

Human mobility in COVID-19 era: a quantitative analysis

Keywords: quantitative analysis, Covid-19 mobility , geometric measures, entropic measures, visitation patterns

Extended Abstract

Facing the unprecedented COVID-19 pandemic raised questions on how to contain the advance of this new disease. In the absence of pharmaceutical strategies, in the first months of the pandemic non-pharmaceutical ones have been enforced by the governments with the intent to contain the advance of the disease. Lockdown measures were implemented all over the world and as a direct consequence, human behavior and mobility habits had been significantly altered. In this context, many models have been built to forecast the spread of COVID-19 among different populations [1]-[2].

Until now, most studies relied on the assumption of a relationship between the number of trips and the number of contacts, and between the number of contacts and the probability of transmission. Researchers have found and shown, that behavior did not remain constant among the different phases of the pandemic, shaping differently according to the stage and driven by awareness [3]-[4]. This leads to the fact that not all humans travels lead to contagion events, and deriving information about virus spread from what is known about human mobility remains a challenge [5]. Despite these difficulties, as scientists, this scenario provides not only the opportunity for developing quantitative description of the effect of the non-pharmaceutical intervention on mobility. It also represent a natural experiment that allows us to test the robustness of individual mobility patterns.

In this work, we aim to quantify these effects by carrying out measures regarding individual mobility. We analyze a large privacy-enhanced longitudinal GPS dataset, including over 180,000 anonymous opted-in individuals trajectories of people living in Massachusetts, and consider their movements across the U.S.A from January to September 2020, replicating the analysis and measures from previous seminal works on the statistical description of human mobility, comparing the periods before and after lockdown restrictions.

In particular, we begin by studying the distribution of the radius of gyration (Fig.1 on the left) [6], finding a change in mobility, where short-range mobility is more probable than before and the flows seem to recover in the third period. The measure confirms this result of the geodesic distance (Fig.1 on the right) where we also suggest the power law best-fits of the distribution tail for the three different periods. It is however remarkable that the relative fraction of long trips $L > 50km$ appears relatively unchanged.

We compute the exploration curve [7], and observe that people's tendency of visiting new places decreased during the lockdown period, with a power law with exponent approx to 0.5, different than 0.65 which is the value observed for the previous and posterior periods (Fig. 2). Besides, the behavior is also visible for the distribution of places visited, observed in the intrinsic reference frame [6] in (Fig. 3).

In order to analyze the complexity and predictability of the trajectories, we use three different entropy measures: i) Random, which depends on the number of visited places, ii) Shannon, which adds the dependency on the relative frequency of visits, assuming subsequent visits are

independent, and iii) Lempel-Ziv estimation (Real entropy), which considers also the order in which visits are done [8]. These different measures allow a progressively finer view of the trajectories, adding different aspects that contribute to the description of the complexity of a single path. As a result, we obtain that, for all three measures, trajectories during lockdown seem to be less complex (Fig. 4). We check if this effect is driven by people visiting fewer places by looking at the ratio between random and real entropy, and find that this is indeed the case (Fig. 4 bottom-right).

Finally, we propose returner-explorers analysis [9] and show that during lockdown restrictions compared to the non-lockdown periods, we have an increased number of returners with respect to explorers (Fig. 5).

Summarizing, in this work we explored the changes in individual mobility habits under COVID-19 non-pharmaceutical intervention. Our analysis provide a set of different measures to appreciate the changes due to Lockdowns that, according to our observation strongly influenced the individual mobility patterns not only by restricting the number of visits, the diversity of the activities done at the destination, or their duration [10], but also strongly modifying the spatial characteristics of the individual mobility networks and the natural attitude of people of exploring new locations.

References

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Period/quantities	N	$ T $	$\langle T \rangle_p$
15 january - 15 march	181778	28782953	158
15 march - 15 may	140913	12701431	90
15 may - september	141285	32096311	227

Table 1: Statistical description of dataset. Total number of users (N), total number of points $|T|$, and average number of points per user $\langle |T| \rangle_p$, for each period considered

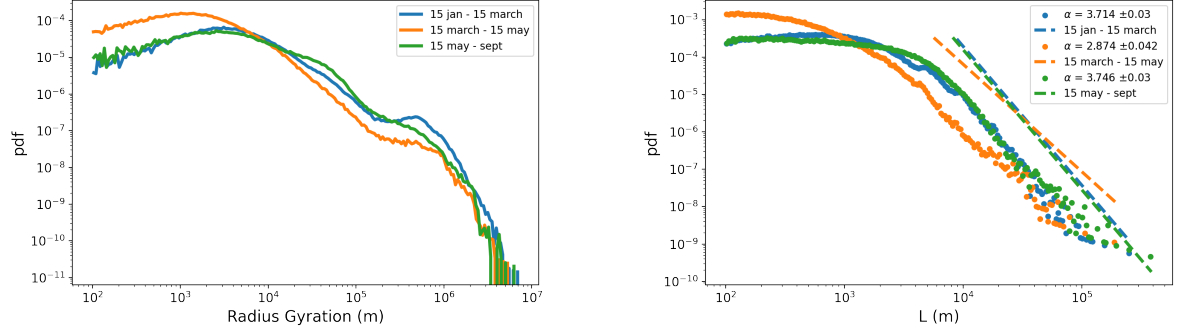


Figure 1: On the left: Distribution of radius of gyration among in three different periods. The lockdown curve is above the other two curve for distances below 5 km, and below up to 1000 km, meaning that medium-distance mobility is redistributed on the short distance one, while preserving long trips mobility. On the right: Distribution of distances among successive stop' points in three different periods and their corrispective power laws. Prevalence of short distance travels and long tail can be observed.

