

# Mapping Time Lags in Epidemics

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## Introduction

The COVID-19 pandemic has prompted a surge in research efforts to understand its transmission dynamics and societal impact. In this study, we focus on Spain, a nation significantly affected by the pandemic, analyzing relationships between daily movement within and between its 52 provinces (Ponce-de-Leon et al 2021) alongside daily counts of COVID-19 active cases. By employing lagged correlation and Granger causality analyses, we aim to unveil the temporal relationships between mobility and disease spread, shedding light on crucial factors influencing the pandemic's trajectory. Such insights help to inform targeted interventions and public health strategies aimed at curbing the spread of infectious diseases.

## Approach

Our study posits a reciprocal relationship between mobility and illness, likely characterized by temporal delays. We anticipate that the trend and temporal dynamics of these interactions vary between provinces. To test these hypotheses, we conduct cross-correlation analyses across a range of lag values and examine the resulting correlation profiles for each province, aiming to elucidate the nuanced temporal patterns of influence between mobility and sickness across Spain's 52 provinces. Having time series of attributes A and B with length M, we calculate cross-correlation with lag N by evaluating the correlation between the first (M-N) values of attribute A and the last (M-N) values of attribute B. By analyzing both directions of correlation, we aim to discern the potential influence of attribute A on attribute B and vice versa, thereby providing a comprehensive assessment of their mutual interactions.

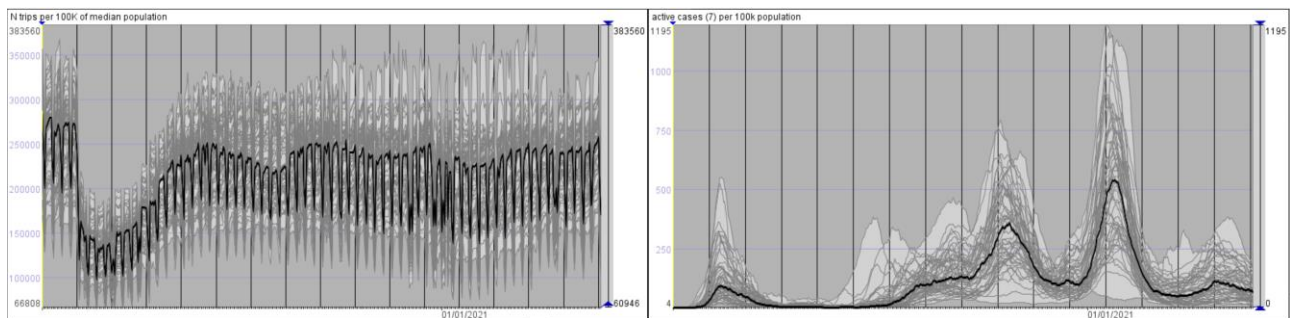


Figure 1. Dynamics of daily mobility in 52 provinces and counts of active cases of COVID. Black line shows daily median values.

Figure 1 depicts the raw data comprising 52 time series spanning over 500 days from February 14, 2020, to May 9, 2021. Both attributes represent daily counts normalized by the population of the respective provinces. Throughout this period, we observe three distinct waves of the epidemic. The initial wave, occurring at the outset, is characterized by a significant decline in mobility due to governmental restrictions. For the purpose of this analysis, we focus on the period from August 1, 2020, to February 28, 2021, encompassing the second and third waves. In Figure 2, we present two directed cross-correlations in the upper part, accompanied by statistics detailing negative and positive values in the bottom section. Notably, a substantial number of negative correlations are evident for lags less than 14 days, gradually decreasing with longer lags. Correlations suggesting a potential impact of trips on COVID-19 cases frequently transition to positive values for lags exceeding 4-5 weeks. Conversely, regardless of the lag duration, the occurrence of positive correlations in the opposite direction remains minimal.

While most of the lines in both time graphs follow the same increasing pattern, we observe several notable outliers. These outliers occur in some of the overseas provinces and in the capital region. To study further details, we applied k-Means clustering to provinces, using both sets of cross-correlations values as features. Centroids of clusters, characterized by

profiles consisting of  $2 \times 43 = 86$  values were projected to a 2D space. Iteratively applying clustering with different target numbers of clusters and observing distributions of cluster centroids in the projection space, we selected the result with  $N_{\text{clusters}} = 7$  that produced good separation of the clusters (Figure 3). On the map, we can observe characteristic spatial distribution of the clusters. Further analysis can be performed for assessing the impact of mobility between provinces.

