Extracting Spatiotemporal Demand for Public Transit from Mobility Data

Trivik Verma*, 1 Mikhail Sirenko, 1 Itto Kornecki, 2 Scott Cunningham, 3 and Nuno A. M. Araújo 4, 5

1 Faculty of Technology, Policy and Management, Delft University of Technology, 2628BX Delft, the Netherlands
2 ETH Zürich, Universitätsstrasse 16, 8092 Zürich, Switzerland
3 Faculty of Humanities and Social Science, University of Strathclyde, 18 Richmond Street, Glasgow G1 1XQ, Scotland, United Kingdom
4 Departamento de Física, Faculdade de Ciências, Universidade de Lisboa, P-1749-016 Lisboa, Portugal
5 Centro de Física Teórica e Computacional, Faculdade de Ciências, Universidade de Lisboa, 1749-016 Lisboa, Portugal

With people constantly migrating to different urban areas, our mobility needs for work, services and leisure are transforming rapidly. The changing urban demographics pose several challenges for the efficient management of transit services. To forecast transit demand, planners often resort to sociological investigations or modelling that are either difficult to obtain, inaccurate or outdated. How can we then estimate the variegated demand for mobility? We propose a simple method to identify the spatiotemporal demand for public transit in a city. Using a Gaussian mixture model, we decompose empirical ridership data into a set of temporal demand profiles representative of ridership over any given day. A case of ≈ 4.6 million daily transit traces from the Greater London region reveals distinct demand profiles. We find that a weighted mixture of these profiles can generate any station traffic remarkably well, uncovering spatially concentric clusters of mobility needs. Our method of analysing the spatiotemporal geography of a city can be extended to other urban regions with different modes of public transit.
INTRODUCTION

According to the UN, every year about 1 billion people migrate [1, 2] to different urban areas around the world [3]. With accelerated migration rates, urban areas expand and citizen needs grow considerably [4]. Public Transit (PT) networks play a significant [5] and challenging role [6] in serving citizens’ business, industrial, social, cultural, educational and recreational needs [7]. A prevalent urban policy of Transit-Oriented Development (TOD) promotes mixed-use of urban areas by encouraging people to live near clusters of amenities and services, built around transit stations. Such development enhances accessibility of the city for a wider group of citizens [8], improves pedestrian access [9], and reduces pollution and congestion by discouraging reliance on private vehicles [10]. Though cities welcome innovation in infrastructure services necessary for sustaining growing populations [11], improved connectivity also threatens to create larger, more sprawling urban areas [12, 13].

Due to the changing transit needs [11] and developments in urban land-use, the planning and management of transit services pose a huge challenge [15]. Transportation demand analysis heavily depends on census-based population statistics and usage estimates from transit authorities [7]. Some researchers emphasise qualitative methods to estimate transport demand, involving direct observation of urban populations [16–18]. Studies that focus on revealing macroscopic urban structures [19–21] develop aggregated Origin-Destination (OD) trajectories of people using mobile mate transport demand, involving direct observation of urban populations [16–18]. Studies that focus on revealing macroscopic urban structures [19–21] develop aggregated Origin-Destination (OD) trajectories of people using mobile phone [22, 23] and twitter data [26]. While there is evidence that urban mobility patterns are reproducible using aggregated statistics of populations [24], this data only accounts for 2–5% of the entire population [24]. What is more, recent work suggests methods based on incomplete statistical data underestimate important trips, especially in larger cities [25]. This general framework of estimating a snapshot of transit demand and adapting future supply to it relies on several parameters, uses incomplete data, and is difficult to compare through time.

Over the past decade, digital services like Automatic Fare Collection (AFC) have been introduced into transit networks worldwide. There is important literature on flow estimation that extracts detailed and complete OD trajectories [29–32] from AFC data. Using complete data, these studies provide aggregated instances of mobility flows between large hotspots in a city, mainly focusing on recovering morphological characteristics of the urban structure [19, 20]. But the spatiotemporal nature of mobility lacks a strong empirical foundation. Identifying the daily demand for mobility across time and space can naturally structure the efficient development and management of PT services catering to our complex mobility needs [33].

We propose a simple method to estimate the varying demand for transportation in time using anonymous, privacy-preserving, complete and freely available entry-only ridership data. Our case uses the data of ≈ 4.6 million daily commutes in the Transport for London (TfL) services in the Greater London Underground network. We find that the daily traffic through this PT network is a mixture of six demand profiles. Using the weights of these profiles, our model is able to reproduce individual network station traffic throughout the day and classify stations into six categories. Upon mapping these categories, we show how these profiles can identify the spatial distribution of varying mobility demand for the PT infrastructure. We discuss how the temporal nature of complex urban demand reveals the spatial structure of the city consisting of central [34], polycentric [30, 35] and concentric [21, 36] zones of development. We expect our method to be useful for data-driven demand analysis of PT infrastructures in any region in the world where complete OD trajectories are not accessible or are only available through proprietary sources.

