

Development of an automatic tool for periodic surveillance of actuarial and demographic indicators

Daniel Alonso, María Luz Durbán Reguera, Bernardo D'Auria

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Contents

Summary	3
Introduction	3
Objectives	3
Motivation	4
Inspiration (needs work)	5
Advantages an open source application over weekly reports in PDF format	5
Why is monitoring mortality/life expectancy metrics important?	6
Metrics computed by the application	6
Excess mortality	7
Cumulative mortality rate	9
Cumulative relative mortality rate	10
Cumulative mortality improvement factor	12
Life expectancy	13
Methodology	16
Data querying and updating	16
Eurostat API querying	16
Death dataset update pipeline	16
INE API querying	16
Population dataset update pipeline	17
Data pre-processing pipeline	17
Pipeline for the deaths dataset	17
Pipeline for the population dataset	17
Data hosting	17
Appendix	17
Appendix A: Python	17

Appendix B: R	17
Appendix C: Project repository tree structure	17
The main project repository (<i>dreth/tfm_uc3m</i>)	17
The data repository (<i>dreth/tfm_uc3m_data</i>)	19

Summary

As a result of the COVID-19 pandemic and its large impact across Spain, the monitoring of demographic measures as a direct result of deaths related to such pandemic and future similarly deadly events has become increasingly important. It is intended with this project to develop a tool in order to easily monitor a selection of demographic measures relating to collective deaths of individuals as a result of relevant worldwide events like the one mentioned previously, or perhaps other smaller scale events which could increase mortality in a likely fashion.

The tool consists of an [open-source](#) shiny dashboard (developed in R) where such measures are displayed in different visualizations across time. The dashboard is containerized using Docker, as to make it possible to run and use in any operating system. Moreover, the database is managed by several Python scripts which acquire the data from the [INE](#) and [Eurostat](#) APIs, treat it, and allocate in a [GitHub repository](#) where it can be updated by anyone running the application with the click of a button within the application itself.

Introduction

The COVID-19 pandemic has led to a widespread and noticeable temporary increase in mortality and reduction in life expectancy throughout Spain. This arises a need to monitor these demographic measures more closely and in real time.

This project consists of an application which allows for active, real-time monitoring of mortality and life expectancy of the population of Spain, through an [open-source](#) shiny web-based dashboard.

The application itself consists of the following functionality:

- Visualizing several mortality metrics:
 - Excess mortality
 - Cumulative mortality rate
 - Cumulative relative mortality rate
 - Mortality improvement factor
- Visualizing life expectancy and constructing life tables
- Visualizing a map of Spain with the previous metrics per autonomous community (CCAA)

All metrics are calculated weekly with data stretching back as far back as 2010.

Objectives

The main objectives of the project are the following:

- Provide an open-source, simple-to-use, web-based, OS-agnostic tool to compute and visualize common mortality-related metrics and life expectancy in time series plots, and static or interactive maps.

- A big focus of the project was to make this application as simple-to-use as possible, while maintaining the management of system requirements extremely low. The purpose of such approach is to allow virtually anyone that desires to monitor any of the metrics to do so by running a simple shell command. We want any user or institution with access to a computer and the internet to be able to monitor these metrics, or any such metrics which could be possibly added in the future without much hassle.
- The project being open-source is also very important, as this allows anyone to take the project and further it, add extra components to it, perhaps other useful mortality-related measures. This makes the project fully auditable and free to use, modify and extend.
- Provide the user the ability to customize the plot parameters significantly.
 - The application itself should have several controls that allow the user to modify visualizations. Some of them are: what years to visualize, what metrics to visualize, what range of weeks to visualize (between 1 and 52), which CCAAs or age groups to aggregate, whether to make the plots interactive (using *plotly*) or static (using *ggplot2*), and so on. Different options will be available for different plots.
- Provide the user the ability to download the plots and the data (with or without filtering).
 - The application shall include a download button with several options for all plots displayed within the application. The user can select the size of the plot from a list of predefined sizes, or specify the image resolution and the format from a list of available ones. We intend to make it so that any plot generated within the app can be downloaded.
- Allow the user to update and upload the data to the corresponding GitHub [repository](#) hosting the data, from within the application.
 - The data is constantly changing, and as soon as the data sources have new data available, the application will tell the user there is new data, and the user will be able to update the data with the click of a button. The updated data will be fetched, ran through the pipeline, and uploaded to the [data repository](#) for the project on GitHub. This ensures that the data is always updated and anyone is able to do so for everyone else from anywhere in the world.
- Have data updated in real-time from the official Spanish sources (INE) and Eurostat (also provided by INE).
 - Every time the app runs, it'll check if there's available data and display the most recent week for which there is data available, this way we allow anyone running the application to see if there is new data whenever the app is ran so they can update it if they desire to do so.

