331)
year,month,MAGNITUD

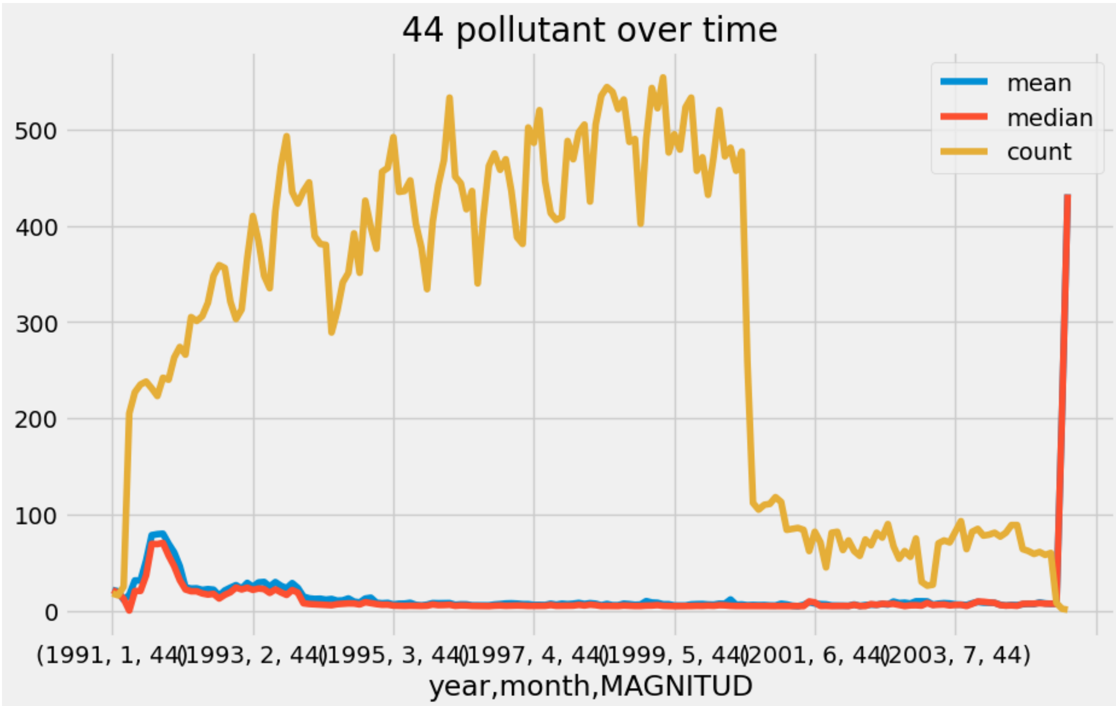

11 pollutant over time
mean
median
count
700
600
500
400
300
200
100
0
(2012, 2, 11)
(2013, 10, 11)
(2015, 6, 11)
(2017, 6, 11)
(2019, 2, 11)
(2020, 10, 11)
(2022, 6, 11)
year,month,MAGNITUD

