LETTER

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A universal model for mobility and migration patterns

Filippo Simini[1,2,3], Marta C. González[4], Amos Maritan[2] & Albert-László Barabási[1,5,6]

Introduced in its contemporary form in 1946 (ref. 1), but with roots that go back to the eighteenth century[2], the gravity law[1,3,4] is the prevailing framework with which to predict population movement[3,5,6], cargo shipping volume[7] and inter-city phone calls[8,9], as well as bilateral trade flows between nations[10]. Despite its widespread use, it relies on adjustable parameters that vary from region to region and suffers from known analytic inconsistencies. Here we introduce a stochastic process capturing local mobility decisions that helps us analytically derive commuting and mobility fluxes that require as input only information on the population distribution. The resulting radiation model predicts mobility patterns in good agreement with mobility and transport patterns observed in a wide range of phenomena, from long-term migration patterns to communication volume between different regions. Given its parameter-free nature, the model can be applied in areas where we lack previous mobility measurements, significantly improving the predictive accuracy of most of the phenomena affected by mobility and transport processes[11–23].

In analogy with Newton's law of gravity, the gravity law assumes that the number of individuals T_{ij} that move between locations i and j per unit time is proportional to some power of the population of the source (m_i) and destination (n_j) locations, and decays with the distance r_{ij} between them as

$$T_{ij} = \frac{m_i^{\alpha} n_j^{\beta}}{f(r_{ij})} \qquad (1)$$

where α and β are adjustable exponents and the deterrence function $f(r_{ij})$ is chosen to fit the empirical data. Occasionally T_{ij} is interpreted as the probability rate of individuals travelling from i to j, or an effective coupling between the two locations[24]. Despite its widespread use, the gravity law has notable limitations:

Limitation one, we lack a rigorous derivation of (1). Whereas entropy maximization[25] leads to (1) with $\alpha = \beta = 1$, it fails to offer the functional form of $f(r)$.

Limitation two, lacking theoretical guidance, practitioners use a range of deterrence functions (power law or exponential) and up to nine parameters to fit the empirical data[5,7,8,11,14].

Limitation three, as (1) requires previous traffic data to fit the parameters [α, β, …], it is unable to predict mobility in regions where we lack systematic traffic data, areas of major interest in modelling of infectious diseases.

Limitation four, the gravity law has systematic predictive discrepancies. Indeed, in Fig. 1a we highlight two pairs of counties with similar origin and destination populations and comparable distance, so according to (1) the flux between them should be the same. Yet, the US census (see Supplementary Information) documents an order of magnitude difference between the two fluxes: only 6 individuals commute between the two Alabama counties, whereas 44 do in Utah.

Limitation five, equation (1) predicts that the number of commuters increases without limit as we increase the destination population n_j, yet