RESULTS

Beyond traditional transportation demand analysis. To measure the changing demand for PT we analyse the passenger entrance counts, \( P_i(t) \), entering a station \( i \) at time interval \( t \) (\( \forall t \in 1, 2, ..., m \)) where each interval is a 15-minute observation window in which the data is collected with \( m \) intervals per day. The variable \( P_i \) is a proxy for the ridership behaviour, an indication of the usage of every station at different times in a day. We use ≈ 4.6 million geolocated observations of daily TfL passengers. Our dataset consists of 264 stations of the Greater London region spanning 24 hours in a day (see the Methods section for details).

Figure 1a represents the average demand for the PT system across all stations in the network throughout the day with the quantile interval showing variations across all stations in the city (see Supplementary Figure 1 for an overview of the entire system traffic). As it is evident from Fig. 1b, aggregate station ridership is symmetric: data from a day shows excellent correlation between the total number of entrances and exits for every station. To understand how station traffic is related to population statistics, we visualise the relationship between the number of total station entrances on a given weekday, \( \sum_t P_i(t) \), and the working adult population of every zone associated with the station (see Supplementary Note 1 for details on estimating population sizes for station zones). Figure 1c shows a very weak relationship between the number of people residing in a zone and the entrances at the corresponding station. The
FIG. 1. Describing the TfL data of station traffic over a representative day.  

a Average Passenger counts $\bar{P}(t)$ for the PT system showing entrances for every 15-minute intervals. The confidence intervals show the quantile interval (10 – 90% of data) and the blue line is the average traffic for each cluster.  

b Relationship between the total entry vs exit counts for every station in the system.  

c Relationship between population and ridership (entry counts) for Voronoi cells that are attributed to every station (see Supplementary Information for estimating population counts for station zones). The number of stations in this figure are less than the total number in the dataset because some stations are outside Greater London for which population estimates were not available.
FIG. 2. Temporal demand profiles over the representative day. Each normal distribution refers to a particular kind of traffic in time and the density estimates $pdf(t)$ measures the likelihood that an individual entering the system belongs to a certain demand profile. $\sum_k pdf(t) = 1$.

weak correlation suggests population statistics are not a good proxy for demand. If people are not using the station closest to them, that may be due to some stations not fulfilling the potential for accessing opportunities in a city. Even though aggregate counts of entrances and exits are matched well (Fig. 1b), an indication of the complexity of the urban demand for mobility can be witnessed in asymmetric correlations between trips made in opposite directions illustrating the increasing use of stations for other activities than work and residential (see Supplementary Note 2 for details). Considering this evidence, census-based populations surveys are not accurate enough to calibrate gravitation models for estimating complex city flows and are often found to underestimate importance of regular home-work trips. Thus, we focus on identifying distinct demand profiles across a day.

Multiple demand profiles for public transit. The time series of entrances at stations represents an aggregation of many different commuting patterns. To interpret the variability in demand, we formulate a simple Gaussian Mixture Model (GMM) (see the Methods section for details) to identify temporal patterns in the time series of $\sum P_i(t)$. The model represents the cumulative transportation demand as normal distributions with varying mean ($\mu_k$), variance ($\sigma_k$) and mixture weights ($\phi_k$) for each demand profile $C_k$. This choice is in part justified by the multimodal distribution of traffic over the PT network across time (Fig. 1a). We identify six demand profiles that are all normally distributed in time (see Supplementary Figure 6 for variation in demand profiles). Figure 2 illustrates the distribution of the characteristic mixtures of subpopulations in the data, each with varying parameters ($\mu$, $\sigma$ and $\phi$; see Supplementary Table 1 for details.)

Each mixture represents one transportation demand profile:

1. Work (W): Morning trips for work;
2. Early Afternoon (LM): Late Workers, tourists, shoppers and miscellaneous activities;
3. Afternoon (A): School and lunchtime traffic, flexible workers, tourists, and shoppers;
4. Residential (R): Evening trips returning from work;
5. Evening (E): Late workers returning home and dinnertime traffic;
6. Nighttime (N): Service industry (restaurant, bars, healthcare) workers, and traffic from entertainment districts.

The profiles mentioned above are generalisations of traffic but there is mixed usage throughout the day: tourists travel at all times and night workers come home in the morning as well. In this work, we do not categorise individual traces into any types.

