Universal Predictability of Mobility Patterns in Cities

Xiao-Yong Yan\(^1,2\), Chen Zhao\(^1\), Ying Fan\(^1\), Zengru Di\(^1\), and Wen-Xu Wang\(^1,3^*\)

\(^1\)School of Systems Science, Beijing Normal University, Beijing 100875, P.R. China
\(^2\)Department of Transportation Engineering, Shijiazhuang Tiedao University, Shijiazhuang 050043, P.R. China
\(^3\)School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, AZ 85287, United States

Despite the long history towards modeling human mobility, we continue to lack a highly accurate but low data requirement approach to predicting mobility patterns in cities. Here, we present a conduction-like stochastic process without adjustable parameter to capture the underlying driving force accounting for human mobility patterns at the city scale. We use various mobility data collected from a number of cities with different characteristics to demonstrate the predictive power of our model, finding that insofar as the spatial distribution of population is available, our model offers universal prediction of mobility patterns in good agreement with real observations, including distance distribution, destination travel constraints and flux. In contrast, the models quite successful in modeling mobility patterns in countries are not applicable in cities, suggesting the diversity of human mobility at different spatial scales. Our model has potential applications in many fields relevant to mobility behavior in cities, without relying on previous mobility measurements.

Predicting human mobility patterns is not only a fundamental problem in geography and spatial economics \(^1\) but also of many practical applications in urban planning \(^2\), traffic engineering \(^3,4\), epidemiology of infectious disease \(^5\) \(-\) \(^7\), emergency management \(^8\) \(-\) \(^10\) and location-based service \(^11\). Since 1940s, many trip distribution models \(^12\) \(-\) \(^18\) have been presented towards addressing this challenging problem, among which the gravity model is the prevailing framework \(^13\). Despite its wide use to predict mobility patterns at different spatial scales \(^19\) \(-\) \(^22\), the gravity model relies on special parameters fitted from systematic collection of traffic data. If lack previous mobility measurements, the gravity model is not applicable. Similar limitation exists in all trip distribution models relying on context-specific parameters, such as the intervening opportunity model \(^12\), the random utility model \(^14\) and so on.

Quite recently, the introduction of radiation model \(^15\) provides a new insight into the long history of modeling population movement. The model is based on a solid theoretical foundation and can precisely reproduce observed mobility patterns ranging from long-term migrations to inter-county commutes. Surprisingly, the model needs exclusively the spatial distribution of population as input without any adjustable parameter. Nevertheless, some evidence has demonstrated that the radiation model may be not applicable to predicting human mobility at the city scale \(^23\) \(-\) \(^24\). Understanding mobility patterns in cities is of paramount importance in the sense that cities are the main environment of disease propagation, traffic congestion and pollution \(^6\) \(-\) \(^25\), partly resulting from human movement. These problems can be resolved through developing more efficient transportation systems and optimizing traffic management strategies, but all of which depend on our ability to predict human travel patterns in cities \(^26\). Despite the success of radiation model in countries, we continue to lack an explicit and comprehensive understanding of the underlying mechanism accounting for the observed mobility patterns in cities. We argue that this is mainly ascribed to the relatively high mobility of residents in cities as compared to larger scales, such as traveling among counties. Inside cities, especially metropolis, high development of traffic systems considerably facilitates travels of residents to locations with more opportunities and attraction, without much regard for time and economical costs. In this sense, the models that are quite successful in reproducing mobile patterns at large spatial scales fail at the city scale. Yet, revealing the underlying driving force and restriction for such mobility so as to predict mobile patterns in cities remains challenging.

In this paper, we develop a heat-conduction-based model without adjustable parameter as an alternative to the radiation model to predict human mobility patterns in a variety of cities. The human mobility problem maps into a heat conduction problem and the attraction of a location associated with population distribution is characterized by heat quantity. Insofar as the distribution of population in different cities are available, our model offers universal prediction of human mobility patterns in several cities as quantified by some key measurements, including distance distribution, destination travel constraints and flux. In contrast, the models that succeed in predicting mobility patterns at large spatial scales, such as in countries, are not applicable at the city scale be-

\(^*\)wenxuwang@bnu.edu.cn
FIG. 1. **Human mobility range at city scale.** (A-C) Spatial distributions of destination selections for traveling from a downtown location (displayed as a diamond-shaped dot) of Beijing. (D-F) Same distribution of travels from a suburban location. From left to right, the panels correspond to real data and results generated by the conduction model and the radiation model. The color bar represents the number of travellers from the origin to a destination.

cause of underestimation of human mobility. Our approach suggests the diversity of human mobility at different spatial scales, deepening our understanding of human mobility behaviors.

**RESULTS**

**Heat conduction model**

The model is derived from a stochastic decision making process of individual's destination selection. Before an individual selects a location to travel, s/he will weigh the benefit of each location’s opportunities. The more opportunities a location has, the higher benefit it offers and the higher chance of it being chosen. Although the number of a location’s opportunities is difficult to be straightforward measured, it can be reflected by the population there. Insofar as the population distribution is available, it is reasonable to assume that the number of opportunities or degree of attraction at a location is proportional to its populations, analogous to the assumption of the radiation model [15].

