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Dynamics diagnosis of the COVID-19 deaths using the Pearson diagram

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A B S T R A C T

The pandemic COVID-19 brings with it the need for studies and tools to help those in charge make decisions. Working with classical time series methods such as ARIMA and SARIMA has shown promising results in the first studies of COVID-19. We advance in this branch by proposing a risk factor map induced by the well-known Pearson diagram based on multivariate kurtosis and skewness measures to analyze the dynamics of deaths from COVID-19. In particular, we combine bootstrap for time series with SARIMA modeling in a new paradigm to construct a map on which one can analyze the dynamics of a set of time series. The proposed map allows a risk analysis of multiple countries in the four different periods of the pandemic COVID-19 in 55 countries. Our empirical evidence suggests a direct relationship between the multivariate skewness and kurtosis. We observe that the multivariate kurtosis increase leads to the rise of the multivariate skewness. Our findings reveal that the countries with high risk from the behavior of the number of deaths tend to have pronounced skewness and kurtosis values.

1. Introduction

The new coronavirus was discovered in December 2019 and named Severe Acute Respiratory Syndrome Coronavirus 2 (abbreviated “SARS-CoV-2”), whose associated disease was named COVID-19 (Coronavirus Disease 19) by the World Health Organization (WHO). This virus first emerged in Wuhan (2020) [1], then spread worldwide, and remains one of the greatest challenges to be addressed on a global scale. The search for rapid insights into the impact of the infection caused by the virus requires global collaboration among researchers from many disciplines and countries, moving faster than is usually the case. World leaders are expected to make life-saving decisions and ensure that unstable patients receive the care they need, improve the economic, social, and psychological situation of the most vulnerable populations, and consider many other factors. This paper considers studying the number of COVID-19 deaths based on the skewness and kurtosis measures.

A variety of topics related to skewness and kurtosis are explored in a literature review. Given their technical and applied importance, Hogg (1974) [2] proposed measurements of kurtosis and skewness for various non-normal distributions. Luo and Schramm (1993) [3] used skewness and kurtosis in the study of cosmological density perturbations. The pattern of negative skewness and excess kurtosis has been sought in stock market returns, see Kim and White (2004) [4]. In Lam et al. (2013) [5], skewness and kurtosis were used in the context of time series for investors’ portfolio optimization. According to Cain et al. (2016) [6], skewness and kurtosis were used univariately and multivariately to measure non-normality for psychological studies. On the topic of non-normal distributions, there is Celikoglu and Tirnakli (2018) [7], who discussed non-normality and the use of q-statistics, such as q-kurtosis. Xu and Shang (2018) [8] performed financial analysis using multiscale entropy based on the use of skewness and kurtosis. Recently, Bono et al. (2020) [9] proposed a comprehensive simulation study to confirm the validity of these measurements. The Pearson diagram consists of the graph in terms of skewness and kurtosis, which is used to classify model types in its family of distributions, as discussed by Krasnoselskikh (2007) [10]. As far as we know, the Pearson diagram has not yet been used to analyze the dynamics of COVID-19 mortality rates.

This paper proposes a new paradigm for analyzing the number of COVID-19 deaths based on a multivariate version of the Pearson diagram. The resulting maps complement other previous map works using quantifiers of information theory (permutation entropy and Fisher information, called Shannon-Fisher causality plane) employed by Fernandes and Araújo (2020) [11] and, recently, in [12–14], as our proposal analyzes other statistical aspects of the stochastic process derived from the number of deaths from COVID-19. The analysis of the obtained maps is performed in two steps: First, we determine the risk profile for each country using the k-means cluster analysis method; second, we analyze the dynamics of the clusters formed in the previous step using the time series of the four different periods of the pandemic of COVID-19. After the analysis, we conclude that the maps provide insights into...
the situation of deaths from COVID-19, help to know how the different decisions of political leaders affect the situation of each country, and the formulation of public policies to combat COVID-19.

This paper is organized as follows. Section 2 presents data to be analyzed. Section 3 addresses how different techniques in branches of Multivariate Analysis, Time Series Analysis and Non Parametric Statistics are combined to answer the under-analysis problem. Section 4 shows the main numerical results. Section 5 concludes this paper.