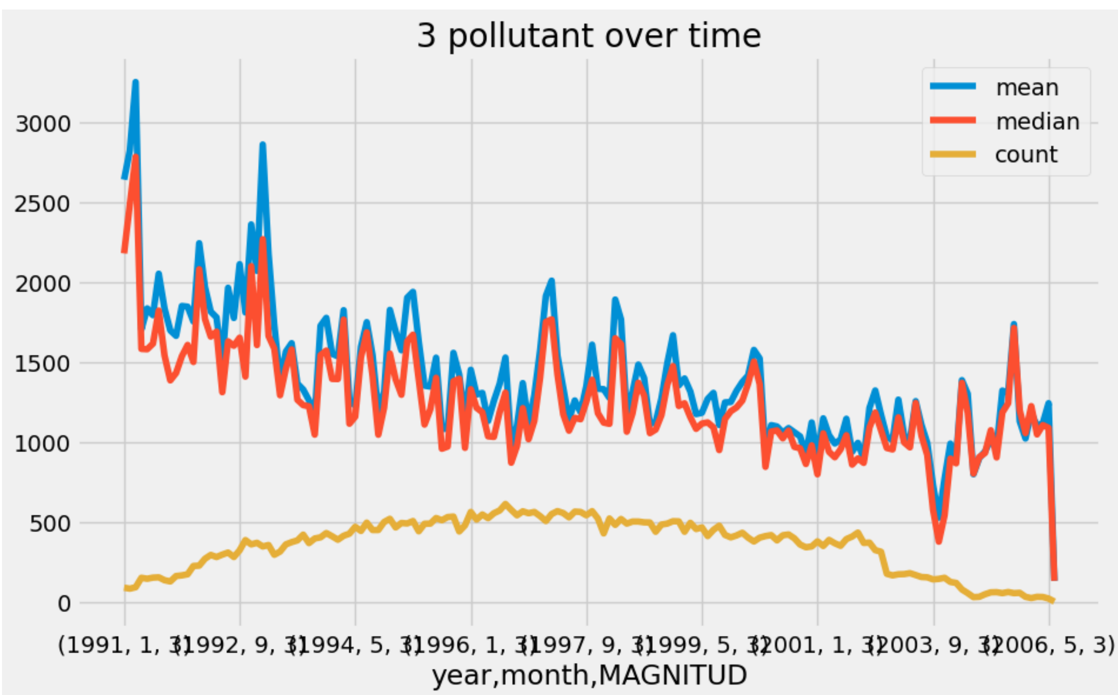


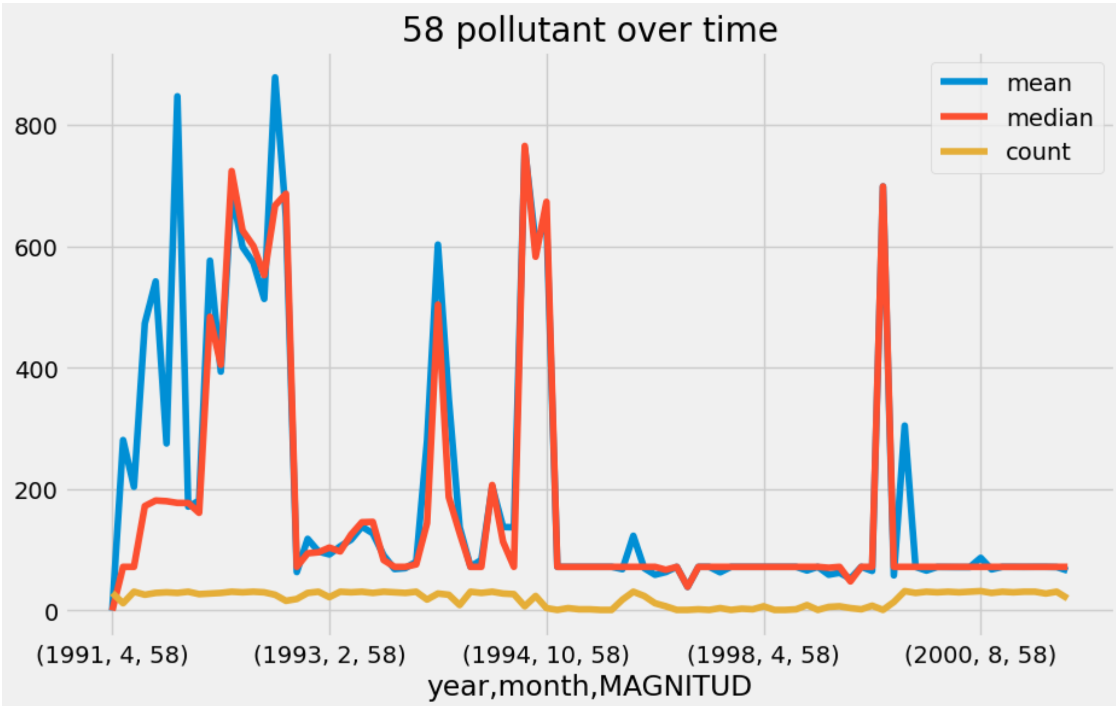
53 pollutant over time
250
200
150
100
50
0
mean
median
count
(2000, 9, 53)
(2014, 7, 53)
(2016, 3, 53)
(2017, 11, 53)
(2019, 7, 53)
(2021, 3, 53)
year,month,MAGNITUD



42 pollutant over time
1600
1400
1200
1000
800
600
400
200
0
mean
median
count
(1991, 1, 42)
(1993, 2, 42)
(1995, 3, 42)
(1997, 4, 42)
(1999, 5, 42)
(2001, 6, 42)
(2003, 7, 42)
year,month,MAGNITUD


44 pollutant over time
mean
median
count
500
400
300
200
100
0
(1991, 1, 44)
(1993, 2, 44)
(1995, 3, 44)
(1997, 4, 44)
(1999, 5, 44)
(2001, 6, 44)
(2003, 7, 44)
year,month,MAGNITUD


3 pollutant over time
mean
median
count
3000
2500
2000
1500
1000
500
0
(1991, 1, 3)
(1992, 9, 3)
(1994, 5, 3)
(1996, 1, 3)
(1997, 9, 3)
(1999, 5, 3)
(2001, 1, 3)
(2003, 9, 3)
(2006, 5, 3)
year,month,MAGNITUD



From the graphs above we can clearly seen the dramatic rise in the number of observations.