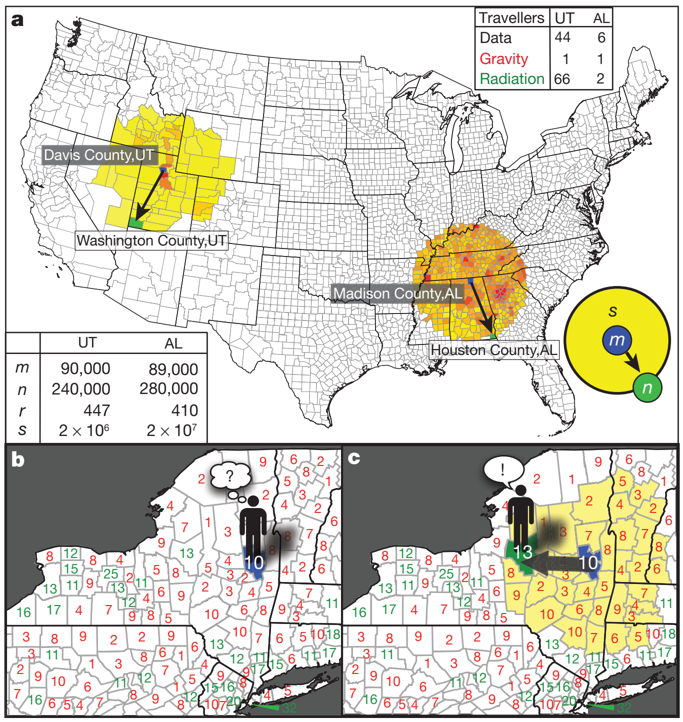

Figure 1 | The radiation model. a, To demonstrate the limitations of the gravity law we highlight two pairs of counties, one in Utah (UT) and the other in Alabama (AL), with similar origin (m, blue) and destination (n, green) populations and comparable distance r between them (see bottom left table). The gravity law predictions were obtained by fitting equation (1) to the full commuting data set, recovering the parameters $[\alpha, \beta, \gamma] = [0.30, 0.64, 3.05]$ for $r < 119$ km, and $[0.24, 0.14, 0.29]$ for $r > 119$ km of ref. 14. The fluxes predicted by (1) are the same because the two county pairs have similar m, n and r (top right table). Yet the US census 2000 reports a flux that is an order of magnitude greater between the Utah counties, a difference correctly captured by the radiation model (**b**, **c**). **b**, The definition of the radiation model: an individual (for example, living in Saratoga County, New York) applies for jobs in all counties and collects potential employment offers. The number of job opportunities in each county (j) is n_j/n_{jobs}, chosen to be proportional to the resident population n_j. Each offer's attractiveness (benefit) is represented by a random variable with distribution $p(z)$, the numbers placed in each county representing the best offer among the n_j/n_{jobs} trials in that area. Each county is marked in green (red) if its best offer is better (lower) than the best offer in the home county (here $z = 10$). **c**, An individual accepts the closest job that offers better benefits than his home county. In the shown configuration the individual will commute to Oneida County, New York, the closest county whose benefit $z = 13$ exceeds the home county benefit $z = 10$. This process is repeated for each potential commuter, choosing new benefit variables z in each case.

[1]Center for Complex Network Research and Department of Physics, Biology and Computer Science, Northeastern University, Boston, Massachusetts 02115, USA. [2]Dipartimento di Fisica "G. Galilei", Università di Padova, CNISM and INFN, via Marzolo 8, 35131 Padova, Italy. [3]Institute of Physics, Budapest University of Technology and Economics, Budafoki út 8, Budapest, H-1111, Hungary. [4]MIT, Department of Civil and Environmental Engineering, 77 Massachusetts Avenue, Cambridge, Massachusetts 02139, USA. [5]Center for Cancer Systems Biology, Dana-Farber Cancer Institute, Boston, Massachusetts 02115, USA. [6]Department of Medicine, Brigham and Women's Hospital, Harvard Medical School, Boston, Massachusetts 02115, USA.

the number of commuters cannot exceed the source population m_i, highlighting the gravity law's analytical inconsistency (see Supplementary Information, Section 4).

Limitation six, being deterministic, the gravity law cannot account for fluctuations in the number of travellers between two locations.

Motivated by these known limitations, alternative approaches like the intervening opportunity model[26] or the random utility model[27] (Supplementary Information, Section 7) have been proposed. Although derived from first principles, these models continue to contain context-specific tunable parameters, and their predictive power is at best comparable to the gravity law[28].

Here we introduce a modelling framework that relies on first principles and overcomes the problems of limitations one to six of the gravity law. Whereas commuting is a daily process, its source and destination is determined by job selection, a decision made over longer timescales. Using the natural partition of a country into counties (for which commuting data are collected), we assume that job selection consists of two steps (Fig. 1 b, c).

Step one, an individual seeks job offers from all counties, including his/her home county. The number of employment opportunities in each county is proportional to the resident population, n, assuming that there is one job opening for every n_{jobs} individuals. We capture the benefits of a potential employment opportunity with a single number, z, randomly chosen from distribution $p(z)$ where z represents a combination of income, working hours, conditions, etc. Thus, each county with population n is assigned n/n_{jobs} random numbers, z_1, z_2, …, $z_{[n/n_{\mathrm{jobs}}]}$, accounting for the fact that the larger a county's population, the more employment opportunities it offers.

Step two, the individual chooses the closest job to his/her home, whose benefits z are higher than the best offer available in his/her home county. Thus lack of commuting has priority over the benefits, that is, individuals are willing to accept lesser jobs closer to their home.