Clustering stations by demand profiles. The demand profiles we identify using the GMM are expressed using three parameters, a mixture component weight, mean and variance. Using this set of values we reconstruct individual station traffic for every station by representing the demand of a station as a linear combination of different types and classifying the station based on the relative value of the weights and the three estimated parameters of the GMM. The estimated probability density reveals the subscription of each station to every mixture (see the Methods section for details on generating station traffic and clustering).

We analyse the different clusters of stations in Fig. 3. Each cluster has a particular shape of average daily traffic entering the station:
FIG. 3. Clusters of generated station traffic. Six clusters of station traffic showing different peculiar patterns of station use. Each sub plot is the time series of generated station traffic $P_k^t(t)$. The confidence intervals show the quantile interval (10% – 90% of data) and the blue line is the average traffic for each cluster. The thin grey lines show all station traffic belonging to a cluster. All 264 stations of the Greater London region are shown here.

1. Central Business District (CBD) stations show a higher number of entrances in the evening compared to the rest of the day. People usually move to the district for using services and business all day and return home at night;

2. Polycentre stations witness similar amount of workbound traffic in the morning and residential traffic in the afternoon, and a high amount of activity throughout the day compared to other clusters. These are large secondary hubs [25] that have mixed use for residences, workplaces and services;

3. Potential feeder stations that are in a zone of transition [36] with changing land-use from a compact and busy CBD to wider residential regions with self-sufficient services. A peak in workbound traffic and a declining residential traffic pattern suggests middle-class housing workers residing in this region possibly feed into the city for work;

4. Inner residential stations may be serving working-class groups but are further away from the CBD (see Supplementary Figure 7). These stations differ from the feeders because of a striking peak in the early morning traffic just before the workbound ridership peaks;

5. Outer residential stations have lesser evening traffic and are much further from the CBD compared to inner residential stations. The lower evening volumes point to the region’s greater residential nature;

6. Finally, commuter stations have a mix of suburban or satellite traffic in the morning and residential traffic in the evening, pointing to some work locations in the vicinity as is expected from clusters of suburban areas.

Figure 4a reports two spatiotemporal scenarios. In the first one (left frame), we show how station clusters are distributed among typical (W and R), midday (LM and N) and nighttime (EN and LN) demand profiles. Note that the CBD is skewing the distribution toward nighttime traffic, possibly because entertainment centres are located close to business districts. The plots also reveal that the PT system in London is used much less in the midday hours in comparison to the regular home-work traffic at other times of the day. The second scenario (Fig. 4a - right frame) shows a prevalence of work (W) and other (LM, N, EN and LN) traffic profiles than residential (R) in the CBD stations. It is possible that many residents in the CBD region who have improved access to bus services and therefore do not use underground transit. Additionally, these residents may be affluent and own a car, live within walking / biking distance of their place of work or are older, non-working citizens. Also, there are more residential and typical stations in the city and these stations have less traffic than the business district. This finding is consistent with the “many-to-few” characterisation of a typical city [30], where many residential areas feed a small number of polycentres and the CBD.
FIG. 4. The spatiotemporal geography of the London public transit system. a The two ternary plots show scenarios of time and space where demand profiles are aggregated by time: typical (W and R), midday (A and EA) and after-work (E and N), and space: work (W), residential (R) and other (A, EA, E and N). b The station clusters mapped onto the Greater London region with locations as the coordinates of the underground service. The gradient in grey is a population map showing the adult working population of the Wards from a 2017 intercensal estimate.

Visualising the station clusters in space in Fig. 4b, mapped onto the public transport system, reveals how the city is organised in concentric circles as argued and proposed by Burgess et al. [21]. The spatial distribution of clusters describes a complex urban structure wherein public transit links the CBD to outer residential spaces through distinct linkage patterns, revealing a monocentric structure with respect to the primary means of underground transportation. Possibly, the users enter the system from the periphery and advance to the CBD for work or other activities. This indicates that most residential areas are spread out at the outskirts of the city, while the stations close to work centres are clustered together in the CBD. The map thus reveals that there is a dense urban core that is the City of London, surrounded by a residential periphery. This is supported by measuring the average travelling distance between the stations, where we find that the stations in work districts are much closer together than ones in residential districts (see Supplementary Figure 8 for details). Our analysis confirms both concentric [21] and polycentric nature [30] of the city. Polycentres also include some National Rail connections, such as Waterloo, Brixton, and Stratford stations. Though some of these outliers appear as important polycentric hubs for the city (for example, Waterloo), the stations themselves may not have many residents in the vicinity using the system. They are important connections which collect residents coming from other cities via the national train network.

