Money Circulation, Trackable Items, and the Emergence of Universal Human Mobility Patterns

Proxy networks permit reliable estimates of statistical features such as degree, flux, and traffic weight distributions. The authors show that despite cultural and national differences, universal properties exist in a diverse set of traffic networks along with important insight into traffic-related phenomena such as the geographic spread of emergent infectious diseases.

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Human mobility in our globalized world has reached a complexity and volume of unprecedented degree. More than 60 million people travel billions of miles on more than 2 million international flights each week. Hundreds of millions of people commute on a complex web of highways and railroads, most of which operate at their maximum capacity. Despite this increasing connectivity and our ability to visit virtually every place on this planet in a matter of days, the magnitude and intensity of modern human traffic has made us more susceptible to threats intimately connected to human travel. For instance, long-range human mobility is responsible for the geographical spread of emergent infectious diseases and plays a key role in human-mediated bioinvasion, the dominant factor in the global biodiversity crisis. A prime example of modern epidemics is severe acute respiratory syndrome (SARS), which first appeared in a Chinese province in 2003 before proliferating and spreading around the world in a matter of weeks, infecting nearly 10,000 individuals worldwide with a mortality of approximately 10 percent. Since then, epidemiologists have devoted an increasing amount of attention and modeling effort to understanding in what way and to what extent modern traffic networks impact and determine the dynamics of emergent diseases, particularly in the face of an imminent H5N1 flu pandemic.[1–5]

In several recent studies, researchers investigated the statistical properties of human transportation networks with a focus on air transportation and long-distance traffic.[6–8] However, human mobility occurs on many length scales, ranging from commuter traffic over short distances to long-range travel by air, and involves diverse modes of transport (buses, light rail, cars, trains, planes, subways, and boats). No comprehensive study exists that incorporates traffic on all spatial scales because it would require collecting and compiling data into a multicomponent data set—a difficult, if not impossible, task particularly on an international scale. Whereas researchers have studied the central statistical features of air transportation networks in detail, it remains unclear

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whether these properties remain unchanged in traffic networks that comprise all other means of transportation and spatial scales. How do these properties depend on the length scale, for example? Are they universal? In what way do they change as a function of length scale? What are the national and regional differences and similarities? To understand human mobility in the 21st century and the dynamics of associated phenomena, particularly the geographic spread of modern diseases, answering these questions is of fundamental importance.

In this article, we report on the discovery of statistical regularities, mathematical laws, and universal characteristics underlying multiscale human mobility. Our study is based on the generation of proxy networks for global human travel behavior from pervasive user data collected at the world's largest bill-tracking Web site (www.wheresgeorge.com) and trajectories of trackable items (known as travel bugs) recorded at a geocaching Web site (www.geocaching.com). From this pervasive data, we extract multiscale human traffic networks for the US and European countries that cover distances of a few to a few thousand kilometers. These proxy networks permit reliable estimates of statistical features such as degree, flux, and traffic weight distributions; we show that, despite cultural and national differences, universal properties do exist, giving us insight into traffic-related phenomena.

Money Circulation and Human Mobility

Confronted with the difficulty of compiling a comprehensive data set of human traffic, Dirk Brockmann and his colleagues proposed in 2006 using the geographic circulation of money as a proxy for human traffic, based on the idea that individuals transport money as they travel and that the total flux of money between a set of cities is proportional to the flux of individuals.[9] The researchers analyzed data collected at the online bill tracker www.wheresgeorge.com, which Hank Eskin founded in 1998. The idea is simple: registered users mark individual dollars, which then enter circulation. When new users come into possession of a marked bill, they can register at the site and report the bill's current location via the zip code. Successive reports of a bill yield a spatiotemporal trajectory with a very high resolution. Since 1998, www.wheresgeorge.com has become the largest bill-tracking Web site worldwide, with more than 3 million registered users and more than 140 million registered bills. Approximately 10 percent of all bills have had hits (defined as a second, third, and so on report after the initial entry), yielding a total of more than 14 million single trajectories consisting of origin (initial entry location) and destination (hit location) X_1 and X_2, respectively.

Proxy networks permit reliable estimates of statistical features such as degree, flux, and traffic weight distributions.