This process, applied in proportion to the resident population in each county, assigns work locations to each potential commuter, which in turn determines the daily commuting fluxes across the country. The model has three unknown parameters: the benefit distribution $p(z)$, the job density n_{jobs}, and the total number of commuters, N_c. We show, however, that the commuting fluxes T_{ij} are independent of $p(z)$ and n_{jobs}, and the remaining free parameter, N_c, does not affect the flux distribution, making the model parameter-free. As the model can be formulated in terms of radiation and absorption processes (see Supplementary Information, Section 2), we will refer to it as the radiation model. To analytically predict the commuting fluxes we consider locations i and j with population m_i and n_j respectively, at distance r_{ij} from each other, and we denote with s_{ij} the total population in the circle of radius r_{ij} centred at i (excluding the source and destination population). The average flux T_{ij} from i to j, as predicted by the radiation model (see Supplementary Information, Section 2), is

$$\langle T_{ij}\rangle = T_i\frac{m_i n_j}{(m_i+s_{ij})(m_i+n_j+s_{ij})} \qquad (2)$$

which is independent of both $p(z)$ and n_{jobs}. Hence (2) represents the fundamental equation of the radiation model, the proposed alternative to the gravity law (1). Here $T_i \equiv \sum_{j\neq i} T_{ij}$ is the total number of commuters that start their journey from location i, which is proportional to the population of the source location, hence $T_i = m_i(N_c/N)$, where N_c is the total number of commuters and N is the total population in the country (Fig. 2g).

Equation (2) resolves limitations one to six of the gravity law: it has a rigorous derivation (resolving limitation one) and has no free parameters (bypassing limitations two and three). To understand the origin of limitation four, we note that a key difference between the radiation model (2) and the gravity law (1) is that the variable of (2) is not the distance r_{ij}, but s_{ij}. Thus the commuting flux depends not only on m_i and n_j but also on the population s_{ij} of the region surrounding the source location. For uniform population density $s_{ij}\approx m_i r_{ij}^2$ and $n = m$, (2) reduces to the gravity law (1) with $f(r) = r^{\gamma}$, $\gamma = 4$ and $\alpha + \beta = 1$. The non-uniform population density, however, is key to resolving the problem of limitation four: equation (2) predicts an order of magnitude difference in Alabama and Utah, in line with the census data (see Fig. 1a). Indeed the population density around Utah is significantly lower than the United States average, thus work opportunities within the same radius are ten times smaller in Utah than in Alabama, implying that commuters in Utah have to travel farther to find comparable employment opportunities. Note also that equation (2) predicts that the number of travellers leaving from a location with population m to one with $n\to\infty$ saturates at $T_{n\to\infty} = \frac{m^2}{(m+s)} + O\left(\frac{1}{n}\right) \leq m$, resolving the unphysical divergence highlighted in limitation five. Finally, T_{ij} in the radiation model is a stochastic variable, predicting not only the average flux between two locations (2), but also its variance (see Supplementary Information, Section 2), resolving the problem of limitation six.

To explore the radiation model's ability to predict the correct commuting patterns, in Fig. 2a we show the commuting fluxes with more than ten travellers originating from New York County. The destinations predicted by the gravity law[14] are all within 400 km from the origin, missing all long distance and many medium distance trips. The gravity law's local performance is equally poor: within the State of New York it grossly overestimates fluxes in the vicinity of New York City and underestimates the fluxes in the rest of the state (Fig. 2a, right column). The radiation model offers a more realistic approximation to the observed commuting patterns, both nationally and state-wide (Fig. 2a, bottom panels). To quantify the observed differences, we compare the measured and the predicted non-zero commuting fluxes for all pairs of counties in the United States. We find that both standard implementations of the gravity law[11,14] ($f(r) = r^{\gamma}$ and $f(r) = e^{dr}$, where d is a fitting parameter with the unit of an inverse length needed to ensure a dimensionless argument to the exponential function) significantly underestimate the high flux commuting patterns, often by an order of magnitude or more (Fig. 2b, c). In contrast, the average fluxes predicted by the radiation model are within the error bars despite the observed six orders of magnitude span in commuting fluxes (Fig. 2d).