To understand the complex nature of urban flows we disentangled station usage into various clusters. Next, we individually examine the correlations between ridership and the adult working population of each zone separated by
FIG. 5. Cluster specific scatter-plot representation of ridership versus adult working population. Relationship between population and ridership (entry counts) for Voronoi cells that are attributed to every station (see Supplementary Note 1 for estimating population counts for station zones). The number of stations in this figure are less than the total number in the dataset because some stations are outside Greater London for which population estimates were not available. Only 238 stations are shown in this plot, as the remaining 26 stations in the dataset are outside the Greater London region for which we cannot estimate population sizes and hence Voronoi tessellations.

station clusters (recall Fig. 1 for this discussion). Figure 5 illustrates that there is a stronger correlation between the ridership at a station and the population within the station’s zone for outer-residential, inner-residential and polycentric clusters. This is intuitive: the number of people taking the train in the morning from a residential station is proportional to the number of people living within the proximity of that station where other activity is also minimal (see Supplementary Note 1 for a discussion on accessibility analysis). Polycentres by definition are secondary hubs that attract people owing to their business/services/residential mix. As expected, the relationship for other clusters, the CBD, mixed commuting and feeder stations, is weak and prone to outliers.

In addition to revealing the CBD of London, our method can reveal other commercial areas in the city. For example, we observe White City Station as being commercial, which corresponds to the concentration of several large businesses, including the British Broadcasting Corporation (BBC) offices and the Westfield Mall, the largest mall in Europe. Since our method is normalised for traffic volume, it also reveals areas which, though relatively low in ridership, are heavily business-oriented. For example, there is a strong work-like ridership pattern in Canary Wharf Station, corresponding to the large financial district in the Isle of Dogs area. Thus, our modelling has the potential to analyse mixed-use of stations which has far-reaching implications in improving services (see Supplementary Note 3 for a use case explanation).

DISCUSSION

Digitisation has enabled an unprecedented amount of anonymous and location-based transit ridership data that is both complete (representative of the entire population using the service) and easily tractable. Our method leverages such information to extract mobility demand profiles across a city over the course of the day. It is independent of trajectories of individuals, thus preserving their privacy. Upon clustering the station traffic generated using these demand profiles, we are able to extract significant information about urban structures of a city. We have applied this method to the Greater London region using a dataset consisting of \( \approx 4.6 \) million transit traces. The empirical results show three key findings.

First, the aggregate usage of a public transit network can be decomposed into distinct temporal demand profiles that represent various classes of daily ridership for work, services, leisure and other combinations of use [39–41]. Second, stations clustered by their traffic patterns suggest that there are concentric zones of development in Greater
London, identifying polycentres, entertainment and tourist locations, residential and highly specialised business districts. Third, larger station show mixed-use demand and stations farther away from the centre of the city are likely to exhibit a prevalent residential ridership. While there is evidence of declining populations and traffic from the central business district [22], there are rhythms to human activity [14] and matching the various demands will lead to efficient transport utilisation across the entire network.

Transportation demand analysis in large metropolitan areas is an important problem that is relevant for urban planning [15]. Researchers either investigate detailed sociological data [16–18] or extract macroscopic urban structures [22–25] as proxy for demand patterns. However, as transit needs evolve, intra-urban mobility structures [19–21] also transform. Incomplete data [25] from digital sources such as social media [26] prove inaccurate for transportation demand analysis [28]. Our empirical framework highlights an important finding that using digital ridership data we are able to extract a set of complete and accurate microscopic demand profiles which are also determinants of macroscopic urban structures in cities.

Though the data reveals a lot of information about the temporal and spatial profiles of traffic in a city, there are certain limiting factors to consider for future research. The model does not achieve high accuracy for predicting traffic (see Supplementary Note 4 for details). Even though our work does not focus on the accuracy of prediction, the data-driven method is able to highlight candidate station locations which suffer from poor ridership (both under and over represented), which in turn could be indicative of an unsatisfactory transport service that is a good case for improvement. Thus, the spatiotemporal geography we have presented is an important framework for assessing spatial use of a city with respect to its transportation infrastructure. Larger cities are increasingly interested in providing safe and secure travel options for nighttime workers and preserving or enhancing their nightlife as a cultural amenity and source of economic revenue. A report published by the Greater London Authority [38] notes that fully a third of London workers work evening and nights, and two-thirds are actively engaging in nighttime activities. In addition, citizens may have very different expectations about how their districts should be used across time [13] and cities are acknowledging those needs [38]. Our results indeed confirm multiple uses of space over time and highlight the very specific districts where different kinds of activities occur, or might be enhanced with appropriate intervention. Our work can be used as a methodology for analysing and repurposing transport data for studies of cohesion, safety and growth.