In contrast to the radiation model’s assumption that individuals tend to select the nearest locations with relatively larger benefit, we enlarge the possible chosen area of individuals to be the whole city regarding to the relatively high mobility at the city scale. As shown in Fig. 1, our assumption leads to much better prediction than that of the radiation model. Nevertheless, the possibility of travel observed from real data still decays as the distance between origin and destination increases. Such natural decay as common in real observations and predicted by different models results from the reduction of attraction associated with a sort of travel costs. For example, the gravity model assumes that the attraction of a location is a function of its distance with respect to the cost associated with travel distance. In the radiation model, individuals prefer nearest locations rather than farther locations with more opportunities due to the hypothesis of limited mobility and high travel cost. Obviously, in both models, the travel-distance-induced cost plays a major role in the decision-making of individuals. However, we argue that in cities, due to the high development of traffic systems, distance-induced travel cost is not the exclusive factor that determines how individuals make decisions, rendering different mobility patterns from the prediction of radiation model and gravity model. In this
FIG. 2. Illustration of the conduction model. Location O (purple circle) is a traveler’s origin, and locations A, B and C are selectable destinations. The probability of choosing a destination is proportional to the destination’s attraction, which decays depending on the distribution of population between the destination and the origin location. For the three destinations, although A is the farthest location away from the origin, it has the biggest attraction despite the decay according to the conduction process, thus it has priority of being selected by a traveler at A. Furthermore, location B has the same total attraction as C, but its expected attraction after decay is higher than that of C due to competition. Hence location B will be selected with a higher probability than C. These scenarios demonstrate the combined effect of distance-induced travel cost and competition on the attraction of locations, as captured by the conduction process. The inset offers definitions of variables used in the model, in which the purple circle (location i) denotes an origin with population $m_i$, blue circle (location j) stands for a destination with population $m_j$, $S_j$ represents the total population in the circle area of radius $r_j$, centered at location j (including $m_i$ and $m_j$).

In case, the effect of competition for resources and opportunities at a location cannot be neglected. For example, suppose there is an attractive place with a lot of resource or comfortable environment. An individual will enjoy working or relaxation in that area so that prefer to go there. However, if many individuals rush to the place, it will become crowded and its attraction will be lost. This scenario is somewhat similar to the story in Arthur’s bar model [27, 28]. Such competition eventually leads to an equilibrium-like resource allocation together with specific mobility patterns in cities. Interestingly, we find that the attraction of a place resulting from the combined effect of distance-induced cost and competition for resource and opportunities can be characterized by heat conduction. In particular, heat quantity is analogous to the total opportunities at a location, but the actual or expected opportunities with respect to competition and travel cost to an individual is the temperature $s$ he can feel originating from heat conduction, as illustrated in Fig. 2. The attraction of a location $i$ if traveling from a location $j$ with total opportunities $o_j$ is defined as $o_j = o_j\left(\frac{1}{S_j} - \frac{1}{M}\right)$, where $S_j$ is the total population in the circle of radius $r_j$, centered at location $j$ (including the origin $i$ and destination $j$), $M$ is the total number of residents (population) in the city (see details in Methods, Derivation of the conduction model). Considering all possible choices and outgoing flux from $i$, we have the travels from location $i$ to location $j$ as

$$T_{ij} = T_i \cdot \frac{m_j\left(\frac{1}{S_j} - \frac{1}{M}\right)}{\sum_{k \neq i} m_k\left(\frac{1}{S_k} - \frac{1}{M}\right)}$$

where $T_i$ is the travels that depart from location $i$, $m_j$ is the population at location $j$ and $N$ is the number of locations in the city. We will then demonstrate the universal predictability of mobility patterns in cities via our model in terms of a variety of real travel data in several cities.

Predicting mobility patterns

We employ human daily travel data collected by GPS, mobile phone and traditional household surveys from four cities (see details in Methods, Data sets and Data preprocessing) to validate the conduction model, in comparison with the performances of the radiation model (see details in Methods, The radiation model).

Figure 4 exemplifies travels from a downtown and a suburban location at Beijing, China predicted by the conduction model and the radiation model in comparison with real data in an intuitive manner. It is obvious that the radiation model underestimates the travel areas in both cases, whereas the travel patterns resulting from our conduction model are quite consistent with empirical evidence, demonstrating the relatively higher mobility in cities than that at larger spatial scale, such as a country, where the radiation model succeeds.

We systematically investigate the travel distance distribution obtained by both models based on real data. Travel distance distribution is an important statistical property to characterize human mobility behaviors [29–31] and reflect economic efficiency of a city [11]. We find that, as shown in Fig. 3, the reproduced distributions of travel distance by the conduction model is in good agreement with the real observation. In contrast, the radiation model underestimates long-distance (longer than about 2 km) travels in all cases. This implies the assumption of the radiation model is inappropriate at the city scale that precludes individuals from relatively long travel beyond nearest locations aiming to select better locations with more opportunities. The success of the conduction model in predicting real travel distance distributions in
cities provides strong evidence for the validity of its basic assumptions.

We next explore the probability of a travel towards a location with population $m$, say, $P_{\text{dest}}(m)$, resulting from both observed data and the models. $P_{\text{dest}}(m)$ is a key quantity to measure the accuracy of origin-constrained mobility models (the radiation model and conduction model used here are all origin-constrained) because that the origin-constrained model cannot ensure the agreement between the modeled travels to a location and the real travels to the same location. In Fig. 4 we can see that our model gives a better or equal prediction of empirical observations than the radiation model.

A more detailed measure of a model’s ability to predict mobility patterns can be implemented in terms of the travel fluxes between all pairs of locations produced by a model in comparison with real observations, as has been used in Ref. 15. As shown in Fig. 4 we find that, except the case of Abidjan, the average fluxes predicted by the radiation model deviate from the real fluxes. Whereas, the results from the conduction model are in reasonable agreement with real observations.