Figure 1 illustrates a sample of bill trajectories with initial entries in five US cities. Shown are bill journeys that lasted a week or less. Clearly, most bills remain in the vicinity of their initial entry, yet a small but significant number have traversed distances of the order of the size of the US, consistent with the intuitive notion that short trips occur more frequently than long ones.

Anomalous Diffusion in Bank Note Dispersal

One of the key results of the 2006 study was the first quantitative estimate of the probability $p(r)$ of a bill traversing a distance r in a short time period, a direct estimate of the probability of humans performing journeys of this distance in a short time period. The researchers based their estimate on a data set of 464,670 individual bills. Over a range of distances between 10 and 3,500 km, this probability follows an inverse power law—that is,

$$p(r) \sim \frac{1}{r^{1+\beta}}, \quad (1)$$

with an exponent $\beta \approx 0.6$. Despite the multitude of transportation options involved, the underlying complexity of human travel behavior, and the US's strong spatial heterogeneity, the probability $p(r)$ follows this simple mathematical law, indicating that underlying universal rules govern human mobility. Moreover, the specific functional form of $p(r)$ has important consequences. If we assume that individual bills perform a spatial random walk with an arbitrary probability distribution $p(r)$ for distances at every step, we can ask, what is the typical distance $X(t)$ from the initial starting point as a function of time? For the ordinary random walks (also known as Brownian motion) that are ubiquitous in the natural sciences, the behavior of $X(t)$ is determined by the standard deviation of the single steps

$$\sigma = \sqrt{\langle r^2 \rangle - \langle r \rangle^2},$$

and irrespective of the particular shape of $p(r)$, the distance $X(t)$ scales according to the square-root law—that is, $X(t) \sim \sqrt{t}$—a direct consequence of the central limit theorem.[10]

However, for a power law of the type observed in bank note dispersal (Equation 1), the variance diverges for exponents $\beta < 2$, so the situation is more complex. It implies that bank note dispersal lacks a typical length scale, is fractal, and the bill trajectories resemble a particular class of random walks known as Lévy flights.[11] In contrast to ordinary random walks, Lévy flights are anomalously diffusive, exhibiting