Motivation

As we saw during the COVID-19 pandemic, the most widely publicized measures shown to the public in order to explain the status of the pandemic and the country as a whole were always related to incidence of the virus, death counts, recovery counts, amount of patients at ICU, hospitalized patients by COVID-19 vs total hospitalized patients, etc. However, **Death counts do not tell the whole story**, a death

count merely tells us that an amount of people died, it does not tell us how much that amount of deaths affect the population. Also, **all these measures are static**, therefore, we cannot see the effect they cause on the population in the long term, which is where measures like the *cumulative relative mortality rate* or *life expectancy* come in, these show the impact of deaths and their long lasting effect relative to the population over time.

As an example, 100 people dying over the course of a week within a municipality of 10,000 inhabitants represents 1% of the population; that same amount of deaths would represent less than 0.01% of the population within a municipality of 1 million inhabitants. Therefore, more robust measures to determine the impact of the deaths caused by a pandemic are needed to really gauge the effect of the pandemic as a whole.

The application allows monitoring some of these measures in real time. Whenever it is desired to fetch new data (if available), the data can be fetched with a click. The measures can be instantly computed with a click and visualized to observe the evolution of the population at any time, by age group, sex and by autonomous community (CCAA) of Spain. Showcasing particular usefulness within events that cause large amounts of deaths (like a pandemic, war, or heat wave) or that reduce the general populations life expectancy (as the application can also visualize the evolution of life expectancy over time).

Inspiration (needs work)

As somewhat of an inspiration, reports like the [COVID-19 vaccine surveillance report: Week 27](#), published by the PHE (Public Health England), show visualizations and analyses where the evolution of mortality metrics is a section of the report. Along with this, the INE currently does not have a report or application calculating these metrics on a per-week basis.

Advantages an open source application over weekly reports in PDF format

There are several advantages an application could potentially have over static, weekly PDF reports like the one previously linked:

- The user has control over the visualizations they desire to see, as there are controls to manipulate the parameters of the visualizations and interact with them.
- The user can download the customized visualizations in their desired resolution or format.
- The user can choose what measures of those available to show.
- As the application is [fully open source](#), developers wanting to expand the application and add extra features and contribute directly to the project's development.
- The measures will be as up-to-date as the data source is. As these reports take time to construct and analyze, they will take longer to be released, so the user can simply open the application and update the database whenever they desire to do so.

Why is monitoring mortality/life expectancy metrics important?

As it is with any demographic measure, knowing general metrics about population is important to many companies, institutions and individuals, to list a few:

- The Government and the Ministry of Health, the main decisionmakers in terms of public health related issues. These two institutions can use these metrics to construct policies or regulations to protect the general health of the population, prioritize or purchase particular medication or medical utensils if needed, etc.
- Insurance companies, those to which customers, companies, governments and other institutions transfer risk in order to protect themselves financially from health-related liabilities or death. Insurance companies directly use life tables to measure risk when providing life insurance to customers, and in order to remain profitable and offer a risk-assessed quality service to their customers these metrics modulate insurance premiums and aid in the process of decisionmaking when it comes to offering a policy to what the company could deem high or low risk customers.
- Ordinary people. Perhaps mere curiosity or desire to be informed, being able to know in a timely manner whether the population is at risk or healthy helps people make choices regarding how to take care of themselves or how to take care of their loved ones.

Metrics computed by the application

The application's visualizations are especially focused on 3 specific mortality metrics inspired by the regular rolling report by UK's Institute and Faculty of Actuaries:

- Cumulative mortality rate
- Cumulative relative mortality rate
- Mortality improvement factor

Given the host of other possible metrics to be included, which are also related to the ones previously mentioned, we decided to include the following two additional metrics as a way to extend the capabilities of the application:

- Excess mortality
- Life expectancy

Excess mortality

The term *excess mortality* (EM) refers to a measurement which corresponds to the difference between the average deaths which have occurred during the n years prior to the current t time. Typically, the window of years to compute the average deaths is often $n = 5$. For the application, a window of $n = 5$ years is used to compute the measurement.

If excess mortality is very high and above zero, then there have been more deaths than the previous n year average, if the number is smaller than zero, then there have been less deaths than the previous n year average.

Excess mortality is used to assess how many more or less deaths than the previous years' average have occurred. This way it's possible to determine if there is an increase in deaths that exceed what has been considered "normal".

During the COVID-19 pandemic the measurement was particularly useful as mortality spiked beyond the expectations of pretty much any country where the pandemic became widespread. Spain is no exception, and during the time where the deaths were at their peak, the excess mortality of that period of time was a highly publicized measure to illustrate how many deaths above what usually occurs happened.