2. Database

In this paper, we analyze the complex dynamics evident in the spread of COVID-19 across 55 countries. The data used for this analysis are the time series of daily deaths associated with COVID-19 from 22-01-2020 to 14-07-2021. Data were obtained from the Our World in Data (OWID) website and from https://github.com/owid/covid-19-data/tree/master/public/data/jhu, and we used R software for all computational and data mining procedures.

Table 1 shows the descriptive measures (mean, median, minimum, maximum, and coefficient of variation) for daily COVID-19 deaths by country. Brazil and the United States are shown in a darker shade because they were the countries with the highest mean daily COVID-19 deaths, whereas the countries in a lighter shade, Iceland and New Zealand, had the lowest mean daily COVID-19 deaths. In addition, in all cases, the means are higher than the medians (indicating a right skew) and the values of the CVs are high (indicating a large dispersion around the mean).

3. Methodology

The main objective of this work is to construct multivariate skewness and kurtosis maps. To that end, we use the Pearson diagram to understand how countries’ decisions about daily deaths from COVID-19 are reflected in the positions on the maps. In this section, we present an overview of the concepts used in this work.

3.1. Background: Time series, bootstrap and multivariate analysis

First, we begin with some concepts related to time series analysis (TSA). TSA refers to a collection of data observed consecutively at equal time intervals. The TSA goal is twofold: to propose a model to describe the dynamics under study and to make predictions.

The time series of daily deaths by COVID-19 per country is our object of study. Countries with few deaths after COVID-19 require a smooth time series model, while countries with more deaths require a more complex model (e.g., with seasonality and stochastic trends). For this step, we adopt the Seasonal Autoregressive Integrated Moving Average (SARIMA) model.

3.1.1. Bootstrap in time series

The bootstrap method is used to represent the distribution for an estimator or test statistic numerically by resampling from a database or estimated data model. There are two main types of bootstraps: parametric and non-parametric. The parametric bootstrap considers a model or estimates for parameters from the data, while the non-parametric bootstrap requires no such estimates. As can be seen in [15], in the case of dependencies such as time series, the procedure becomes more complicated and less direct than the proposal in the context of independence (Efron, 1979 [16]). In the parametric context, we capture the dependency structure using a fitted model from the data, for example a finite ARMA process. The bootstrap algorithm with moving blocks can be executed by dividing the series into small blocks and resampling the blocks with replacement so that the structure within the blocks is preserved. This method is implemented in the software R with the library boot and the function tsboot [17].

The use of bootstrap on time series is necessary to calculate multivariate skewness and kurtosis, which we discuss in more detail in this article. The parametric bootstrap method provides better estimates of multivariate skewness and kurtosis than the non-parametric approach, which is a central point of this article because they are the necessary measures for constructing the Pearson diagram-inspired map. The chosen method is the parametric bootstrap, although it is also possible to use the non-parametric approach.

3.1.2. SARIMA process

A time series \(\{X_t; t = 1, \ldots, n\}\) can be understood by the result of three components [18]:

\[X_t = m_t + s_t + R_t,\]

where \(m_t, s_t, \text{ and } R_t\) represent the trend, seasonal and stationary random components, respectively. According to Brockwell and Davis (2016) [18], taking \(d\) and \(D\) as nonnegative integers, \(X_t\) follows a \(SARIMA(p, d, q) \times (P, D, Q)\)-process with period \(s\) if the delayed series \(Y_t =\)
In this article, the seasonality of the model is considered weekly, since it is possible to identify the cases where COVID-19 falls on the weekend and rises at the beginning of the week. Fig. 1 illustrates the Brazilian death number from 22-01-2020 to 04-06-2021. It can be observed that there are cycles that justify a seasonal approach.