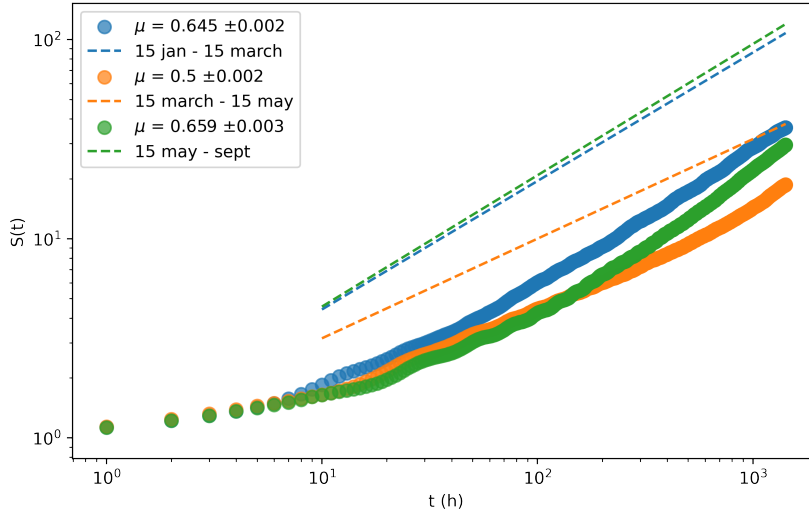


Figure 2: Average number of stop points visited in time. During lockdown the rate of discovery is lower then the other two periods.

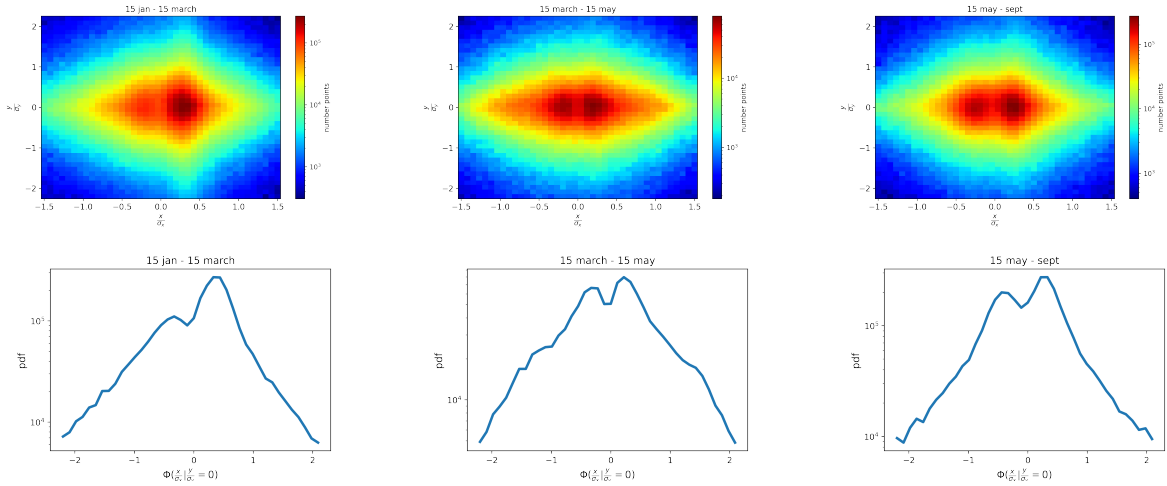


Figure 3: Top: Distribution of positions of people stops' points in their intrinsic reference frames rescaled by the variance of the rotated coordinates in the x,y-rotated axes. From left to right different periods (15 january - 15 march, 15 march - 15 may, 15 may - september). Bottom: Distribution conditioned to $\frac{y}{\sigma_y} = 0$. During lock-down two poles are present. Things that reamin partially also after lockdown. As the axis are scaled by the variance it is not visible the real distance. During the lockdown the figure is zoomed in both directions. So even though the shape are very similar it maybe the case that the functionality of the two peaks are different.