Note that the boxplot method used here cannot provide an explicit comparison to distinguish the performance of the two models. For example, in Fig. 4E, although the results deviate from the empirical data significantly, the boxes are still colored by green, suggesting the need of an alternative statistical method. Thus we exploit the Sørensen similarity index (see details in Methods, Sørensen similarity index) to quantify the degree of similarity with real observations so as to offer a better comparison. We have also applied both models to another four U. S. Cities to make a more comprehensive comparison (details can be seen in Supplementary information, Section S1). The results are shown in Fig. 5. For all studied cases, our conduction model outperforms the radiation model and exhibits relatively high index values, say, about 0.7, indicating that our model captures the underlying mechanism that drives human movement in cities.

DISCUSSION

We have developed a conduction model as an alternative to the radiation model to reproduce and predict mobile behaviors in cities with different sizes, economic levels and cultural backgrounds. Our model needs only population distributions as input without adjustable parameter. The mobility patterns resulting from the model are in good agreement with real data with respect to travel distance distribution, destination travel constraints and flux, suggesting that the model captures the fundamental mechanisms governing the human daily travel behaviors.
FIG. 5. Comparing the observed fluxes with the predicted fluxes in four cities. (A-D) Travel fluxes predicted by the conduction model. (E-H) Travel fluxes predicted by the radiation model. The grey points are scatter plot for each pair of locations. The blue points represent the average number of predicted travels in different bins. The boxplots obtained via standard statistical method [32] represent the distribution of the number of predicted travels in different bins of the number of observed travels. A box is marked in green if the line $y = x$ lies between 10% and 91% in that bin and in red otherwise.

FIG. 6. Comparison between the prediction ability of conduction and radiation model in terms of Sørensen similarity index (SSI). SSI is calculated from Eq. [10]. 8 cities in three countries are studied.

The radiation model, despite its parameter-free nature and good performance at large spatial scale, cannot offer a satisfactory prediction of mobility patterns at the city scale. The problem lies in the underestimation of relatively high mobility at the city scale. In particular, the radiation model assumes that the limited mobility prevents people from selecting a farther location with more opportunities than their vicinity locations to gain more benefits. This assumption is reasonable at the inter-city scale, but inappropriate in cities. The conduction model can successfully overcome this problem by casting mobile behavior in cities into the framework of heat-conduction-process. Insofar as only population distribution is available, our model offers the best prediction of mobile patterns at city scale at the present, significantly deepening our understanding of human mobility in cities and demonstrating the universal predictability of mobility patterns at the city scale.

We have also compared the conduction model with three classical parameterized models: the gravity model [13], the intervening opportunity model [12] and the rank-based model [17] (see details in Supplementary information, Section S2). Although in rare cases the parameterized models can yield better predictive accuracy than the conduction model, their parameter-dependence nature limits their application scope to the
A conduction model for mobility prediction

We employ the heat conduction process to model the decay of available opportunities (actual attraction) of a location $i$ starting from a location $j$ with total opportunities $o_j$. Since the number of a location’s total opportunities is proportional to its population, we assume that initially the heat quantity $Q_j$ (i.e. the total opportunities $o_j$) of a location $j$ is $m_j c \Theta_0$, where $m_j$ is the number of population at location $j$ and can be interpreted as the mass at the location, $c$ is the specific heat capacity and $\Theta_0$ is the initial temperature of $j$. Then we rank all other $N-1$ locations based on their distances to location $j$ and number the closest location as 1, the second closest location as 2, etc. and assume initially the heat quantities of these locations are all zero. According to the heat conduction process, the heat quantity conducted from $j$ to its closest location is

$$Q_1 = m_j c \Theta_1 = m_j c (\Theta_0 - \Theta_1),$$

where $\Theta_1$ is the temperature of location 1, which can be described in terms of $\Theta_0$ as

$$\Theta_1 = \frac{m_j}{m_j + m_1} \Theta_0. \quad (3)$$

Similarly, the heat quantity conducted to the second closest location is

$$Q_2 = m_2 c \Theta_2 = (m_j + m_1) c (\Theta_1 - \Theta_2) \quad (4)$$

and the temperature is

$$\Theta_2 = \frac{m_j + m_1}{m_j + m_1 + m_2} \Theta_1 = \frac{m_j}{m_j + m_1 + m_2} \Theta_0. \quad (5)$$

Recursively, we can derive heat quantity conducted to the $i$th location as

$$Q_i = \frac{m_i m_j c \Theta_0}{S_{ji}}, \quad (6)$$

where $S_{ji}$ is the total mass (population) in the circle of radius $r_{ij}$ centred at location $j$ (including the location $j$ and location $i$, see the inset of Fig. 2). For each individual at location $i$, the heat acquired from location $j$ is

$$q_i = \frac{Q_i}{m_i} = \frac{m_j c \Theta_0}{S_{ji}}. \quad (7)$$

Consequently, when reaching thermal equilibrium, the heat conducted to each individual have the same quantity

$$q^* = \frac{m_j c \Theta_0}{M}. \quad (8)$$

Therefore, for each individual at location $i$ the actual difference of heat quantity conducted from location $j$, or the number of available opportunities of location $j$, is

$$o'_j = q_i - q^* = m_j c \Theta_0 (\frac{1}{S_{ji}} - \frac{1}{M}). \quad (9)$$

We next use a similar analytical framework presented in Ref. [13] to derive the expression of our mobility model. We assume the benefit of an available opportunity with a single number $z$, randomly chosen from distribution $p(z)$. Thus, each location with available opportunities $o'$ is assigned $o'$ random numbers. Because of the assumption

