01_preliminary_IT_study
—
Notebook implementation of *"A preliminary view at 2020 mortality data from ISTAT"*

This notebook aims at reproducing the original study by **F. Ricciato (@Eurostat)** published on CROS portal on **April 16th, 2020**.

disclaimer :
The purpose of this notebook is mostly didactic. The data used when running this notebook are fetched directly fetched from the provider (*ISTAT*) website. While they are always the latest available/updated, they do no necessarily correspond to those used in the original study. The methodological approach adopted here is purely descriptive, it involves no statistical modelling. Note that the methodology is actually not discussed in this notebook, refer to the original publication to this aim. The notebook does not aim at performance either, still it is generic enough to be repurposed for different similar datasets as long as metadata are "descriptive enough".

Table of Contents:

note: cells need to be run sequentially!

The study deals with early reports on the beginning of 2020 mortality in Italy and is entitled:

[1]:
```
COUNTRY = "IT"
YEAR = 2020
PROVIDER = "ISTAT"
print('"\033[1mA preliminary view at %s mortality data from %s\033[0m"' % (YEAR,␣
↪PROVIDER))
```

```
"A preliminary view at 2020 mortality data from ISTAT"
```

Concerning data extraction, while the latest available version of the original study is from April 16th, please note:

[2]:
```
from datetime import datetime
print("Last update/running of this notebook: \033[1m%s\033[0m" % datetime.
↪today())
```

```
Last update/running of this notebook: 2020-05-07 01:03:40.424613
```

0.1 Setting and checking the environment first

Let's run some setup necessary to import the dependency(ies) required to run the project... First, some generic packages, including a few to handle date/time data since we deal with timeseries:

[3]:
```
import os, sys
import json
import time
from datetime import timedelta # and datetime above
import calendar
```

In the following, we will take care of setting the ready-to-run environment even when libraries/packages are missing. This will ensure you can always run this notebook, in particular on a remote platform (*e.g.*, `binder`, `Google colab`,...). However, you should probably consider running this notebook in a virtual environment (`conda -n env` or `virtualenv`) so as to make these installs temporary and/or isolated.

Essential for the running of the notebook, besides the basic `numpy` package, is the `pandas` package use for common data handling and processing:

[4]:
```
import numpy as np
try:
    import pandas as pd
except ImportError:
    try:
        !{sys.executable} -m pip install pandas
    except:
```

```
        raise IOError("!!! Sorry, you're doomed, you won't be able to run this␣
↪notebook... !!!")
    else:
        print("! Package pandas installed on-the-fly !")
```

[5]:
```
# %%bash # testing google-colab for instance
# [[ ! -e /colabtools ]] && exit
# `which python` -m pip install pandas
```

Note that the geopandas package is also used as soon as basic 'geoprocessing' (simple vector data ingestion and map representation) is involved:

[6]:
```
try:
    import geopandas as gpd
except ImportError:
    try:
        !{sys.executable} -m pip install geopandas
    except:
        print("! Package geopandas not installed !")
    else:
        print("! Package geopandas installed on-the-fly !")
```

You will also need to import the pyeudatnat package that contains various useful functions/methods for metadata-based data ingestion:

[7]:
```
try:
    import pyeudatnat
except ImportError:
    try:
        # import google.colab
        !{sys.executable} -m pip install git+https://github.com/eurostat/
↪pyeudatnat.git
        # !{sys.executable} -m pip install pyeudatnat
    except:
        raise IOError("Sorry, you're doomed: package pyeudatnat not installed !")
    else:
        print("! Package pyeudatnat installed on-the-fly !")

try:
    from pyeudatnat.base import datnatFactory
    from pyeudatnat.misc import Structure
    from pyeudatnat.misc import Type, Datetime
except:
    pass
```

```
/Users/gjacopo/Developments/pyEUDatNat/pyeudatnat/geo.py:48: UserWarning:
! Missing happygisco package (https://github.com/eurostat/happyGISCO) - GISCO
web services not available !
```

```
  warnings.warn('\n! Missing happygisco package
(https://github.com/eurostat/happyGISCO) - GISCO web services not available !')
```

Last, we will use the `matplotlib` package to render the various illustrations of the original study:

[8]:
```
try:
    import matplotlib
except ImportError:
    raise IOError("Guess what: you're doomed...")
else:
    import matplotlib.pyplot as mplt
    import matplotlib.dates as mdates
    from matplotlib.ticker import FuncFormatter, MaxNLocator, IndexLocator
finally:
    _FIGSIZE_, _DPI_ = (7,4), 140 # just some default display size/resolution␣
 ↪inside this notebook...
%matplotlib inline
```

0.2 Data ingestion

The ingestion of the data is entirely defined through the metadata (see resources listed in the "Data resources" section), *e.g.* information regarding source file location, format (although this can be inferred), *etc*... in that case the JSON file 'ITmetadata.json' contained in this directory. If it does not exist, we download this file from the github repository:

[9]:
```
THISDIR = !pwd
META = os.path.join(THISDIR[0], 'ITmetadata.json')
try:
    assert os.path.exists(META)
except:
    !wget -O $META https://raw.githubusercontent.com/gjacopo/morbstat/master/
 ↪ITmetadata.json
with open(META, 'r') as fp:
    metadata = json.load(fp)
print("Content of the metadata file '%s':\n" % os.path.basename(META))
metadata
```

```
Content of the metadata file 'ITmetadata.json':
```

[9]:

```
{'country': {'code': 'IT', 'name': 'Italia'},
 'lang': {'code': 'it', 'name': 'italian'},
 'file': 'comune_giorno.csv',
 'fmt': 'csv',
 'source': 'https://www.istat.it/it/files/2020/03/comune-giorno.zip',
 'enc': 'latin1',
 'sep': ',',
```

```
'datefmt': '%m%d',
'index': {'reg_code': {'name': 'REG',
  'desc': 'Codice Istat della Regione di residenza.',
  'type': 'int',
  'values': None},
 'prov_code': {'name': 'PROV',
  'desc': 'Codice Istat della Provincia di residenza.',
  'type': 'int',
  'values': None},
 'region': {'name': 'NOME_REGIONE',
  'desc': 'Regione di residenza.',
  'type': 'str',
  'values': None},
 'province': {'name': 'NOME_PROVINCIA',
  'desc': 'Provincia di residenza.',
  'type': 'str',
  'values': None},
 'city': {'name': 'NOME_COMUNE',
  'desc': 'Comune di residenza.',
  'type': 'str',
  'values': None},
 'city_code': {'name': 'COD_PROVCOM',
  'desc': 'Comune di residenza (classificazione Istat al 01/01/2020)',
  'type': 'str',
  'values': None},
 'age': {'name': 'CL_ETA',
  'desc': 'Classe di età in anni compiuti al momento del decesso',
  'type': 'int',
  'values': {'0': '0',
   '1': '1-4',
   '2': '5-9',
   '3': '10-14',
   '4': '15-19',
   '5': '20-24',
   '6': '25-29',
   '7': '30-34',
   '8': '35-39',
   '9': '40-44',
   '10': '45-49',
   '11': '50-54',
   '12': '55-59',
   '13': '60-64',
   '14': '65-69',
   '15': '70-74',
   '16': '75-79',
   '17': '80-84',
   '18': '85-89',
```

```
  '19': '90-94',
  '20': '95-99',
  '21': '100+'}},
'date': {'name': 'GE',
 'desc': 'Giorno di decesso (formato variabile: MeseMeseGiornoGiorno).',
 'type': 'str',
 'values': None},
'm_15': {'name': 'MASCHI_15',
 'desc': 'numero di decessi maschili nel 2015.',
 'type': 'int',
 'values': None},
'm_16': {'name': 'MASCHI_16',
 'desc': 'numero di decessi maschili nel 2016.',
 'type': 'int',
 'values': None},
'm_17': {'name': 'MASCHI_17',
 'desc': 'numero di decessi maschili nel 2017.',
 'type': 'int',
 'values': None},
'm_18': {'name': 'MASCHI_18',
 'desc': 'numero di decessi maschili nel 2018.',
 'type': 'int',
 'values': None},
'm_19': {'name': 'MASCHI_19',
 'desc': 'numero di decessi maschili nel 2019.',
 'type': 'int',
 'values': None},
'm_20': {'name': 'MASCHI_20',
 'desc': 'numero di decessi maschili nel 2020.',
 'type': 'int',
 'values': None},
'f_15': {'name': 'FEMMINE_15',
 'desc': 'numero di decessi femminili nel 2015.',
 'type': 'int',
 'values': None},
'f_16': {'name': 'FEMMINE_16',
 'desc': 'numero di decessi femminili nel 2016.',
 'type': 'int',
 'values': None},
'f_17': {'name': 'FEMMINE_17',
 'desc': 'numero di decessi femminili nel 2017.',
 'type': 'int',
 'values': None},
'f_18': {'name': 'FEMMINE_18',
 'desc': 'numero di decessi femminili nel 2018.',
 'type': 'int',
 'values': None},
```

```
  'f_19': {'name': 'FEMMINE_19',
   'desc': 'numero di decessi femminili nel 2019.',
   'type': 'int',
   'values': None},
  'f_20': {'name': 'FEMMINE_20',
   'desc': 'numero di decessi femminili nel 2020.',
   'type': 'int',
   'values': None},
  't_15': {'name': 'TOTALE_15',
   'desc': 'numero di decessi totali nel 2015.',
   'type': 'int',
   'values': None},
  't_16': {'name': 'TOTALE_16',
   'desc': 'numero di decessi totali nel 2016.',
   'type': 'int',
   'values': None},
  't_17': {'name': 'TOTALE_17',
   'desc': 'numero di decessi totali nel 2017.',
   'type': 'int',
   'values': None},
  't_18': {'name': 'TOTALE_18',
   'desc': 'numero di decessi totali nel 2018.',
   'type': 'int',
   'values': None},
  't_19': {'name': 'TOTALE_19',
   'desc': 'numero di decessi totali nel 2019.',
   'type': 'int',
   'values': None},
  't_20': {'name': 'TOTALE_20',
   'desc': 'numero di decessi totali nel 2020.',
   'type': 'int',
   'values': None}},
 'nan': 9999,
 'desc': 'Descrizione e tracciato record dati comunali giornalieri.docx'}
```

Using the `datnatFactory` method, simply define the data structure:

[10]:
```python
MortDatIT = datnatFactory(country = "IT")
dIT = MortDatIT(META)
print("Data source: %s - file: \033[94m%s\033[0m" % (dIT.source, dIT.file))
print("Example of data field - number of female deaths in 2016: \033[94m%s\033[0m" % dIT.meta['index']['f_16'])
```

```
Data source: https://www.istat.it/it/files/2020/03/comune-giorno.zip - file:
comune_giorno.csv
```

Example of data field - number of female deaths in 2016: {'name': 'FEMMINE_16', 'desc': 'numero di decessi femminili nel 2016.', 'type': 'int', 'values': None}

Actually, we already define some metadata variables that we will use in the remaining of this notebook (note that this info could be directly inferred when ingesting the data without setting it directly into the metadata file):

[11]:
```
FMT = dIT.meta.get('fmt') or dIT.meta.get('file','.').split('.')[1]
ENC = dIT.meta.get('enc',None)
SEP =  dIT.meta.get('sep',None)
DTYPE = {v['name']: Type.upytname2npt(v['type']) for v in dIT.meta.
 ↪get('index',{}).values()}
print("Some basic metadata information: \n- field types: %s \n- format: '%s' \n-␣
 ↪encoding: '%s' \n- separator: '%s'"
      % (DTYPE,FMT,ENC,SEP))
```

```
Some basic metadata information:
- field types: {'REG': dtype('int64'), 'PROV': dtype('int64'), 'NOME_REGIONE':
dtype('<U'), 'NOME_PROVINCIA': dtype('<U'), 'NOME_COMUNE': dtype('<U'),
'COD_PROVCOM': dtype('<U'), 'CL_ETA': dtype('int64'), 'GE': dtype('<U'),
'MASCHI_15': dtype('int64'), 'MASCHI_16': dtype('int64'), 'MASCHI_17':
dtype('int64'), 'MASCHI_18': dtype('int64'), 'MASCHI_19': dtype('int64'),
'MASCHI_20': dtype('int64'), 'FEMMINE_15': dtype('int64'), 'FEMMINE_16':
dtype('int64'), 'FEMMINE_17': dtype('int64'), 'FEMMINE_18': dtype('int64'),
'FEMMINE_19': dtype('int64'), 'FEMMINE_20': dtype('int64'), 'TOTALE_15':
dtype('int64'), 'TOTALE_16': dtype('int64'), 'TOTALE_17': dtype('int64'),
'TOTALE_18': dtype('int64'), 'TOTALE_19': dtype('int64'), 'TOTALE_20':
dtype('int64')}
- format: 'csv'
- encoding: 'latin1'
- separator: ','
```

Let's now retrieve the data *on-the-fly*. Hence everytime you launch this notebook, the original data are collected from *ISTAT* website. The main advantage is that you will always get the newest/latest available data, hence you will be able to update the study. The main drawback is that … you will use your bandwidth everytime! Note however that the method `load_data` also accepts a `caching` parameter that enable use to load/save the data from/to a cache. Note the purpose of this notebook, check the implementation of the `pyeudatnat` package if interested.

Many ways to actually fetch the data, but we'd rather exploit the meta information available above:

[12]:
```
dIT.load_data(fmt = FMT, encoding = ENC, sep = SEP, dtype = DTYPE)
print ("Data extracted on %s" % Datetime.datetime(Datetime.TODAY(), fmt='%d/%m/
 ↪%Y'))
```

```
Data extracted on 07/05/2020
```

```
/Users/gjacopo/Developments/pyEUDatNat/pyeudatnat/io.py:939: UserWarning:
! 'CSV' data loaded in dataframe !
  warnings.warn("\n! '%s' data loaded in dataframe !" % f.upper())
```

Let's also simplify the work by broadcasting the dataset into a local variable (not optimal though…):

[13]:
```
data = dIT.data
print("Number of records: \033[1m%s\033[0m - Number of fields (columns):␣
↪\033[1m%s\033[0m"
      % data.shape)
```

```
Number of records: 841031 - Number of fields (columns): 26
```

Let's have a first look at the data:

[14]:
```
data.head(5)
```

[14]:
```
   REG  PROV NOME_REGIONE NOME_PROVINCIA NOME_COMUNE COD_PROVCOM  CL_ETA  \
0    1     1     Piemonte         Torino       Agliè      001001      17
1    1     1     Piemonte         Torino       Agliè      001001      18
2    1     1     Piemonte         Torino       Agliè      001001      18
3    1     1     Piemonte         Torino       Agliè      001001      17
4    1     1     Piemonte         Torino       Agliè      001001      18

     GE  MASCHI_15  MASCHI_16  ...  FEMMINE_17  FEMMINE_18  FEMMINE_19  \
0  0102          0          0  ...           0           1           0
1  0104          0          0  ...           0           0           0
2  0105          0          0  ...           0           0           0
3  0106          1          0  ...           0           0           0
4  0106          0          0  ...           0           0           0

   FEMMINE_20  TOTALE_15  TOTALE_16  TOTALE_17  TOTALE_18  TOTALE_19  \
0           0          0          0          0          1          0
1           0          0          1          0          0          0
2           0          0          0          0          0          0
3           0          1          0          0          0          0
4           0          0          0          0          1          0

   TOTALE_20
0          0
1          0
2          1
3          0
4          0

[5 rows x 26 columns]
```

What are the fields? It should be consistent with the metadata file we introduced earlier…