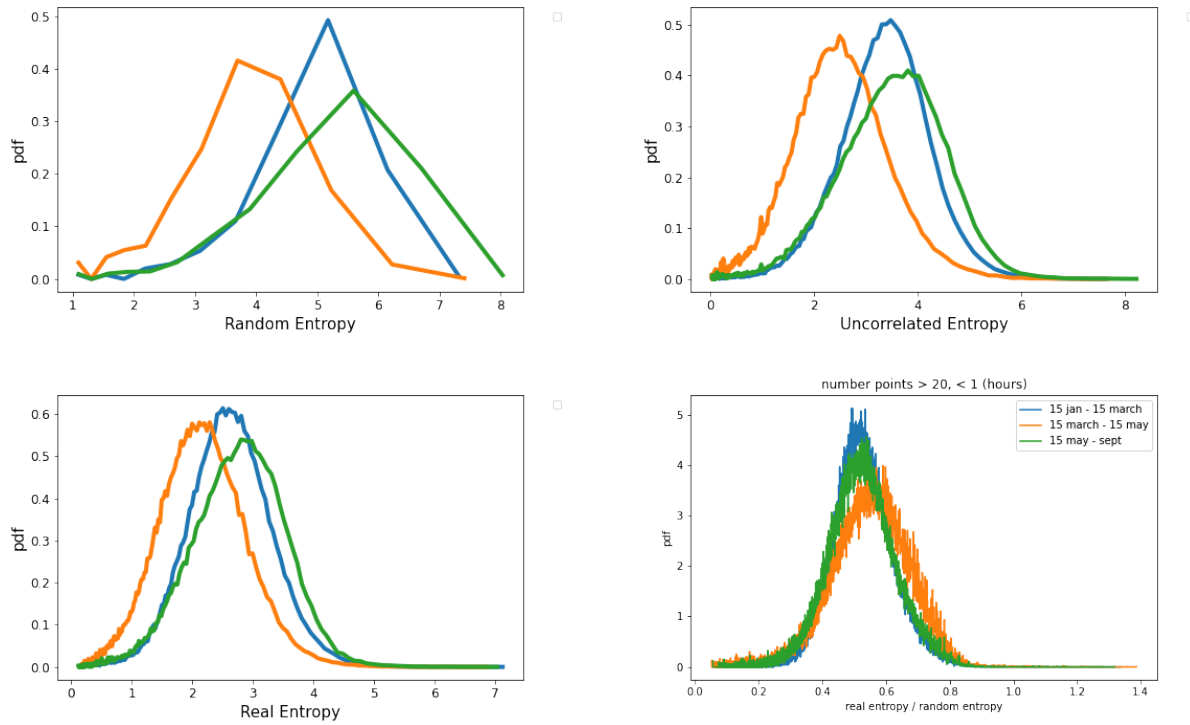


Figure 4: Distribution (from left to right, top to bottom). Random entropy, Uncorrelated entropy, Real entropy: during lockdown, the distributions are moved on the left with respect the other two periods, indicating in all three cases less complexity. On the bottom right is shown the ratio between Random and Real entropy. This plot highlights that during lockdown restriction, real entropy is closer to the random with respect to the other periods. This means that even though all three measures suggest that the complexity of the trajectories are smaller during lockdown, the main contribution to complexity (uncertainty) lays on the total number of visited places.

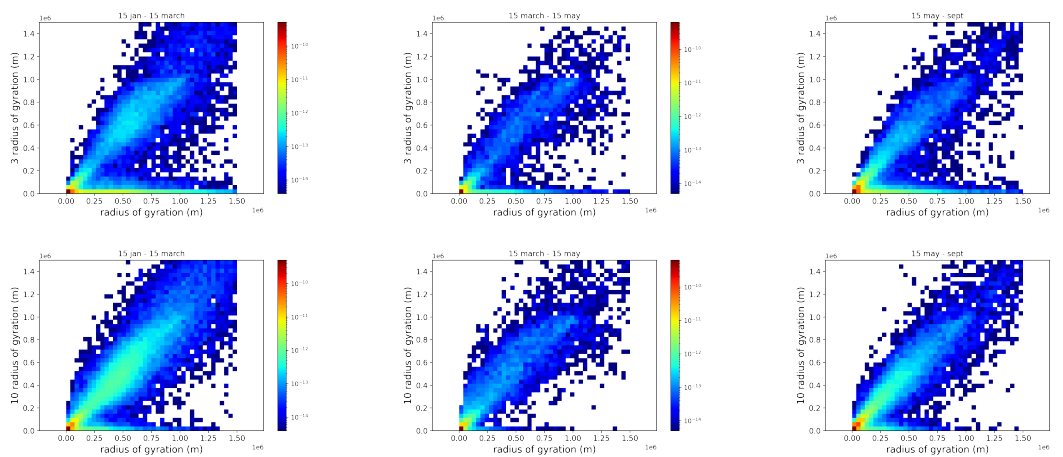


Figure 5: Distribution of (radius of gyration, k- radius of gyration) in three different periods. From top to bottom $k = 3, 10$. From left to right period of measure (15 january - 15 march, 15 march - 15 may, 15 may - september). In both (3-10) cases we find that the tail of low k -radius of gyration, high radius of gyration is longer after and before lockdown restrictions rather then during.