Without requiring detailed origin-destination trajectories, which has become a common tool in urban studies, important information about urban structures could very well prompt studies in the direction of sustainable transit-oriented development [6, 44] and their potential negative impacts on displacing communities [13], promoting urbanisation [14] and exacerbating sprawl [46, 47]. Our quantitative analysis of transportation demand has the potential to initiate new developments in extracting precise micro-scale OD matrices useful for urban planning on a city level by studying distributions of amenities around stations and correlating their use with generalised demand profiles. Since our method is generative, given mixed use of space, new stations can be planned or old ones re-designed, to match traffic demand for new technology hubs, social housing neighbourhoods or secondary or tertiary centres of tourism. Our method can be straightforwardly expanded to other transit networks, including multi-modal systems, and can therefore become a critical tool for urban and transit planners.

**METHODS**

**Transport Data**

We use the London Underground Passenger Count dataset as a proxy for ridership, which is provided freely by TfL [18]. The dataset describes the average number of entrances and exits to and from each station in the Underground Network, represented as a time series spanning 24 hours. The time series is aggregated at 15-minute intervals, resulting in 96 data points per station for a total of 264 stations. We remove instances of erroneous or zero counts for every station between the times of 02:00 am and 05:00 am where the PT network is not in function. This represents an average of all days in the month of November 2017, separated into weekdays and weekends. We carry out our analysis on only the weekday data. The data description provided by TfL claims that November 2017 illustrates a typical sample of winter travelling behaviour in the year and has been adjusted for any disruptions in the Underground service (such as related to weather, malfunctions and accidents or community events). For details on sources of error, see Supplementary Note 4.
Gaussian Mixture Model

To identify the subpopulations of demand profiles in the ridership data, we formulate a GMM. GMMs are formed so subpopulations can be automatically learned from a large dataset without annotating any data points in advance with user-defined labels. Thus, a formulation of this type constitutes a class of unsupervised learning algorithms. The foundation of these models is built upon a mixture of several normal distributions. In the case of a passenger count dataset of a public transit system, our assumption is that the underlying distribution of the overall traffic at a station per day follows the sum of multiple scaled normal distributions with their means at different times representing local minima. Translating this mixture onto a standard GMM means that each distribution learned from the model represents one specific temporal demand profile. It is useful to observe than a data point in any one normal distribution does not necessarily classify that person entering a station as belonging to a specific demand type. A GMM is probabilistic in nature that associates a likelihood to each data point of belonging to a specific normal distribution.

A GMM is characterised by three parameters: individual mixture weights $\phi_k$, mixture means $\mu_k$ and variances $\sigma_k$ for all mixtures $C_k$. For our case of TfL data, let the number of mixtures be $k = 6$ (see Supplementary Figure 6 for effects of variations in $k$). Given our input data in the form of a time-series and the number of demand profiles (mixtures) we specify, the formulated GMM first estimates a-posteriori the unknown parameters ($\phi_k, \mu_k, \sigma_k$) using an expectation maximisation algorithm [49].

The probability distribution of the data $x$ in a GMM is given by,

$$ p(x) = \sum_{k=1}^{K} \phi_k N(x \mid \mu_k, \sigma_k), \quad (1) $$

$$ N(x \mid \mu_k, \sigma_k) = \frac{1}{\sigma_k \sqrt{2\pi}} \exp \left( -\frac{(x - \mu_k)^2}{2\sigma_k^2} \right), \quad (2) $$

$$ \sum_{k=1}^{K} \phi_k = 1. \quad (3) $$

Equation (3) shows that each mixture $C_k$ is marked by its associated weight such that the total probability distribution normalises to 1.

Generation of individual station traffic

Using the Gaussian mixture model formulation and estimating the parameters for the cumulative set of observations in the data we are able to generate individual station traffic. The process of estimating the densities at every station involves two steps. First, we sample the normal mixture using the distribution of each identified demand profile $p(C_k) = \phi_k$. Second, we sample each data point belonging to the station from the distribution of mixture $C_k$ using $p(x \mid C_k) = N(x \mid \mu_k, \sigma_k)$. Though we estimate densities at each station for observations that belong to the dataset, traffic for a new station that records out-of-sample observations could also be estimated using the parameters for our formulation.