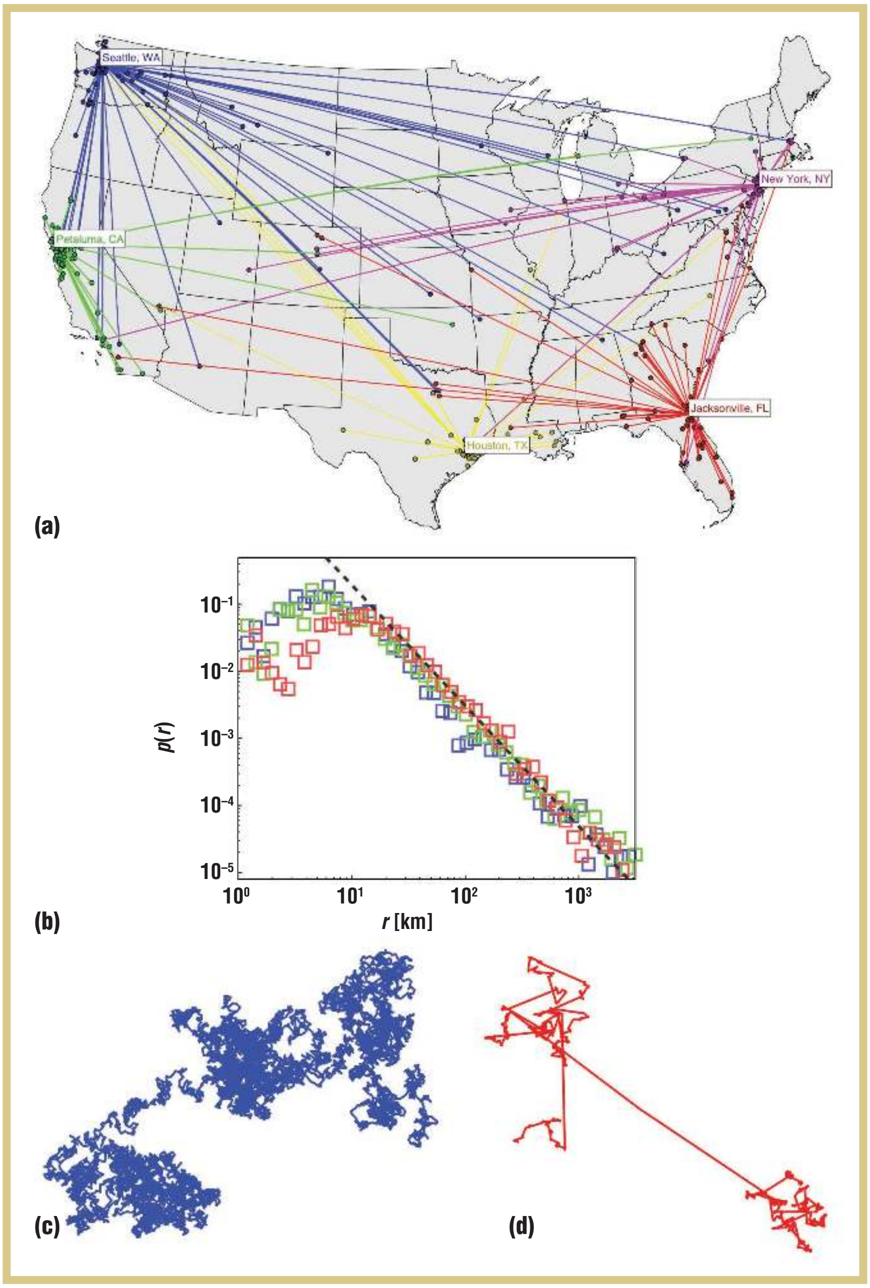


Figure 1. Short time trajectories of dollar bills in the US. (a) Lines connect origin and destination locations of bills that traveled for less than a week. (b) The probability $p(r)$ of traveling a distance r in a short time period of less than a week. The dashed line indicates the inverse power law of Equation 1 in the text. The colors indicate trajectories that started in large cities (blue), intermediate cities (green), and small towns (red). (c) Two-dimensional trajectory of an ordinary random walk or Brownian motion. (d) Trajectory of a superdiffusive Lévy flight, the geometry of which consists of small clusters interconnected by long leaps.

a scaling relation that depends on the exponent β:

$$X(t) \propto t^{1/\beta}. \qquad (2)$$

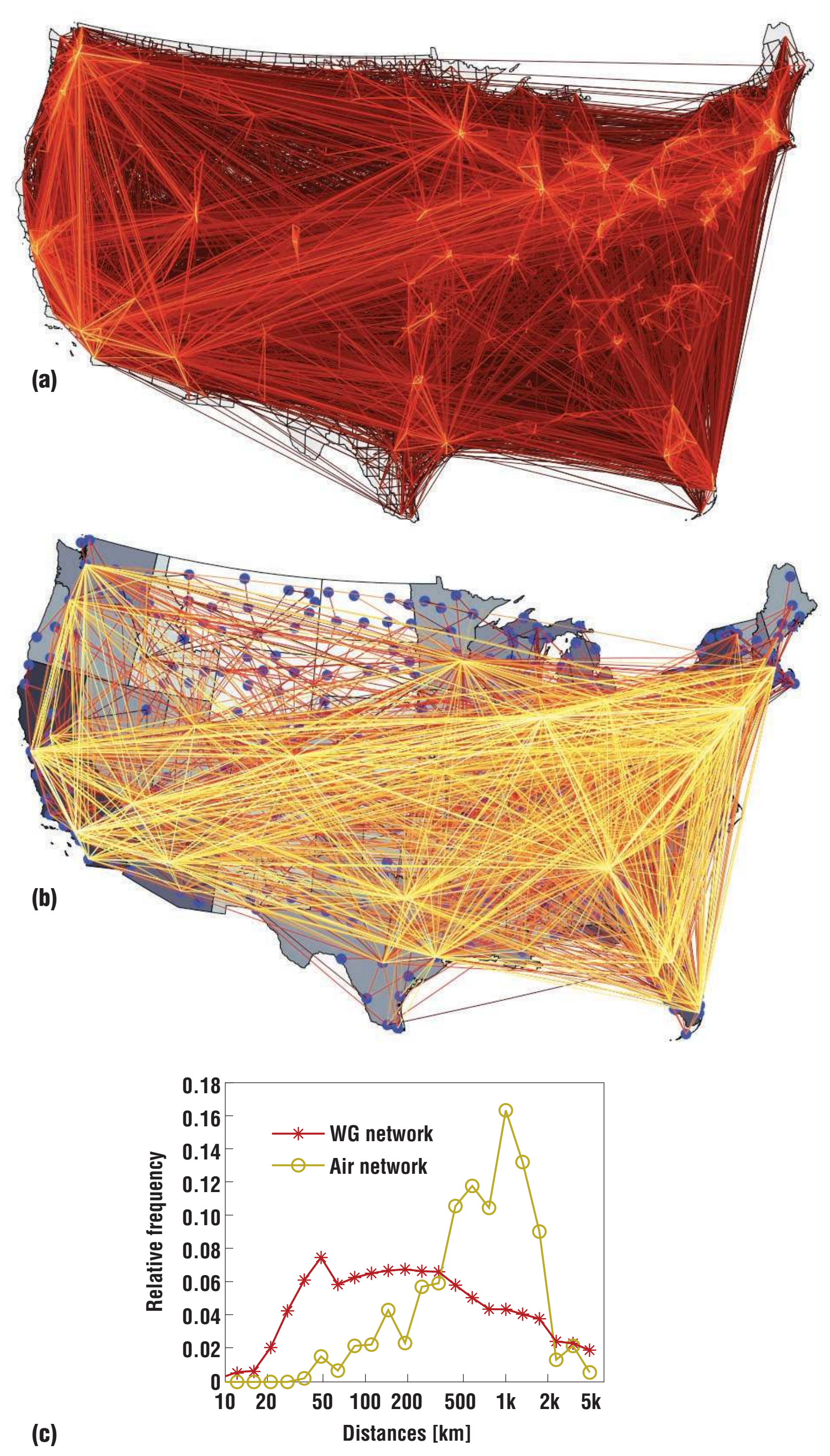
Because $\beta < 2$, Lévy flights are superdiffusive; they disperse faster than—and their geometrical structure differs considerable from—ordinary random walks. The discovery that bank note dispersal and therefore human travel behavior lacks a scale and is related to Lévy flights was a major breakthrough in understanding human mobility on global scales. This result is particularly intriguing because researchers have observed similar power laws and Lévy flight dispersal in foraging animals such as albatrosses, deer, and marine predators as well[12–14]; a recent study on mobile phone dynamics has since validated these results,[15] indicating that similar underlying rules determine emergent mobility patterns.