3.1.3. Multivariate skewness and kurtosis

As discussed by Koizumi et al. (2014) [19], let \(x_i, x_j\) be p-dimensional random vectors with mean \(\mu\) and covariance matrix \(\Sigma\). Then the population measures of skewness and kurtosis defined by Mardia [20] are respectively given by:

\[
\begin{align*}
\beta_1 &= \mathbb{E} \left[ \left( x_i - \mu \right)^\top \Sigma^{-1} (x_i - \mu)^2 \right] \\
\beta_2 &= \mathbb{E} \left[ \left( x_i - \mu \right)^\top \Sigma^{-1} (x_i - \mu)^2 \right],
\end{align*}
\]

where \(\mathbb{E}(.)\) means the expected value, \(x_i\) and \(x_j\) are independent random vectors and identically distributed.

Let us now consider the sample versions for Eqs. (2) and (3). Let \(x_1, x_2, \ldots, x_N\) be an N-point random sample drawn from the p-variate normal law with mean \(\mu\) and covariance matrix \(\Sigma\). The sample mean
vector $\mathbf{x}$ and sample covariance matrix $S$ are respectively given by:

$$\mathbf{x} = \frac{1}{N} \sum_{j=1}^{N} x_j,$$

and

$$S = \frac{1}{N} \sum_{j=1}^{N} (x_j - \bar{x})(x_j - \bar{x})^T.$$

In this way, the measures of multivariate sample skewness and kurtosis in [20] are defined as follows:

$$b_{1,p} = \frac{1}{N^2} \sum_{j=1}^{N} \sum_{i=1}^{N} \left[ (x_i - \bar{x})^T S^{-1} (x_j - \bar{x}) \right]^3$$

(4)

and

$$b_{2,p} = \frac{1}{N} \sum_{i=1}^{N} \left[ (x_i - \bar{x})^T S^{-1} (x_i - \bar{x}) \right]^2.$$ 

(5)
Fig. 4. Brazil series fractions.

Fig. 5. Skewness and kurtosis map for the first fraction of the daily COVID-19 death series.
Let $b_{1,p}$ and $b_{2,p}$ in (4) and (5), then for $N$ large,
\[
z_{1,p} = \frac{N}{6} b_{1,p}
\]
follows a $\chi^2$ distribution with $(p+1)(p+2)/6$ degrees of freedom and
\[
z_{2,p} = \frac{b_{2,p} - \frac{N-1}{N}p(p+2)}{\sqrt{\frac{N}{6}p(p+2)}}
\]
follows a normal distribution. Some decision rules based on $z_{1,p}$ and $z_{2,p}$ can be formulated:

- If the statistic $z_{1,p}$ in (6) is significant, the joint distribution has significant symmetry for the set of $p$ variables;
- If the statistic $z_{2,p}$ in (7) is significant, the joint distribution has significant kurtosis;
- If at least one of these tests is significant, it is concluded that the underlying pooled population is not normal.

In this paper, having obtained the skewness and kurtosis in Eqs. (4) and (5), we can obtain features related to the joint distributions of the differential equation given by (Pearson, 1895 [21]):

\[
p(x) = \frac{a + (x - \lambda)}{b_0 + b_1(x - \lambda) + b_2(x - \lambda)^2} = 0,
\]

where $p'(x) = d[p(x)]/dx$,
\[
b_1 = \frac{4\beta_0 - 3\beta_1}{10\beta_2 - 12\beta_1 - 18\mu_2},
\]
\[
a = b_1 = \sqrt{\beta_2}\sqrt{\beta_1 + \frac{\beta_2 + 3}{10\beta_2 - 12\beta_1 - 18}}
\]
and
\[
b_2 = \frac{2\beta_0 - 3\beta_1 - 6}{10\beta_2 - 12\beta_1 - 18}.
\]

The shape of the Pearson’s distributions depends on two dimensionless parameters defined by:
\[
\beta_1 = \frac{\mu_1}{\mu_2} \quad \text{and} \quad \beta_2 = \frac{\mu_2}{\mu_2},
\]
where $\mu_2 = \text{E}[(X - EX)^2]$ and, in this point, $\sqrt{\beta_1}$ and $\beta_2$ are univariate analogues for the measures of skewness (2) and kurtosis (3), respectively. These parameters characterize the skewness and kurtosis for the respective distribution. Fig. 2 exhibits the Pearson diagram having highlighted areas for some distributions in the Pearson system:

- Type 0: Gaussian distribution ($\beta_1$, $\beta_2$) = (0, 3);
- Type I: Beta distribution with non-zero skewness;
- Type II: Beta distribution with zero skewness ($\beta_1 = 0$ and $\beta_2 < 3$);
- Type III: Gamma distribution;
- Type IV: Non standard distribution;
- Type V: Inverse-gamma distribution;
- Type VI: F-distribution;
- Type VII: Student distribution ($\beta_1 = 0$ and $\beta_2 > 3$).