We can see an example of the most generalized EM plot the application can produce:

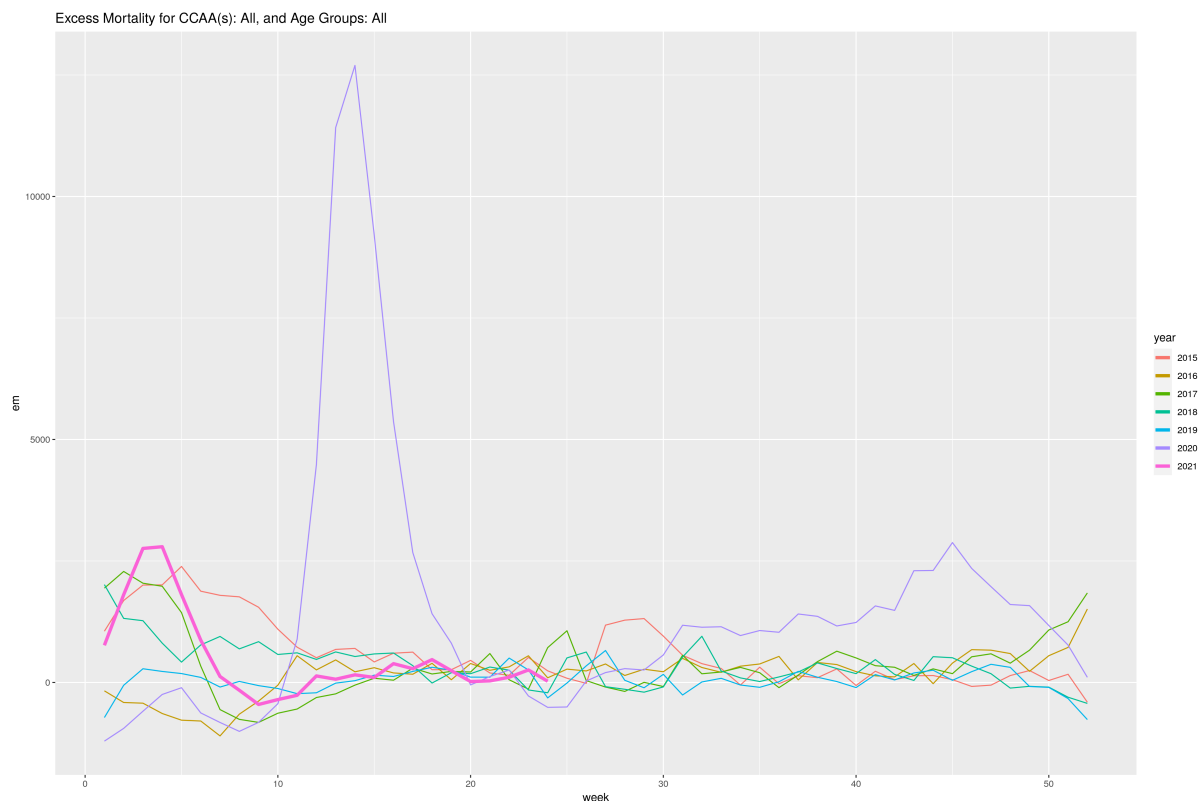


Figure 1: Excess mortality, from 2015 up to week 24 of 2021

In Figure 1, we can clearly notice a pattern where 2020 severely exceeded the mortality expected value of the previous 5 years. Particularly during the 1st wave of COVID-19 (around march, april and may), and towards the end of the year (around october, november and december).

As a result of the COVID-19 pandemic, future measures calculated after 2020 must exclude 2020 and 2021 from the calculation as the death counts are anomalous compared to previous and subsequent years prior the COVID-19 pandemic.

For the years between 2021 and 2027 inclusive, the application uses the same 5-year moving average used for 2020, meaning the average deaths corresponding to week w for $2015 \leq y \leq 2019$. After 2027 or prior to 2021 the average death counts used are computed from the 5 year window prior to the year(s) selected. For example, the average deaths for $w = 1$, 2019 will correspond to the average deaths during $w = 1$ for the years $2014 \leq y \leq 2018$, and the average deaths for $w = 1$, 2022 will correspond to the same average deaths observed on $w = 1$ for the years $2015 \leq y \leq 2019$.

The EM for week w of year y is computed as follows:

$$EM_{w,y} = \frac{D_{w,y}}{\overline{D_{w,y-5,y}}}$$

Where:

- $D_{w,y}$: death count for week w of year y
- $\overline{D_{w,y-5,y-1}}$: average death count for week w of years $y - 5, y - 4, \dots, y - 1$.

Exact definition:

$$EM_{w,y} = \frac{D_{w,y}}{\frac{1}{n} \sum_{k=1}^n D_{w,y-k}}$$

Where:

- $D_{w,y}$: death count for week w of year y
- n : years to look back to, default is $n = 5$
- $D_{w,y-k}$: death count for week w of year $y - k$, where k starts at $k = 1$ and ends at n with $k \in \mathbb{N}$.