A Multiscale Network Perspective

The initial bank note dispersal study focused on the process's dynamical features, but the data set was too small to investigate multiscale human mobility from a network perspective and analyze human traffic with methods from complex network theory.[16] For this, we would have to estimate the flux of bills between individual cities in the US instead of just focusing on distance distributions. Based on a data set of more than 10 million records—a factor of 20 larger than the original data set—we report here on the first network perspective analysis of multiscale mobility in the US based on money circulation.

In our approach, we define the network as a set of locations or nodes labeled n that we chose to be the 3,109 counties in the US, excluding Alaska and Hawaii. These nodes are connected by weights $W_{mn} \geq 0$, which represent the flux rate of bills from county m to n in bills per day. We thus encode the entire network structure in a $3{,}109 \times 3{,}109$ flux matrix W. Because each location has a well-defined geographical position, we can visualize this multiscale US traffic network as a geographically embedded network, as shown in Figure 2. Qualitatively,

Figure 2. Network comparison. (a) and (b) Colors indicate the magnitude of the flux of dollar bills in the US, with bright lines representing heavy flux and dark lines weak flux. In (b) the US air transportation network, the lines indicate connections between the 413 major airports in the US; the color represents the magnitude of passenger connections per day. (c) A histogram compares the relative frequency of distances in the multiscale traffic network obtained from the www.wheresgeorge.com (WG) data set with the air transportation network.



we can see that prominent East Coast–West Coast fluxes exist in the network, yet the strongest connections are short- to intermediate-length connections. This fact is particularly visible when compared with the US air transportation network shown in Figure 2c. Air transportation predominantly serves long-distance travel, and although 2.35 million passengers travel on the network daily (according to the International Air Transport Association), it represents only a small subset of the multiscale traffic network depicted in Figure 2a. The histogram in the figure illustrates these properties more quantitatively, comparing the relative frequency of distances in the multiscale www.wheresgeorge.com network to the air transportation network. Clearly, most distances served by air transportation peak at 1,000 km, whereas distances in the www.wheresgeorge.com network are broadly distributed across a wide range, from a few to a few thousand kilometers. To understand human mobility on all spatial scales, we must include all methods of transportation indirectly inherent in the www.wheresgeorge.com money circulation network.