We also note the periodic nature of pollution levels rises and falls. This is a very common pattern where Air pollution becomes actually worse during winter. Air pollution is often worse in winter due to a combination of meteorological and human-made factors. Cold, still air can cause atmospheric inversion layers to form, trapping pollutants close to the ground and leading to episodes of high levels of air pollution. Additionally, households often burn more fuel for heating during the winter months, leading to increased emissions of pollutants such as particulate matter, nitrogen oxides, and carbon monoxide. Lastly, areas with high population density and limited wind movement, such as cities and towns, tend to experience worse air quality in winter due to the buildup of pollutants.

Why air pollution is worse in winter?

Now we explore more granular hourly data:

[96]:
```
df_hourly = df.groupby(["MAGNITUD"])[cols].agg(['mean', "median", "count"])
df_hourly_mean = df.groupby(["MAGNITUD"])[cols].agg(["mean"])
```

[106]:
```
df_hourly_mean.T.style.highlight_max(color = 'lightgreen', axis = 0)
```

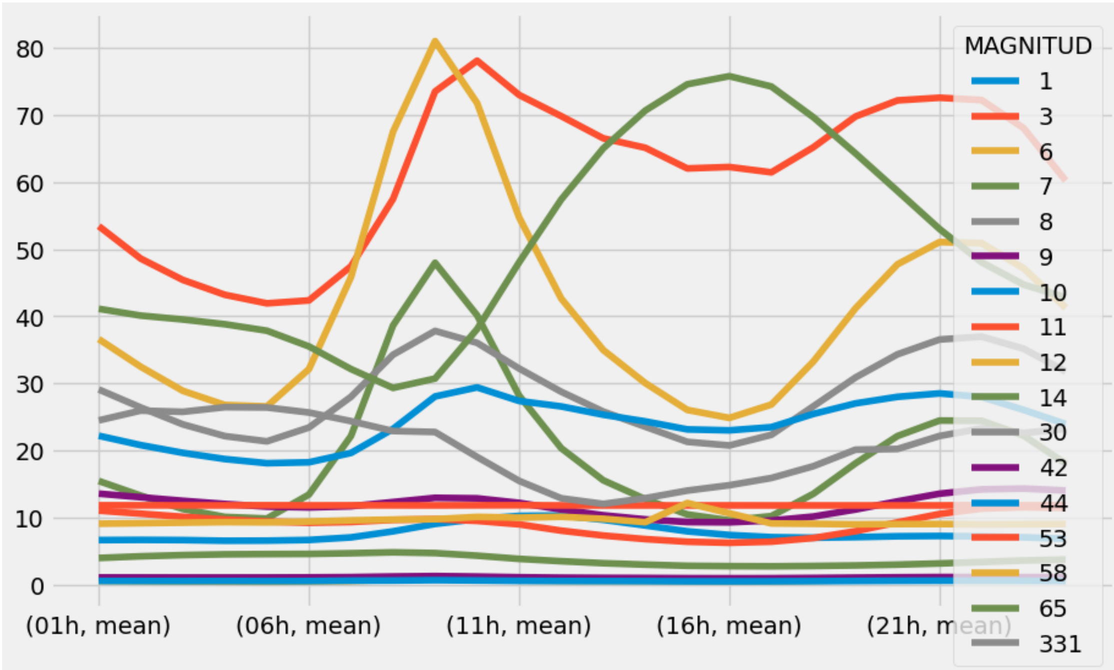
[106]: <pandas.io.formats.style.Styler at 0x7f0558cd2e50>

[107]:
```
df_hourly_mean.T.style.highlight_min(color = 'lightgreen', axis = 0)
```

[107]: <pandas.io.formats.style.Styler at 0x7f0558cb48e0>

[99]:
```
df_hourly_mean.T.plot()
```

[99]: <AxesSubplot: >



From the graph above we notice that the generally the worst hour is on average for largest amount of pollutants: 6, 7, 8, 12, 30, 42 and 44. We also noticed that the best hour for nearly similar mix of pollutants is 16h.

We find similar data patterns in the following article: What Time of Day Is Air Pollution Lowest?