The systematic failure of the gravity law is particularly evident if we measure the probability $P_{\mathrm{dist}}(r)$ of a trip between locations at distance r (Fig. 2e), and the probability of trips towards a destination with population n, $P_{\mathrm{dest}}(n)$ (Fig. 2f). For $P_{\mathrm{dist}}(r)$ the radiation model clearly follows the peak around 40 km in the census data. The prediction based on the gravity law lacks this peak and thus it overestimates by three orders of magnitude the number of short distance trips. Similarly, the gravity law overestimates the low n values of $P_{\mathrm{dest}}(n)$ by nearly an order of magnitude.

Another important mobility measure is the conditional probability $p(T\,|\,m,n,r)$ to observe a flux of T individuals from a location with population m to a location with population n at a distance r. The gravity law predicts a highly peaked $p(T\,|\,m,n,r)$ distribution around the average $\langle T\rangle_{mnr} = \sum_T p(T|m,n,r)T$ (Fig. 2h–j), because, according to (1) pairs of locations with the same (m, n, r) have the same flux. In contrast the radiation model predicts a broad $p(T\,|\,m,n,r)$ distribution, in reasonable agreement with the data.

To show the generality of the model in Fig. 3 we test its performance for four socio-economic phenomena: hourly travel patterns, migrations, communication patterns and commodity flows. We find that the radiation model offers an accurate quantitative description of mobility and transport spanning a wide range of time scales (hourly mobility, daily commuting, yearly migrations), capturing diverse processes (commuting, intra-day mobility, call patterns, trade), collected via a wide range of tools (census, mobile phones, tax documents) on different continents (America, Europe). The agreement with data of such diverse nature is somewhat surprising, suggesting that the hypotheses behind the model capture fundamental decision mechanisms that, directly or indirectly, are relevant to a wide span of mobility and transport-driven processes.