**METHODS**

A. Derivation of the conduction model

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that an individual selects a location with the largest benefit to travel, the probability of an individual at location \( i \) selecting location \( j \) to travel is

\[
p_{ij} = \int_0^\infty dz P_{ij}(z)P_k(\sum_{k \neq i, k \neq j} o_k'(< z)), \tag{10}
\]

where \( P_{ij}(z) \) is the probability that the maximum value is extracted from \( p(z) \) after the number \( o'_j \) trials is equal to \( z \), \( P_k(\sum_{k \neq i, k \neq j} o_k'(< z) \) is the probability that the number \( \sum_{k \neq i, k \neq j} o_k \) extracted from the distribution \( p(z) \) is less than \( z \). Due to the fact that

\[
P_{ij}(z) = \frac{dP_{ij}(< z)}{dz} = o'_j p(< z) o'_i \frac{dp(< z)}{dz} \tag{11}
\]

and

\[
P_k(\sum_{k \neq i, k \neq j} o_k'(< z) = p(< z) \sum_{k \neq i, k \neq j} o_k', \tag{12}
\]

we can have

\[
p_{ij} = o'_j \int_0^\infty dz \frac{dp(< z)}{dz} p(< z) \sum_{k \neq i, k \neq j} o_k' = \frac{o'_j}{\sum_{k \neq i} o'_k}. \tag{13}
\]

Combining Eqs. (13) and (14) and given the number \( T_i \) of travels departed from location \( i \), the average number of travels from location \( i \) to \( j \) is

\[
T_{ij} = T_i p_{ij} = T_i \frac{m_j (\frac{1}{S_j} - \frac{1}{M})}{\sum_{k \neq i} m_k (\frac{1}{S_k} - \frac{1}{M})}. \tag{14}
\]

B. The radiation model

The radiation model \cite{15} is a parameter-free model to predict travel fluxes among different locations based on population distribution:

\[
T_{ij} = T_i \frac{m_j m_j}{(m_i + s_{ij})(m_i + m_j + s_{ij})}, \tag{15}
\]

where \( T_{ij} \) is the travels departed from location \( i \) to location \( j \), \( T_i \) is the total travels departed from location \( i \), \( m_i \) is the population at location \( i \), \( m_j \) is the population at location \( j \), \( s_{ij} \) is the total population in the circle of radius \( r_{ij} \) centered at location \( i \) (excluding the origin \( i \) and destination \( j \)).

C. Data sets

Data set of Beijing taxi passengers. The data set is the travel records of taxi passengers in Beijing in a week \cite{42}. When a passenger gets on or gets off a taxi, the coordinates and time are recorded automatically by a GPS-based device installed in the taxi. From the data set we extract 1,070,198 taxi passengers travel records.

Data set of Shenzhen taxi passengers. The Shenzhen taxi passengers tracker data has the same data format as that of Beijing. The data set records 2,338,576 trips of taxi passengers from 13,798 taxis in Shenzhen from 18 Apr. 2011 to 26 Apr. 2011.

Data set of Abidjan mobile phone users. The data set contains 607,167 mobile phone users’ movements between 381 cell phone antennas in Abidjan, the biggest city of Ivory Coast, during a two-week observation period \cite{43}. Each movement record contains the coordinates (longitude and latitude) of origin and destination. The data set is based on the anonymized Call Detail Records (CDR) of phone calls and SMS exchanges between five million of Orange’s customers in Ivory Coast. To protect customers’ privacy, the customer identifications have been anonymized by Orange Company.

Chicago travel tracker survey data set. Chicago travel tracker survey was conducted by Chicago Metropolitan Agency for Planning during 2007 and 2008, which provides a detailed travel inventory for each member of 10,552 household in the greater Chicago area. The survey data are available online at http://www.cmap.illinois.gov/travel-tracker-survey/. Since some participants provided one-day travel records but others provided two-days, to maintain consistency, we only extract the first-day travel records from the data set. The extracted data include 87,041 trips, each of which includes coordinates of the trip’s origin and destination.

D. Data preprocessing

The raw travel data of four cities contain latitude and longitude coordinates of each traveler’s origin and destination. The raw data cannot be immediately used in mobility models. Alternatively, we used coarse-grained travel data through partitioning a city into a number of zones, each of which corresponds to a location in literature \cite{3}. Because of the absence of natural partition in cities (in contrast to states or counties), we simplicity partition all city into equal-area square zones, each of which is of 1 km². Figure 7 shows the zone partition results and the number of zones in four cities. We assign an origin (or destination) zone ID to each travel if the travel’s origin (or destination) falls into the range of that zone. Then we can accumulate the total number \( T_i \) of travels departed from an arbitrary zone \( i \), and the total number \( T_{ij} \) of travels from zone \( i \) to zone \( j \). In general, the number of travels departed from a zone is propor-
a proportional to the population of the zone [15]. The spatial distributions of population density estimated from travel data in the four cities are shown in Fig. 7.

E. Sørensen similarity index

Sørensen similarity index is a statistic tool to identifying the similarity between two samples. It has been widely used for dealing with ecological community data [33]. Ref. [18] used a modified version of the index to measure if real fluxes are correctly reproduced (on average) by mobility prediction models, defined as

$$SSI = \frac{1}{N^2} \sum_i \sum_j 2 \min(T_{ij}', T_{ij}) \frac{T_{ij}'}{T_{ij} + T_{ij}}.$$  

(16)

where $T_{ij}'$ is the travels from location $i$ to $j$ predicted by models and $T_{ij}$ is the real travels. Obviously, if each $T_{ij}'$ is equal to $T_{ij}$, the index is 1; if all $T_{ij}'$s are far away from the real values, the index is close to 0.

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Supplementary Information

S1. APPLICATION OF CONDUCTION MODEL TO FOUR ADDITIONAL U. S. CITIES

A. Data collection and preprocessing

We collected travel survey data from the Metropolitan Travel Survey Archive website (http://www.surveyarchive.org/), which records more than 40 U. S. cities’ travel survey archives. Most surveys contain information of citizens, including their households, vehicles and a diary of their trips on a given day (including each trip’s origin and destination location, start and end time, trip mode and purpose). Through checking the data we find that for most data sets the trip-endpoints are labeled by TAZ code or ZIP code. Due to the difficulty in converting the codes to geographic coordinates, we only use the survey data sets of four U. S. cities (New York, Seattle, Detroit and the Twin Cities) that contains the information of trip-endpoint’s geographic coordinates (latitude and longitude).