[15]:
```
print("Fields of the data: \033[94m%s\033[0m" % list(data.columns))
try:
    assert set(list(data.columns)) == set([v['name'] for v in metadata['index'].
 ↪values()])
except:
    print("Mismatch between metadata and actual columns in the dataset")
```

```
Fields of the data: ['REG', 'PROV', 'NOME_REGIONE', 'NOME_PROVINCIA',
'NOME_COMUNE', 'COD_PROVCOM', 'CL_ETA', 'GE', 'MASCHI_15', 'MASCHI_16',
'MASCHI_17', 'MASCHI_18', 'MASCHI_19', 'MASCHI_20', 'FEMMINE_15', 'FEMMINE_16',
'FEMMINE_17', 'FEMMINE_18', 'FEMMINE_19', 'FEMMINE_20', 'TOTALE_15',
'TOTALE_16', 'TOTALE_17', 'TOTALE_18', 'TOTALE_19', 'TOTALE_20']
```

0.3 Data preparation

Let's get rid of those records with no data, *i.e.* with `NAN` values (*e.g.* '9999' for this dataset) in the `T_20` column of total number of deaths in 2020 (*i.e.*, data not yet collected):

[16]:
```
T_20 = dIT.meta.get('index')['t_20']['name']
print("- field of total deaths in 2020: \033[94m%s\033[0m" % T_20)
NAN = dIT.meta.get('nan')
print("- value of NAN mask: \033[94m%s\033[0m" % NAN)
data.drop(data.loc[data[T_20]==NAN].index, inplace=True)
print("Number of cleaned records: \033[1m%s\033[0m - Number of fields (unchanged.
 ↪..): \033[1m%s\033[0m"
      % data.shape)
```

```
- field of total deaths in 2020: TOTALE_20
- value of NAN mask: 9999
Number of cleaned records: 198076 - Number of fields (unchanged...):
26
```

Once the data cleaned, let's have a further look at some basic information, for instance concerning spatial coverage (information regarding province and cities/municipalities for which data have been collected in 2020):

[17]:
```
CITY = dIT.meta.get('index')['city']['name']
print("- field of city names: \033[94m%s\033[0m" % CITY)
CITY_CODE = dIT.meta.get('index')['city_code']['name']
print("- field of city codes: \033[94m%s\033[0m" % CITY_CODE)

comuni = data[CITY].unique()
print("\nCities/municipalities in the study: \033[94m%s\033[0m" % comuni)
print("Number of cities/municipalities: \033[1m%s\033[0m" % len(comuni))
```

```
- field of city names: NOME_COMUNE
- field of city codes: COD_PROVCOM
```

```
Cities/municipalities in the study: ['Agliè' 'Almese' 'Avigliana' ...
'Villaputzu' 'Villasimius' 'Villasor']
Number of cities/municipalities: 1450
```

or the actual temporal coverage (prior to the year of study):

[18]:
```
years = [int("20%s" % tot.split('_')[1]) for tot in data.columns if tot.
 ↪startswith(T_20.split('_')[0])]
ystart, yend =  min(years), max(years)
nyears = len(years)
print('Temporal coverage - Data collections considered: \033[1m[%s, %s]\033[0m'␣
 ↪% (ystart, yend))
```

```
Temporal coverage - Data collections considered: [2015, 2020]
```

Let's have a further look at the time series and the dates covered by the collections in the various years:

[19]:
```
DAY = dIT.meta.get('index')['date']['name']
print("- field of day: \033[94m%s\033[0m" % DAY)
data[DAY].head(5)
```

```
- field of day: GE
```

[19]:
```
0    0102
1    0104
2    0105
3    0106
4    0106
Name: GE, dtype: object
```

Actually, this is special coding of the days in the form "MonthDay" ("*MeseMeseGiornoGiorno*"), as described in the metadata. We introduce some basic functions to make date format conversions easier in the following:

[20]:
```
DATEFMT = dIT.meta.get('datefmt')
print("- date format: \033[94m%s\033[0m" % DATEFMT)
print("The 'day' field %s is described as follow: \033[94m'%s'\033[0m"
      % (DAY,dIT.meta.get('index')['date']['desc']))

def get_daymonth(ge):
    try:
        ge = datetime.strptime(ge, DATEFMT)
    except ValueError:  # deal with 29/02
        ge = time.strptime(ge, DATEFMT)
```

```
    except TypeError:   pass
    try:
        return ge.day, ge.month
    except:
        return ge.tm_mday, ge.tm_mon
def get_datetime(ge, year):
    d = dict(zip(['d', 'm', 'y'], [*get_daymonth(ge), year]))
    return Datetime.datetime(d, fmt='datetime')
```

```
- date format: %m%d
The 'day' field GE is described as follow: 'Giorno di decesso (formato
variabile: MeseMeseGiornoGiorno).'
```

Let's try to understand the purpose of these very basic methods:

[21]:
```
today = datetime.today()
print("Today's date is represented in 'datetime' format as: %s" % today)
today_ge = '%02d%02d' % (today.month, today.day) # or also: datetime.
 ↪strftime(today, DATEFMT)
print("If today's date was present in the IT dataset, it would be represented in␣
 ↪the \033[1m%s\033[0m field as: \033[1m'%s'\033[0m"
      % (DAY,today_ge))
print("\nWhat 'get_daymonth' does, is simply return the '(day,month)' formatted␣
 ↪date, whatever the input format:")
print("- given today=%s, get_daymonth(today) returns %s" %␣
 ↪(today,get_daymonth(today)))
print("- given today='%s', get_daymonth(today) returns %s" %␣
 ↪(today_ge,get_daymonth(today)))
print("\nThen 'get_datetime' retrieves the matching '(day,month)' of a given␣
 ↪date in any other year:")
print("- given today=%s, get_datetime(today,2019) returns %s" %␣
 ↪(today,get_datetime(today,2005)))
print("- given today='%s', get_datetime(today, 1912) returns also %s" %␣
 ↪(today_ge,get_datetime(today,1912)))
print("Note in particular for the leap day:")
print("- get_datetime('0229',2000) returns %s" % get_datetime('0229',2000))
try:
    print("- get_datetime('0229',2019) returns %s" % get_datetime('0229',2019))
except ValueError:
    print("- get_datetime('0229',2019) fails as we could expect...")
```

```
Today's date is represented in 'datetime' format as: 2020-05-07 01:03:58.416502
If today's date was present in the IT dataset, it would be represented in the
GE field as: '0507'

What 'get_daymonth' does, is simply return the '(day,month)' formatted date,
whatever the input format:
```

```
- given today=2020-05-07 01:03:58.416502, get_daymonth(today) returns (7, 5)
- given today='0507', get_daymonth(today) returns (7, 5)

Then 'get_datetime' retrieves the matching '(day,month)' of a given date in any
other year:
- given today=2020-05-07 01:03:58.416502, get_datetime(today,2019) returns
2005-05-07 00:00:00
- given today='0507', get_datetime(today, 1912) returns also 1912-05-07 00:00:00
Note in particular for the leap day:
- get_datetime('0229',2000) returns 2000-02-29 00:00:00
- get_datetime('0229',2019) fails as we could expect...
```

Given the DAY (*i.e.*, "GE") column, we can find out about the first and last days represented in the study:

[22]:
```
dstart, dend = data[DAY].min(), data[DAY].max()
print('Period of data collection considered: \033[1m[%s/%s, %s/%s]\033[0m' % \
      (*get_daymonth(dstart), *get_daymonth(dend)))
```

```
Period of data collection considered: [1/1, 28/3]
```

Considering the temporal corevage (over >4 years), we introduce a year of reference to define the (maximal) length of the time series:

[23]:
```
YREF = 2000
print("A leap year for sure: %s!" % YREF)
dstartref, dendref = get_datetime(dstart, YREF), get_datetime(dend, YREF)

span = Datetime.span(since=dstartref, until=dendref)
ndays = span.days + 1 # +1 because dates are inclusive
print('Max lenght of the time series, i.e. number of days covered by the data␣
 ↪collection: \033[1m%s days\033[0m'
      % ndays)
```

```
A leap year for sure: 2000!
Max lenght of the time series, i.e. number of days covered by the data
collection: 88 days
```

One more consideration regarding the presence of a leapday in the time-series:

[24]:
```
leapday = Datetime.datetime({'y':YREF, 'm':2, 'd':29}, fmt='datetime')
spanleap = Datetime.span(since=dstartref, until=leapday)
ileapday = spanleap.days # note that indexing starts at 0
print('Time series will be padded in position: \033[1m%s\033[0m corresponding to␣
 ↪leapday 29/02' % ileapday)
```

```
Time series will be padded in position: 59 corresponding to leapday
29/02
```

We also introduce, for the rest of the study, an timeline index based on the longest possible time series (for instance during the YREF leap year):

[25]:
```
idx_timeline = pd.date_range(start=dstartref, end=dendref, freq=timedelta(1))
assert len(idx_timeline) == ndays
print(idx_timeline)
```

```
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10', '2000-01-11', '2000-01-12',
               '2000-01-13', '2000-01-14', '2000-01-15', '2000-01-16',
               '2000-01-17', '2000-01-18', '2000-01-19', '2000-01-20',
               '2000-01-21', '2000-01-22', '2000-01-23', '2000-01-24',
               '2000-01-25', '2000-01-26', '2000-01-27', '2000-01-28',
               '2000-01-29', '2000-01-30', '2000-01-31', '2000-02-01',
               '2000-02-02', '2000-02-03', '2000-02-04', '2000-02-05',
               '2000-02-06', '2000-02-07', '2000-02-08', '2000-02-09',
               '2000-02-10', '2000-02-11', '2000-02-12', '2000-02-13',
               '2000-02-14', '2000-02-15', '2000-02-16', '2000-02-17',
               '2000-02-18', '2000-02-19', '2000-02-20', '2000-02-21',
               '2000-02-22', '2000-02-23', '2000-02-24', '2000-02-25',
               '2000-02-26', '2000-02-27', '2000-02-28', '2000-02-29',
               '2000-03-01', '2000-03-02', '2000-03-03', '2000-03-04',
               '2000-03-05', '2000-03-06', '2000-03-07', '2000-03-08',
               '2000-03-09', '2000-03-10', '2000-03-11', '2000-03-12',
               '2000-03-13', '2000-03-14', '2000-03-15', '2000-03-16',
               '2000-03-17', '2000-03-18', '2000-03-19', '2000-03-20',
               '2000-03-21', '2000-03-22', '2000-03-23', '2000-03-24',
               '2000-03-25', '2000-03-26', '2000-03-27', '2000-03-28'],
              dtype='datetime64[ns]', freq='D')
```

0.4 Figure 1 - Map of ANPR municipalities included in the data set

Similarly to the mortality dataset, the geographical dataset that will help us identify (and locate) cities/municipalities in the dataset is represented by a metadata info file, namely the JSON file 'ITmetadata.json' that should be contained in this directory:

[26]:
```
GEOMETA = os.path.join(THISDIR[0], 'ITmetageo.json')
try:
    assert os.path.exists(GEOMETA)
except:
    !wget -O $GEOMETA https://raw.githubusercontent.com/gjacopo/morbstat/master/
 ↪ITmetageo.json
dgeoIT = MortDatIT(GEOMETA)
```

Note the location and format (shapefile files in a remote zip file) of the source datasets:

[27]:
```
print("Source file: %s" % dgeoIT.meta.source)
print("Datasets: \033[94m'%s'\033[0m" % dgeoIT.meta.file)
```

```
Source file: http://www.istat.it/storage/cartografia/confini_amministrativi/non_
generalizzati/Limiti01012020.zip
Datasets: '['Com01012020_WGS84.shp', 'Com01012020_WGS84.shx',
'Com01012020_WGS84.dbf', 'Com01012020_WGS84.prj']'
```

We will load the geographical data using that same `load_data` method as earlier. Because of the way it is implemented (the package `pyeudatnat` uses `geopandas` for the representation and handling of geographical/vector datasets), the data will need to be loaded on the disk (hence the option `on_disk=True` below). In addition, because the format of the data is known (shapefile), we ensure only this file is loaded (the option `infer_fmt=False` will prevent from trying to load all the other files ['.shx', '.dbf', '.prj'] that normaly accompany the shapefile '.shp'). You could also add the keyword option `fmt='shapefile'` below:

[28]:
```
dgeoIT.load_data(on_disk=True, infer_fmt=False)
print ('Geo information retrieved on \033[1m%s\033[0m' % Datetime.
 ↪datetime(Datetime.TODAY(), fmt='%d/%m/%Y'))
```

```
Geo information retrieved on 07/05/2020

/Users/gjacopo/Developments/pyEUDatNat/pyeudatnat/io.py:939: UserWarning:
! 'SHP' data loaded in dataframe !
  warnings.warn("\n! '%s' data loaded in dataframe !" % f.upper())
/Users/gjacopo/Developments/pyEUDatNat/pyeudatnat/io.py:1086: UserWarning:
! File 'Limiti01012020/Com01012020/Com01012020_WGS84.shx' will not be loaded !
  warnings.warn("\n! File '%s' will not be loaded !" % file)
/Users/gjacopo/Developments/pyEUDatNat/pyeudatnat/io.py:1086: UserWarning:
! File 'Limiti01012020/Com01012020/Com01012020_WGS84.dbf' will not be loaded !
  warnings.warn("\n! File '%s' will not be loaded !" % file)
/Users/gjacopo/Developments/pyEUDatNat/pyeudatnat/io.py:1086: UserWarning:
! File 'Limiti01012020/Com01012020/Com01012020_WGS84.prj' will not be loaded !
  warnings.warn("\n! File '%s' will not be loaded !" % file)
```

We can check the projection used for representing the data. In that case ('WGS84' or 'EPSG:32632' code), data are simply represented by their geographical (latitute/longitude) coordinates:

[29]:
```
print(dgeoIT.data.crs)
dgeoIT.data.crs
```

```
epsg:32632
```

[29]:
```
<Projected CRS: EPSG:32632>
Name: WGS 84 / UTM zone 32N
Axis Info [cartesian]:
- E[east]: Easting (metre)
- N[north]: Northing (metre)
Area of Use:
```

```
- name: World - N hemisphere - 6°E to 12°E - by country
- bounds: (6.0, 0.0, 12.0, 84.0)
Coordinate Operation:
- name: UTM zone 32N
- method: Transverse Mercator
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

[30]:
```
print('Attributes of the geodata (including geometries): \033[94m%s\033[0m' %␣
    ↪list(dgeoIT.data.columns))
dgeoIT.data.head(5)
```

```
Attributes of the geodata (including geometries): ['COD_RIP', 'COD_REG',
'COD_PROV', 'COD_CM', 'COD_UTS', 'PRO_COM', 'PRO_COM_T', 'COMUNE', 'COMUNE_A',
'CC_UTS', 'SHAPE_LENG', 'SHAPE_AREA', 'SHAPE_LEN', 'geometry']
```

[30]:
```
   COD_RIP  COD_REG  COD_PROV  COD_CM  COD_UTS  PRO_COM PRO_COM_T  \
0        1        1         1     201      201     1077    001077
1        1        1         1     201      201     1079    001079
2        1        1         1     201      201     1089    001089
3        1        1         1     201      201     1006    001006
4        1        1         1     201      201     1007    001007

        COMUNE COMUNE_A  CC_UTS    SHAPE_LENG    SHAPE_AREA     SHAPE_LEN  \
0   Chiaverano     None       0  18164.369945  1.202212e+07  18164.236621
1  Chiesanuova     None       0  10777.398475  4.118911e+06  10777.318814
2       Coazze     None       0  41591.434852  5.657268e+07  41591.122092
3       Almese     None       0  17058.567837  1.787564e+07  17058.439037
4     Alpette     None       0   9795.635259  5.626076e+06   9795.562269

                                            geometry
0  POLYGON ((414358.390 5042001.044, 414381.796 5...
1  POLYGON ((394621.039 5031581.116, 394716.100 5...
2  POLYGON ((364914.897 4993224.894, 364929.991 4...
3  POLYGON ((376934.962 4999073.854, 376960.555 4...
4  POLYGON ((388890.737 5030465.123, 388945.987 5...
```

In particular, the geographical (vector) information is specifically provided through the `geometry` field of the dataset as a set of `shapely` structures:

[31]:
```
dgeoIT.data['geometry'].head(5)
```

[31]:
```
0    POLYGON ((414358.390 5042001.044, 414381.796 5...
1    POLYGON ((394621.039 5031581.116, 394716.100 5...
2    POLYGON ((364914.897 4993224.894, 364929.991 4...
```