The bill circulation network quantified by the flux matrix W can give important insight into the statistical features of human mobility across the US. To quantify these features, we concentrate on the flux of bills in and out of a node given by

$$F_m^{in} = \sum_n W_{mn} \quad F_m^{out} = \sum_n W_{nm}, \qquad (3)$$

respectively. These flux measures are a direct proxy for a node's overall traffic capacity. Next, we investigate a node's in and out degree defined according to

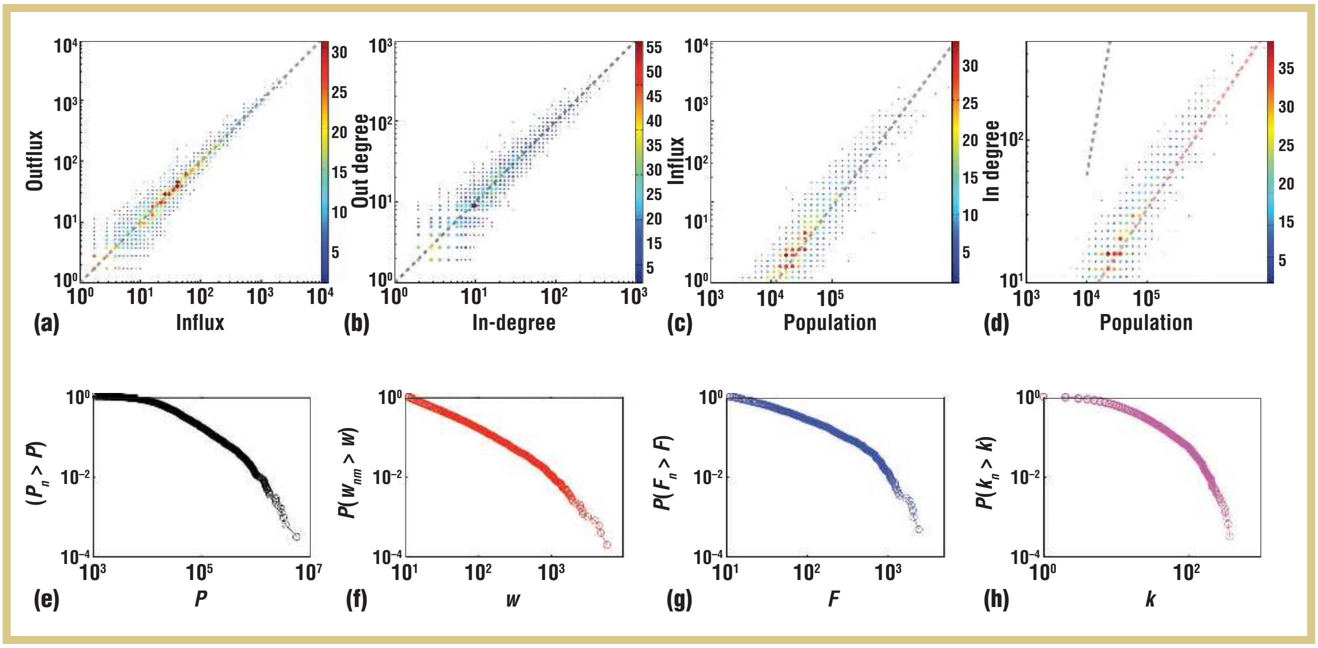


Figure 3. Network flux. (b) The correlation of bill flux (a) in F^{in} and (b) out F^{out} and a node's in and out degree for all 3,109 nodes in the network. The dashed lines represent the linear relationships $F^{in} = F^{out}$ and $k^{in} = k^{out}$, respectively. (c) The functional dependence of influx F^{in} and (d) in degree k^{in} on a node's population size P. Bill flux depends linearly on population size (gray dashed line), whereas the degree exhibits a sublinear dependence (pink dashed line). (e) Cumulative probability distributions of the nodes' population, (f) the weight matrix elements W_{nm}, (g) the bill flux in and out of nodes W_n, and (h) the nodes' degree k_n.