In practice, it is possible to identify groups of points in these maps that are driven by the same probability distribution.

### 4. Results

In this section, we present an application to real data of daily deaths from COVID-19. Based on the values of multivariate skewness and kurtosis, we construct a dynamic Pearson diagram for four partitions of each considered time series to identify dynamic groups of countries that monitor the spread and prevalence of SARS-CoV-2 (COVID-19) and provide subsidies to support public policy formulation and decision making. We hypothesize that the formation of groups may be an important tool to categorize which countries were socially and economically affected by the pandemic in 2020–2021. It is important to mention that the need to use a clustering technique is closely associated with the possibility of analyzing the relationships of similarities between countries. Thus, the clusters formed aim to maximize the similarity between the elements of a group (intra-group similarity) and minimize the similarity between elements of different groups (inter-group similarity), [13,22]. Furthermore, we clarify that cluster number (three) in our empirical evidence is associated with the four phases of COVID-19. For more details, see: [23–26]. In this way, the discussion is divided into two distinct phases. First, a fit analysis of the series is conducted. Then, the construction of the Pearson diagram and the interpretation of the results are performed.

The first part deals with the fitting of each of the four parts of the time series under consideration using the $SARIMA(p, d, q) \times (P, D, Q)$ process. The specific submodels of this class were selected based on...
Fig. 7. Skewness and kurtosis map for the second fraction of the daily COVID-19 death series.

Fig. 8. Skewness and kurtosis map for the third fraction of the daily COVID-19 death series.
the Akaike information criterion. For illustration, Figs. 3 and 4 show the fitting results for the US and Brazil, respectively. It can be seen that seasonal and trend factors are present. The adjustments were close to the generated series and reflected well the behavior of the whole series, although some specific peaks in the series were not captured. Table 2 shows the model type obtained from SARIMA and the p-values obtained by the Ljung–Box test for the resulting residuals. For most of the observed time series, only one non-seasonal factor had to be included in the modeling. Based on the last table, we compute the covariance matrix with the parametric bootstrap in time series using the estimates of the selected models needed to compute (4) and (5).

After obtaining the estimates of multivariate skewness and kurtosis for each country, we created the maps and performed cluster analysis using k-means (Johnson and Wichern, 2007 [27]). Kurtosis is a statistical measure of how much the tails of the distribution deviate from the tails of a normal distribution. The classification platykurtic means that the observed kurtosis is smaller than that of the normal distribution; mesokurtic, the observed kurtosis is equal to the normal distribution; leptokurtic, the observed kurtosis is larger than that of the normal distribution. Our results suggest a mathematical relationship between kurtosis and skewness. Looking at the time evolution of the number of deaths at COVID-19, we observe an increase in the kurtosis, which leads to an increase in the skewness modulus. For the countries studied, the distributions generally deviate significantly from normality. The leptokurtic observation includes extreme events.

In Fig. 5 we see that we have formed three groups. The expected value for skewness is 0 for a multivariate normal distribution, as shown in Meghan et al. (2016) [6]. For this reason, we can see in Fig. 5 that group 3 is closest to 0 for the asymmetry values. As for the kurtosis, we have highlighted group 2 with Spain, Israel and Switzerland. If we look at the behavior of the three countries in Fig. 6, we see that the number of deaths by COVID-19 increases for the corresponding scales. The countries in group 1 are moving away from group 3.

Table 3 lists the statistics given in Eqs. (6) and (7) and their respective p-values. It can be seen that the statistics are significant and thus the joint distribution of countries has significant symmetry.

Fig. 7 shows that Spain, Switzerland, and Israel are no longer in the extreme group on the map, reflecting actions taken by countries to combat COVID-19. Note that France, a neighbor of Spain, is among the most extreme countries on the map, along with Mexico and Ukraine. Group 3 shows asymmetry close to 0, while group 2 again shows countries close to asymmetry group 1, but with some countries with increasing kurtosis, such as Iran.