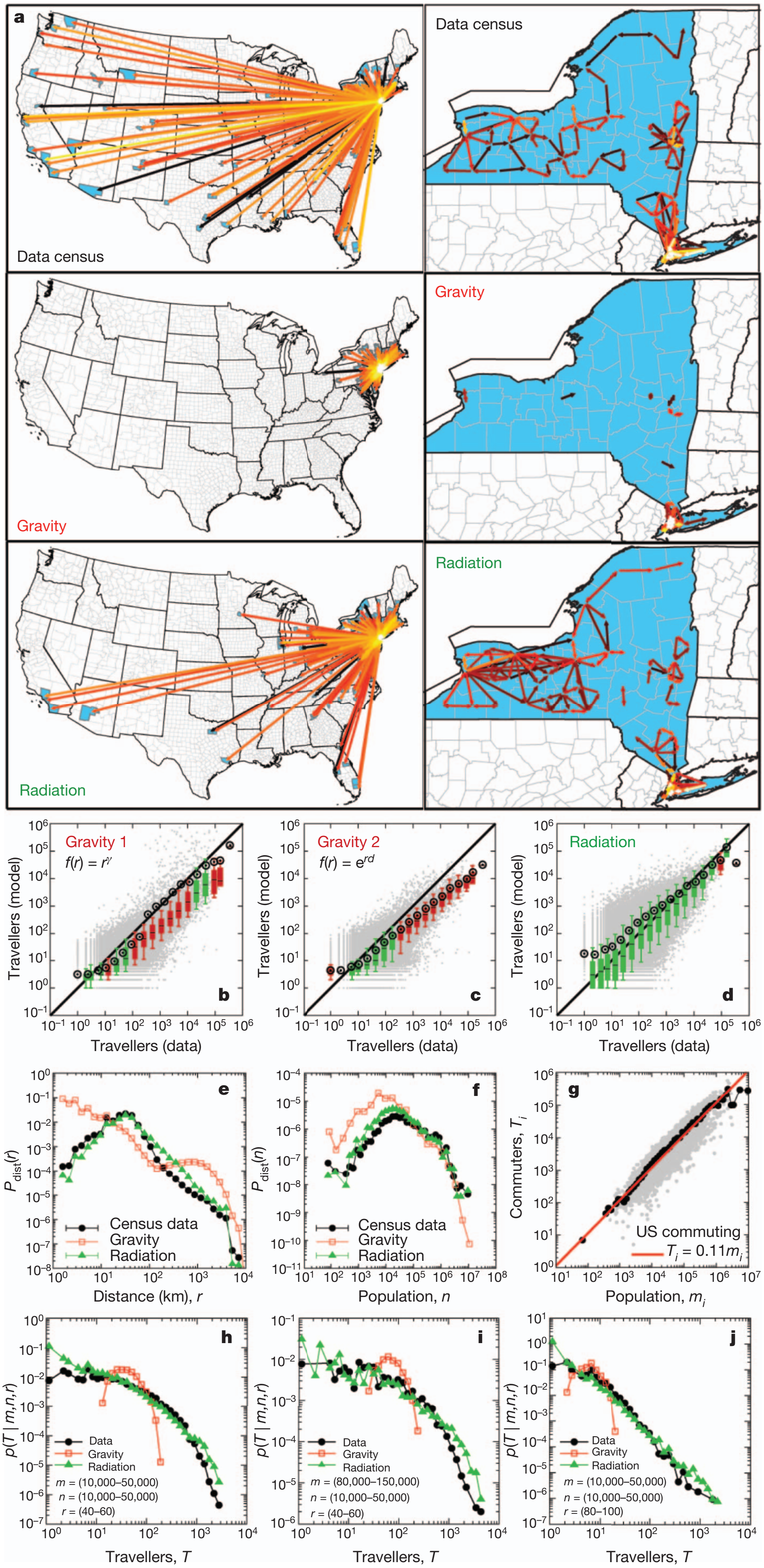

Figure 2 | Comparing the predictions of the radiation model and the gravity law. **a**, National mobility fluxes with more than ten travellers originating from New York County (left panels) and the high intensity fluxes (over 1,100 travellers) within the state of New York (right panels). Arrows represent commuters fluxes, the colour capturing flux intensity: black, 10 individuals (fluxes below ten travellers are not shown for clarity), white, >10,000 individuals. The top panels display the fluxes reported in US census 2000, the central panels display the fluxes fitted by the gravity law with[14] $f(r) = r^{\gamma}$, and the bottom panels display the fluxes predicted by the radiation model. **b**–**d**, Comparing the measured flux, T_{ij}^{data}, with the predicted flux, T_{ij}^{GM} and T_{ij}^{Rad}, for each pair of counties. We compare the census data with two formulations of the gravity law, $f(r) = e^{dr}$ (**c**) and $f(r) = r^{\gamma}$ (**b**), and with the radiation model (**d**). Grey points are scatter plot for each pair of counties. A box is coloured green if the line $y = x$ lies between the 9th and the 91st percentiles in that bin and is red otherwise. The black circles correspond to the mean number of predicted travellers in that bin. **e**, Probability of a trip between two counties that are at distance r (in km) from each other, $P_{\mathrm{dist}}(r)$. **f**, Probability of a trip towards a county with population n, $P_{\mathrm{dest}}(n)$. **g**, The number of commuters in a county, T_i, is proportional to its population, m_i. **h**–**j**, Conditional probability $p(T \mid m,n,r)$ to observe a flow of T individuals from a location with population m to a location with population n at a distance r for three triplets (m,n,r). The gravity law predicts a highly peaked distribution around the average value $\langle T \rangle_{mnr}$, in disagreement with census data and the radiation model, which both show a broad distribution.