Cumulative mortality rate

The *cumulative mortality rate* (CMR) represents the ratio between the sum of all deaths during the first week of a year up to a user-defined week of the same year, and the population at that same user-defined week and year, where weeks must be $1 \leq w \leq 52$.

This ratio can be used standalone to gauge the amount of deaths in a time period divided by the population alive at that time period, but, it is most commonly used in this project as a component of the more informational *cumulative relative mortality rate* or *mortality improvement factor*.

The ratio is computed, depending on user selection, for years stretching as far back as 2010 and as updated as the current year. It can only be computed for any specified range between 1 and week w .

The CMR for year y and up to week s is computed as follows:

$$CMR_{w,y} = \frac{\sum_{w=1}^s D_{w,y}}{P_{w,y}}$$

Where:

- $D_{w,y}$: death count for week w of year y .
- $P_{w,y}$: population at week w of year y
- s : upper bound of week for which the death count is computed, with $1 \leq s \leq 52$ and $s \in \mathbb{N}$.

Cumulative relative mortality rate

The *cumulative relative mortality rate* (*CRMR*) corresponds to the ratio of the difference between the cumulative mortality rate (*CMR*) at a specified week and the average *CMR* between years $n - k$ and $n - 1$ inclusive, and the average *CMR* in that same range of years for their last week (the 52nd week).

The *CRMR* allows us to show the medium to long-term effect of catastrophic or mortality-rising events on the population based on the *CMR*.

The effect of long-lasting events like the COVID-19 pandemic clearly show how mortality can part away from the mean significantly and how the cumulative effect of such mortality can rise to unprecedented levels for relatively long periods of time.

This particular metric can be affected significantly by events which we might perceive as not-so-dramatic when they occur (perhaps like a severe heat wave), but it lets us historically see how much worse or better (in terms of mortality) a given time period can be.

Here is an example plot of the *CRMR* we can generate for all age groups, sexes and CCAA aggregated:

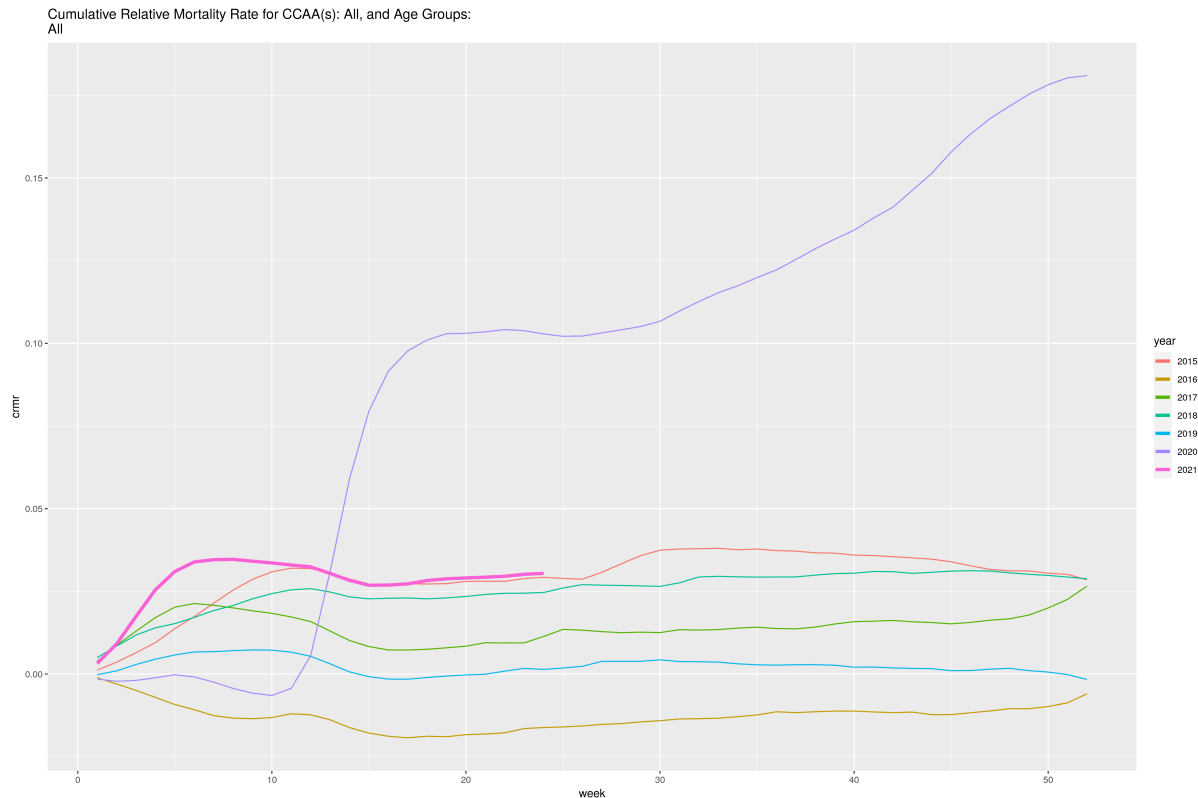


Figure 2: *CRMR*, from 2015 up to week 24 of 2021

As we can notice in Figure 2, 2020 severely exceeded the previous years' *CRMR* throughout the year right after the pandemic started, and the trend was sustained throughout the whole year. The dramatic increase towards the first wave of the pandemic completely skews the y-axis scale of the plot. We can also notice how the start of 2021 was also out of the ordinary, eventually returning to levels seen around 2015 (a year previously considered particularly bad for mortality in Spain), as the pandemic has continued to extend, but with a significantly smaller *CRMR* than that of 2020 given the widespread vaccinations and

more experienced treatment of the virus.

In our particular case, the metric has been computed using the average CMR for years between 2010 and 2019. 2020 is explicitly excluded, as the effect of the COVID-19 pandemic would skew our perspective on 2021 mortality and further years.

The CMR for the last week of those years is averaged as it includes the entire year, given that the CMR is computed for a range of weeks starting at week 1 and ending at week s , for this metric we compute the denominator for week $s = 52$ and the numerator for a specified week range.

The $CRMR$ for week w of year y has been computed as follows:

$$CRMR_{w,y} = \frac{CMR_{w,y} - \frac{1}{10} \sum_{y=2010}^{2019} CMR_{w,y}}{\frac{1}{10} \sum_{y=2010}^{2019} CMR_{w=52,y}}$$

Where:

- $CMR_{w,y}$ is the *cumulative mortality rate* at week w of year y

Cumulative mortality improvement factor

The *cumulative mortality improvement factor* (*CMIF*) at a specific week w of a year y is an actuarial measure defined as the ratio of the difference between the *CMR* at week w for the previous year $y - 1$ and the *CMR* at week w for the current year y , and the *CMR* at week 52 for the previous year $y - 1$.

The *CMIF* is used to assess how much mortality is improving within specific age ranges, or the population as a whole. By “improvement factor” we mean that it could either get “better” or get “worse”, the “better” the *CMIF* gets, the lower the mortality is, the “worse” it gets, the opposite, meaning mortality will be higher.

This measure is an excellent one when it comes to determining a population’s longevity. If the improvement factor is high, then the older the population can become, in some ways, very similarly to life expectancy.

The metric is particularly useful for older age groups, which during the COVID-19 pandemic saw a significant increase in mortality as a result of it being a virus especially dangerous to older age groups and it also being very easily spread throughout populations. In Spain in particular, retirement homes are very commonly used to house retired elderly people. The virus was unfortunately spread among some retirement homes causing very high mortality. These events directly affect the improvement factor negatively. Improvement factors are especially useful in insurance, where they’re often used to compute projections for life insurance policies.

As a way to exemplify, we can also show a plot for the *CMIF*, as plotted through the application:

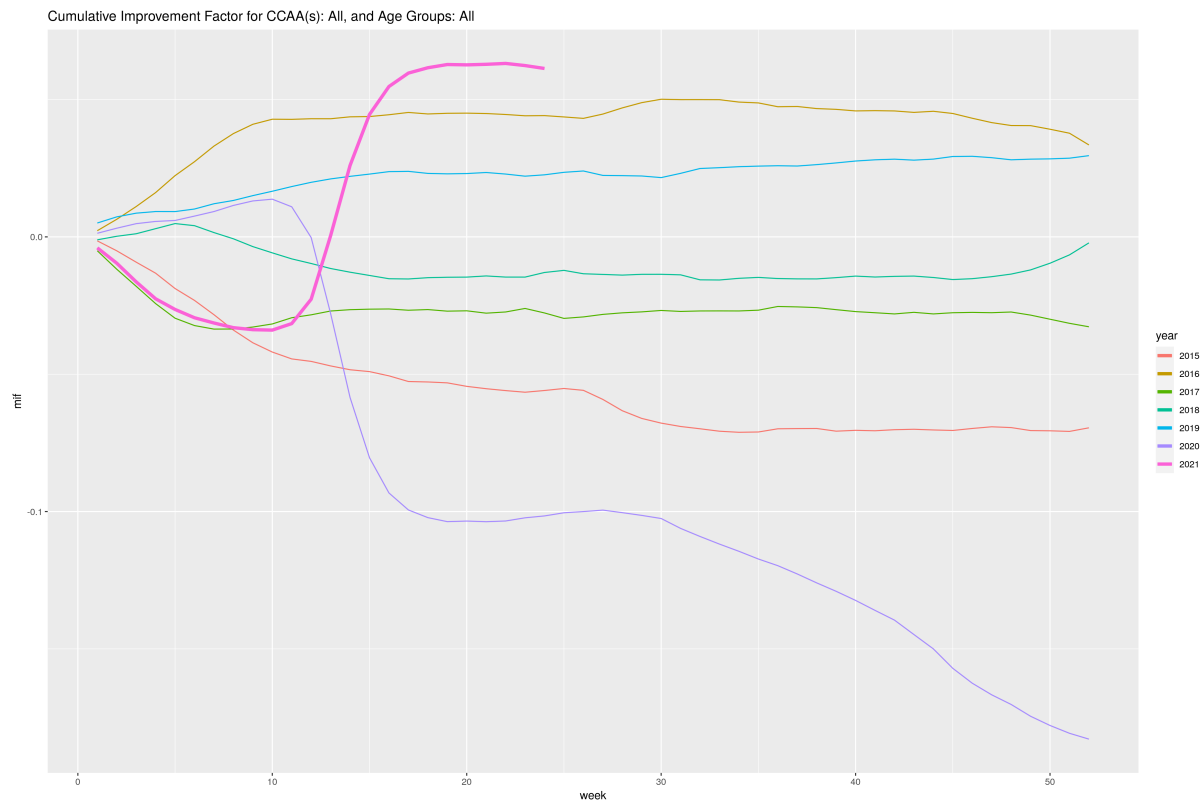


Figure 3: *CMIF*, from 2015 up to week 24 of 2021

As for the *CMIF* visualized in Figure 3, it is clear how significant the decline of the *CMIF* is for 2020, and how noticeable of an improvement the widespread vaccination has been during 2021.

Comparatively we can say that rises in *CRMR* correspond with declines in *CMIF*.

For the application in particular, the *CMIF* can be computed for years above 2011, as the data only stretches as far back as 2010 and the measure looks back 1 year.

The *CMIF* for week w of year y is computed as follows:

$$CMIF_{w,y} = \frac{CMR_{w,y-1} - CMR_{w,y}}{CMR_{w=52,y-1}}$$

Where:

- $CMR_{w,y}$ is the *cumulative mortality rate* at week w of year y

Life expectancy

Life expectancy (LE) is a measure that estimates the time an organism is expected to live. It is computed for a specific age group A using a *life table*, which is a table commonly used in actuarial science, demography and life insurance policy risk modelling that shows the probability that a person of a certain age or age group will die before reaching their next birthday or entering the next age group. The last column of it commonly corresponds with the *life expectancy* for that age or age group based on that probability of death.

LE at birth would correspond to the *LE* of the youngest age group in the table, assuming we don't have the *infant mortality rate (IMR)*.

The purpose of this measure is to track how long we should expect our population to live. As an upper limit on how old we should expect the population to become. It is widely used in insurance to calculate insurance premiums on life insurance policies, and to determine if it's even profitable to offer such policies to an individual. A very old individual would be surcharged for a life insurance policy or be rejected altogether when attempting to acquire the policy given their high risk of death and very low life expectancy.

It also gives us a perspective on perhaps how developed a country is, given that most developed countries have relatively high life expectancy for their population.

For the purposes of this application, it is useful to track the effect mortality has on how long we should expect the Spanish population to live. In particular, mortality as a result of the COVID-19 pandemic has affected life expectancy significantly, however, perhaps not in a permanent way, as mortality eventually goes back to the mean, and with it, so does life expectancy.

As we need to compute *LE* for specific weeks/years and display them as a time series, we must then calculate a *life table* per week.

The process is largely inspired from the following methodology explained on the [MEASURE evaluation website](#). However, it was adapted to fit weekly measures by taking data one year prior to the specified

week. Calculations after the step 2 described below are nearly identical to those displayed on the previously linked article.

To compute LE we must first compute a life table as follows, note that each step also corresponds to a column of the life table in the same order:

1. Compute the age-specific death rate ${}_n m_x$:

$${}_n m_x = \frac{\sum_{x,x+n} D_{w,y}}{\sum_{x,x+n} P_{w,y}}$$

Where:

- $\sum_{x,x+n} D_{w,y}$ corresponds to the sum of deaths between week w of the year y and week w of the year $y + 1$ for individuals aged between x and $x + n$.

- $\sum_{x,x+n} P_{w,y}$ corresponds to the population at week w of the year y for individuals aged between x and $x + n$.

2. Compute the proportion of individuals alive at the start of an age interval which are no longer alive at the end of that age interval (they die at some point during the interval), ${}_n q_x$:

- a. For non open-ended age groups:

$${}_n q_x = 1 - \frac{1}{e^{n \cdot {}_n m_x}}$$

- b. For open-ended age groups (ex. 90+ year olds):

$${}_n q_x = 1$$

Where:

- n is the length of the age interval. INE and Eurostat data is grouped in age interval lengths of $n = 5$.
- e is the exponential function.