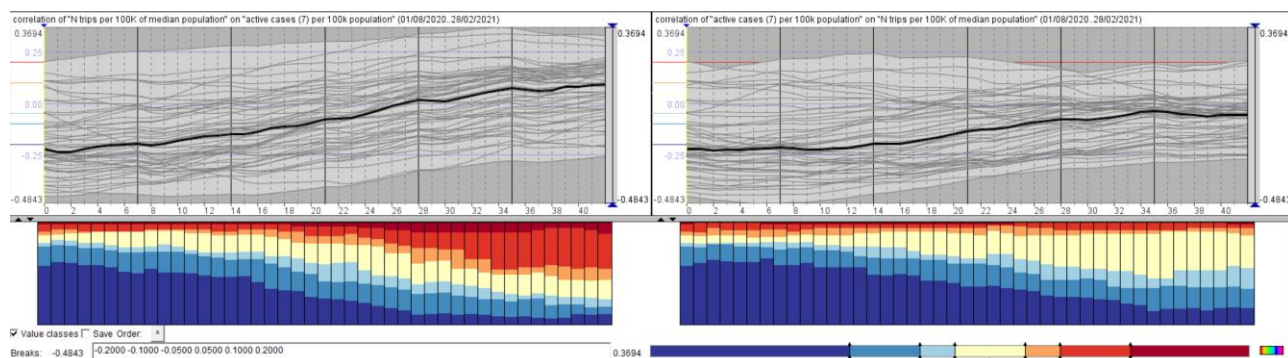


Figure 2. Directional cross-correlations of population-normalized counts of trips and COVID cases with lags from 0 to 42. Black line represents median values. Segmented histograms in the bottom show dynamics of negative (blue colors) and positive (red colors) values for different lags.

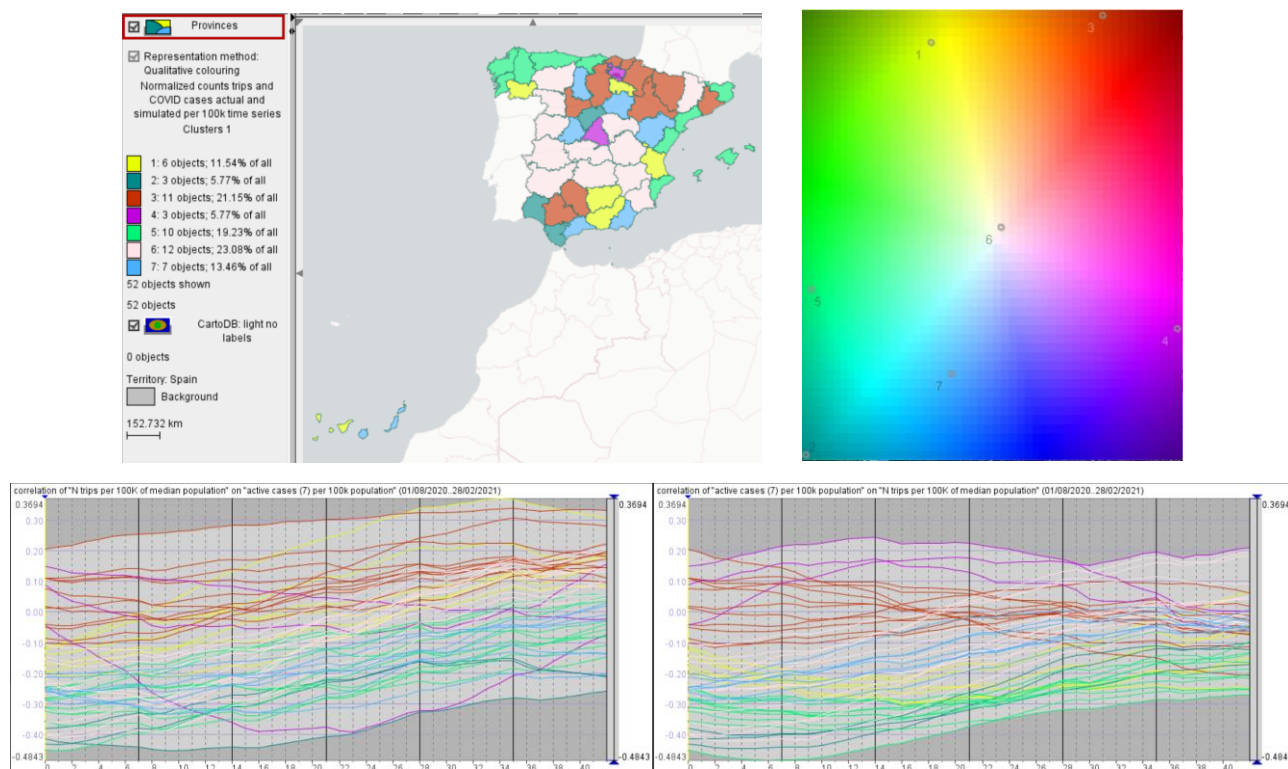


Figure 3. Clusters of spatial distribution of cross-correlation profiles over different time lags. Embedding of cluster centroids is used for assigning colors to the clusters, aiming at reflecting the similarity of clusters by the similarity of colors (Andrienko et al 2020).

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## References

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