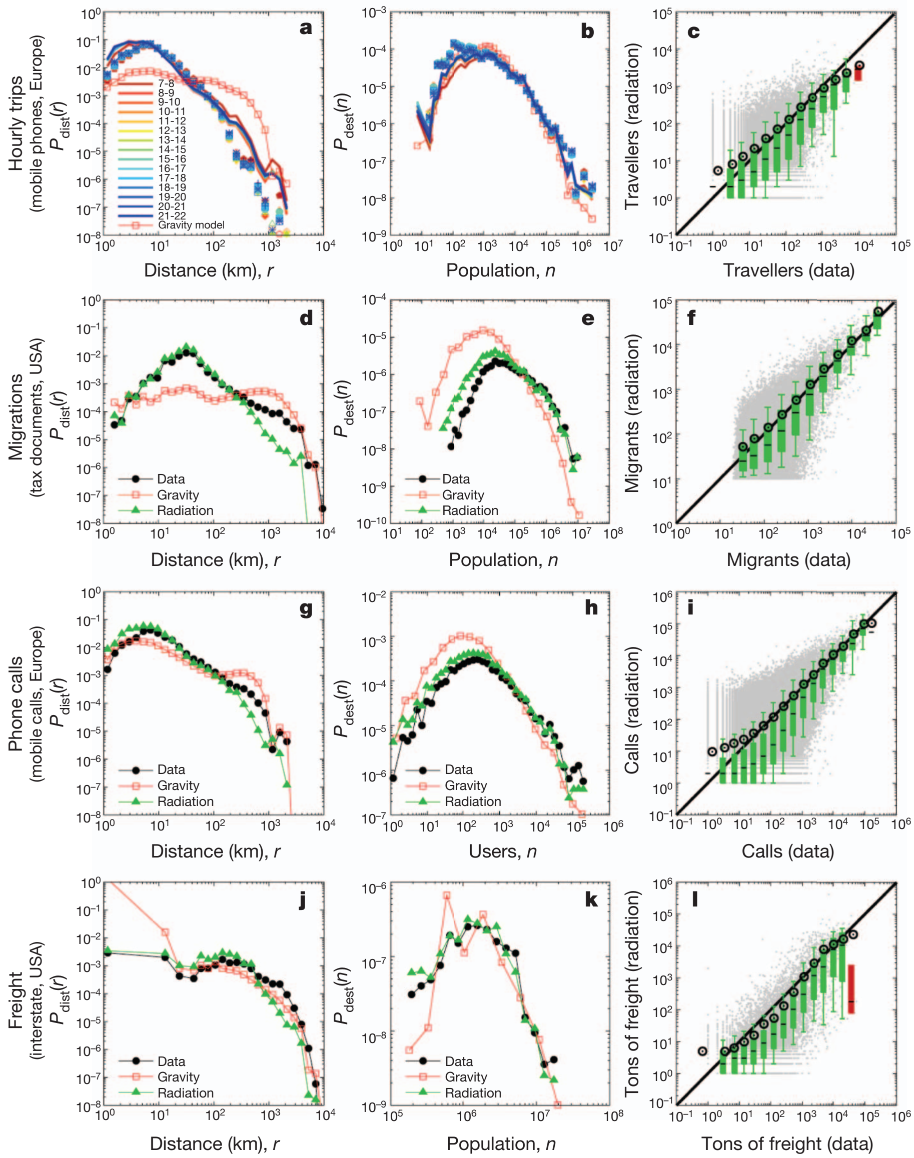

Figure 3 | Beyond commuting. **a**–**c**, Testing the radiation model on hourly trips extracted from a mobile phone database of a western European country. The anonymized billing records[29,30] cover the activity of approximately ten million subscribers. We analysed a 6-month period, recording the user locations with tower resolution hourly between 7am and 10pm, identifying all trips between municipalities. **a**, Probability of a trip between two municipalities at distance r, $P_{\mathrm{dist}}(r)$, shown for 14-hourly time intervals. Radiation model predictions are solid lines; gravity law's aggregated fit over 24 h is a red line with empty squares. **b**, Probability of a trip towards a municipality with population n, $P_{\mathrm{dest}}(n)$. **c**, Comparing the measured flux, T_{ij}^{data}, with the predicted flux, T_{ij}^{Rad}, for each pair of municipalities with $T_{ij}^{\mathrm{data}}, T_{ij}^{\mathrm{Rad}} > 0$, for commuting trips extracted by identifying each user's home and workplace from the locations where the user made the most calls. **d**–**f**, Testing (2) on long-term migration patterns, capturing the number of individuals that relocated from one US county to another during tax years 2007–2008 as reported by the US Internal Revenue Service. **g**–**i**, Phone call volume between municipalities extracted from the anonymized mobile phone database. The number of phone calls between users living in different municipalities during a period of 4 weeks resulted in 38,649,153 calls placed by 4,336,217 users. We aggregated the data to obtain the total number of calls between every pair of municipalities. **j**–**l**, Commodity flows in the US extracted from the Freight Analysis Framework (FAF), which offers a comprehensive picture of freight movement among US states and major metropolitan areas by all modes of transportation. For each data set we measured the quantities discussed in **a**–**c**.