```
3    POLYGON ((376934.962 4999073.854, 376960.555 4...
4    POLYGON ((388890.737 5030465.123, 388945.987 5...
Name: geometry, dtype: geometry
```

We will 'join' the information from both datasets by matching the field/attribute that represent the city code in the two datasets:

[32]:
```
CITY_CODE = dIT.meta.get('index')['city_code']['name']
print("- field uniquely identifying cities/municipalities in mortality dataset:␣
 ↪\033[94m%s\033[0m" % CITY_CODE)
PRO_COM_T = dgeoIT.meta.get('index')['PRO_COM_T']['name']
print("- field uniquely identifying cities/municipalities in geographical␣
 ↪reference dataset: \033[94m%s\033[0m" % PRO_COM_T)
code_comuni = Structure.uniq_list(data[CITY_CODE].to_list())
assert len(code_comuni) == len(comuni)
```

```
- field uniquely identifying cities/municipalities in mortality dataset:
COD_PROVCOM
- field uniquely identifying cities/municipalities in geographical reference
dataset: PRO_COM_T
```

Note that the 'join' operation is not an actual 'join', instead we filter out the geographical datasets to keep only those cities/municipalities that are also present in the mortality dataset:

[33]:
```
geodata = dgeoIT.data[dgeoIT.data.set_index(PRO_COM_T).index.isin(code_comuni)]
geodata.head(5)
```

[33]:
```
    COD_RIP  COD_REG  COD_PROV  COD_CM  COD_UTS  PRO_COM PRO_COM_T  \
3         1        1         1     201      201     1006    001006
11        1        1         1     201      201     1020    001020
15        1        1         1     201      201     1066    001066
19        1        1         1     201      201     1024    001024
31        1        1         1     201      201     1139    001139

                 COMUNE COMUNE_A  CC_UTS    SHAPE_LENG    SHAPE_AREA  \
3                Almese     None       0  17058.567837  1.787564e+07
11           Banchette     None       0  13861.283510  2.028854e+06
15        Castellamonte     None       0  56627.619939  3.870630e+07
19             Beinasco     None       0  18927.804428  6.734254e+06
31  Luserna San Giovanni     None       0  31182.813988  1.774138e+07

       SHAPE_LEN                                           geometry
3   17058.439037  POLYGON ((376934.962 4999073.854, 376960.555 4...
11  13861.181642  MULTIPOLYGON (((410556.045 5035845.088, 410737...
15  56627.197389  MULTIPOLYGON (((399851.593 5035334.590, 399858...
19  18927.661943  POLYGON ((389377.696 4987362.417, 389538.013 4...
31  31182.577534  POLYGON ((362241.646 4966621.595, 362247.927 4...
```

We simply map the remaining geometries (that exclusively correspond to cities present in the mortality dataset) to get a visual hint on the representativeness of the samples in the dataset (samples mostly concentrated around the Lombardia region):

[34]:
```
f, ax = mplt.subplots(1, figsize=(16, 16))
geodata.plot(ax=ax)
ax.set_axis_off()
ax.set_title('Figure 1: Map of ANPR municipalities included in the data set')
mplt.show()
```

Figure 1: Map of ANPR municipalities included in the data set

1 Figure 2 - Daily and cumulated deaths for all municipalities in the data set

We now represent the daily and cumulated deaths for the entire population and for all municipalities present in the dataset.

Simply group by date and sum the total counts of deaths per year ("TOTAL_**") over all other remaining fields (*e.g.*, age class and cities):

[35]:
```
dailydeaths = pd.DataFrame()
for y in years:
    TCOL = dIT.meta.get('index')['t_%s' % str(y)[2:]]['name']
    dailydeaths[y] = data.groupby(DAY)[TCOL].agg('sum')
dailydeaths.head(5)
```

[35]:

	2015	2016	2017	2018	2019	2020
GE						
0101	585	507	656	657	534	513
0102	617	529	761	668	587	571
0103	608	546	720	595	563	589
0104	621	561	733	628	527	538
0105	644	520	766	671	534	545

We also possibly pad the data for non-leap years on the date 29/02:

[36]:
```
print("Counts on 29/02 \033[1mbefore\033[0m padding:\n %s" % dailydeaths.
 ↪iloc[ileapday-1:ileapday+1,:])
for y in years:
    if calendar.isleap(y): continue
    yloc = dailydeaths.columns.get_loc(y)
    dailydeaths.iloc[ileapday,yloc] = dailydeaths.iloc[ileapday-1,yloc]
print("Counts on 29/02 \033[1mafter\033[0m padding:\n %s" % dailydeaths.
 ↪iloc[ileapday-1:ileapday+1,:])
```

```
Counts on 29/02 before padding:
       2015  2016  2017  2018  2019  2020
GE
0228    527   510   581   560   590   568
0229      0   489     0     0     0   551
Counts on 29/02 after padding:
       2015  2016  2017  2018  2019  2020
GE
0228    527   510   581   560   590   568
0229    527   489   581   560   590   551
```

Note that at this stage, the table is indexed by the `DAY` (*i.e.*, 'GE') field (in the form *'MeseMeseGiornoGiorno'*). Instead we want to set the index to the known dates and reindex with the actual timeline since days may be missing (?):

[37]:
```
print('Initial index: %s' % dailydeaths.index)
dailydeaths.set_index(dailydeaths.index.to_series().apply(lambda ge:␣
↪get_datetime(ge,YREF)), inplace=True)
dailydeaths = dailydeaths.reindex(idx_timeline, fill_value=0)
# instead of dailydeaths.set_index(idx_rng, inplace=True)
print('Index reset to actual timeline an garanteed complete days: %s' %␣
↪dailydeaths.index)
```

```
Initial index: Index(['0101', '0102', '0103', '0104', '0105', '0106', '0107',
'0108', '0109',
       '0110', '0111', '0112', '0113', '0114', '0115', '0116', '0117', '0118',
       '0119', '0120', '0121', '0122', '0123', '0124', '0125', '0126', '0127',
       '0128', '0129', '0130', '0131', '0201', '0202', '0203', '0204', '0205',
       '0206', '0207', '0208', '0209', '0210', '0211', '0212', '0213', '0214',
       '0215', '0216', '0217', '0218', '0219', '0220', '0221', '0222', '0223',
       '0224', '0225', '0226', '0227', '0228', '0229', '0301', '0302', '0303',
       '0304', '0305', '0306', '0307', '0308', '0309', '0310', '0311', '0312',
       '0313', '0314', '0315', '0316', '0317', '0318', '0319', '0320', '0321',
       '0322', '0323', '0324', '0325', '0326', '0327', '0328'],
      dtype='object', name='GE')
Index reset to actual timeline an garanteed complete days:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10', '2000-01-11', '2000-01-12',
               '2000-01-13', '2000-01-14', '2000-01-15', '2000-01-16',
               '2000-01-17', '2000-01-18', '2000-01-19', '2000-01-20',
               '2000-01-21', '2000-01-22', '2000-01-23', '2000-01-24',
               '2000-01-25', '2000-01-26', '2000-01-27', '2000-01-28',
               '2000-01-29', '2000-01-30', '2000-01-31', '2000-02-01',
               '2000-02-02', '2000-02-03', '2000-02-04', '2000-02-05',
               '2000-02-06', '2000-02-07', '2000-02-08', '2000-02-09',
               '2000-02-10', '2000-02-11', '2000-02-12', '2000-02-13',
               '2000-02-14', '2000-02-15', '2000-02-16', '2000-02-17',
               '2000-02-18', '2000-02-19', '2000-02-20', '2000-02-21',
               '2000-02-22', '2000-02-23', '2000-02-24', '2000-02-25',
               '2000-02-26', '2000-02-27', '2000-02-28', '2000-02-29',
               '2000-03-01', '2000-03-02', '2000-03-03', '2000-03-04',
               '2000-03-05', '2000-03-06', '2000-03-07', '2000-03-08',
               '2000-03-09', '2000-03-10', '2000-03-11', '2000-03-12',
               '2000-03-13', '2000-03-14', '2000-03-15', '2000-03-16',
               '2000-03-17', '2000-03-18', '2000-03-19', '2000-03-20',
               '2000-03-21', '2000-03-22', '2000-03-23', '2000-03-24',
               '2000-03-25', '2000-03-26', '2000-03-27', '2000-03-28'],
              dtype='datetime64[ns]', freq='D')
```

We introduce two additional time-series for comparison, the count of deaths averaged over all the years prior to the year of study (years_exc):

[38]:
```
years_exc = years.copy()
years_exc.remove(YEAR)

avdailydeathsexc = dailydeaths[years_exc].mean(axis = 1, skipna =True)
avdailydeathsexc
```

[38]:
```
2000-01-01    587.8
2000-01-02    632.4
2000-01-03    606.4
2000-01-04    614.0
2000-01-05    627.0
              ...
2000-03-24    490.0
2000-03-25    493.4
2000-03-26    487.8
2000-03-27    486.6
2000-03-28    505.4
Freq: D, Length: 88, dtype: float64
```

and the average count of deaths by week:

[39]:
```
weeklydeaths = dailydeaths.resample('W').mean()
weeklydeaths.head(5)
```

[39]:
```
                  2015        2016        2017        2018        2019  \
2000-01-02  601.000000  518.000000  708.500000  662.500000  560.500000
2000-01-09  630.714286  539.857143  721.142857  656.285714  559.714286
2000-01-16  601.714286  532.714286  754.714286  644.285714  598.142857
2000-01-23  611.428571  531.857143  701.571429  613.571429  582.428571
2000-01-30  607.428571  542.000000  654.285714  589.000000  595.142857

                  2020
2000-01-02  542.000000
2000-01-09  558.428571
2000-01-16  556.571429
2000-01-23  547.285714
2000-01-30  550.857143
```

For displaying the data (likewise the figures in the original publication), we introduce our own 'house-made' plotting function to further simplifying the automated display of time-series:

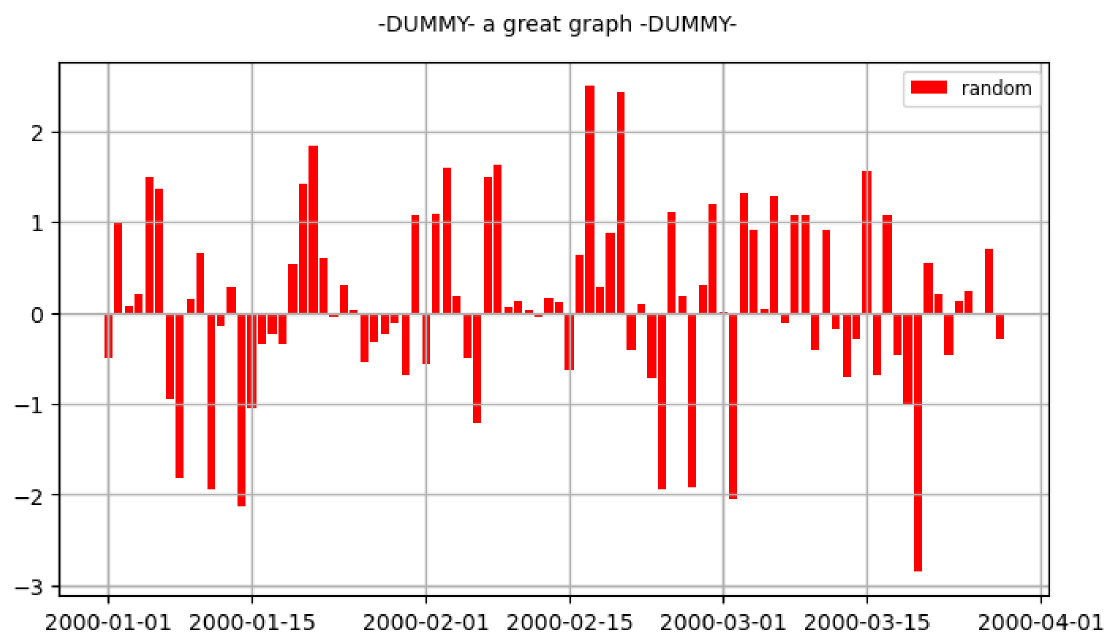
[40]:
```
def plot_one(dat, index = None, one = None, bar=False,
             fig=None, ax=None, figsize=_FIGSIZE_, dpi=_DPI_, shp = (1,1),
             marker='v', color='r', linestyle='-', label='',
             grid = False, xticks = None, xticklabels = None, xrottick = False,
             locator = None, formatter = None,
```

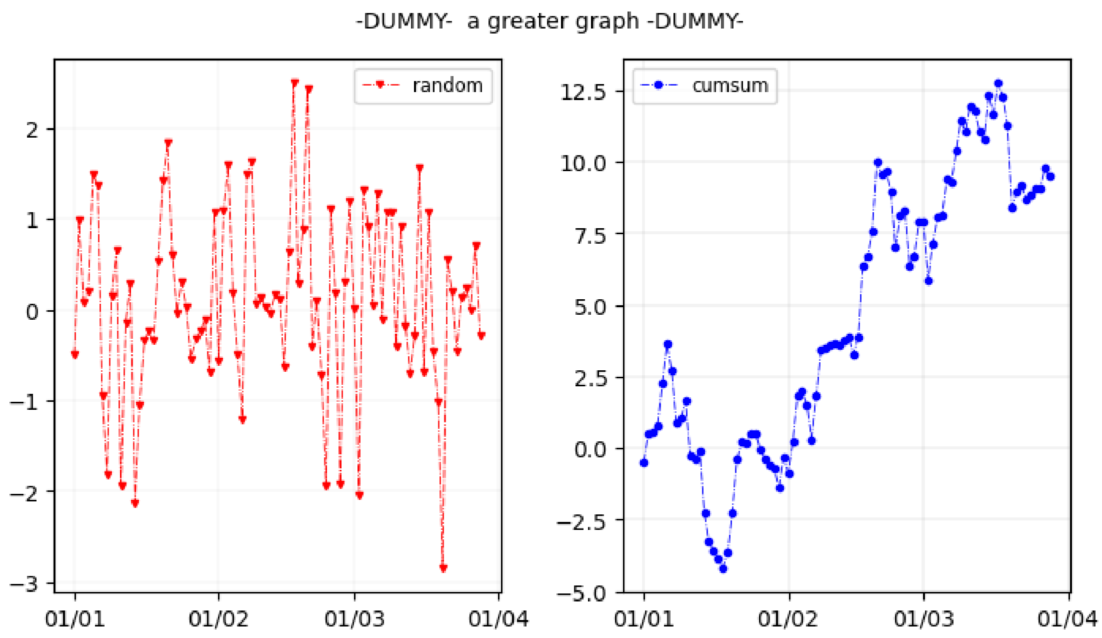
```
              xlabel='', ylabel='', title = '', suptitle=''):
    if ax is None:
        if shp in (None,[],()): shp = (1,1)
        if dpi is None:
            fig, pax = mplt.subplots(*shp, figsize=figsize,␣
↪constrained_layout=True)
        else:
            fig, pax = mplt.subplots(*shp, figsize=figsize, dpi=dpi,␣
↪constrained_layout=True)
        if isinstance(pax,np.ndarray):
            if pax.ndim == 1:     ax_ = pax[0]
            else:                ax_ = pax[0,0]
        else:
            ax_ = pax
    else:
        ax_, pax = ax, None
    if index is None:
        index = dat.index
    if bar is True:
        ax_.bar(dat.index.values,
                dat.loc[index] if one is None else dat.loc[index, one],
                color=color, label=label)
    else:
        ax_.plot(dat.loc[index] if one is None else dat.loc[index, one],
                 c=color, marker=marker, markersize=3, ls=linestyle, lw=0.6,
                 label=label)
    ax_.set_xlabel(xlabel), ax_.set_ylabel(ylabel)
    if grid is not False:        ax_.grid(linewidth=grid)
    if xticks is not None:       ax_.set_xticks(xticks)
    if xticklabels is not None:  ax_.set_xticklabels(xticklabels)
    if xrottick is not False:    ax_.tick_params(axis ='x',␣
↪labelrotation=xrottick)
    if formatter is not None:    ax_.xaxis.set_major_formatter(formatter)
    if locator is not None:      ax_.xaxis.set_major_locator(locator)
    ax_.legend(fontsize='small')
    if title not in ('',None):  ax_.set_title(title,  fontsize='medium')
    if fig is not None and suptitle not in ('',None):
        fig.suptitle(suptitle,  fontsize='medium')
    if pax is not None:
        return fig, pax
```

Let's see quickly how this works in practice on a dummy example:

[41]:
```
ts = pd.Series(np.random.randn(ndays), index=idx_timeline)
plot_one(ts,index=slice(dstartref,dendref), bar=True, label='random', dpi=100,␣
↪grid = 1,
         suptitle='-DUMMY- a great graph -DUMMY-'
```