Clustering stations

As the time series data of passenger counts is aggregated by 15-minute intervals, we implicitly map the generated station traffic into a matrix where each row can be interpreted as station traffic over different times in a day. $P_i(t_j)$ is the measure of use of station $i$ at time-step $t_j$ (Table I). To curb the skewing effects of larger stations that also witness incoming and outgoing traffic to and from other cities, we normalise the passenger counts such that $\sum_{t} P_i(t) = 1 \forall$ stations $i$. Columns showing traffic over all stations at every time-step $t_j$ have long-tail distributions and each station traffic vector $[t_1, t_2, t_3, ..., t_n]$ is a multi-modal distribution. Given this description, we formulate a multivariate GMM for clustering stations into six characteristic station types.
TABLE I. **Data schema for the feature matrix used for clustering.** Each station has \( n \) features \( t_j \) where every column (feature) represents the passenger traffic count \( P(t_j) \) at each time interval of 15 minutes. As an example, \( P_3(t_3) \) is the passenger traffic entering station 3 at time interval 05:30am - 05:45am, generated using our modelling approach.

| Feature Matrix |
|----------------|
| Station | \( t_1 \) | \( t_2 \) | \( t_3 \) | ... | \( t_n \) |
| 1       | .       | .       | .       | .   | .   |
| 2       | .       | .       | .       | .   | .   |
| 3       | .       | .       | \( P_3(t_3) \) | .   | .   |
| ...     | .       | .       | .       | .   | .   |
| m       | .       | .       | .       | .   | .   |

To model the multivariate GMM case, we use the formulation,

\[
p(\bar{x}) = \sum_{k=1}^{K} \phi_k \mathcal{N}(\bar{x} \mid \bar{\mu}_k, \Sigma_k),
\]

\[
\mathcal{N}(\bar{x} \mid \bar{\mu}_k, \Sigma_k) = \frac{1}{\sigma_k \sqrt{2\pi}} \exp\left(-\frac{(\bar{x} - \bar{\mu}_k)^2}{2\sigma_k^2}\right),
\]

where Eq. 5 is the probability density function of the multivariate normal distribution, \( \bar{\mu}_k \) represents the means and \( \Sigma_k \) the covariance matrices [50].

To cluster station traffic that follow similar trends over a day, we utilise the expectation step of the expectation-maximisation algorithm [49] which forms the basis of a GMM. Using the estimated model parameters for the multivariate distributions, we find the likelihood that a station traffic pattern (\( \bar{x} \)) belongs to a mixture \( C_k \) by calculating,

\[
p(C_k \mid \bar{x}) = \frac{\phi_k \mathcal{N}(\bar{x} \mid \bar{\mu}_k, \Sigma_k)}{\sum_{k=1}^{K} \phi_k \mathcal{N}(\bar{x} \mid \bar{\mu}_k, \Sigma_k)}.
\]

**DATA AVAILABILITY**

All datasets that support the findings of this study are publicly available (as cited in the references) and a version used in the study can be collected, requested or directly downloaded from the following link: https://github.com/mikhailsirenko/spacetimegeo

**CODE AVAILABILITY**

The GMM representation together with all the necessary functions for running the model are available in python at the following link on github: https://github.com/mikhailsirenko/spacetimegeo

[1] Jonathan V. Beaverstock and Joanne Smith. Lending Jobs to Global Cities: Skilled International Labour Migration, Investment Banking and the City of London. *Urban Studies*, 33(8):1377–1394, October 1996.

[2] Jonathan Darling. Forced migration and the city: Irregularity, informality, and the politics of presence. *Progress in Human Geography*, 41(2):178–198, April 2017.

[3] Department of Economic and Social Affairs (DESA) United Nations. Crossnational comparisons of internal migration: An update on global patterns and trends. United Nations, Department of Economic and Social Affairs, Population Division.

[4] William Alonso. A Theory of the Urban Land Market. *Papers in Regional Science*, 6(1):149–157, 1960.

[5] Jean-Paul Rodrigue, Claude Comtois, and Brian Slack. *The geography of transport systems*. Routledge, London; New York, third edition edition, 2013.

[6] Yuerong Zhang, Stephen Marshall, and Ed Manley. Network criticality and the node-place-design model: Classifying metro station areas in Greater London. *Journal of Transport Geography*, 79:102485, July 2019.
[7] Avishai Ceder. *Public Transit Planning and Operation: Modeling, Practice and Behavior, Second Edition*. CRC Press, March 2016. Google-Books-ID: b84dCgAAQBAJ.

[8] Adie Tomer, Elizabeth Kneebone, Robert Puentes, and Alan Berube. Missed Opportunity: Transit and Jobs in Metropolitan America. Technical report, Brookings Institution, May 2011.

[9] Hank Dittmar and Gloria Ohiand. *The New Transit Town: Best Practices In Transit-Oriented Development*. Island Press, June 2012. Google-Books-ID: ZrR6PQjkJ4R4C.

[10] Peter Calthorpe. *The Next American Metropolis: Ecology, Community, and the American Dream*. Princeton Architectural Press, 1993. Google-Books-ID: WtKU5L0ajA8C.