We enumerate all trips in terms of the coordinates of their origins and destinations from the four data sets. Table S1 shows the number of trips and some other data descriptions of the four cities. According to the methods presented in section Methods, Data preprocessing in main text, we partition each city into equal-area square zones, each of which is of 1 km². Figure S1 shows the zone partition results and the population density distribution of the four cities.

TABLE S1. Data summary of four U. S. cities.

| City       | Year | Households | No. of Trips | No. of Zones |
|------------|------|------------|--------------|--------------|
| New York   | 1998 | 10,971     | 69,282       | 3,006        |
| Seattle    | 2006 | 4,746      | 62,277       | 3,175        |
| Detroit    | 1994 | 7,300      | 53,583       | 4,056        |
| Twin Cities| 2001 | 8,961      | 35,469       | 2,684        |

B. Prediction results

(1) Travel distance distribution

Figure S2 shows the travel distance distributions produced by the conduction model as well as the radiation model. We can see that the conduction model can precisely reproduce the observed distributions of travel distance, whereas the results from the radiation model deviate from the real data.

(2) Destination travel constraints

Figure S3 shows the destination travel constraints produced by the two models. It is obvious that the results from the conduction model are in good agreement with the real data. In Fig. S3 and Fig. 4(D) in the main text, we can observe that the radiation model also performs well in five U. S. cities in terms of the destination travel constraints. We argue that this may be ascribed to the relatively homogeneous population distributions in U. S. cities, as shown in Fig. S1 and Fig. 7 in main text. In contrast, for the two cities in China with inhomogeneous population distributions, the radiation model cannot offer good prediction. This fact suggests that the radiation model is likely to be applicable to cities with homogeneous characteristics to predict the destination travel constraints, whereas the conduction model provides universal prediction in good agreement with empirical data in vast scope.

(3) Travel fluxes for all pairs of locations

We compare the travel fluxes between all pairs of locations produced by the radiation model and the conduction model with real data. As shown in Fig. S4, we find that the average fluxes predicted by both models deviate from real observations to some extent. The prediction errors result from the low sampling rate in the household travel surveys. For instance, in New York, there are 3,006 zones and the travel matrix contains more than $9 \times 10^6$ elements in principle. However, the survey only record...
99,282 trips. In other word, more than 99% of the real travel matrix’ elements are zero. In contrast, the travel matrices established by the models are always full filled (although some elements’ value is very small). Thus the fluxes from the models inevitably deviate from the insufficient samples of real fluxes. We believe adequate sampling rate of real fluxes will allow a fair comparison between reproduced results and real observations to validate our model.

**S2. COMPARING CONDUCTION MODEL WITH PARAMETERIZED MODELS**

Since 1940s, many trip distribution models have been proposed for predicting human or freight mobility patterns. The gravity model [S1] and intervening opportunity model [S2] are two widely used models among them. Since both of them rely on special parameters estimated from real traffic data to predict mobility model, we name them parameterized models. A recently presented rank-based model [S3] also belongs to the parameterized models, although it needs very low input information to reproduce some key characteristics of human mobility patterns. In this section, we will compare the prediction performance of the conduction model with those of parameterized models.

**A. The parameterized models**

(1) **The gravity model**

The gravity model [S1] originates from an analogy with Newton’s gravity law and has many modified versions so far. The original gravity model has the form

\[ T_{ij} = \alpha \frac{m_i m_j}{r_{ij}^3}, \]  

(S1)

where \( T_{ij} \) is the travels departed from location \( i \) to location \( j \), \( m_i \) and \( m_j \) are the populations of origin and destination, and \( r_{ij} \) is the distance between \( i \) and \( j \). This model has a very similar form with Newton’s gravity law, but the model’s prediction results may violate the origin constraint \( T_i = \sum_j T_{ij} \) and the destination constraint \( T_j = \sum_i T_{ij} \). To ensure the constraints, one can alternatively use the doubly constrained gravity model [S4]

\[ T_{ij} = A_i T_i B_j T_j f(r_{ij}), \]  

(S2)

where \( T_i \) is the total travels departed from location \( i \), \( T_j \) is the total travels arrived at location \( j \), \( f(r_{ij}) \) is a function of the distance \( r_{ij} \), \( A_i = 1/\sum_j B_j T_j f(r_{ij}) \) and \( B_j = 1/\sum_i A_i T_i f(r_{ij}) \) are balancing factors. The two factors are interdependent, meaning that the calculation of one set requires the values of the other set. An iterative process is necessary to calculate \( A_i \) and \( B_j \), but it demands high computational complexity. To simplify the calculation, one can use the singly constrained versions,
either origin or destination constrained, of the gravity model by setting one set of the balancing factors $A_i$ or $B_j$ equal to one.

Here we employ the origin-constrained gravity model \cite{S4} to predict mobility patterns in cities, described as

$$T_{ij} = T_i \frac{m_j f(r_{ij})}{\sum_{k\neq i} m_k f(r_{ik})}. \quad (S3)$$

The distance function $f(r_{ij})$ can be of any forms, such as power or exponential function. Based on numerical test, we find that the gravity model with power function $f(r_{ij}) = r_{ij}^{-\beta}$ gives better description of the cities’ mobility patterns than the exponential function (see Fig. S5 and Fig. S6). Thus we use the power distance function, the parameter $\beta$ of which is estimated by fitting the real travel data of eight cities (see details in S2.2).