In Fig. 8 only Ukraine remained in the red group, the group with the highest absolute kurtosis has more than 3 countries and an even larger number of European countries. At the beginning of the pandemic, British rulers pursued a denial policy toward COVID-19, resulting in a large number of deaths controlled by social isolation measures, testing for COVID-19, and others. However, the relaxation of the policy with the small number of cases led to an even stronger second wave, shown in the map in Abbire, Fig. 8. If you look at the ellipse of the group 2 confidence region, you can see that there are countries that belong to both confidence regions.

In Fig. 9, which shows the proportion of recent data, Brazil, South Africa, Russia, and Indonesia are in group 1 with the highest absolute values for kurtosis and asymmetry, and they are countries where mortality rates remain high. In contrast, the other two groups show the same behavior as before. And, as in the previous fractions, there are some countries that seem to be getting closer to the more isolated countries, such as Poland. It is worth noting that Brazil had problems from the beginning with the pandemic caused by COVID-19. The government did not cope well with the measures to prevent mass infections and the spread of the SARS-COV-2 virus between health system crises. In several states, the current period is the most critical in terms of the number of daily deaths because of relaxed and flexible quarantine regulations and slow vaccination of the population due to decisions.
The article proposes an approach using multivariate skewness and kurtosis maps according to the Pearson diagram to compare mortality according to COVID-19 in 55 countries. The SARIMA process is one of those that can well describe the series of daily deaths by COVID-19 in countries. When we break down the series, we are left with a simpler model like ARIMA. If we fit it well, we have a good model and consequently our bootstrap with the estimates of the model parameters, resulting in a more accurate bootstrap series. By computing the parametric bootstrap, we obtain estimates of multivariate skewness and kurtosis, and in this way, we can produce maps based on the Pearson diagram. Using the maps of multivariate kurtosis and skewness, we performed clustering to identify groups of countries and see how their positions on the map reflected their ranks. For each portion in the series, three groups were formed on the maps. Using the proposed diagram, it was possible to show a direct mathematical relationship between multivariate skewness and kurtosis. Thus, given the temporal evolution of the spread of SARS-CoV-2, countries had great difficulty in preventing this spread and containing the virus. Our graph shows that the increase in daily deaths leads to an increase in multivariate skewness and kurtosis. Dynamic analysis at the country

made during the pandemic. In Russia, on the other hand, vaccination is more advanced than in Brazil, but also slower. The country has been confronted with a new variant that has led to a sharp increase in daily deaths.

5. Conclusion
and group levels confirms the epidemiological hypothesis that the dynamics of the spatial and temporal spread of COVID-19 resemble a wave, meaning that the virus reached countries or groups of countries by different routes. For this reason, we observed temporal mobility concerning the epicenter of COVID-19. It is worth mentioning the merit of some countries (including New Zealand, Taiwan, Vietnam, and Australia) in implementing the measures recommended by the World Health Organization (WHO) and effective public policies to combat the spread and containment of COVID-19. Otherwise, reactive countries have performed poorly and generally massaged the social and economic well-being of their populations (Brazil, United States, United Kingdom). These are examples of countries that, at various times, adopted policies that were opposed by their rulers and contradicted the measures recommended by WHO to combat COVID-19.

Thus, through the multivariate skewness and kurtosis maps, we have a new approach to mortality data from COVID-19 that allows the use of time series concepts and does not focus solely on prediction, as was done by Arunkumar et al. (2021) [28] and Demir and Kirisci (2021) [29].

Based on a combination of time series and multivariate analysis techniques, we have developed a method for mapping COVID-19 mortality that takes into account the behaviour of the latent distributions behind the observed series, as well as their extreme events in the areas of excessive peaks and tails. The proposed map is able to promote the diagnosis of COVID-19 mortality by considering phase transitions in a static and dynamic way. In this sense, we understand our proposal as a promising tool for the dynamic analysis of COVID-19 deaths and hope that it can be used by governments to support the decision-making process.
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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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