Uncovering the differences and similarities between physical and virtual mobility

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Extended Abstract

In recent years, scientists have witnessed an explosion of extensive geolocated datasets related to human movement, enabling them to quantitatively study individual and collective mobility patterns and to generate models that can capture and reproduce the spatio-temporal structures and regularities in human trajectories [1]. Human mobility studies are especially important for applications such as estimating migration flows, traffic forecasting, urban planning, mitigating pollution, and epidemic modelling [2–4]. A particularly rich source of data has been from geotagged traces, including Call Data Records (CDRs) and location-based social networking services (LSBNs). There are several common regularities that have been observed across these studies, including bursty activity rates [5], tendencies to visit a select few locations disproportionately more than others, and a decreasing likelihood to explore as time goes on [6]. On the basis of these findings, a series of phenomenological models have been proposed to explain observed regularities [7, 8].

However, with the advent of the World Wide Web, it is possible to define and study an entirely new dimension of human mobility, that is, in the virtual space, a feature that has been rapidly gaining attention [9, 10]. This is of course natural, given that an increasing fraction of human activities such as shopping, information consumption, education, and social interaction are being replaced by their online counterparts. This phenomenon is relatively recent (on a biological time-scale) and much remains to be uncovered; therefore, a better understanding of the long-term impacts of such changes in behaviour and the corresponding challenges is crucial.

Increasing evidence suggests that online activity, including virtual mobility, is governed by similar mechanisms influencing offline activity [11] Furthermore, many statistical regularities observed in physical movement have also been observed in virtual movement, including the distribution of visitation frequencies to locations, power-law distributions of activity rates in on-line bookmarking, and in the special case of virtual worlds, the heavy-tailed distribution of displacements (a feature that is unreproducible in most online movement, due to the lack of a metric space). Even more strikingly, a method of characterization of individuals according to whether they have exploratory or saturation behaviour in terms of location discovery, has been successfully adapted to Web browsing [12], leading to similar findings as those obtained from the analyses of physical trajectories [13].

At first blush, the observed similarity in mobility trends in physical and virtual domains is rather surprising. In particular, physical movement is necessarily constrained by temporal and economic costs in terms of moving from one location to the other. Yet, no such limitations exist while navigating the Web, which is neither economically (for the most part) nor spatially bounded. Furthermore, despite the recent spate of research on online activities, there are relatively fewer studies conducting a direct comparison between physical and virtual mobility. While much has been said about their commonalities, less attention has been devoted to their differences, specifically, the role played by the inherent spatial costs in physical movement.

To fill this gap, we conduct a systematic analysis of the similarities and differences between online and offline movement. We study one virtual and two physical datasets, finding that the differences arising from the cost associated with spatial movement, manifest as differences in temporal mobility statistics primarily at shorter time-scales corresponding to the intra-day regime (see Figure 1A–E). Once we move to the time-independent space of events, that is sequences of location visits, these differences dissipate, and the statistical patterns are essentially indistinguishable, pointing to a common mechanism underlying both behaviours (see Figure 1F–G).