(2) The intervening opportunities (I.O.) model

The I.O. model \cite{S2} argues that trip making is not directly related to distance but to the relative accessibility of opportunities for satisfying the objective of the trip. The model’s basic assumption is that for every trip departed from a location, there is a constant probability $p$ that determines a traveler being satisfied with a single opportunity. If a location $j$ has $m_j \Theta$ opportunities (we assume the number of opportunities at a location $j$...
is proportional to its population \( m_j \), the probability of a traveler being attracted by location \( j \) is \( \alpha m_j \), where \( \alpha = p \Theta \).

Consider now the probability \( q_i \) of not being satisfied by any of the opportunities offered by the \( j \)th destinations away from the origin \( i \), we can write

\[
q_i^j = q_i^{j-1}(1 - \alpha m_j) \tag{S4}
\]

or

\[
\frac{q_i^j - q_i^{j-1}}{q_i^{j-1}} = -\alpha m_j = -\alpha(S_{i,j} - S_{i,j-1}), \tag{S5}
\]

where \( S_{ij} \) is the total population between location \( i \) and \( j \) (including \( i \) and \( j \)). Assuming that the number of destinations is large, we can treat \( q \) and \( S \) as continuous variables. Then Eq. (S5) can be rewritten as

\[
\frac{dq_i}{q_i(S)} = -\alpha dS. \tag{S6}
\]

After integration we obtain

\[
q_i(S) = \frac{e^{-\alpha S}}{1 - e^{-\alpha M}}, \tag{S7}
\]

where \( M \) is the total population in the city. Note that the trip departed from location \( i \) to location \( j \) is equal to

\[
T_{ij} = T_i[q_i(S_{i,j-1}) - q_i(S_{ij})]. \tag{S8}
\]

Combining Eq. (S8) and Eq. (S7), we obtain the I. O. model:

\[
T_{ij} = T_i \frac{e^{-\alpha(S_{i,j} - m_j)} - e^{-\alpha S_{ij}}}{1 - e^{-\alpha M}}. \tag{S9}
\]

(3) The rank-based model

The rank-based model \([S2]\) assumes that the probability of an individual traveling from an origin to a destination depends (inversely) only upon the rank-distance between the destination and the origin. The model is described as

\[
T_{ij} = T_i \frac{R_i(j)^{-\gamma}}{\sum_{k \neq i}^N R_i(k)^{-\gamma}}, \tag{S10}
\]

where \( R_i(j) \) is the rank-distance from location \( j \) to \( i \) (e.g., if \( j \) is the closest location to \( i \), \( R_i(j) = 1 \); if \( j \) is the second closest location to \( i \), \( R_i(j) = 2 \)) and \( \gamma \) is an adjustable parameter.

B. Estimating model parameters

Before applying the parameterized models, it is necessary to estimate their parameters. The goal of the parameter estimation is to maximize the accuracy of reproducing real mobility patterns by the models. Here we use...
Hyman method \cite{S4}, a standard method for calibrating gravity model in transportation planning \cite{S4}, to identify the gravity model’s parameter.

Hyman method aims to find an optimal parameter to minimize the difference between modeled average travel distance and real average travel distance

$$E(\beta) = |\bar{r}(\beta) - \bar{r}| = \left| \frac{\sum_i \sum_j T_{ij}(\beta) r_{ij}}{\sum_i \sum_j T_{ij}(\beta)} - \frac{\sum_i \sum_j T_{ij} r_{ij}}{\sum_i T_{ij}} \right|,$$

where $\bar{r}(\beta)$ is the average distance given by the gravity model with parameter $\beta$, $\bar{r}$ is the real average travel distance, $T_{ij}(\beta)$ is the number of travels from zone $i$ to $j$ generated by the gravity model and $T_{ij}$ is the real number of travels from zone $i$ to $j$. It is not easy to solve the equation $E(\beta) = 0$. Hyman suggests to use the secant method to address this problem, described by the following process:

**Step 1.** Give an initial estimate of $\beta_0 = 1/\bar{r}$.

**Step 2.** Calculate a trip matrix using the gravity model with the parameter $\beta_0$ and obtain a modelled average travel distance $\bar{r}(\beta_0)$. Estimate a better value of $\beta$ by means of

$$\beta_1 = \beta_0 \bar{r}(\beta_0)/\bar{r}$$

**Step 3.** Applying the gravity model with the newest estimated value of $\beta$ to calculating a new trip matrix and obtain a new modelled average travel distance $\bar{r}(\beta)$ to compare with $\bar{r}$. If they are sufficiently close, terminate the iteration and accept the latest estimated value of $\beta$ as the best estimate; otherwise go to step 4.

**Step 4.** Obtain a better estimate of $\beta$ via:

$$\beta_{i+1} = \frac{(\bar{r} - \bar{r}(\beta_{i-1})) \beta_i - (\bar{r} - \bar{r}(\beta_i)) \beta_{i-1}}{\bar{r}(\beta_i) - \bar{r}(\beta_{i-1})}$$

**Step 5.** Repeat steps 3 and 4 until $\bar{r}(\beta)$ is sufficiently close to $\bar{r}$.

The estimated parameters of the gravity model, as well as the I.O. model and rank-based model by Hyman method are listed in Table S2 for different cities.

### C. Comparison among different models

**1. Travel distance distribution**

Figure S7 shows the travel distance distribution predicted by different models. We see that both the gravity model and the rank-based model can reproduce the observed distributions of travel distance in most cases, but the I. O. model’s results have significant deviation from the real data. Although in some cases the results of the gravity model (or rank-based model) are better than those of the conduction model, the gravity model needs a distance-decay function with adjustable parameters to match real data, whereas our model relies solely on the population distribution without free parameters.