$$k_m^{in} = \sum_n A_{mn} \quad k_m^{out} = \sum_n A_{nm}, \tag{4}$$

where the elements A_{nm} are entries in the adjency matrix. These elements are either one or zero, depending on whether nodes n and m are connected. A node's degree quantifies its connectivity—that is, to how many other nodes a given node is connected. An important but expected feature of the bill circulation network is its degree of symmetry. Figure 3a depicts the correlation of the bill flux in and out of each node, and Figure 3b shows a correlogram of the in and out degrees. These quantities exhibit a linear relationship subject to fluctuations,

$$F_n^{in} \approx F_n^{out} \text{ and } k_n^{in} \approx k_n^{out}, \tag{5}$$

indicated by the dashed lines in the figure. Note also that the flux values' magnitude ranges over nearly four orders of magnitude, an indication of the network's strong heterogeneity; this is further illustrated by the cumulative distributions of the weights W_{nm}, the fluxes F_n, and the degrees k_n of all the nodes in the network, as depicted in Figures 3f through 3h. All quantities are broadly distributed across a wide range of scales, which researchers have also observed in air transportation networks.[7,17] An important issue in transportation theory is the development of a plausible evolutionary mechanism that can account for the emergence of these distributions, a task that has yet to be accomplished. As of today, no plausible theory for human traffic networks predicts the precise functional form of the distributions shown in Figures 3f through 3h.

Scaling Laws

To reveal additional structure in multiscale human mobility networks, we investigated the functional relation of the quantities defined in Equations 4 and 5—that is, the functional relation of fluxes and degrees with respect to a node's population size. Figure 3c illustrates the statistical relationship between a node's population size P and the bill flux into a node. The dashed line in the figure represents a linear relationship with slope 1, indicating that traffic through a node grows linearly with population size:

$$F(P) \sim P. \tag{6}$$

Intuitively, we expect this—the larger a node's population, the more traffic flows into it. However, correlating a node's degree against population size indicates a sublinear relationship

$$k(P) \sim P^{\xi}, \tag{7}$$

with an exponent $\xi \approx 0.7$, contrasting the intuitive notion that a node's connectivity grows linearly with population size as well. From the scaling relations in Equations 6 and 7, we can determine an important property of multiscale mobility networks. The typi-

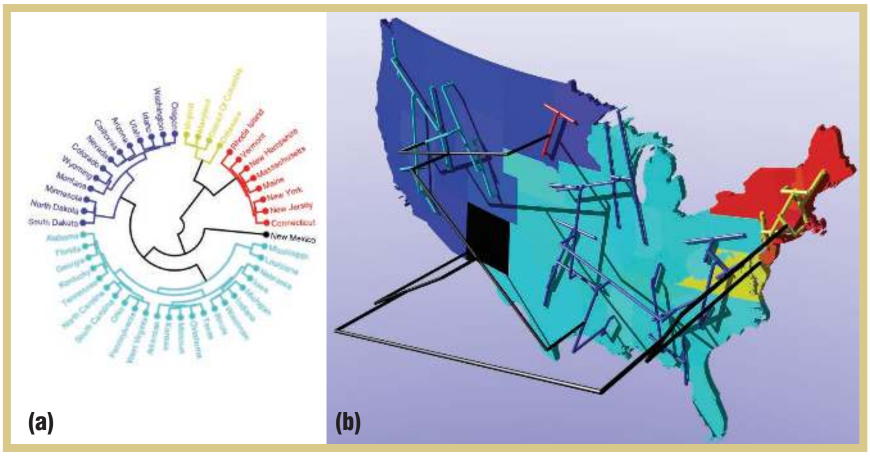


Figure 4. Hierarchical clustering of the www.wheresgeorge.com network weights on the state level. A distance between two states is the inverse of their network weight; we performed hierarchical clustering on the resulting distance matrix. The hierarchical linkage algorithm takes the two closest nodes, connects them as the first two leafs of the tree, and replaces them by a single node with average distances to all other states. This forms (a) the linkage tree (dendrogram), with increasing cluster size visualized by the corresponding tree edge's length. We cut the resulting tree at a fixed level to produce clusters, illustrated by (b) different colors on the map. We determined the number of clusters as the largest number of clusters constantly obtained for thresholds differing at least by 0.02.

cal strength of a connection $\bar{W}$ is given by the ratio of flux and degree, so we obtain heuristically

$$\bar{W}(P) \propto P^{1-\xi}. \tag{8}$$

Equations 7 and 8 imply that larger counties aren't only connected to a larger number of other counties but also that every connection's typical strength is stronger. The universal exponent ξ determines both relations, and they hold over nearly four orders of magnitude, a surprising regularity. Again, no theory exists that can predict these scaling relations and the value of the exponent ξ.