This is due to the diurnal cycle, in which levels of pollutants can increase in the morning due to increased activity and decreased air circulation, and decrease in the afternoon due to increased air circulation and decreased activity. This cycle is affected by factors such as temperature, wind speed, sunlight, and mixing of air.

We analyze the relationship between altitude and concentration of particles in the air, and present your conclusions in graphical form.

[29]:
```
corr = df.corr()
corr["ALTITUD"].sort_values()
```

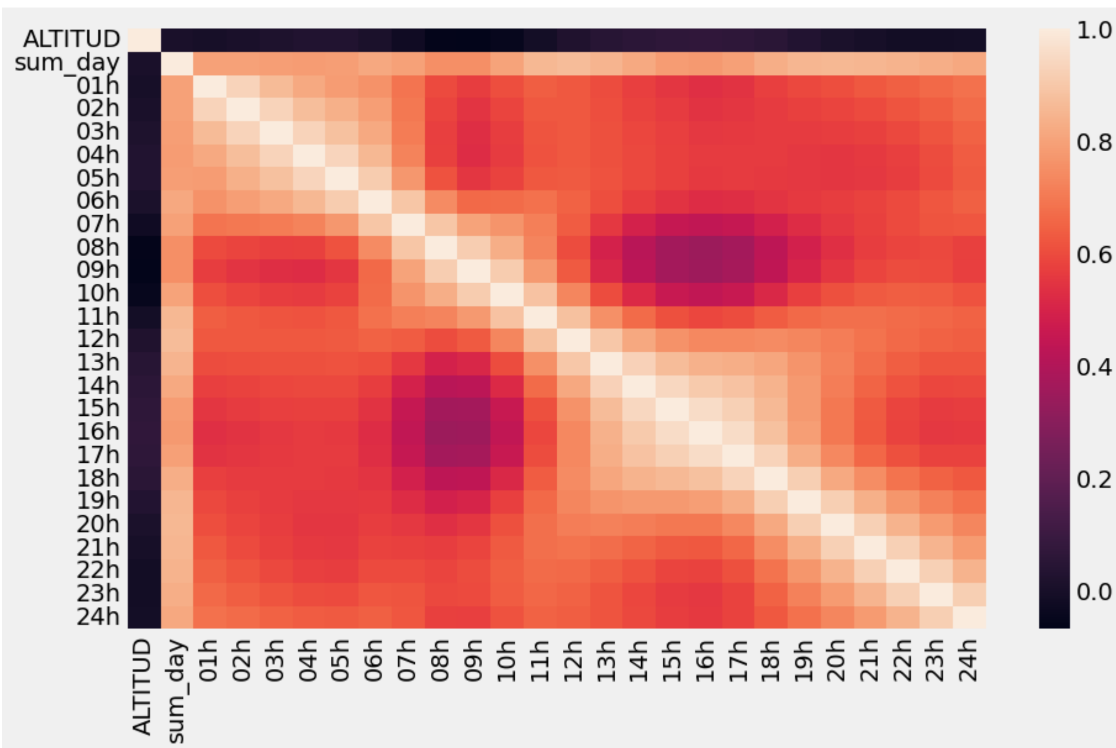
```
/tmp/ipykernel_679253/1270252458.py:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  corr = df.corr()
```

[29]:
```
LONGITUD        -0.104412
CODI COMARCA    -0.070486
09h             -0.067970
65              -0.065791
08h             -0.060106
MAGNITUD        -0.052438
10h             -0.049168
CODI EOI        -0.043374
CODI INE        -0.043374
3               -0.035921
30              -0.035770
44              -0.033091
42              -0.028931
6               -0.028159
07h             -0.024233
11              -0.023837
1               -0.021489
9               -0.019179
23h             -0.016602
22h             -0.014888
11h             -0.013039
331             -0.010567
58              -0.010439
24h             -0.009751
53              -0.009676
21h             -0.004768
7               -0.003579
12              -0.003321
8               -0.003199
01h             -0.002495
month           -0.000258
day              0.000256
sum_day          0.005850
02h              0.006570
20h              0.009954
06h              0.010558
03h              0.017351
12h              0.021584
04h              0.024476
05h              0.027573
19h              0.028619
13h              0.042666
18h              0.049340
14h              0.054391
10               0.054506
15h              0.062837
17h              0.063772
```

```
16h              0.066618
year             0.067959
14               0.108582
LATITUD          0.580733
ALTITUD          1.000000
Name: ALTITUD, dtype: float64
```