To illustrate the effect of the heterogeneous population distribution on commuting fluxes, in Supplementary Fig. 8a–f we show the commuting landscape generated by (2) from the perspective of two individuals, one in Davis county, Utah, and the other in Clayton County, Georgia, with comparable populations of 238,994 and 236,517, respectively. If the population was uniformly distributed, the landscape seen by a potential employee would be simple: the farther is a job, the less desirable it is (Supplementary Fig. 8a, d). Yet, the observed variations in population density significantly alter the local commuting landscape, as shown in Supplementary Fig. 8b, e where we coloured the US counties based on their distance to the commuter's home county (Supplementary Fig. 8a, d) and then moved them closer or further from the origin so that the new distance reflects the true likelihood of representing a commuting destination.

Despite the observed differences in the perspective of individual commuters, the radiation model helps us uncover a previously unsuspected scale-invariance in commuting patterns. Indeed, according to (2), the probability of one trip from i to j (equal to T_{ij}/T_i) is scale invariant under the transformation $m_i \rightarrow \lambda m_i$, $n_j \rightarrow \lambda n_j$ and $s_{ij} \rightarrow \lambda s_{ij}$. Empirical evidence for this statistical self-similarity is offered in Fig. 4a, b (see also Supplementary Information, Section 8).

In summary, the superior performance of the radiation model can significantly improve the accuracy of predictive tools in all areas affected by mobility and transport processes[11,12], from epidemiology[13] and

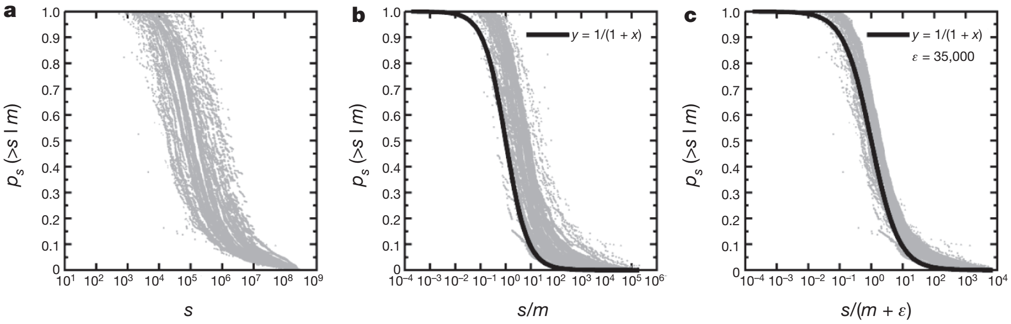

Figure 4 | Unveiling the hidden self-similarity in human mobility. a, The probability $p_s(>s \mid m)$ to observe a trip from a location with population m to a destination in the region beyond a population s from the origin (m varies between 200 and 2,000,000). **b**, According to the radiation model $p_s(>s \mid m) = 1/(1 + s/m)$, a homogeneous function of the ratio s/m. Plotting $p_s(>s \mid m)$ versus s/m, the curves approach the theoretical result $y = 1/(1 + x)$. **c**, The collapse improves if we account for the home field advantage in job search by always adding $\varepsilon = 35{,}000$ to the population of the commuter's home county.

spreading processes[17] to urban geography[18–21] and flow of resources in economics[22]. The parameter-free modelling platform we introduced can predict commuting and transport patterns even in areas where such data are not collected systematically, as it relies only on population densities, which is relatively accurately estimated throughout the globe.

Despite its superior performance the radiation model can absorb further improvements. For example, consider the fact that an individual has a home-field advantage when searching for jobs in the home county, being more familiar with local employment opportunities. We can incorporate this by adding $\varepsilon/n_{\text{jobs}}$ additional employment opportunities to his/her home county, achieved through an effective increase $m \rightarrow m + \varepsilon$ of the home county population, so the adjusted law is now invariant under the $(m + \varepsilon) \rightarrow \lambda(m + \varepsilon)$ and $s \rightarrow \lambda s$ transformation. We find that the rescaling of the commuting probability improves dramatically (Fig. 4c), indicating that the home field advantage offers an effective boost in employment opportunities that is equivalent with an additional $\varepsilon = 35{,}000$ individuals in the home county population. Furthermore, the adjusted radiation model shows a better or equally good agreement with the real data in all tested measures (Supplementary Fig. 6), demonstrating that equation (2) is not a rigid end point of our approach, but offers a platform that can be improved upon in specific environments.

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Supplementary Information is linked to the online version of the paper at www.nature.com/nature.

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