```
        )

tsc = ts.cumsum()
locator = mdates.DayLocator(bymonthday=1)
formatter = mdates.DateFormatter('%d/%m')
fig, ax = plot_one(ts, index=slice(dstartref,dendref), label='random', shp=(1,2),
                   linestyle='-.', grid = 0.1,
                   dpi=100, locator = locator, formatter = formatter
                  )
plot_one(tsc, index=slice(dstartref,dendref), label='cumsum', fig=fig, ax=ax[1],
         grid = 0.2, linestyle='dashdot', color='b', marker = 'o',
         suptitle='-DUMMY-  a greater graph -DUMMY- ',
         locator = locator, formatter = formatter
        )
```

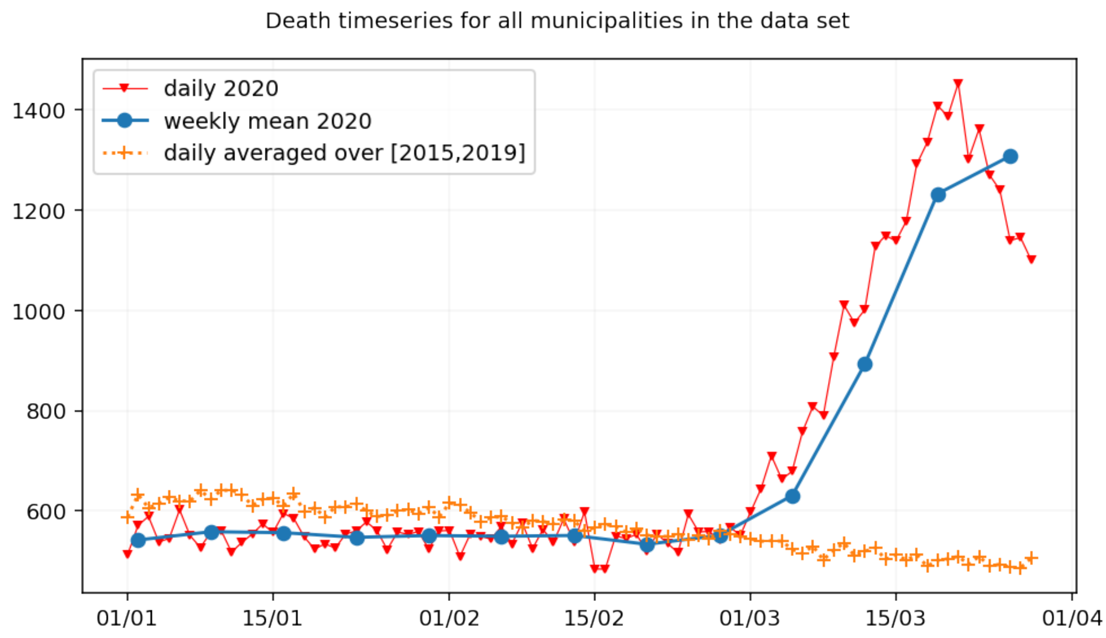




Now, we can use it to plot the 3 created series all together to get a first 'flavour' of the temporal evolution:

[42]:
```
locator = mdates.DayLocator(bymonthday=[1,15])
formatter = mdates.DateFormatter('%d/%m')

fig, ax = plot_one(dailydeaths, one = YEAR, index=slice(dstartref,dendref),␣
 ↪label='daily %s' % YEAR,
                    suptitle = 'Death timeseries for all municipalities in the␣
 ↪data set', grid = 0.1,
                    locator = locator, formatter = formatter
                   )

ax.plot(weeklydeaths.loc[dstartref:dendref, YEAR],
        marker='o', markersize=6, linestyle='-', label='weekly mean %s' % YEAR
       )

ax.plot(avdailydeathsexc.loc[dstartref:dendref],
        marker='+', linestyle=':',
        label='daily averaged over [%s,%s]' % (min(years_exc),max(years_exc))
       )

ax.legend()
```

[42]: <matplotlib.legend.Legend at 0x11764e4d0>



We introduce another "house-made" plotting method:

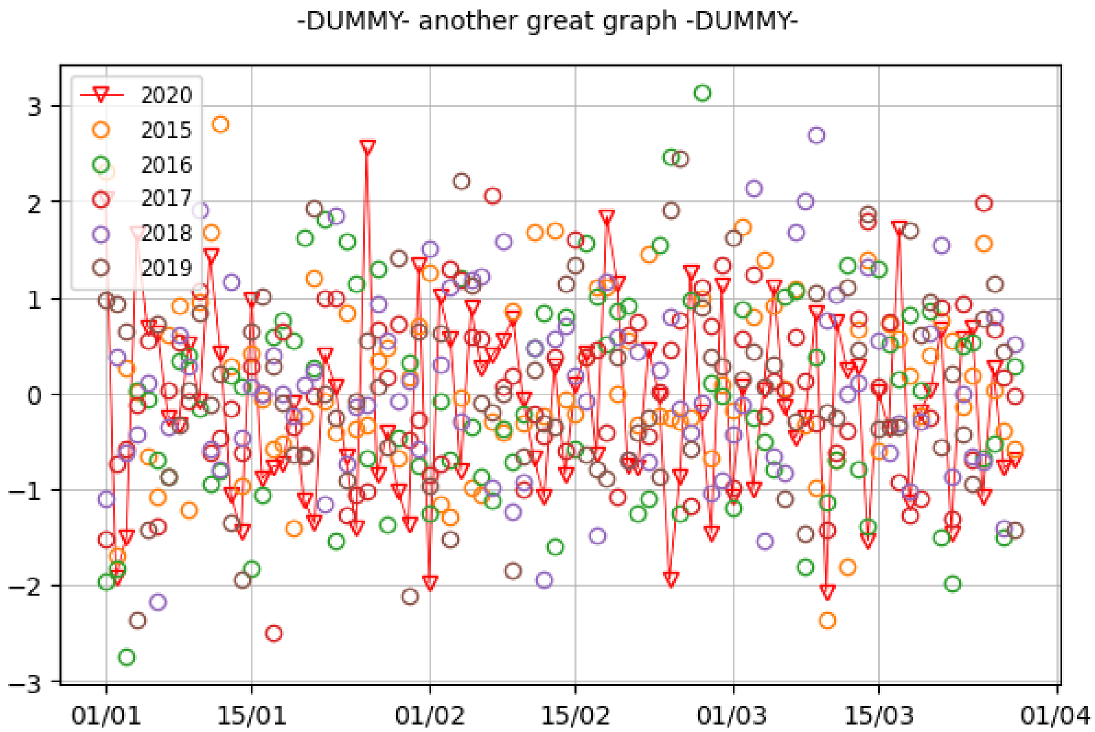
[43]:
```
def plot_oneversus(dat, index = None, one = None, versus = None,
                   fig=None, ax=None, shp = (1,1), dpi=_DPI_,
                   xlabel='', ylabel='', title = '', xrottick = False, legend = None,
                   grid = False, suptitle = '', locator = None, formatter = None):
    if ax is None:
        if shp in (None,[],()): shp = (1,1)
        if dpi is None:     fig, pax = mplt.subplots(*shp, constrained_layout=True)
        else:               fig, pax = mplt.subplots(*shp, dpi=dpi, constrained_layout=True)
        if isinstance(pax,np.ndarray):
            if pax.ndim == 1:     ax_ = pax[0]
            else:                 ax_ = pax[0,0]
        else:
            ax_ = pax
    else:
        ax_, pax = ax, None
    if index is None:
        index = dat.index
    if one is not None:
        ax_.plot(dat.loc[index,one], ls='-', lw=0.6, c='r',
                 marker='v', markersize=6, fillstyle='none')
```

```
        next(ax_._get_lines.prop_cycler)
    if versus is None:
        versus = dat.columns
        try:    versus.remote(one)
        except: pass
    ax_.plot(dat.loc[index,versus], ls='None', marker='o', fillstyle='none')
    ax_.set_xlabel(xlabel), ax_.set_ylabel(ylabel)
    if grid is not False:       ax_.grid(linewidth=grid)
    if xrottick is not False:   ax_.tick_params(axis ='x',␣
↪labelrotation=xrottick)
    if locator is not None:     ax_.xaxis.set_major_locator(locator)
    if formatter is not None:   ax_.xaxis.set_major_formatter(formatter)
    if legend is None:
        legend = [one]
        legend.extend(versus)
    ax_.legend(legend, fontsize='small')
    if title not in ('',None):  ax_.set_title(title,  fontsize='medium')
    if suptitle not in ('',None):
        fig.suptitle(suptitle,  fontsize='medium')
    if pax is not None:
        return fig, pax
```

Again, let's see quickly how this works in practice on a dummy example:

```
[44]: ts = pd.DataFrame(np.random.randn(ndays, nyears), index=idx_timeline,␣
       ↪columns=years)
      plot_oneversus(ts,index=slice(dstartref,dendref), one=YEAR, versus=years_exc,␣
       ↪dpi=100, grid = 0.5,
                     suptitle='-DUMMY- another great graph -DUMMY-',
                     locator = locator, formatter = formatter
                    )
```

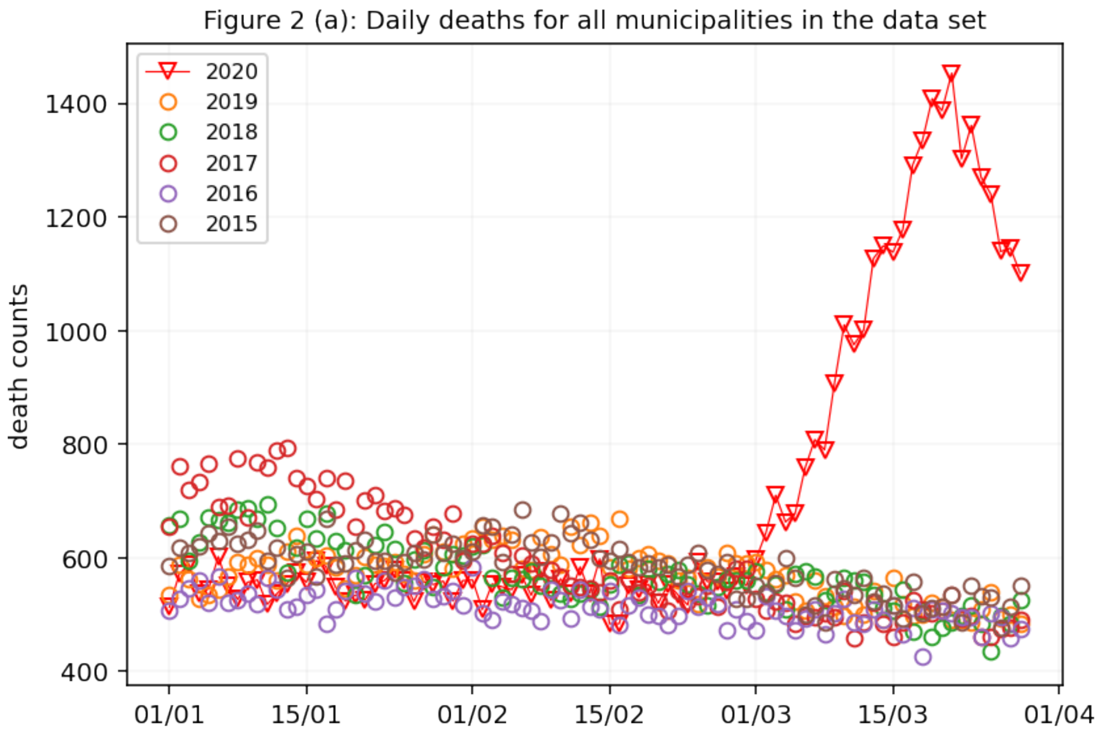
```
[44]: (<Figure size 600x400 with 1 Axes>,
       <matplotlib.axes._subplots.AxesSubplot at 0x1176a6650>)
```



and let's use it to represent the temporal evolution of the different time series for the available years:

[45]:
```
plot_oneversus(dailydeaths, one = YEAR, versus = years_exc[::-1], grid = 0.1,
               ylabel='death counts', title = 'Figure 2 (a): Daily deaths for␣
 ↪all municipalities in the data set',
               locator = locator, formatter = formatter
              )
```

[45]:
```
(<Figure size 840x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x117740fd0>)
```



Following, we also create the timeseries of cumulated counts:

[46]:
```
cumdailydeaths = dailydeaths.cumsum(axis = 0)
cumdailydeaths.head(5)
```

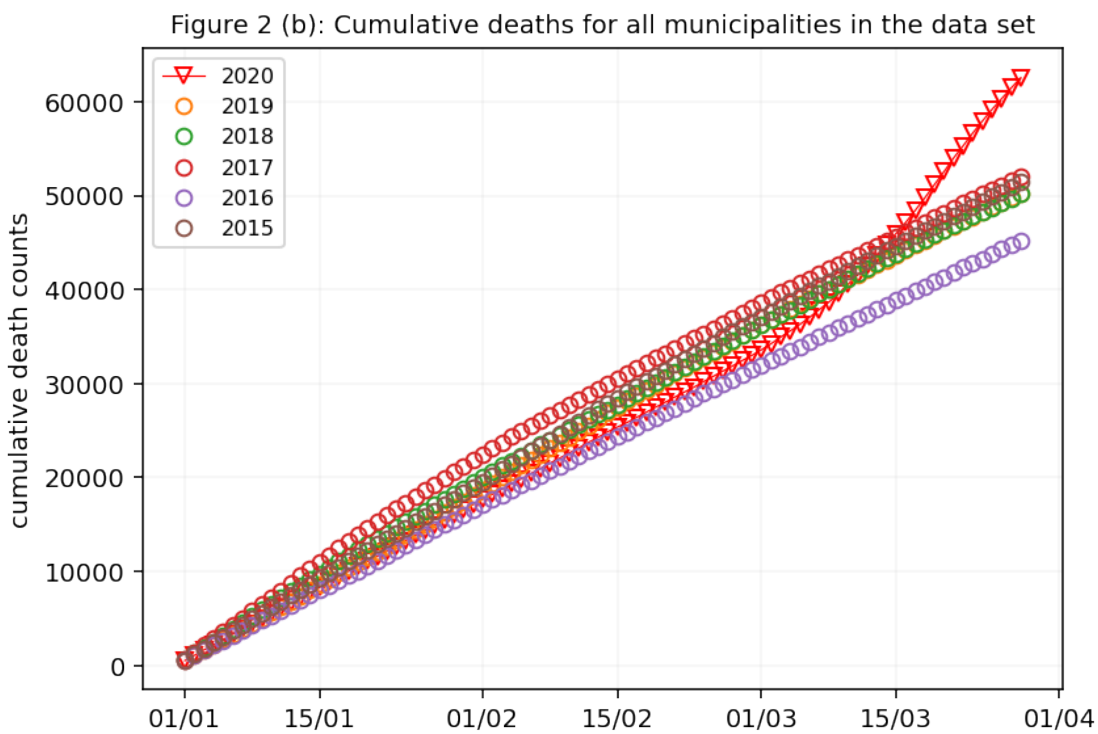
[46]:

	2015	2016	2017	2018	2019	2020
2000-01-01	585	507	656	657	534	513
2000-01-02	1202	1036	1417	1325	1121	1084
2000-01-03	1810	1582	2137	1920	1684	1673
2000-01-04	2431	2143	2870	2548	2211	2211
2000-01-05	3075	2663	3636	3219	2745	2756

and display it:

[47]:
```
plot_oneversus(cumdailydeaths, one = YEAR, versus = years_exc[::-1], grid = 0.1,
               ylabel='cumulative death counts',
               title = 'Figure 2 (b): Cumulative deaths for all municipalities␣
 ↪in the data set',
               locator = locator, formatter = formatter
              )
```

[47]:
```
(<Figure size 840x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x11773fbd0>)
```



2 Figure 3 - Age distribution of total deaths in the period 15-21 March

First we set the period of interest:

[48]:
```
dstart = get_datetime('0315',YREF)
week = dstart.isocalendar()[1]
dend = dstart + timedelta(6) # ddays[-1]
ddays = ['%02d%02d' % (d.month,d.day) for d in [dstart + timedelta(i) for i in␣
↪range(6)]]
```

We will use the specific field with class ages in the dataset. That's also where the metadata information comes handy:

[49]:
```
AGE = dIT.meta.get('index')['age']['name']
print("- field of age classes: \033[94m%s\033[0m" % AGE)
FORMATTER = dIT.meta.get('index')['age']['values']
print("- range of age classes: \033[94m%s\033[0m" % FORMATTER)
```