[30]:
```
corr = df[["ALTITUD", "sum_day"] + cols].corr()

sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

[30]: <AxesSubplot: >

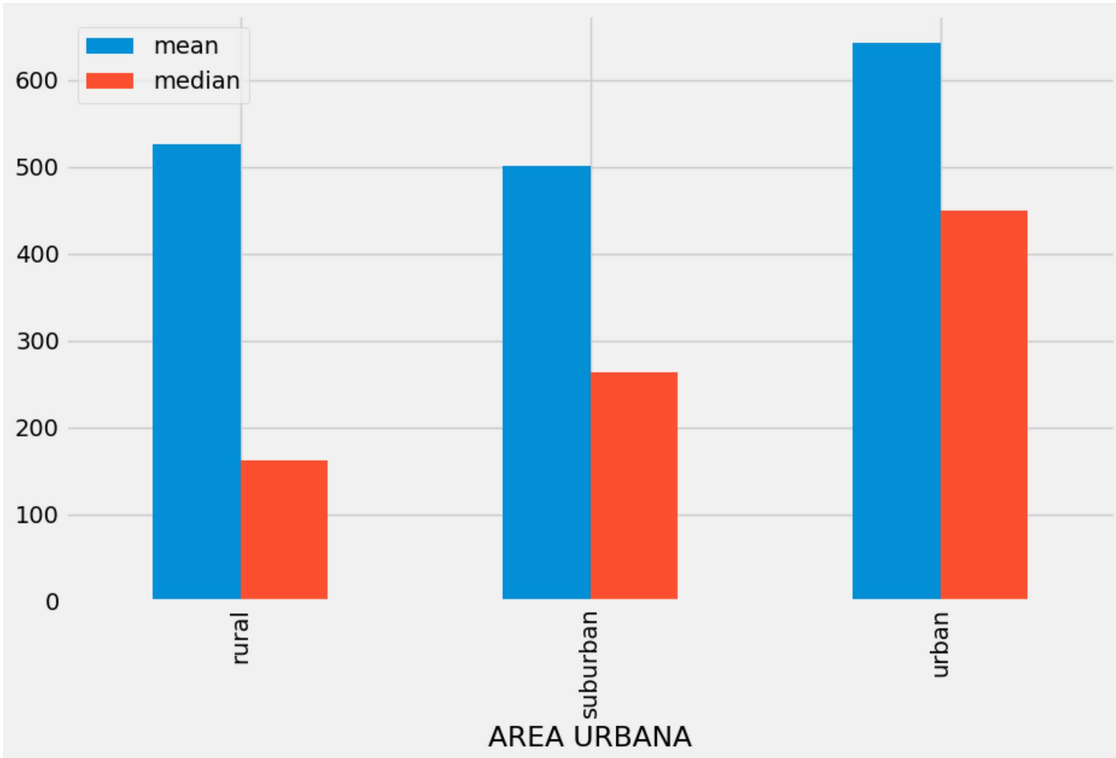


We find no significat correlation between altitude and concentration of particles in the air.

We Analyze the concentration of pollutants in urban, suburban and rural areas, and present your conclusion in graphical form.

[31]:
```
df.groupby(['AREA URBANA'])["sum_day"].agg(['mean', "median"]).plot(kind="bar")
```

[31]: <AxesSubplot: xlabel='AREA URBANA'>



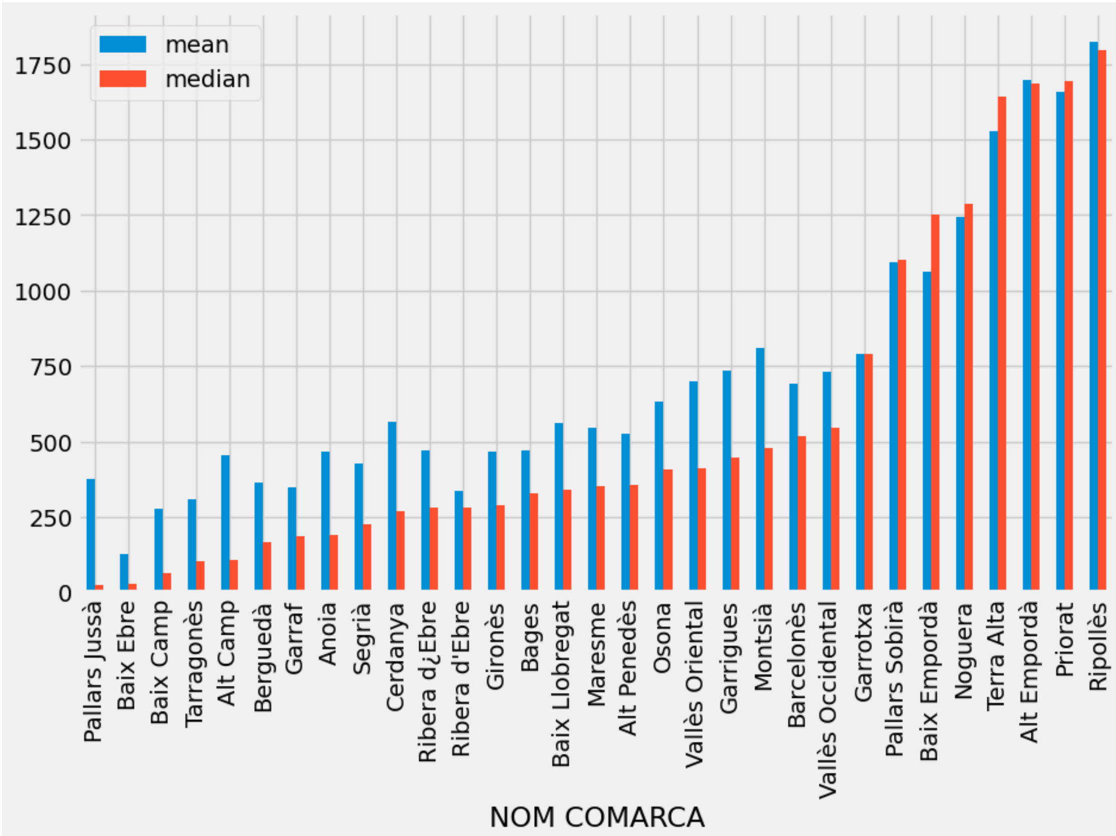
We find by far more pollution in urban areas on average and median. On median suburban are more polluted than rural areas.

Rank the cities in the dataset according to their level of pollution, and create best-5 and worst-5 lists.

Here we rank comarcas from best to worst:

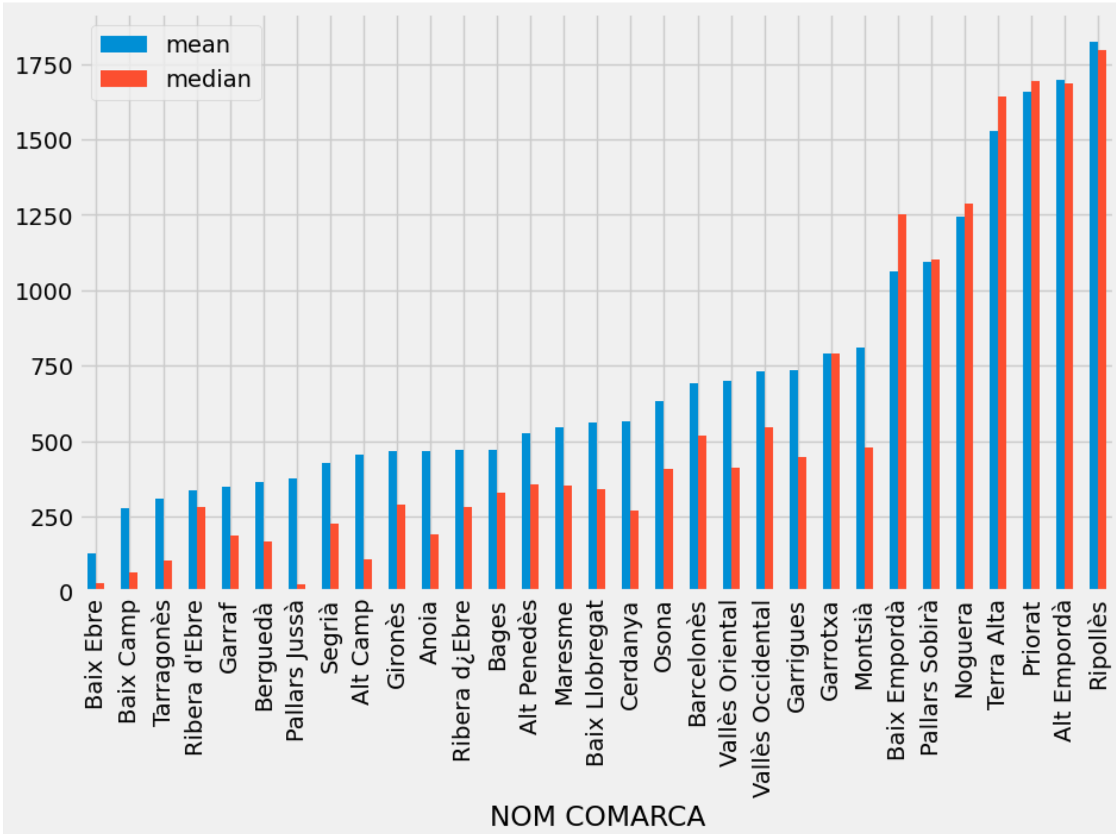
[32]:
```
df.groupby(['NOM COMARCA'])["sum_day"].agg(['mean', "median"]).
 ↪sort_values(by='median').plot(kind="bar")
```

[32]: `<AxesSubplot: xlabel='NOM COMARCA'>`



[34]:
```
df.groupby(['NOM COMARCA'])["sum_day"].agg(['mean', "median"]).
↪sort_values(by='mean').plot(kind="bar")
```

[34]: <AxesSubplot: xlabel='NOM COMARCA'>



[36]:
```
df.groupby(['NOM COMARCA', "MAGNITUD" ])["sum_day"].agg(['mean', "median"]).
    ↪sort_values(by='mean')
```

[36]:
```
                                 mean   median
NOM COMARCA     MAGNITUD
Pallars Jussà   6            3.013423      2.4
Baix Ebre       6            5.308080      4.8
Alt Camp        6            5.977174      5.4
Segrià          44           6.477778      5.2
Bages           44           6.626375      5.7
…                                 …        …
Ripollès        14        1825.318131   1797.0
Baix Empordà    14        1895.151279   1880.0
Pallars Jussà   14        2136.343627   2123.0
Baix Llobregat  3         2161.889456   2179.0
                58        2744.966667    699.0