3. Use the previously calculated measure ${}_n q_x$ to compute l_x :

- a. For the first value we set $l_0 = 100,000$

- b. For the subsequent values, we calculate the next values using the previous one as a sequence:

$$l_{x+n} = l_x * (1 - {}_n q_x)$$

Where:

- x corresponds to the numbering of the age group, (ex. for *less than 5 year olds* which is our first age group, we have l_0 , then l_1 , and so on)

- $x + n$ corresponds to the next age group after x

4. Compute the number of deaths occurred within each age interval ${}_n d_x$:

$${}_n d_x = l_x * {}_n q_x$$

Where:

- The measure is calculated for individuals aged between x and $x + n$

5. Calculate the person-years of life of all individuals in each age interval x to $x + n$, ${}_n L_x$:

$${}_n L_x = \frac{{}_n d_x}{{}_n m_x}$$

6. We calculate the cumulative person-years of life after age x , T_x . Therefore, for the first age group in the table, the value of T_x will correspond to the sum of all ${}_n L_x$, the entire 5th column. For the second age group, it'll be the sum of all ${}_n L_x$ with the exception of the ${}_n L_x$ value of the first age group, and so on.

So:

a. For the last age group:

$$T_x = {}_n L_x$$

b. For the other age groups:

$$T_x = \sum_{k=g}^{19} {}_n L_x$$

Where:

- g is the number of the age group for which we want to compute the measure, so for group 1, $g = 1$, and so on.

- The sum goes up to 19, as there are 19 age groups in our computation.

7. We compute the *life expectancy* (LE) of each age group as follows:

$$e_x = \frac{T_x}{l_x}$$

Methodology

Data querying and updating

The data querying process goes over two APIs, the Eurostat API and the INE API.

Eurostat API querying

In order to query the Eurostat API, we need to execute several queries using the `query_eurostat` function defined in the `functions.py` script.

The queries are executed through the `query.py` script, lines #26-40 upon user request.

Death dataset update pipeline

As the Eurostat API returns a JSON, we must convert this response object into a workable pandas dataframe and eventually a CSV file, for easier storage and updating.

The pipeline followed from when the data is obtained until it's updated the data hosted in the repository is the following, with the exception of the `data manipulation pipeline`, an intermediate step:

1. Open the `update_database.log` log file, in which diagnostic messages related to the query are printed temporarily until the query is over.
2. Create an empty list where obtained raw datasets from the API will be added to.
3. Run a nested loop where we iterate over each age group (19 age groups) and sex (3 sexes, male, females and total) and the Eurostat API is queried for each combination of sex and age group. The queried data is queried as far back as the data is provisional (Week 1, 2020 at the time of writing).
4. Each obtained dataset is passed through the `generate_death_df` function defined in the `functions.py` script, which runs the steps described in the `pipeline for the death dataset` section. Thereby generating a partial dataset for the current `age+sex` looping combination.
5. The previously generated partial dataset is added to the `death_datasets` list created previously.
6. The datasets within the `death_datasets` list are all concatenated using the `pandas.concat` function.
7. The updated dataset is passed as a parameter of the `perform_update_datasets` function, which in turn checks the currently available dataset within the repository file tree, imports it, updates all the provisional data and appends the newly obtained data if available.
8. The acquired/updated dataset is exported as a CSV file.

INE API querying

To query the INE API, a single query is executed using the `query_INE_pop` function defined in the `functions.py` script.

The function executes a single query with data starting at the date defined by the *start* parameter of the function, whose default value is *20100101*, corresponding to the 1st of January, 2010. This single query returns a JSON response with all the data.

Population dataset update pipeline

The INE API returns a JSON file with somewhat unique formatting, therefore in order to manipulate the

Data pre-processing pipeline

Pipeline for the deaths dataset

Pipeline for the population dataset

Data hosting

Appendix

Appendix A: Python

Appendix B: R

Appendix C: Project repository tree structure

The project consists of two repositories and their respective **subfolders**, **files** and **databases**:

The main project repository (*dreth/tfm_uc3m*)

- **api**: Contains all files related to the querying, acquisition, manipulation of new data from the two aggregated data sources (INE and Eurostat), along with various log files used to keep track of some metadata from the data sources (last updated data and provisional data).
 - **logs**: This folder contains log files used in the DB info section of the application to display diagnostic info about the databases.
 - * **earliest_eurostat_provisional.log**: Eurostat marks data as provisional when it can still be updated, as new deaths might occur. This file logs the earliest data entry marked as provisional.
 - * **last_eurostat_update.log**: This file logs the last week for which there is available and updated data from Eurostat for Spain within the database *demo_r_mwk2_05*.
 - * **last_ine_update.log**: This file logs the last week for which there is available and updated data from INE for table No. *9681*.
 - **dbs_check.py**: This script obtains a small sample of data from Eurostat and Ine and checks when the earliest provisional data point is, what is the latest obtainable week of data from both Eurostat and INE and writes it in the log files contained within **logs**.
 - **functions.py**: This script contains all the functions used for fetching, manipulating and outputting the data obtained from the aggregated data sources' respective APIs (Eurostat and INE).