```
- field of age classes: CL_ETA
```

```
- range of age classes: {'0': '0', '1': '1-4', '2': '5-9', '3': '10-14',
'4': '15-19', '5': '20-24', '6': '25-29', '7': '30-34', '8': '35-39', '9':
'40-44', '10': '45-49', '11': '50-54', '12': '55-59', '13': '60-64', '14':
'65-69', '15': '70-74', '16': '75-79', '17': '80-84', '18': '85-89', '19':
'90-94', '20': '95-99', '21': '100+'}
```

For this illustration, we will create a dictionary of dataframes indexed by gender: 't', 'f' and 'm'. We then proceed like for the previous dataset `dailydeaths`, simply grouping by date and age class, then *resp.* summing the 't', 'f' and 'm' counts of deaths per year (*resp.*, "TOTAL_**", "F_**" and "M_**") over all other remaining fields (*e.g.*, cities):

[50]:
```
ageofdeaths = dict.fromkeys(['t','f','m'])
for k in ageofdeaths.keys():
    deaths = pd.DataFrame()
    for y in years:
        COL = dIT.meta.get('index')['%s_%s' % (k,str(y)[2:])]['name']
        d = data.groupby([AGE,DAY])[COL].agg('sum')
        if leapday >= dstart and leapday <= dend:
            # well... we should do something to be truly generic here... next␣
↪time!
            pass
        deaths[y] = d[d.index.get_level_values(DAY).isin(ddays)].groupby(AGE).
↪agg('sum')
    ageofdeaths.update({k: deaths})
ageofdeaths['f'].head(5)
```

[50]:

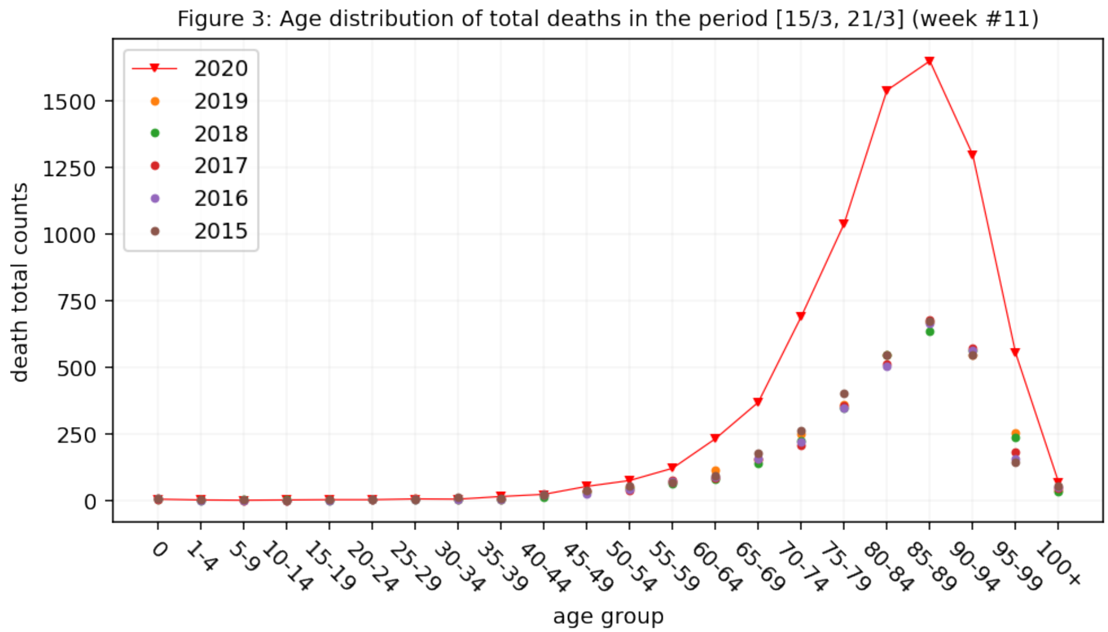
	2015	2016	2017	2018	2019	2020
CL_ETA						
0	1	5	1	1	5	0
1	1	0	2	0	0	0
2	0	0	0	1	0	0
3	0	0	0	0	0	0
4	0	0	0	0	1	2

We then represent together the series for the different years:

[51]:
```
fig, ax = plot_one(ageofdeaths['t'], one = YEAR, label = YEAR,
                   marker = 'v', color = 'r', linestyle = '-', xrottick = -45,␣
↪grid = 0.1,
                   xlabel = 'age group', ylabel = 'death total counts',
                   title = 'Figure 3: Age distribution of total deaths in the␣
↪period [%s/%s, %s/%s] (week #%s)' %
                       (*get_daymonth(dstart), *get_daymonth(dend), week),
                   xticks = list(range(len(FORMATTER.keys()))), xticklabels =␣
↪list(FORMATTER.values())
                  )
```

```
next(ax._get_lines.prop_cycler)
ax.plot(ageofdeaths['t'][years_exc[::-1]],
        marker='o', markersize=3, linestyle='None'
       )

ax.legend(years[::-1])
```

[51]: <matplotlib.legend.Legend at 0x11769ea50>



3 Figure 4 - Relative increment of 2020 over baseline in 15-21 March per age group

The previously generated dataset `ageofdeaths` is used to relative increment of 2020 over baseline in 15-21 March per age group:

[52]:
```
for k in ageofdeaths.keys():
    deaths = ageofdeaths[k]
    deaths['base'] = deaths[years_exc].mean(axis = 1)
    deaths['rinc'] = deaths[YEAR].sub(deaths.base).div(deaths.base)
```

We define the period of interest:

[53]:
```
astart, aend = 11, max(map(int,list(FORMATTER.keys())))
rages, sages = range(astart, aend+1), slice(astart, aend)
```

```
print("Age ranges considered in '65+': \033[1m%s\033[0m" % [FORMATTER[str(i)]␣
↪for i in rages])
```

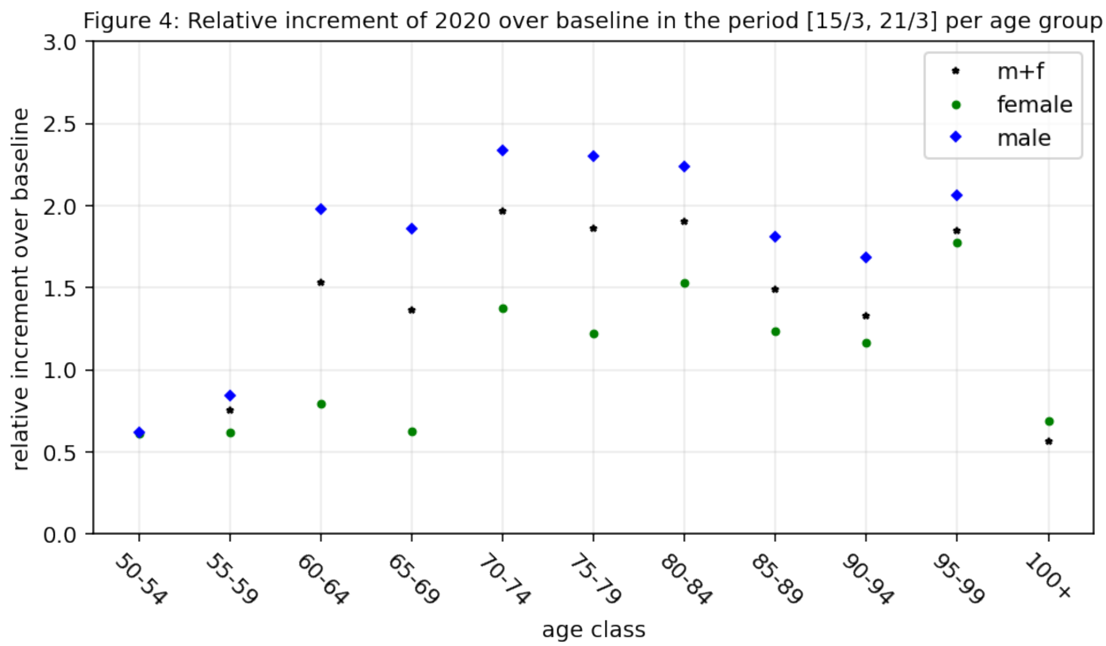
Age ranges considered in '65+': ['50-54', '55-59', '60-64', '65-69',

'70-74', '75-79', '80-84', '85-89', '90-94', '95-99', '100+']

that we use then for generating the figure:

[54]:
```
def func_formater(val, pos):
    try:        return FORMATTER[str(int(val))]
    except:     return ''

fig, ax = plot_one(ageofdeaths['t'], index = sages, one = 'rinc',
                   marker = '*', color = 'k', linestyle = 'None',
                   xrottick = -45, grid = 0.2,
                   xlabel = 'age class', ylabel = 'relative increment over␣
↪baseline', label = 'm+f',
                   title = 'Figure 4: Relative increment of %s over baseline in␣
↪the period [%s/%s, %s/%s] per age group' %
                        (YEAR, *get_daymonth(dstart), *get_daymonth(dend)),
                   formatter = FuncFormatter(func_formater), locator =␣
↪IndexLocator(base=1,offset=0)
                  )
ax.plot(ageofdeaths['f'].loc[sages,'rinc'],
        marker='o', color='g', markersize=3, linestyle='None', label='female'
       )

ax.plot(ageofdeaths['m'].loc[sages,'rinc'],
        marker='D', color='b', markersize=3, linestyle='None', label='male'
       )

ax.set_ylim([0,3]) # hard-coded like in the figure... sorry
ax.legend()
```

[54]: <matplotlib.legend.Legend at 0x117723210>



4 Figure 5 - Empirical cumulative distribution of excess deaths in 15-21 March 2020 per age group

We compute the empirical cumulative distribution of excess deaths in 15-21 March 2020 per age group:

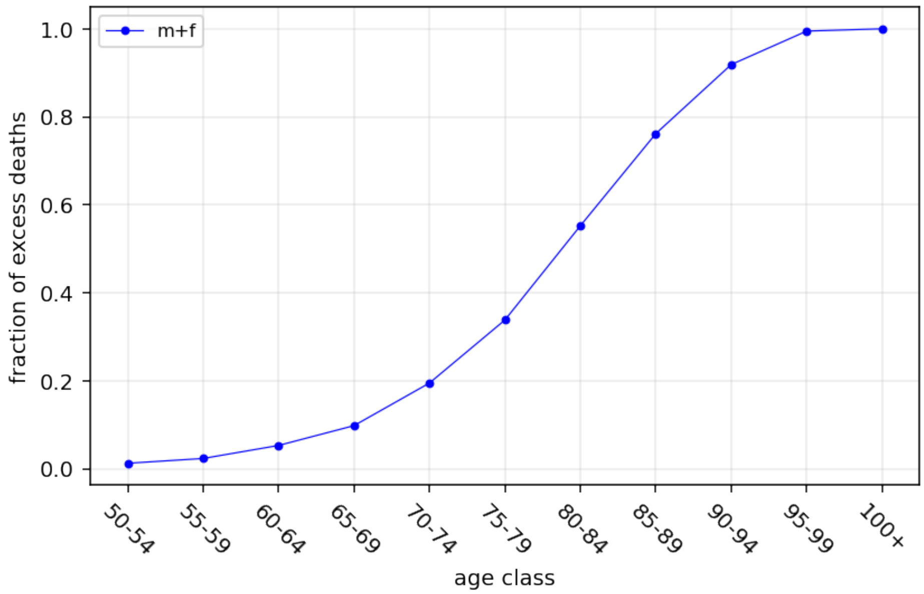
[55]:
```
incdeaths = ageofdeaths['t'].apply(lambda row: row[YEAR] - row['base'], axis=1)
cumdeaths = incdeaths.cumsum(axis = 0, skipna =True)
```

then plotting the empirical cumulative distribution of excess deaths in the considered period:

[56]:
```
plot_one(cumdeaths/max(cumdeaths), index = sages,
         marker = 'o', color = 'b', xrottick = -45, grid = 0.2,
         xlabel = 'age class',  ylabel = 'fraction of excess deaths', label =␣
 ↪'m+f',
         title = 'Figure 5: Empirical cumulative distribution of excess deaths␣
 ↪in the period [%s/%s, %s/%s] per age group' %
              (*get_daymonth(dstart), *get_daymonth(dend)),
         formatter = FuncFormatter(func_formater), locator =␣
 ↪IndexLocator(base=1,offset=0)
         )
```

[56]:
```
(<Figure size 980x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x1177a4cd0>)
```

Figure 5: Empirical cumulative distribution of excess deaths in the period [15/3, 21/3] per age group



5 Figure 6 - Daily and cumulated deaths of males aged 65+

Given the age classes considered above (range of ages rages), we extrac the daily deaths for the male population (hence looking at "M_**" field) over 65 similarly to what we have done for dailydeaths, just introducing a filter of the input data:

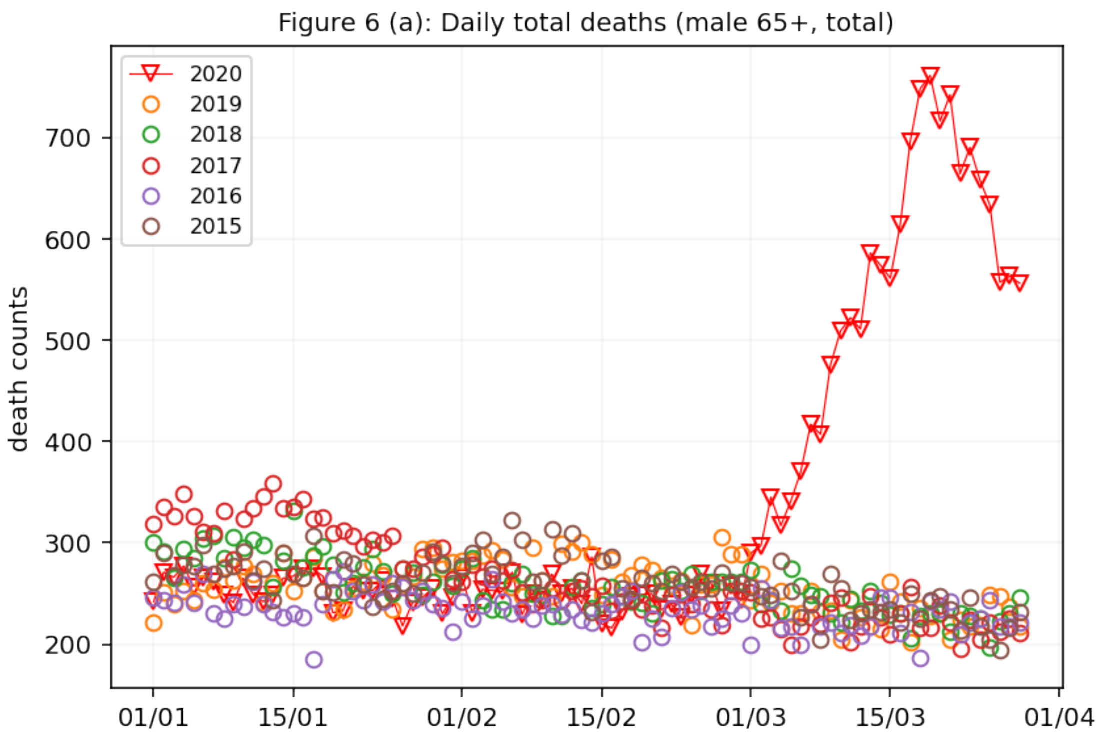
```
[57]: dailydeaths_m65 = pd.DataFrame()
for y in years:
    MCOL = dIT.meta.get('index')['m_%s' % str(y)[2:]]['name']
    dailydeaths_m65[y] = data[data[AGE].isin(rages)].groupby(DAY)[MCOL].
 ↪agg('sum')
    if not calendar.isleap(y):
        yloc = dailydeaths_m65.columns.get_loc(y)
        dailydeaths_m65.iloc[ileapday,yloc] = dailydeaths_m65.
 ↪iloc[ileapday-1,yloc]
dailydeaths_m65.set_index(dailydeaths_m65.index.to_series().apply(lambda ge:␣
 ↪get_datetime(ge,YREF)), inplace=True)
dailydeaths_m65 = dailydeaths_m65.reindex(idx_timeline, fill_value=0)
```

and then render the data:

```
[58]: locator = mdates.DayLocator(bymonthday=[1,15]) # mdates.
 ↪WeekdayLocator(interval=2)
formatter = mdates.DateFormatter('%d/%m')
```

```
plot_oneversus(dailydeaths_m65, one = YEAR, versus = years_exc[::-1], grid = 0.1,
                ylabel='death counts', title = 'Figure 6 (a): Daily total deaths␣
 ↪(male 65+, total)',
                locator = locator, formatter = formatter
               )
```

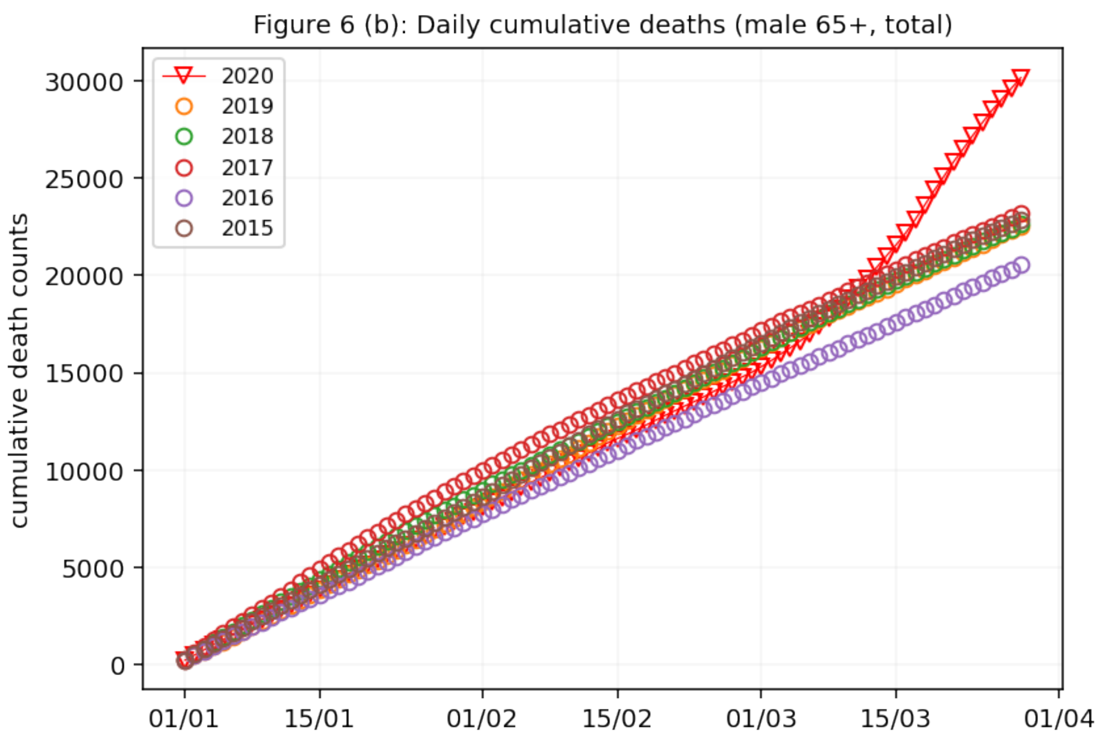
[58]:
```
(<Figure size 840x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x1176d4f50>)
```



Using `dailydeaths_m65`, it is then straightforward to compute and represent the cumulated deaths:

[59]:
```
cumdailydeaths_m65 = dailydeaths_m65.cumsum(axis = 0)

plot_oneversus(cumdailydeaths_m65, one = YEAR, versus = years_exc[::-1], grid =␣
 ↪0.1,
                ylabel='cumulative death counts',
                title = 'Figure 6 (b): Daily cumulative deaths (male 65+, total)',
                locator = locator, formatter = formatter
               )
```

[59]:
```
(<Figure size 840x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x117666550>)
```



6 Figure 7 - Total deaths in the period 1-21 March per individual municipalities

We introduce (now only) a new field in the original dataset in the form of a reference date (in the leap year `YREF`) as a way to handle the time series (where the year used in the index is actually irrelevant, only the day/month information is of use):

[60]:
```
dstart, dend = get_datetime('0301',YREF), get_datetime('0321',YREF)
data.insert(0, 'GE_DATE', data[DAY].apply(lambda row: get_datetime(row, YREF)))
data.head()
```

[60]:
```
     GE_DATE  REG  PROV NOME_REGIONE NOME_PROVINCIA NOME_COMUNE COD_PROVCOM  \
0 2000-01-02    1     1     Piemonte         Torino       Agliè      001001
1 2000-01-04    1     1     Piemonte         Torino       Agliè      001001
2 2000-01-05    1     1     Piemonte         Torino       Agliè      001001
3 2000-01-06    1     1     Piemonte         Torino       Agliè      001001
4 2000-01-06    1     1     Piemonte         Torino       Agliè      001001

   CL_ETA    GE  MASCHI_15  ...  FEMMINE_17  FEMMINE_18  FEMMINE_19  \
0      17  0102          0  ...           0           1           0
1      18  0104          0  ...           0           0           0
2      18  0105          0  ...           0           0           0
3      17  0106          1  ...           0           0           0
```

```
4      18  0106          0  ...          0          0          0

   FEMMINE_20  TOTALE_15  TOTALE_16  TOTALE_17  TOTALE_18  TOTALE_19  \
0           0          0          0          0          1          0
1           0          0          1          0          0          0
2           0          0          0          0          0          0
3           0          1          0          0          0          0
4           0          0          0          0          1          0

   TOTALE_20
0          0
1          0
2          1
3          0
4          0

[5 rows x 27 columns]
```

Because we look now at cities/municipalities individually, we will be examining the following fields:

[61]:
```
CITY_CODE = dIT.meta.get('index')['city_code']['name']
print("- field of city/municipality codes: \033[94m%s\033[0m" % CITY_CODE)
PROV_CODE = dIT.meta.get('index')['prov_code']['name']
print("- field of province codes: \033[94m%s\033[0m" % PROV_CODE)
PROVINCE = dIT.meta.get('index')['province']['name']
print("- field of province names: \033[94m%s\033[0m" % PROVINCE)
```

```
- field of city/municipality codes: COD_PROVCOM
- field of province codes: PROV
- field of province names: NOME_PROVINCIA
```

Grouping by city/municipality enables us to actually estimate the sum of total deaths in the period considered (between dstart and dend). We also introduce the baseline figure for each city/municipality as the maximum number of deaths over the previous years':

[62]:
```
citydeaths = pd.DataFrame()
for y in years:
    TCOL = dIT.meta.get('index')['t_%s' % str(y)[2:]]['name']
    citydeaths[y] = data[data['GE_DATE'].between(dstart, dend, inclusive=True)] ␣
 ↪ \
        .groupby(CITY_CODE)[TCOL].agg('sum')
citydeaths['base'] = citydeaths.loc[:,years_exc].max(axis=1)
citydeaths.head(5)
```

[62]:
```
             2015  2016  2017  2018  2019  2020  base
COD_PROVCOM
001001          1     3     1     3     3     7     3
```

```
001006          2    1    2    3    2    3    3
001013          5   10    9    5    4    5   10
001020          3    1    1    4    1    6    4
001024         16   10    9   17   18   27   18
```

It is easy to operate over all cities present in the dataset:

[63]:
```
cities = data.loc[:,[CITY, CITY_CODE, PROVINCE, PROV_CODE]].drop_duplicates()
assert len(cities) == len(comuni) # remember: that was data[CITY].unique()
cities.head(10)
```

[63]:
```
            NOME_COMUNE COD_PROVCOM NOME_PROVINCIA  PROV
0                 Agliè      001001         Torino     1
203              Almese      001006         Torino     1
748           Avigliana      001013         Torino     1
1197          Banchette      001020         Torino     1
1391           Beinasco      001024         Torino     1
2286          Bosconero      001033         Torino     1
2637             Bruino      001038         Torino     1
3102   Buttigliera Alta      001045         Torino     1
4141         Carmagnola      001059         Torino     1
5038      Castellamonte      001066         Torino     1
```

but instead, we select, like in the study, only a bunch of them for annotation on the graph:

[64]:
```
comuni = ['Albino', 'Bergamo', 'Brescia', 'Codogno', 'Crema',
          'Milano', 'Nembro', 'Parma', 'Piacenza', 'San Giovanni Bianco']
comunitable = cities.loc[cities[CITY].isin(comuni)]
comunitable.set_index(comunitable[CITY_CODE], inplace=True)
comunitable
```

[64]:
```
                    NOME_COMUNE COD_PROVCOM NOME_PROVINCIA  PROV
COD_PROVCOM
015146                   Milano      015146         Milano    15
016004                   Albino      016004        Bergamo    16
016024                  Bergamo      016024        Bergamo    16
016144                   Nembro      016144        Bergamo    16
016188      San Giovanni Bianco      016188        Bergamo    16
017029                  Brescia      017029        Brescia    17
019035                    Crema      019035        Cremona    19
033032                 Piacenza      033032       Piacenza    33
034027                    Parma      034027          Parma    34
098019                  Codogno      098019           Lodi    98
```

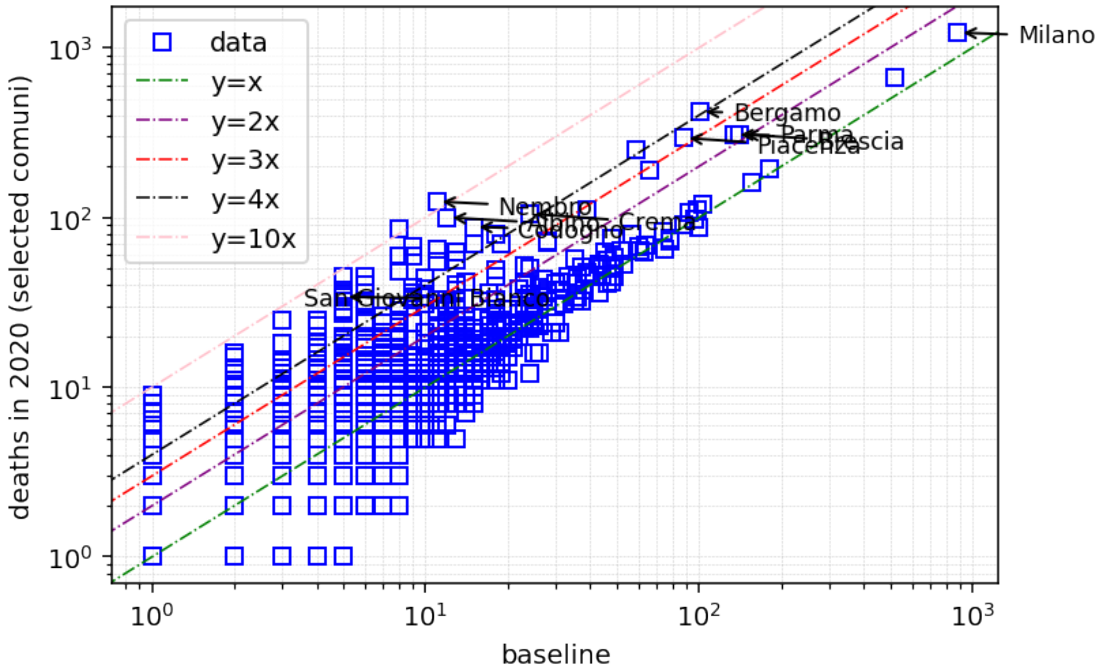
and we display everything together:

[65]:
```
fig, ax = mplt.subplots(dpi=_DPI_)
citydeaths.plot(loglog=True,  x='base', y=YEAR, # kind='scatter',
```

```
                ls='None', color='b', marker='s', fillstyle='none',␣
↪label='data', ax=ax
               )

xlim, ylim = ax.get_xlim(), ax.get_ylim()
x = np.arange(0, 10**4, 1)
for i, c in zip([1,2,3,4,10], ['g', 'purple', 'red', 'k', 'pink']):
    ax.loglog(x, i * x, label = 'y=%sx' % ('' if i==1 else str(i)), ls='-.',␣
↪lw=0.8, c=c)
ax.set_xlim(xlim), ax.set_ylim(ylim)
ax.grid(linewidth=0.3, which="both", ls='dotted')

for index in comunitable.index:
    xpos, ypos = citydeaths.loc[index,'base'], citydeaths.loc[index,YEAR]
    r = np.random.random() +1
    ax.annotate(comunitable.loc[index,CITY],
                (xpos, ypos),
                xytext=(xpos+r*10**np.log10(xpos), ypos-r*10**(np.
↪log10(ypos)-1)),
                arrowprops=dict(arrowstyle='->'),
                size=9, ha='center')

ax.set_xlabel('baseline')
ax.set_ylabel('deaths in %s (selected comuni)' % YEAR)
ax.set_title('Figure 7: Total deaths in the period %s - %s per individual␣
↪municipalities' %
             (Datetime.datetime(dstart, fmt='%d %b'), Datetime.datetime(dend,␣
↪fmt='%d %b')),  fontsize='medium'),
ax.legend()
```

[65]: `<matplotlib.legend.Legend at 0x103584fd0>`

Figure 7: Total deaths in the period 01 Mar - 21 Mar per individual municipalities



We also propose to spatially represent the relative increment of deaths with respect to the baseline. Besides computing the actual increment, we also retrieve the `CITY_CODE` index (*i.e.* 'COD_PROVCOM') and insert it as a column that we rename 'PRO_COM_T':

[66]:
```
citydeaths['rinc'] = citydeaths[YEAR].sub(citydeaths.base).div(citydeaths.base)
citydeaths[PRO_COM_T] = citydeaths.index
citydeaths.head(5)
```

[66]:

	2015	2016	2017	2018	2019	2020	base	rinc	PRO_COM_T
COD_PROVCOM									
001001	1	3	1	3	3	7	3	1.333333	001001
001006	2	1	2	3	2	3	3	0.000000	001006
001013	5	10	9	5	4	5	10	-0.500000	001013
001020	3	1	1	4	1	6	4	0.500000	001020
001024	16	10	9	17	18	27	18	0.500000	001024

The 'PRO_COM_T' variable is actually used to 'left join' (`merge`) the `citydeaths` data together with the geographical data `geodata` on city vectorial representation:

[67]:
```
geodata = geodata.merge(citydeaths, on=PRO_COM_T)
geodata.head(5)
```

[67]:

	COD_RIP	COD_REG	COD_PROV	COD_CM	COD_UTS	PRO_COM	PRO_COM_T	\
0	1	1	1	201	201	1006	001006	