[218 rows x 2 columns]
```

0.2.1 More granular data on pollutant 8 for algo.

[38]:
```
df[df['MAGNITUD'] == 8 ]["NOM ESTACIO"].value_counts()
```

[38]:
```
Perafort (Puigdelfí)                 11261
Tarragona (Sant Salvador)            11123
Tarragona (Bonavista)                11055
Constantí                            11037
Manresa                              10896
                                     …
Gavà (c/Girona - c/Progrés)           1232
Sta. Coloma de Gr. (c/ Bruc)           942
Vila-seca (IES Vila-seca)              877
Barcelona (Torre Girona)               282
el Prat de Llobregat (Sant Cosme)        5
Name: NOM ESTACIO, Length: 96, dtype: int64
```

[39]:
```
df[df['MAGNITUD'] == 8].groupby(['year', 'month', "NOM ESTACIO"])['sum_day'].
↪agg(['mean', "median", "count"])
```

[39]:
```
                                                mean  median  count
year month NOM ESTACIO
1991 1     Badalona                       776.933333   834.0     30
           Barcelona (Poblenou)          1054.903226  1090.0     31
           Barcelona (St. Gervasi)       1760.058824  1663.0     17
           L'Hospitalet de Llobregat     1002.200000  1049.5     30
           Montcada i Reixac             1318.033333  1317.0     30
…                                                …       …      …
2023 1     Vandellòs (Viver)              150.680000   116.0     25
           Vila-seca (IES Vila-seca)      394.520000   312.0     25
           Viladecans - Atrium            589.360000   611.0     25
           Vilafranca del Penedès         191.800000   147.0     25
           Vilanova i la Geltrú           436.000000   465.0     25