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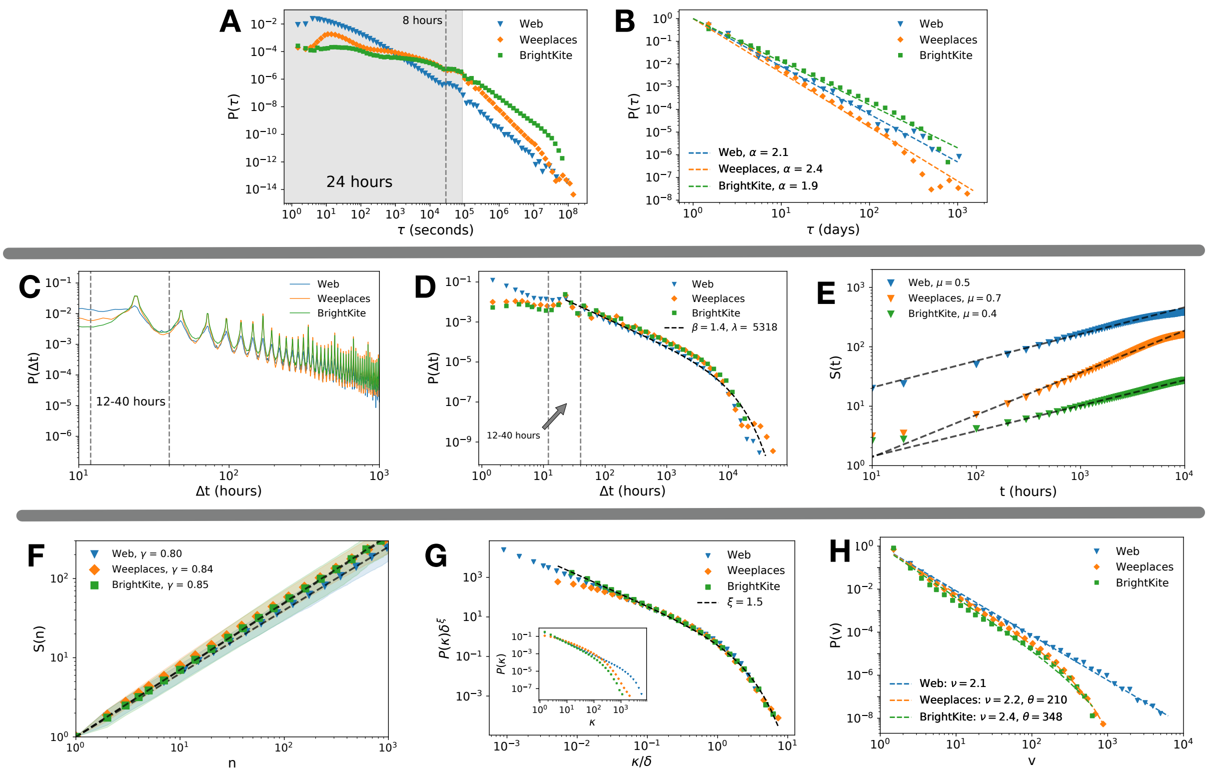

Figure 1: **(A)** $P(\tau)$ plotted at the resolution of seconds, indicating noticeably more rapid activity in Web browsing as compared to moving between physical locations. The latter exhibits distinct scaling regimes at the intra- and inter-day levels, with a flatter distribution in the intra-day regime. Hourly features disappear at the resolution of days **(B)** where all three datasets exhibit a scaling of the form $P(\tau) \sim \tau^{-\alpha}$. **(C)** The distribution of inter-return times plotted with linear bins. Each peak corresponds to integer-days, and all three datasets indicate a clear circadian pattern. **(D)** Inter-return time distributions plotted with logarithmic bins. All three datasets follow a truncated power-law form $p(\Delta t) \sim \Delta t^{-\beta} \exp(-\Delta t/\lambda)$ shown as dashed curve. **(E)** The number of discovered unique locations as a function of time $S(t)$. While, all datasets scale sub-linearly $S(t) \sim t^{\mu}$ (fits shown as dashed curves), an order of magnitude separates the number of discovered locations in the Web as compared to physical movement. **(F)** The number of unique locations visited as a function of event count $S(n)$. Unlike for $S(t)$, the trends in all three datasets are similar, whereby $S(n) \sim n^{\gamma}$ with $\gamma \approx 0.8$. **(G)** The recency effect is present in both the virtual and physical domains, with the distribution of unique intermediate locations visited, before returning to a given location $P(\kappa)$ following a truncated power-law distribution, $P(\kappa) \sim \kappa^{-\xi} \exp(-\kappa/\delta)$, with a common scaling exponent $\xi \approx 1.5$ (inset). After rescaling, with respect to the cut-offs, all three distributions collapse on to the same curve (shown as dashed line).**(H)** The frequency distribution of location visits for all three datasets follow the form $P(v) \sim v^{-\nu}$ with roughly similar exponents, however we note the presence of exponential cut-offs $\exp(-v/\theta)$ in the physical mobility distributions.