Topological US Hierarchies

The www.wheresgeorge.com network encodes US travel information in the form of money fluxes, so each node—in this case, a county—is geographically embedded and hence is a node in a geography distance network. An important question lies in the similarities and differences between these two networks. In Figure 3, we observed that the www.wheresgeorge.com network encodes at least some information about geography in terms of distance distributions. Here, we derive a non-distributional property—namely, highly connected subunits (clusters) from the graph—and check if they correspond to geographical clusters. We use a hierarchical clustering algorithm, which recursively agglomerates nearby nodes to form a tree or dendrogram. To do this, we need a network distance, which we define between nodes n and m as

$$V_{nm} = \frac{1}{W_{nm}} \text{ for } n \neq m. \tag{9}$$

The idea behind this choice is simple: We can interpret the coupling of two nodes as reflected by the traffic W_{nm} as how effectively close two places are, and the reciprocal can provide a phenomenological definition of their distance. The algorithm selects the pair (n, m) with the smallest V_{nm} and replaces n and m by a new group node. Hence, we must specify how to measure distances not only between nodes but also between clusters. For this, we use average linkage clustering, which implies calculating the mean distance between elements of each cluster A and B:

$$d(A,b) = \frac{1}{|A||B|} \sum_{a \in A, b \in B} d(a,b). \tag{10}$$

The edge "heights" in this tree are proportional to the distances of the parent to its children, so we can cut at some (height) distance from the root to produce a set of disjoint sets (clusters). For the www.wheresgeorge.com state network, we performed hierarchical clustering on the 48- × 48-state matrix $\boldsymbol{M}$. We define this matrix in the same way as the county matrix $\boldsymbol{W}$—that is, each element M_{nm} represents the overall bill flux between states n and m. Depending on the threshold, the www.wheresgeorge.com network exhibits k = 5 state clusters with a varying number of cluster elements; see Figure 4. When visualizing this money clustering on the network level, we observe that travel clusters also correspond to geographical clusters. Moreover, we can interpret these clusters as historically grown natural communities because they essentially consist of the west, the northeast, the center, and central east. This indicates that geospatial coherence and neighborhood relationships are essentially encoded in the network flow's topology.

Beyond the US with Geocaching

Although scaling relations in the dynamics of money circulation such as in Equation 2 and the topological properties of multiscale human mobility networks such as in Equations 7 and 8 are of fundamental importance for understanding global human traffic, it remains unclear whether the observed properties are specific to the US or whether they represent universal features inherent in most traffic networks in developed countries. Do these scaling laws hold for other countries as well? Are broad distributions present in European mobility networks,

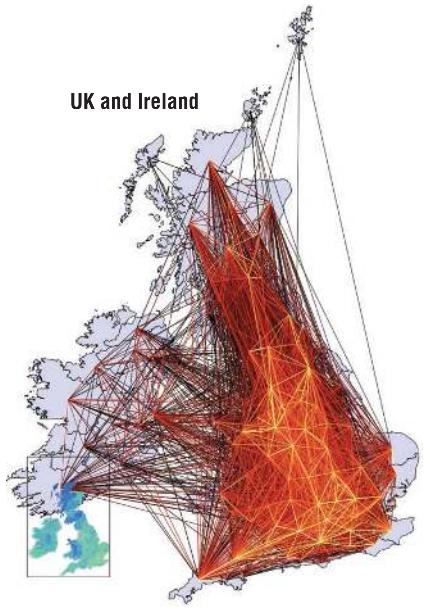
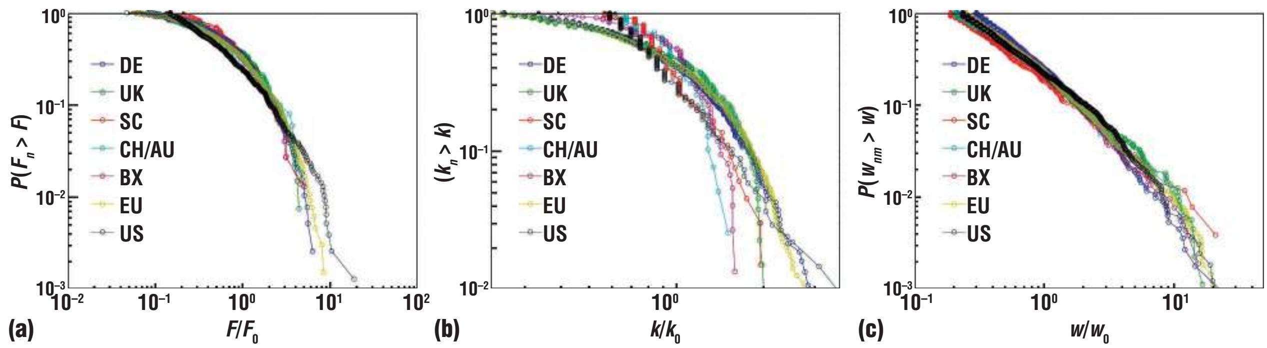