[18973 rows x 3 columns]
```

[67]:
```
df[df['MAGNITUD'] == 8].groupby(['year', 'month', "NOM ESTACIO"])['sum_day'].
↪agg(['mean']).reset_index()["NOM ESTACIO"].nunique()
```

[67]:
```
96
```

[68]:
```
df[df['MAGNITUD'] == 8].groupby(['year', 'month', "NOM ESTACIO"])['sum_day'].
↪agg(['mean']).reset_index()["NOM ESTACIO"].unique()
```

[68]:
```
array(['Badalona', 'Barcelona (Poblenou)', 'Barcelona (St. Gervasi)',
       "L'Hospitalet de Llobregat", 'Montcada i Reixac',
       'Sant Adrià de Besòs', 'Vallcebre', 'Cercs (St. Corneli)',
```

```
        'la Nou de Berguedà (Malanyeu)', 'Constantí', 'Manresa',
        'Perafort (Puigdelfí)', 'Tarragona (Bonavista)',
        'Tarragona (pl. Generalitat)', 'Vila-seca',
        'la Pobla de M./el Morell', 'Tarragona (Sant Salvador)',
        'Igualada', 'Martorell', 'Terrassa', 'Vic', 'Sarrià de Ter',
        'Granollers (av. Joan Prim)', 'Mollet del Vallès', 'Reus',
        'Mataró', 'Barcelona (Sagrera)', 'Cercs (St. Jordi)', 'Lleida',
        'Sabadell (pl. Creu de Barberà)', 'Sant Fost de Campsentelles',
        'Sabadell', 'Sant Celoni', 'Rubí', 'Sta. Coloma de Gr. (c/ Bruc)',
        'Sant Cugat del Vallès', 'Tarragona (Universitat Laboral)',
        'Vilanova i la Geltrú', 'Fornells de la Selva (escola municipal)',
        'Barcelona (Sants)', 'Granollers (c/ Joan Vinyoli)',
        'Sta. Perpètua de Mogoda', 'Vilafranca del Penedès',
        'Barcelona (Eixample)', 'Santa Coloma de Gramenet',
        'Barcelona (Gràcia - Sant Gervasi)', 'Barberà del Vallès',
        'Sant Andreu de la Barca', 'el Prat de Llobregat (església)',
        'Sant Vicenç dels Horts (Ribot)', 'Gavà (c/Girona - c/Progrés)',
        'Cornellà de Llobregat (Allende - Bonveí)',
        'Tarragona (Parc de la Ciutat)', 'Cercs (Sant Jordi)',
        'Bellver de Cerdanya', 'Barcelona (Ciutadella)',
        'Girona (parc de la Devesa)', 'Gavà', 'Cubelles (Poliesportiu)',
        'Tona', 'Alcover', 'Vallcebre (campanar)',
        'Santa Perpètua de Mogoda', 'Castellet i la Gornal',
        'Cercs (Sant Corneli)', 'Vandellòs (Els Dedalts)',
        'Vandellòs (Viver)', 'Berga', 'Barcelona (Parc Vall Hebron)',
        'Montseny (La Castanya)', 'Granollers', 'Viladecans - Atrium',
        'el Prat de Llobregat (Sant Cosme)', 'Tona (Zona Esportiva)',
        "L'Ametlla de Mar", 'Sta. Margarida i els Monjos (La Ràpita)',
        'El Prat de Llobregat (Jardins de la Pau)', 'Amposta',
        'Sitges (Vallcarca)', 'Vandellòs (Barranc del Terme)',
        'Barcelona (Torre Girona)', 'Manlleu', 'Montsec',
        'El Prat de Llobregat (Sagnier)', 'Barcelona (Palau Reial)',
        'Girona (Escola de Música)', 'Pallejà (Roca de Vilana)', 'Alcanar',
        'Sant Vicenç dels Horts', 'Sant Feliu de Ll. (CEIP Marti i Pol)',
        'Sitges (Vallcarca - Oficines)', 'Juneda (Pla del Molí)', 'Begur',
        'Santa Pau', 'Barcelona (Observatori Fabra)',
        'Vila-seca (IES Vila-seca)'], dtype=object)
```

[42]:
```python
df[df['MAGNITUD'] == 8].groupby(['year', 'month', "NOM ESTACIO"])['sum_day'].
↪agg(['mean']).reset_index()
```

[42]:

	year	month	NOM ESTACIO	mean
0	1991	1	Badalona	776.933333
1	1991	1	Barcelona (Poblenou)	1054.903226
2	1991	1	Barcelona (St. Gervasi)	1760.058824
3	1991	1	L'Hospitalet de Llobregat	1002.200000
4	1991	1	Montcada i Reixac	1318.033333

```
...    ...  ...                        ...          ...
18968  2023    1         Vandellòs (Viver)   150.680000
18969  2023    1  Vila-seca (IES Vila-seca)   394.520000
18970  2023    1        Viladecans - Atrium   589.360000
18971  2023    1     Vilafranca del Penedès   191.800000
18972  2023    1        Vilanova i la Geltrú   436.000000

[18973 rows x 4 columns]
```

0.3 Prediction

To Build and publish an algorithm to predict the average concentration of one pollutant of your choice per month for the next 24 months - on average for all stations.

We have chosen the pollutant 8 as its the most frequent and We have aggregated the data by day and then month. We also label encoded the stations. We used Random Forest regressor to predict the target values for the next 24 months. The algo is available at GitHub and Ocean Protocol.

To Build and publish an algorithm to predict the concentration of one pollutant of your choice for each hour of the day from February 15 to 28 - on average for all stations. We add time features and label encoded the stations. We used Random Forest regressor to predict the target values for the next 14 days. The algo is available at GitHub and Ocean Protocol.

0.4 Summary

[ ]:

```

```