Excess Mortality in the Age of COVID-19

Data Mining for Insights into Death

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ABSTRACT

In wake of the ongoing COVID-19 pandemic, much data has been collected to better and further understand the situation. This data in combination with regularly collected mortality data has the potential to reveal interesting patterns. Our project will investigate the relationship between mortality rates and COVID-19.

CCS CONCEPTS

• Applied computing~Life and medical sciences~Health care information systems

KEYWORDS

COVD-19, Mortality, Data Mining, Excess Mortality, Coronavirus, Pandemic, Data Collection

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1 Motivation

When a global pandemic hits, there are many questions to answer. There is no stopping death wholesale, but how did the COVID-19 Pandemic affect death rates both worldwide and at a more granular scale? How well does excess mortality serve to illustrate the effects of COVID-19? Are any public health policies effective at limiting excess mortality?

2 Literature Survey

A substantial amount of research has been done in regards to the pandemic's effects on mortality rates. Unfortunately, factors such as availability of testing supplies and political influences on public health messaging result in substantial differences between countries and subregions in reporting deaths as attributable to COVID-19 [2, 3, 6]. As a result of these differences public health research has often focused on a different metric: excess mortality, which refers to the number of deaths occurring over and above predicted mortality rates for a population [4]. The variation between reported COVID-19 mortality and excess mortality rates can be staggering: one example country reported 300,000 COVID-19 deaths but had over one million projected deaths over and above expected baseline mortality rates [6]. The majority of prior work focuses on either total excess mortality, a value that is relatively easier to state with confidence, or excess mortality directly attributable to COVID-19.

Predicted mortality rates establish a baseline upon which to compare mortality rates during the pandemic. The four-year period between 2015-2019 is commonly used to create these predicted rates[6, 4, 9], though some models opt to use different periods for a variety of reasons[2, 4, 5]. One of the primary challenges in creating an accurate baseline is the presence of non-pandemic-related factors that affect mortality rates. Changes in population demographics such as age can exhibit a powerful effect on actual mortality[1].

One article in particular, What has happened to non-COVID mortality during the pandemic?[8], does seek to address the same basic question that our project is focused on. While the scope of said article is restricted solely to the United Kingdom, it does provide a possible roadmap for our own inquiries. Another (admittedly pre-print) article presents a possibility for teasing out changes in specific non-

COVID-19 mortality types by projecting current mortality rate subtype units in lieu of local units [7].

3 Proposed Work

3.1 Preprocessing

Both datasets are pre-cleaned with no evidence of missing or erroneous values based on human observation of random samples.

Integration will require work. We need to truncate COVID to include only the 35 countries contained in HMD. Country codes use in each dataset are largely the same, with the exception of Australia, France, Great Britain, Germany, and New Zealand. Additionally, HMD splits Great Britain into three separate categories (England and Wales, Scotland, and Northern Ireland) which will need to be internally merged in HMD before combining with COVID.

Dates between COVID and HMD must also be reconciled. HMD contains weekly data in a YYYY/WW format while COVID contains daily data in a YYYY/MM/DD format. Using pandas, we will resample the daily COVID data to weekly to match HMD (summing "new" data and using the first value for "total" data). At the same time, HMD dates will be converted to YYYY/MM/DD format to aid in searching for specific dates.

Finally, HMD splits mortality data into male, female, and combined categories. To match COVID, the male and female subcategories can be dropped from the dataset.

3.2 Derived Data

Once the datasets are merged, we plan to transform the mortality totals into a smoothed kernel density estimate. This will form the basis of a regression that will inform the expected mortality totals absent COVID after 2020. These expected totals can be compared to reported totals to derive excess mortality.

3.3 Design and Evaluation

We will compare our excess mortality numbers to those of prior work in the field. In addition, we will use expected mortality rates for specific causes (e.g., suicide, traffic fatalities, heart disease) and COVID case numbers to parse a number of questions, including whether published COVID death totals are under- or overcounted and how the rates of other sources of mortality were affected by the pandemic.

4 Data Set

We will be utilizing 2 data sets:

Human Mortality Database (HMD), which contains mortality data by week and age group for 38 countries Accessed at: https://www.mortality.org/ and COVID-19 Dataset (COVID) which contains Global COVID Statistics by country and date Accessed at: https://ourworldindata.org/explorers/coronavirus-data-explorer

Human Mortality Database

Name	Type	Description
CountryCode	Nominal String	Identifies country
Year	Ordinal Integer	Year in 1 year increments
Week	Ordinal Integer	Week from 1-52 from 1st full week of year
Sex	Nominal String	male, female, and combined
D0_14	Ordinal float	# of deaths age 0 to 14 (float due to transforming input data)
D15_64	Ordinal float	# of deaths age 15 to 64 (float due to transforming input data)
D65_74	Ordinal float	# of deaths age 65 to 74 (float due to transforming input data)
D75_84	Ordinal float	# of deaths age 75 to 84 (float due to transforming input data)
D85p	Ordinal	# of deaths age 85+

	float	
DTotal	Ordinal integer	Total # of deaths for all age groups

COVID-19 Dataset

Name	Type	Description
iso_code	Nominal String	Identifies country
Date	Ordinal String	Date in MM/DD/YYYY format
total_cases	Ordinal Integer	Daily total of COVID cases; does not decrease with recovery or death
new_cases	Ordinal Integer	Daily new cases reported
total_deaths	Ordinal Integer	Daily total of COVID cases
new_deaths	Ordinal Integer	Daily new deaths reported
total_cases_per_million	Ordinal float	total_cases per million
new_cases_per_million	Ordinal float	New_cases per million
hops_patients	Ordinal Integer	Daily total of COVID cases hospitalized; does decrease with recovery or death
population	Ordinal integer	Population of country; does not change

5 Evaluation Methods

For now, we think we will be running various regression tests on different categories to see which attributes might affect each other. Keeping in mind that correlation does not imply causation, of course, finding the patterns will lead to more interesting questions that we can explore later. We will also likely be using some sort of clustering technique to see what situations can be compared and contrasted. We might do K-nearest neighbors, although we have not covered that yet in the course material (there's some linear algebra background here that we can leverage as a team), and we also might treat precaution data as transactional data to see what precautions show up together frequently.

6 Tools

We will be using Python/Pandas to process the data and do most of the heavy lifting. As a team, we are most familiar with that language and have had some prior experience working with Python and Pandas to deal with large data sets. Many things are built in with Pandas, which should make mining for interesting information easier. For visualization's sake, we are interested in working with Tableau. We have seen how powerful that tool can be in the Information Visualization course, and while we are not exactly sure what we want to visualize, we know that Tableau gives us many options. Of course, we will be using GitHub to keep track of changes collaboratively.

7 Milestones

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