- **query.py**: This script will run a pre-constructed pipeline where the data is systematically queried per age group, manipulated and where new entries are added to the *.csv* files contained within the **data** folder.
- **dashboard**: Contains all files that allow the shiny app itself to run along with shapefiles for displaying maps, shell scripts to check the databases' last update and last provisional status and the shell script to update the database from within the app.
 - **www**: This is a special shiny folder that includes files
 - * **maps** Contains 2 folders which themselves contain the shapefiles for the map displayed using leaflet and the map displayed using ggplot2 in the maps section.
 - **map_shapefiles**: Contains the shapefiles used to display the map using the leaflet library.
 - **map_shapefiles_ggplot**: Contains the shapefiles used to display the map using the ggplot2 library.
 - * **scripts**: This folder contains some shell scripts used when updating the database or to show diagnostic information about the databases from within the app at launch.
 - **check_dbs.sh**: This script is ran every time the app is launched. This shell script runs **dbs_check.py** from the **api** folder.
 - **update_database.sh**: This is the update database script, basically checks the date, runs the **query.py** and **dbs_check.py** script from the **api** folder, appending new data (if available) to the data currently in the cloned repository tree. Then it copies the new files into the **dreth/tfm_uc3m_data** repository, then it commits and pushes the files to that repository.
 - * **dimension.js**: This javascript file is used within the application to capture the screen resolution in order to adjust the height of some plots within the app.
 - * **styles.css**: This stylesheet is used to modify the style of a few elements in the app like the update database button, width and border within tables displayed, etc.
 - **global.R**: This file does several things:
 1. Import the libraries required to run the app.
 2. Run the diagnostic database checking script **check_dbs.sh**.
 3. Read the data from the **data** folder.
 4. Assign the names of the databases from where the data was fetched.
 5. Define all the variables used in the **ui.R** script for all the fields used in the app's UI.
 6. Load the shapefiles and append the CCAA codes and IDs to their respective databases.
 7. Define all the functions used to calculate the measures the app calculates, so the *CMR*, *CRMR*, *CMIF*, *EF*, *LE* and the *death count* hidden option.
 8. Define all the functions to generate the tables used in the plotting function *plot_metric()* defined in **server.R**.
 - **server.R**: This is the server file for the shiny app, it has all the definitions for what each input or output should take and do during runtime.
 - **ui.R**: This is the UI file, it defines how the entire UI and controls for the application are.

- **data**: This folder is a subtree of the [dreth/tfm_uc3m_data](#) repository, therefore, it contains all the data used in the application along with logs showing diagnostic and historical information about database updates.
 - **ccaa_guide**: This folder contains files used to match CCAA names with their Eurostat denomination, as there can be multiple denominations for a single CCAA at times (like it happens with Madrid and Canarias). The files are in several different formats.
 - **logs**: This folder contains the log files used to display diagnostic information about database updates (dates).
 - * **update_database.log**: This log file contains the date the database was last updated, it is written to every time the database is updated.
 - * **update_history.log**: This log file contains the dates in which the database has been updated (historically).
 - **death.csv**: This plaintext file is the database file for the app containing the deaths database, corresponds to a query to the *demo_r_mwk2_05* database to Eurostat for Spain data, with all the cleaning and manipulation seen in the python scripts within the **api** folder.
 - **pop.csv**: This plaintext file is the database file for the app containing the deaths database, corresponds to a query to the *9681* database to INE, with all the cleaning and manipulation seen in the python scripts within the **api** folder.
- **docker**: This folder contains the *Dockerfile* used to build the docker container.
 - **Dockerfile**: This file is used to build the docker container.
- **docs**: Folder containing the documentation for the application.
 - *README.md*: Application documentation and instructions on use.
- **paper**: Folder containing this report and all the files the report depends on.
- *README.md*: Readme file explaining how to run the app and some basic information about it.

The data repository ([dreth/tfm_uc3m_data](#))

- **ccaa_guide**: This folder contains files used to match CCAA names with their Eurostat denomination, as there can be multiple denominations for a single CCAA at times (like it happens with Madrid and Canarias). The files are in several different formats, like *.txt* and *.p*. The *.p* file corresponds to a binarized python object representing a python dictionary with the contents of the *.txt* file.
- **logs**: This folder contains the log files used to display diagnostic information about database updates (dates).
 - **update_database.log**: This log file contains the date the database was last updated, it is written to every time the database is updated.
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- **pop.csv**: This plaintext file is the database file for the app containing the deaths database, corresponds to a query to the *9681* database to INE, with all the cleaning and manipulation seen in the python scripts within the **api** folder.
- *README.md*: Readme file explaining the source of the data and where the repository stems from, as well as linking to the main repository [dreth/tfm_uc3m](#)