[11] L. M. A. Bettencourt, J. Lobo, D. Helbing, C. Kuhnert, and G. B. West. Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Sciences*, 104(17):7301–7306, 2007. arXiv: 1011.1669v3 ISBN: 0027-8424.

[12] JEFFREY R. HENIG. Gentrification and displacement within cities: A comparative analysis. *Social Science Quarterly*, 61(3/4):638–652, 1980.

[13] Casey Dawkins and Rolf Moeckel. Transit-Induced Gentrification: Who Will Stay, and Who Will Go? *Housing Policy Debate*, 26(4-5):801–818, September 2016.

[14] Robin James Smith and Tom Hall. No Time Out: Mobility, Rhythmicity and Urban Patrol in the Twenty-Four Hour City. *The Sociological Review*, June 2013.

[15] David Byrne. Complexity Theory and Planning Theory: A Necessary Encounter. *Planning Theory*, 2(3):171–178, November 2003.

[16] Stephen W. Raudenbush and Robert J. Sampson. Ecometrics: Toward a science of assessing ecological settings, with application to the systematic social observation of neighborhoods. *Sociological Methodology*, 29(1):1–41, August 1999. Publisher: John Wiley & Sons, Ltd (10.1111).

[17] Brian D. Taylor, Douglas Miller, Hiroyuki Iseki, and Camille Fink. Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas. *Transportation Research Part A: Policy and Practice*, 43(1):60–77, January 2009.

[18] Javier Gutiérrez, Osvaldo Daniel Cardozo, and Juan Carlos García-Palomares. Transit ridership forecasting at station level: an approach based on distance-decay weighted regression. *Journal of Transport Geography*, 19(6):1081–1092, November 2011.

[19] Urban Spatial, Structure Author, Alex Anas, Richard Arnott, Kenneth A Small, and Kenneth A Small1. American Economic Association Urban Spatial Structure. *Journal of Economic Literature*, 36(3):1426–1464, 1998.

[20] Marc Barthélémy. Spatial networks. *Physics Reports*, 499(1-3):1–101, 2011. arXiv: 1010.0302 Publisher: Elsevier B.V. ISBN: 0370-1573.

[21] Ernest W. Burgess. The Growth of the City: An Introduction to a Research Project. In John M. Marzluff, Eric Shuglenberger, Wilfried Endlicher, Marina Alberti, Gordon Bradley, Clare Ryan, Ute Simon, and Craig ZumBrunnen, editors, *Urban Ecology: An International Perspective on the Interaction Between Humans and Nature*, pages 71–78. Springer US, Boston, MA, 2008.

[22] A. Noulas, C. Mascolo, and E. Frias-Martínez. Exploiting Foursquare and Cellular Data to Infer User Activity in Urban Environments. In *2013 IEEE 14th International Conference on Mobile Data Management*, volume 1, pages 167–176, June 2013.

[23] Francesco Calabrese, Giusy Di Lorenzo, Liang Liu, and Carlo Ratti. Estimating Origin-Destination Flows Using Mobile Phone Location Data. *IEEE Pervasive Computing*, 10(4):36–44, April 2011.

[24] Thomas Louail, Maxime Lenormand, Oliva G. Cantó, Ricardo Herranz, Enrique Frias-Martínez, José J. Ramasco, and Marc Barthelemy. From mobile phone data to the spatial structure of cities. *Scientific Reports*, 4(1):5276, May 2014. arXiv: 1401.4540v1 Publisher: Nature Publishing Group.

[25] Thomas Louail, Maxime Lenormand, Miguel Picornell, Oliva García Cantú, Ricardo Herranz, Enrique Frias-Martínez, José J Ramasco, and Marc Barthelemy. Uncovering the spatial structure of mobility networks. *Nature Communications*, 6, 2015. arXiv: 1501.05269 ISBN: 2041-1723 (Electronic)\(\times\)2041-1723 (Linking).

[26] Graham McNeill, Jonathan Bright, and Scott A. Hale. Estimating local commuting patterns from geolocated Twitter data. *EPJ Data Science*, 6(1):1–16, December 2017.

[27] Marta C. González, César A. Hidalgo, and Albert-László Barabási. Understanding individual human mobility patterns. *Nature*, 453(7196):779–782, June 2008.

[28] Chico Q. Camargo, Jonathan Bright, and Scott A. Hale. Diagnosing the performance of human mobility models at small spatial scales using volunteered geographic information. *arXiv:1905.07964* [physics], May 2019. arXiv: 1905.07964.

[29] Jin Park, Dong-Jun Kim, and Yongaek Lim. Use of Smart Card Data to Define Public Transit Use in Seoul, South Korea. *Transportation Research Record: Journal of the Transportation Research Board*, 2063(1):3–9, January 2008. Publisher: SAGE PublicationsSage CA: Los Angeles, CA ISBN: 0361-1981.