Figure 5. Geocaching. The lines symbolize the flux for trackable items among counties in the UK. As in Figure 2, the colors represent the flux magnitude between connected counties. The histograms along the bottom illustrate statistical properties of travel bug networks for European countries. Nodes in this network are counties in the countries Germany (DE); the UK and Ireland (UK); Norway, Sweden, Finland, and Denmark (SC); Switzerland and Austria (CH/AU); Netherlands, Belgium, and Luxembourg (BX); all of these nations (EU); and the US. (a) The cumulative distribution of travel bug flux into a node, (b) the degree's cumulative distribution, and (c) cumulative distribution of the weights in the network. Despite national and cultural differences, all three statistical properties are similar and nearly collapse on the same curves.



and do they exhibit the same shape? To what extent can we expect national differences and similarities? One important hypothesis to test is to what extent national differences and cultural diversity in Europe affect the structure of human mobility networks. Unfortunately, www.wheresgeorge.com is a US-specific site, so these questions are beyond the data set's reach.

To circumvent this difficulty and address some of these questions, we analyzed data from another Web site called www.geocaching.com, which is a modern treasure hunt based on GPS technology. In geocaching, players hide boxes (caches) containing items of more or less value in geographically interesting places and publish the longitude/latitude coordinates on the site. Other players then use this positional information to locate the cache within 10 meters using their GPS devices; when found, they log their visit and exchange gifts by taking items out of the cache and placing other items in it. Superimposed on geocaching are trackable items or "travel bugs" that have become a major component of the game. Travel bugs are marked with a unique identifier or tag registered at www.geocaching.com. When found in a cache, players take them out and put them in the next cache they find. The bug's entire trajectory is recorded on the Web site and can be monitored by its owner. Because geocaching is popular in many countries, travel bugs cross national boundaries and can help address questions about human mobility on an international level. We analyzed the dispersal characteristics of more than 200,000 travel bugs that visited more than 200 countries worldwide over a total distance of more than 1 billion km.

Similar to the money circulation network, we computed the flux matrix W_{nm} of trackable items among counties (nodes) for various European countries: the UK, the Benelux countries, Germany, Austria, Switzerland, Norway, Sweden, Finland, and Denmark. Figure 5 shows a flux network for the UK and Ireland. Qualitatively, this network shares the same topological features as the dollar bill circulation network in the US: long-distance connections exist but strong short-range connections outweight them. Geocaching and the associated activity of transporting trackable items is certainly not representative of the entire population; the data set is subject to the behavioral biases of the individuals who participate in the game. But we can address an important issue by analyzing the flux network of trackable items not so much by what systematic deviations these biases introduce but rather what statistical features are robust against such biases. The bottom of Figure 5 shows a surprising result of our analysis of travel bug flow networks across various European countries, with the cumulative distributions of the total flux F of trackable items into a node, the degrees k of the nodes, and the weights W of the network for various European countries. Surprisingly, weights, fluxes, and degrees exhibit nearly identical distributions in all countries considered, and the travel bug network for the US agrees with the other networks over a wide range of scales. This is the first direct indication that multiscale mobility networks possess universal features across national and cultural boundaries.

Our findings are of fundamental importance for understanding a multitude of spatiotemporal phenomena triggered by human traffic. We're optimistic that, in the near future, researchers can satisfactorily offer plausible explanations of the properties and quantities we observed, such as the exponents in Equations 2 and 7.

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