**2. Destination travel constraints**

Figure S7 shows the destination travel constraints produced by the models. We see that the results from the conduction model are in equal or better agreement with the real data than those of the other models in all cases. It is noteworthy that the rank-based model shows the worst performance in this aspect. We speculate that the fact that the rank-based model do not make use of the population data at destination locations accounts for the big difference from real observations.

**3. Travel fluxes between all pairs of locations**

| City     | Gravity | I. O. | Rank-based | Avg. distance |
|----------|---------|------|------------|---------------|
| Beijing  | 1.71    | 5.71×10^{-6} | 1.14 | 5.50          |
| Shenzhen | 1.63    | 3.41×10^{-6} | 1.19 | 4.77          |
| Abidjan  | 2.43    | 3.94×10^{-5} | 1.36 | 2.47          |
| Chicago  | 2.14    | 2.69×10^{-4} | 1.15 | 9.49          |
| New York | 2.28    | 5.45×10^{-4} | 1.20 | 11.71         |
| Seattle  | 1.93    | 2.65×10^{-4} | 1.12 | 8.30          |
| Detroit  | 2.02    | 4.59×10^{-4} | 1.13 | 8.94          |
| Twin Cities | 1.93    | 3.56×10^{-4} | 1.04 | 8.15          |

**FIG. S7.** Comparing the travel distance distributions generated by different models. (A) Beijing. (B) Shenzhen. (C) Abidjan. (D) Chicago. (E) New York. (F) Seattle. (G) Detroit. (H) Twin Cities.
We compare the travel fluxes between all pairs of locations predicted by models with empirical data. As shown in Fig. S9 and Fig. S10, we observe that all the predicted average fluxes from the conduction model, the gravity model and the rank-based model are comparable with the real fluxes to some extent. To give a more explicit comparison among different models, we use Sørensen similarity index as an alternative to measure the degree of agreement between reproduced travel matrices and empirical observations. Figure S11 shows that on the average the accuracy of conduction model is higher than I. O. model and rank-based model. Although in some cases the gravity model can yield better prediction accuracy than the conduction model, the gravity model needs parameter estimated from previous mobility measurements. In contrast, the conduction model only require the population distribution as input, so that have broader scope of applications.

S3. RELATIONSHIP AMONG THE TRIP DISTRIBUTION MODELS

To deepen our understanding of the underlying mechanism in the trip distribution models explored in this paper, we discuss the relationship among them. We will first show that, in a particular case of uniform population distribution, the conduction model, radiation model, I. O. model and rank-based model can all transform into gravity (or gravity-like) model. Next, we will show that these models can be classified into two categories of modelling frameworks: sequential selection and global selection.

A. Uniform population distribution

Consider a particular case of a uniform population distribution (i.e. $S_{ji} = \rho \pi r_{ij}^2$, where $\rho$ is the population density), we can write the conduction model (Eq. (1) in the main text) as

$$T_{ij} = T_i \frac{m_j(r_{ij}^2 - \frac{r_i^2}{4})}{\sum_{k \neq i} N_k(r_{ik}^2 - \frac{r_i^2}{4})},$$  \hspace{1cm} (S14)

where $A$ is the area of the city. Comparing with Eq. (S3), we can realize that Eq. (S14) is actually a gravity model with the distance function $f(r_{ij}) = r_{ij}^2 - \frac{r_i^2}{4}$. This function is a power law with a cut-off (see Fig. S12(A)). Since the population is not uniformly distributed in real cities, we can not directly use such distance function in the gravity model to predict travel fluxes. Alternatively, we have to estimate its parameters by relying on real traffic data before applying the gravity model. However, we may directly choose a population function, such as $f(S_{ji}) = \frac{s_{ji}}{S_{ji}} - \frac{1}{4}$, to be used in the conduction model in the sense that the heterogeneity of population distribution has been captured by $S_{ji}$. Figure S12(B) shows the relationship between the population $S_{ji}$ and travel proportion $T_{ij}/T_i$ in the case of Abidjan, which is in agreement with the population function.

When the population distribution is of uniform distribution ($s_{ij} = \rho \pi r_{ij}^2$), the radiation model [S6] is reduced to

$$T_{ij} \propto T_i m_j r_{ij}^{-4},$$  \hspace{1cm} (S15)

which is actually a gravity model with a power-law distance function associated with power exponent $\beta = 4$. Comparing with the uniform version of conduction model (having a power exponent $\beta = 2$), the selection scope of an individual in the radiation model is relatively more local. The radiation model can characterize the mobility patterns at the country scale (the estimated power exponent of gravity law in the case of U. S. state-wide commuting trips is 3.05 [S6], which does not significantly deviate from 4), but it is not applicable to predicting city mobility patterns. Table S2 shows that the estimated power exponents of the cities are subject to the range 1.63 – 2.43, quite close to the exponent in Eq. (S14) but different from that in Eq. (S15).
The I. O. model can be also transformed into a gravity-like form in the case of uniform population distribution:

\[ T_{ij} \propto T_i (e^{\alpha m_j} - 1)e^{-\alpha S_{ij}} = T_i (e^{\alpha m_j} - 1)e^{-\lambda r_{ij}}, \]  

(S16)

where \( \lambda = \alpha \rho \pi \). The distance function is of high-order exponential form, implying the lack of long-distance travel generated by the model. Thus it is not surprising that the I. O. model usually underestimates long-distance travels, as shown in Fig. S7.