```
1        1        1         1     201      201      1020     001020
2        1        1         1     201      201      1066     001066
3        1        1         1     201      201      1024     001024
4        1        1         1     201      201      1139     001139

                 COMUNE COMUNE_A  CC_UTS  ...     SHAPE_LEN  \
0                Almese     None       0  ...  17058.439037
1             Banchette     None       0  ...  13861.181642
2         Castellamonte     None       0  ...  56627.197389
3              Beinasco     None       0  ...  18927.661943
4  Luserna San Giovanni     None       0  ...  31182.577534

                                            geometry  2015 2016  2017  2018  \
0  POLYGON ((376934.962 4999073.854, 376960.555 4...     2    1     2     3
1  MULTIPOLYGON (((410556.045 5035845.088, 410737...     3    1     1     4
2  MULTIPOLYGON (((399851.593 5035334.590, 399858...     6   10     6     3
3  POLYGON ((389377.696 4987362.417, 389538.013 4...    16   10     9    17
4  POLYGON ((362241.646 4966621.595, 362247.927 4...     9    7    12     9

   2019  2020  base      rinc
0     2     3     3  0.000000
1     1     6     4  0.500000
2     9     9    10 -0.100000
3    18    27    18  0.500000
4    12    11    12 -0.083333

[5 rows x 22 columns]
```

and we can represent it here:

[68]:
```
f, ax = mplt.subplots(1, figsize=(16, 16))
geodata.plot(column='rinc', legend=True, ax=ax)
ax.set_axis_off()
ax.set_title('Figure 7.5: Relative increment over selected cities/municipalities␣
↪(comuni)')
mplt.show()
```

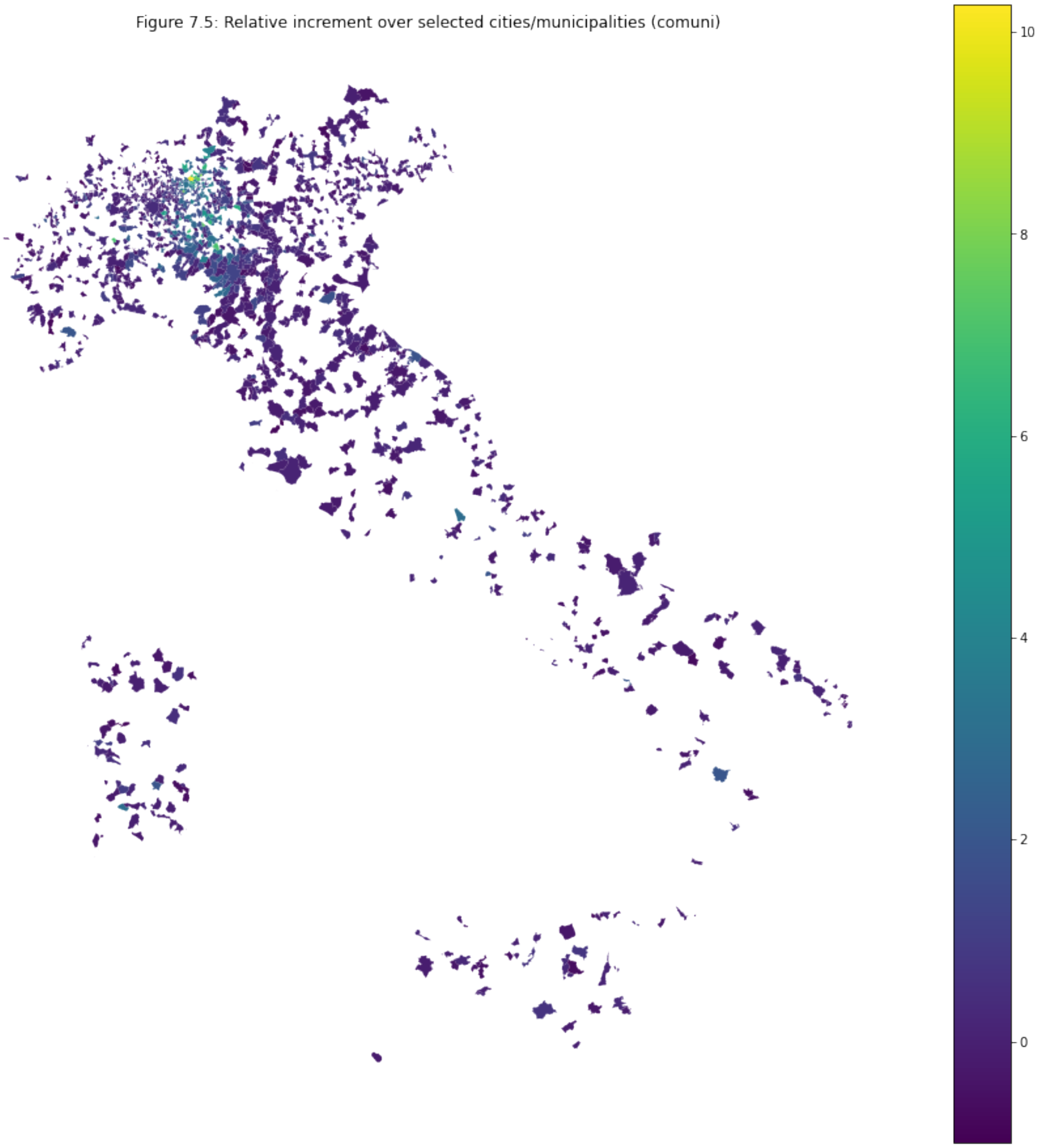


Figure 7.5: Relative increment over selected cities/municipalities (comuni)

7 Figures 8 - 12: Daily and cumulative deaths over individual cities

Let's pick a city among those analysed in the study:

```
[69]: fign = {'Codogno':8, 'Nembro':9, 'Orzinuovi':10, 'Brescia':11, 'Bergamo':12
        }
comune = 'Codogno' # 'Nembro' # 'Orzinuovi' # 'Brescia' # 'Bergamo'
comune_code = cities.loc[cities[CITY]==comune].loc[:,CITY_CODE].values.
 ↪tolist()[0]
provincia = cities.loc[cities[CITY]==comune].loc[:,PROVINCE].values.tolist()[0]
```

```
print("Analysing the 'comune di' \033[1m%s\033[0m in 'provincia di'␣
↪\033[1m%s\033[0m (#\033[1m%s\033[0m)"
      % (comune,provincia,int(comune_code)))
```

```
Analysing the 'comune di' Codogno in 'provincia di' Lodi
(#98019)
```

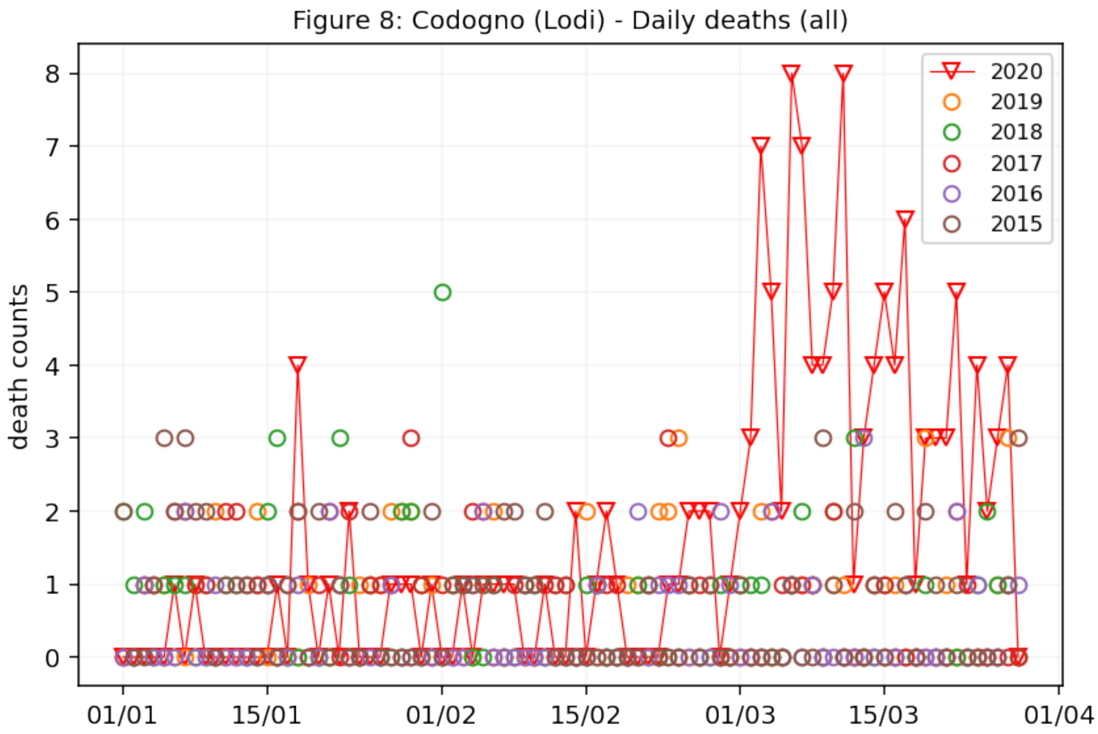
Grouping by date (DAY, *i.e.* 'GE') the data over the comune and aggregating the totals for the different years is what we need:

[70]:
```
TCOLS = [dIT.meta.get('index')['t_%s' % str(y)[2:]]['name']
         for y in years]
dailydeaths = data[data[CITY]==comune].groupby(DAY).agg({t:'sum' for t in TCOLS})

dailydeaths.set_index(pd.Index(dailydeaths.index.to_series().apply(lambda ge:␣
↪get_datetime(ge,YREF))),
                      inplace=True)
dailydeaths.sort_index(inplace=True)
dailydeaths = dailydeaths.reindex(idx_timeline, method='pad').rename(columns={t:
↪int('20%s' %t[-2:]) for t in TCOLS})
```

Let's display the total daily deaths for the selected city:

[71]:
```
locator = mdates.DayLocator(bymonthday=[1,15]) # mdates.
↪WeekdayLocator(interval=2)
formatter = mdates.DateFormatter('%d/%m')

plot_oneversus(dailydeaths, one = YEAR, versus = years_exc[::-1],
               ylabel='death counts', grid=0.1,
               title = 'Figure %s: %s (%s) - Daily deaths (all)' %␣
↪(fign[comune],comune,provincia),
               locator = locator, formatter = formatter
              )
```

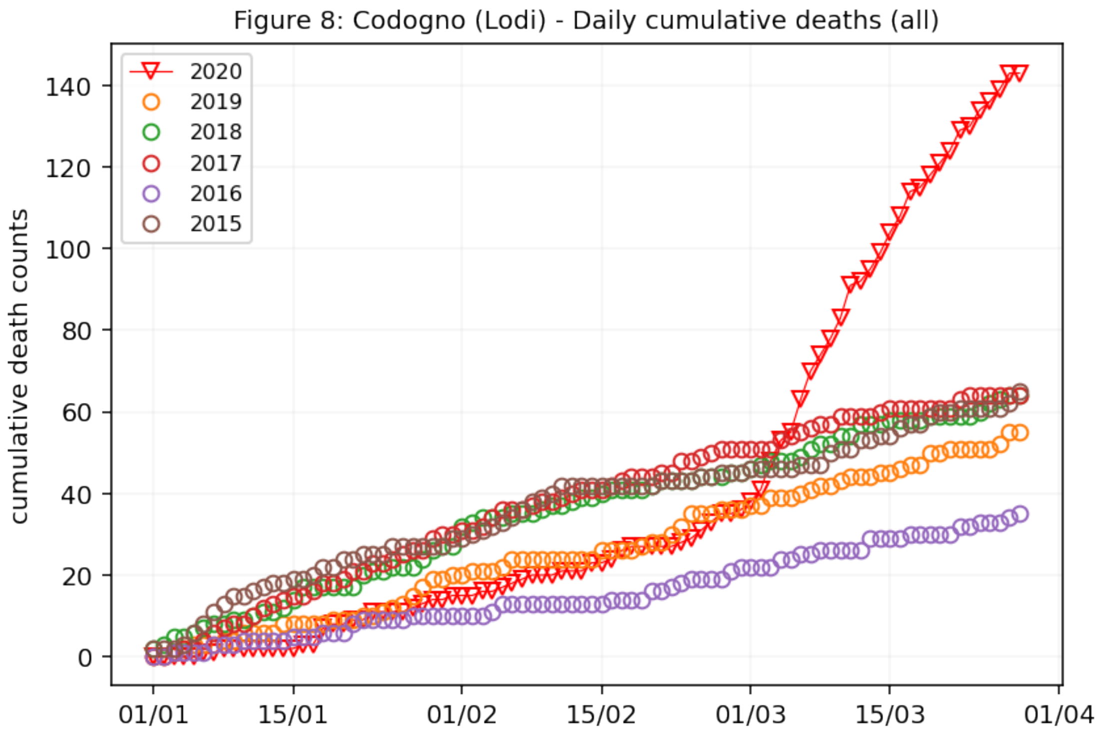
[71]:
```
(<Figure size 840x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x1177f1a50>)
```



as well as the cumulative deaths:

[72]:
```
cumdailydeaths = dailydeaths.cumsum(axis = 0)

plot_oneversus(cumdailydeaths, one = YEAR, versus = years_exc[::-1],
               ylabel='cumulative death counts', grid=0.1,
               title = 'Figure %s: %s (%s) - Daily cumulative deaths (all)' %␣
 ↪(fign[comune],comune,provincia),
               locator = locator, formatter = formatter
              )
```

[72]:
```
(<Figure size 840x560 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x11785db50>)
```

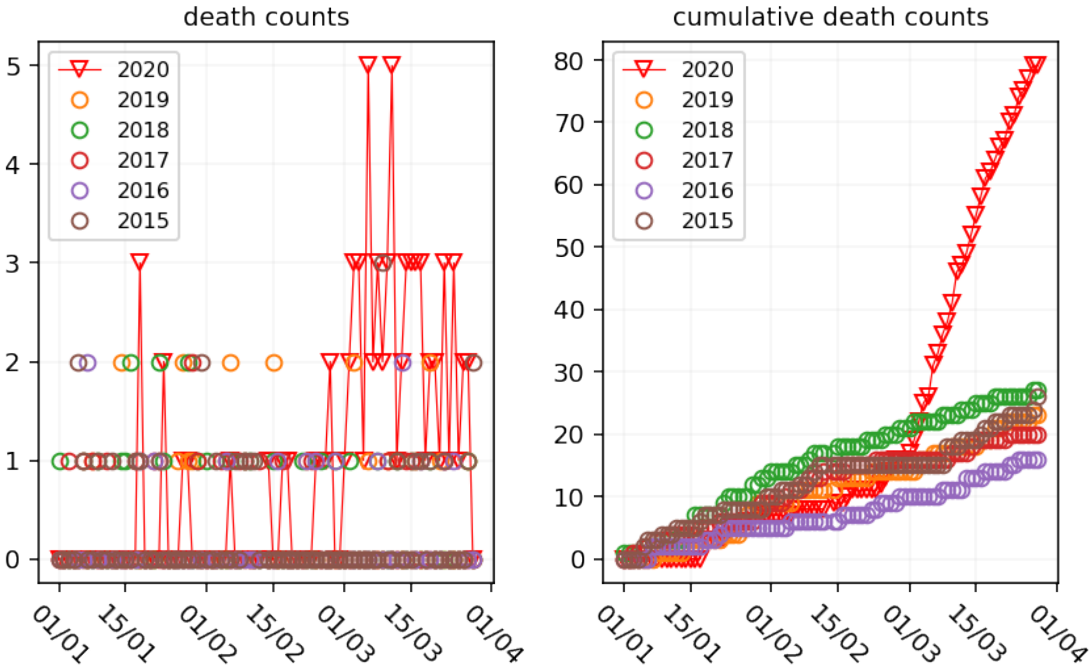


Similarly, we can process the data regarding the male population of 65y.o. and over in Codogno:

[73]:
```
MCOLS = [dIT.meta.get('index')['m_%s' % str(y)[2:]]['name'] for y in years]

dailydeaths_m65 = data[(data[CITY]==comune) & (data[AGE].isin(rages))].
 ↪groupby(DAY).agg({t:'sum' for t in MCOLS})
dailydeaths_m65.set_index(pd.Index(dailydeaths_m65.index.to_series().
 ↪apply(lambda ge: get_datetime(ge,YREF))),
                          inplace=True)
dailydeaths_m65.sort_index(inplace=True)
dailydeaths_m65 = dailydeaths_m65.reindex(idx_timeline).rename(columns={m:
 ↪int('20%s' % m[-2:]) for m in MCOLS})

cumdailydeaths_m65 = dailydeaths_m65.cumsum(axis = 0)

fig, ax = plot_oneversus(dailydeaths_m65, one = YEAR, versus = years_exc[::-1],␣
 ↪shp = (1,2),
                         title='death counts', grid=0.1, xrottick = -45,
                         locator = locator, formatter = formatter
                        )

plot_oneversus(cumdailydeaths_m65, one = YEAR, versus = years_exc[::-1], fig =␣
 ↪fig, ax=ax[1],
```