[30] Camille Roth, Soong Moon Kang, Michael Batty, and Marc Barthelemy. Structure of Urban Movements: Polycentric Activity and Entangled Hierarchical Flows. *PLOS ONE*, 6(1):e15923, January 2011.

[31] Chen Zhong, Stefan Müller Arisona, Xianfeng Huang, Michael Batty, and Gerhard Schmitt. Detecting the dynamics of urban structure through spatial network analysis. *International Journal of Geographical Information Science*, 28(11):2178–2194, November 2014.

[32] Ying Long and Jean-Claude Thill. Combining smart card data and household travel survey to analyze jobs–housing relationships in Beijing. *Computers, Environment and Urban Systems*, 53:19–35, September 2015.

[33] Manlio De Domenico, Albert Solé-Ribaltera, Sergio Gómez, and Alex Arenas. Navigability of interconnected networks under random failures. *Proceedings of the National Academy of Sciences*, 111(23):8351–8356, June 2014.
[34] Raymond E. Murphy. *The Central Business District: A Study in Urban Geography*. Routledge, July 2017. Google-Books-ID: fDwrDwAAQBAJ.

[35] R Louf, P Jensen, and M Barthelemy. Emergence of hierarchy in cost-driven growth of spatial networks. *P Natl Acad Sci USA*, 110:8824–8829, 2013.

[36] Homer Hoyt. *The Structure and Growth of Residential Neighborhoods in American Cities*. U.S. Government Printing Office, 1939. Google-Books-ID: VtjZdGSOWhgC.

[37] Michael Batty. *Urban Modelling. Algorithms, Calibrations, Predictions*. Cambridge University Press, 1976.

[38] London at night - an evidence base for a 24-hour city, November 2018. Library Catalog: www.london.gov.uk.

[39] Rein Ahas, Anto Aasa, Siiri Silm, and Margus Tiru. Daily rhythms of suburban commuters’ movements in the Tallinn metropolitan area: Case study with mobile positioning data. *Transportation Research Part C: Emerging Technologies*, 18(1):45–54, February 2010.

[40] P Gordon, H W Richardson, and H L Wong. The Distribution of Population and Employment in a Polycentric City: The Case of Los Angeles. *Environment and Planning A: Economy and Space*, 18(2):161–173, February 1986.

[41] Maxime Lenormand, Miguel Picornell, Oliva G. Cantú-Ros, Thomas Louail, Ricardo Herranz, Marc Barthelemy, Enrique Frias-Martinez, Maxi San Miguel, and José J. Ramasco. Comparing and modelling land use organization in cities. *Royal Society Open Science*, 2(12):150449, December 2015.

[42] W. R. Tobler. A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, 46(sup1):234–240, June 1970.

[43] Fenne M Pinkster and Willem R Boterman. When the spell is broken: gentrification, urban tourism and privileged discontent in the Amsterdam canal district. *cultural geographies*, 24(3):457–472, July 2017. Publisher: SAGE Publications Ltd.

[44] Enrica Papa and Luca Bertolini. Accessibility and Transit-Oriented Development in European metropolitan areas. *Journal of Transport Geography*, 47:70–83, July 2015.

[45] Dena Kasraian, Kees Maat, and Bert van Wee. The impact of urban proximity, transport accessibility and policy on urban growth: A longitudinal analysis over five decades. *Environment and Planning B: Urban Analytics and City Science*, 46(6):1000–1017, July 2019.

[46] Alain Bertaud and Stephen Malpezzi. The Spatial Distribution of Population in 48 World Cities: Implications for Economies in Transition. *Center for Urban Land Economics Research, University of Wisconsin*, 32(1):54–55, 2003.

[47] Frans Dieleman and Michael Wegener. Compact City and Urban Sprawl. *Built Environment (1978-)*, 30(4):308–323, 2004.

[48] London Underground passenger counts data.

[49] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum Likelihood from Incomplete Data via the EM Algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38, 1977. Publisher: [Royal Statistical Society, Wiley].

[50] Emil Eirola and Amaury Lendasse. Gaussian Mixture Models for Time Series Modelling, Forecasting, and Interpolation. In Allan Tucker, Frank Höppner, Arno Siebes, and Stephen Swift, editors, *Advances in Intelligent Data Analysis XII*, Lecture Notes in Computer Science, pages 162–173, Berlin, Heidelberg, 2013. Springer.

**AUTHOR CONTRIBUTIONS**

All authors designed the study. TV, IK, MS, SC and NA evaluated the data. TV, MS and SC developed the model. All authors analyzed the results and wrote the manuscript.

**COMPETING INTERESTS**

The authors declare no competing interests.