The rank-based model uses rank-distance rather than spatial distance to predict the travels between locations. When the population are uniformly distributed in cities, the rank-distance between the locations is proportional to the square of the spatial distance, such that the rank-based model can be written as

\[ T_{ij} \propto T_i r_{ij}^{-2\gamma}. \]  

(S17)

The distance function in Eq. (S17) is a power law with the power exponent around 2 (see Table S2). It can thus yield similar results to the travel distance distribution resulting from the gravity model and the conduction model (see Fig. S7). However, in the rank-based model the information of destination population is ignored, rendering inconsistency with the destination travel constraints, as shown in Fig. S8.

Take together, insofar as given uniform population distributions, the conduction model, radiation model, I. O. model and rank-based model can all transform into gravity (or gravity-like) model. Although these models have different hypothesis, they share similar underlying mechanism: the probability that an individual selects a location to travel is decreased along with the increment of some prohibitive factors. In gravity model, the factor is spatial distance; in rank-based model is the rank-distance; in I. O. model, radiation model or conduction model is the population between the locations. The key difference lies in the fact that gravity model, I. O. model and rank-based model need adjustable parameters.

FIG. S9. Comparing the observed fluxes with the predicted fluxes for three Asian and African cities.
FIG. S10. Comparing the observed fluxes with the predicted fluxes for five U.S. cities.
to quantify the decrement, whereas in radiation model and conduction model, the decrement is naturally determined by population distribution.

**B. Sequential selection and global selection**

According to the decision-making process of traveler’s destination selection, the frameworks of predicting mobility patterns can be classified into two categories. The first category includes the I. O. model and radiation model, in which each traveler ranks possible destinations in ascending order according to the distance to his/her origin. An individual first decides whether to travel to the first destination in terms of a probability which is determined by some specific rules (see schematic in Fig. S13(B)). If the individual abandons the destination, the second one will be considered in terms of the same probability. Analogously, all possible destinations will be considered step by step until the individual decides to travel to a chosen one. We name such step-by-step decision-making process *sequential selection*. The modeling framework can be described in a unified form:

\[ q_i^j = q_i^{j-1}(1 - \theta_j), \]  

where \( q_i^j \) is the probability of excluding the 1st to \( j \)th destinations departed from the origin \( i \) and \( \theta_j \) is the probability of selection \( j \)th destination insofar as the 1st to \( (j - 1) \)th destinations are not selected. Thus, the probability of select \( j \) to travel can be expressed as a joint probability

\[ p_{ij} = q_i^{j-1}\theta_j. \]  

The I. O. model can be derived by assuming that the probability \( \theta_j \) is proportional to the population of destination \( j \) (i.e. \( \theta_j = \alpha m_j \)). After some calculations (see details in section S2.1), we finally have

\[ p_{ij} = \frac{e^{-\alpha(S_{ij} - m_i)} - e^{-\alpha S_{ij}}}{1 - e^{-\alpha M}}, \]  

which is probability of selecting destination \( j \) departed from \( i \) in the I. O. model.

Similarly, assuming that the probability \( \theta_j \) is the ratio of the population of destination \( j \) to the total population
between locations $i$ and $j$, we have

$$q'_i = q''_i^{-1} (1 - m_j/S_{ij}) = \prod_j \frac{S_{ij} - 1}{S_{ij}} \frac{m_i}{S_{ij}}$$

(S21)

and

$$p_{ij} = q''_j^{-1} \frac{m_j}{S_{ij}} = \frac{m_i m_j}{S_{ij-1} S_{ij}}$$

(S22)

which is nothing but the radiation model.

Distinct forms of probability $\theta_i$ can lead to different versions of models that subject to the framework of sequential selection. For instance, assuming the probability $\theta_i$ is the ratio of $m_j$ to the remaining population $M - S_{ij} + m_j$, we can obtain

$$q'_i = q''_i^{-1} \left(1 - \frac{m_j}{M - S_{ij} + m_j}\right) = \prod_j \frac{M - S_{ij}}{M - S_{ij} + m_j} = \frac{M - S_{ij}}{M}$$

(S23)

and

$$p_{ij} = q''_i^{-1} \frac{m_j}{M - S_{ij} + m_j} = \frac{m_j}{M}$$

(S24)

which is the uniform selection model [S7].

Note that in sequential selection model there is always a possibility of that the traveler does not select any destination unless the system is infinite [S8]. Obviously, the probability is $p_{ii} = 1 - \sum_j p_{ij}$. In other words, a traveler stays at the origin with probability $p_{ii}$. For I. O. model, $p_{ii} = (1 - e^{-\alpha M_i})/(1 - e^{-\alpha M})$; for radiation model and uniform selection model, $p_{ii} = m_i/M$.

The second category, named *global selection*, includes the gravity model, conduction model and rank-based model. In global selection model’s decision-making process, a traveler evaluates the attractions of all possible destinations simultaneously and selects a destination to travel with a probability proportional to the destination’s attraction (see schematic in Fig. S13 C)). The unified framework can be described as

$$p_{ij} = \frac{A_j}{\sum_j A_j}$$

(S25)

where $A_j$ is the attraction of destination $j$. If we solely use population to capture the destination’s attraction, the uniform selection model is given; if we use some functions to describe the decay of attraction as the (real or rank) distance increases, we can obtain gravity or rank-based model (see Eq. (S3) and Eq. (S10)); if the attraction naturally decays associated with the population between destination and origin, the conduction model is derived.

Despite the difference between the two modeling frameworks, both sequential and global selection models imply the preference for closer destinations in human travel decision-making; in sequential selection model, the closer destination has a higher priority to be selected; in global selection model, the attraction of a closer destination decays slowly than that of a farther one. Although both frameworks capture the decision-making process of travelers to some extent, our comparison study (Fig. S7-S11) demonstrates that at the city scale, global selection models perform better than sequential selection models.

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