```
                 title='cumulative death counts', grid=0.1, xrottick = -45,
                 suptitle = 'Figure %s: %s (%s) - Daily and daily cumulative␣
↪deaths (male 65+)'
                     % (fign[comune],comune,provincia),
                 locator = locator, formatter = formatter
                )
```

Figure 8: Codogno (Lodi) - Daily and daily cumulative deaths (male 65+)



8 Figure 13 - Total deaths in the week 15-21 March by groups of municipalities within the same province

We look at statistics for groups of municipalities and consider the following timeline and 'province' entities:

[74]:
```
dstart, dend = get_datetime('0315',YREF), get_datetime('0321',YREF)

provinces = data.loc[:,[PROVINCE, PROV_CODE]].drop_duplicates()
print("Number of provinces represented in the dataset: \033[1m%s\033[0m" %␣
↪len(provinces))
provinces.head(10)
```

```
Number of provinces represented in the dataset: 103
```

```
[74]:                       NOME_PROVINCIA  PROV
0                                Torino     1
27679                          Vercelli     2
31916                            Novara     3
38546                             Cuneo     4
50379                              Asti     5
55125                        Alessandria    6
65073  Valle d'Aosta/Vallée d'Aoste        7
68042                           Imperia     8
71875                            Savona     9
78709                            Genova    10
```

Similarly to the analysis run for Figure 7, we analyse total death counts for different groups of municipalities within the same province. However, the baseline this time will be the average death count for the previous years instead of the max:

```
[75]: provdeaths = pd.DataFrame()
for y in years:
    TCOL = dIT.meta.get('index')['t_%s' % str(y)[2:]]['name']
    provdeaths[y] = data[data['GE_DATE'].between(dstart, dend, inclusive=True)] ␣
 ↪ \
        .groupby(PROV_CODE)[TCOL].agg('sum')
provdeaths['base'] = provdeaths.loc[:,years_exc].mean(axis=1)
assert len(provinces) == len(provdeaths)
provdeaths.head(5)
```

```
[75]:     2015  2016  2017  2018  2019  2020  base
PROV
1          64    78    69    71    88   116  74.0
2          18    16    17    11    18    37  16.0
3          47    47    54    35    57   108  48.0
4          42    44    41    45    52    68  44.8
5          28    31    24    24    26    32  26.6
```

Actually, we will keep only those provinces that registered 10+ death events over the considered period in 2020:

```
[76]: provdeaths.drop(provdeaths[provdeaths[YEAR]<10].index, inplace=True)
print("Number of provinces that recorded 10+ deaths during the considered period:
 ↪ \033[1m%s\033[0m"
      % len(provdeaths))
provdeaths.head(5)
```

```
Number of provinces that recorded 10+ deaths during the considered period:
84
```

[76]:
```
      2015  2016  2017  2018  2019  2020  base
PROV
1       64    78    69    71    88   116  74.0
2       18    16    17    11    18    37  16.0
3       47    47    54    35    57   108  48.0
4       42    44    41    45    52    68  44.8
5       28    31    24    24    26    32  26.6
```

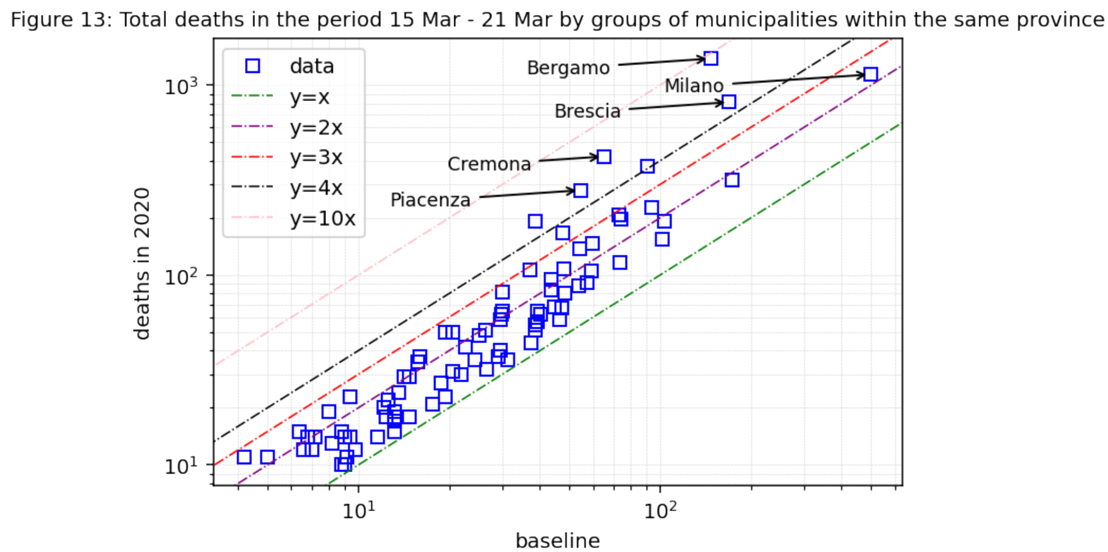
[77]:
```
province = ['Piacenza', 'Cremona', 'Brescia', 'Bergamo', 'Milano']
provtable = provinces.loc[provinces[PROVINCE].isin(province)]
provtable.set_index(provtable[PROV_CODE], inplace=True)
provtable
```

[77]:
```
     NOME_PROVINCIA  PROV
PROV
15           Milano    15
16          Bergamo    16
17          Brescia    17
19          Cremona    19
33         Piacenza    33
```

[78]:
```
fig, ax = mplt.subplots(dpi=_DPI_)
provdeaths.plot(loglog=True,  x='base', y=YEAR, # kind='scatter',
                ls='None', color='b', marker='s', fillstyle='none',␣
 ↪label='data', ax=ax
               )

xlim, ylim = ax.get_xlim(), ax.get_ylim()
x = np.arange(0, 10**4, 1)
for i, c in zip([1,2,3,4,10], ['g', 'purple', 'red', 'k', 'pink']):
    ax.loglog(x, i * x, label = 'y=%sx' % ('' if i==1 else str(i)), ls='-.',␣
 ↪lw=0.8, c=c
             )
ax.set_xlim(xlim), ax.set_ylim(ylim)
ax.grid(linewidth=0.3, which="both", ls='dotted')

for index in provtable.index:
    xpos, ypos = provdeaths.loc[index,'base'], provdeaths.loc[index,YEAR]
    r = np.random.random() +1
    ax.annotate(provtable.loc[index,PROVINCE],
                (xpos, ypos),
                xytext=(xpos-r*10**(np.log10(xpos)-0.4), ypos-r*10**(np.
 ↪log10(ypos)-1)),
                arrowprops=dict(arrowstyle='->'),
                size=9, ha='center')

ax.set_xlabel('baseline')
```

```
ax.set_ylabel('deaths in %s' % YEAR)
ax.set_title('Figure 13: Total deaths in the period %s - %s by groups of␣
 ↪municipalities within the same province' %
             (Datetime.datetime(dstart, fmt='%d %b'), Datetime.datetime(dend,␣
 ↪fmt='%d %b')),  fontsize='medium'),
ax.legend()
```

[78]: <matplotlib.legend.Legend at 0x1178ac850>



9 Figures 14 - 16: Daily and cumulative deaths over individual provinces

As we did for figures 8-12, we select this time a province represented in the dataset:

[79]:
```
fign = {'Bergamo':14, 'Lodi':15, 'Parma':16}
provincia = 'Bergamo' # 'Lodi' # 'Parma'
provincia_code = cities.loc[cities[PROVINCE]==provincia].loc[:,PROV_CODE].values.
 ↪tolist()[0]
print("Analysing the 'provincia di' \033[1m%s\033[0m (#\033[1m%s\033[0m)"
      % (provincia,int(provincia_code)))
```

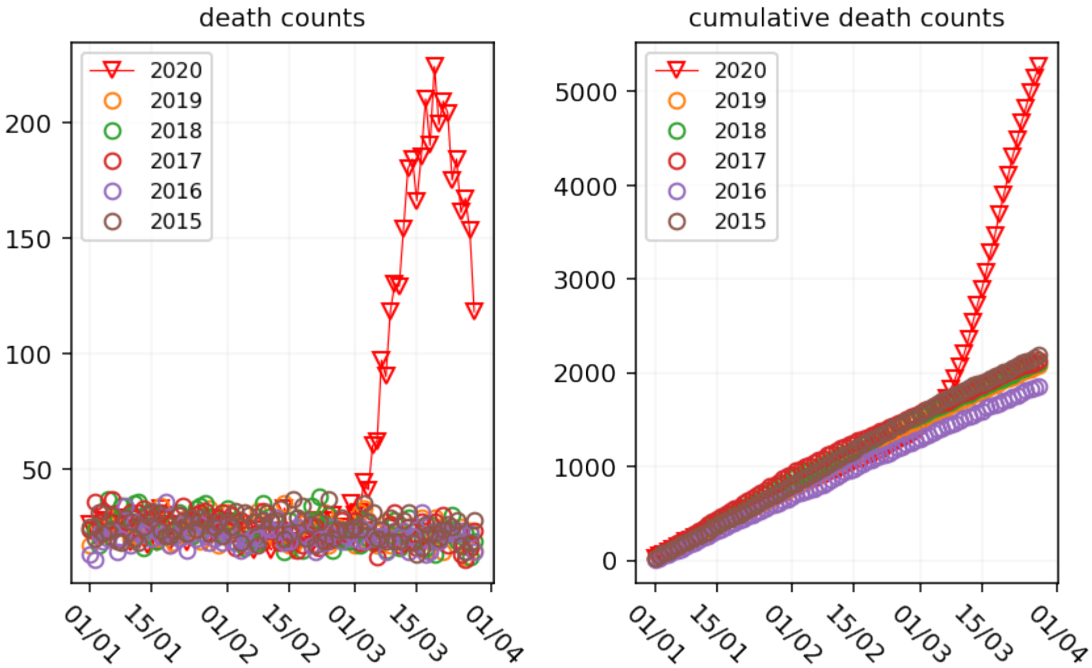
```
Analysing the 'provincia di' Bergamo (#16)
```

and we run a similar 'analysis' to actually report the total daily death counts and daily cumulative death counts:

[80]:
```
dailydeaths = pd.DataFrame()
for y in years:
    TCOL = dIT.meta.get('index')['t_%s' % str(y)[2:]]['name']
```

```
    dailydeaths[y] = data[data[PROV_CODE]==provincia_code].groupby(DAY)[TCOL].
 ↪agg('sum')
    if not calendar.isleap(y):
        yloc = dailydeaths.columns.get_loc(y)
        dailydeaths.iloc[ileapday,yloc] = dailydeaths.iloc[ileapday-1,yloc]
dailydeaths.set_index(dailydeaths.index.to_series().apply(lambda ge:␣
 ↪get_datetime(ge,YREF)), inplace=True)
dailydeaths = dailydeaths.reindex(idx_timeline, fill_value=0)

cumdailydeaths = dailydeaths.cumsum(axis = 0)

locator, formatter = mdates.DayLocator(bymonthday=[1,15]), mdates.
 ↪DateFormatter('%d/%m')

fig, ax = plot_oneversus(dailydeaths, one = YEAR, versus = years_exc[::-1], shp␣
 ↪= (1,2),
                         title='death counts', grid=0.1, xrottick = -45,
                         locator = locator, formatter = formatter
                        )

plot_oneversus(cumdailydeaths, one = YEAR, versus = years_exc[::-1], fig = fig,␣
 ↪ax=ax[1],
               title='cumulative death counts', grid=0.1, xrottick = -45,
               suptitle = 'Figure %s: Daily deaths and cumulative deaths (all) -␣
 ↪Province of %s'
                   % (fign[provincia],provincia),
               locator = locator, formatter = formatter
              )
```

Figure 14: Daily deaths and cumulative deaths (all) - Province of Bergamo



ibid for total daily death counts and daily cumulative death counts when considering the male population of 65 y.o. and over:

[81]:
```
dailydeaths_m65 = pd.DataFrame()
for y in years:
    MCOL = dIT.meta.get('index')['m_%s' % str(y)[2:]]['name']
    dailydeaths_m65[y] = data[(data[PROV_CODE]==provincia_code) & (data[AGE].
 ↪isin(rages))].groupby(DAY)[MCOL].agg('sum')
    if not calendar.isleap(y):
        yloc = dailydeaths_m65.columns.get_loc(y)
        dailydeaths_m65.iloc[ileapday,yloc] = dailydeaths_m65.
 ↪iloc[ileapday-1,yloc]
dailydeaths_m65.set_index(dailydeaths_m65.index.to_series().apply(lambda ge:␣
 ↪get_datetime(ge,YREF)), inplace=True)
dailydeaths_m65 = dailydeaths_m65.reindex(idx_timeline, fill_value=0)

cumdailydeaths_m65 = dailydeaths_m65.cumsum(axis = 0, skipna =True) # default

locator, formatter = mdates.DayLocator(bymonthday=[1,15]), mdates.
 ↪DateFormatter('%d/%m')

fig, ax = plot_oneversus(dailydeaths_m65, one = YEAR, versus = years_exc[::-1],␣
 ↪shp = (1,2),
```

```
            title='death counts', grid=0.1, xrottick = -45,
            locator = locator, formatter = formatter)

plot_oneversus(cumdailydeaths_m65, one = YEAR, versus = years_exc[::-1], fig =␣
 ↪fig, ax=ax[1],
            title='cumulative death counts', grid=0.1, xrottick = -45,
            suptitle = 'Figure %s: Daily deaths and cumulative deaths (males␣
 ↪65+) - Province of %s'
               % (fign[provincia],provincia),
            locator = locator, formatter = formatter)
```