

Human Mobility from theory to practice: Data, Models and Applications

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ABSTRACT

The inclusion of tracking technologies in personal devices opened the doors to the analysis of large sets of mobility data like GPS traces and call detail records. This tutorial presents an overview of both modeling principles of human mobility and machine learning models applicable to specific problems. We review the state of the art of five main aspects in human mobility: (1) human mobility data landscape; (2) key measures of individual and collective mobility; (3) generative models at the level of individual, population and mixture of the two; (4) next location prediction algorithms; (5) applications for social good. For each aspect, we show experiments and simulations using the Python library "scikit-mobility" developed by the presenters of the tutorial.

CCS CONCEPTS

• **Information systems** → **Data mining**; • **Computing methodologies** → *Modeling methodologies*.

KEYWORDS

Human Mobility; Artificial Intelligence; Data Science; Generative Models; Predictive Algorithms

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1 TOPIC AND RELEVANCE

The availability of geo-spatial mobility data (e.g., GPS traces, mobile phone records, social media records) is a trend that will grow in the near future. In particular, this will happen when the shift from traditional vehicles to autonomous, self-driving, vehicles, will change individual and public transportation, transforming our society, the economy and the environment. For this reason, understanding and modeling human mobility is of paramount importance for many

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present and future applications such as traffic forecasting, urban planning, estimating migratory flows, and epidemic modeling [12]. In this tutorial we will present a concise and intuitive overview on both the fundamental modeling principles of human mobility and artificial intelligence models applicable to specific mobility-related problems¹. Starting from the general laws that govern human mobility, we will drive the audience through the main models for human mobility highlighting the parallelism between statistical and deep learning models, presenting the recent advances of the latter that are nowadays representing the state-of-the-art in many human mobility tasks, like next location prediction. To this end, we will review the state of the art of five aspects:

(1) The human mobility data landscape

A natural starting point is to describe the nature of empirical data which has been used in mobility research. In this part, we outline the main data sources available for mobility research and the relevant information that can be extracted from them. [3, 4, 6, 17, 35]

(2) Under the microscope: Measuring individual and collective mobility patterns

In this part, we will review some of the fundamental metrics and representations used to characterize human mobility, such as trip distance [8, 13], radius of gyration [13, 24, 25], mobility entropy [19, 34], origin-destination matrix [7], mobility motifs [30], and more.

(3) Agents on the move: simulating mobility patterns

This part will review the state of the art for generative models at both the individual level (i.e., generation of individual spatio-temporal trajectories) [2, 15, 23–25, 33] and the population level (i.e., generation of mobility flows) [16, 31, 32, 39].

(4) Where's next? AI for human mobility

After a short review of various artificial intelligence and machine learning models for human mobility [21, 22, 36, 38, 43] we will review recent advances based on deep learning, with particular focus on next location prediction [10, 18, 40, 41, 44].

(5) Human mobility for Social Good and future challenges

In this part, we will show how developing accurate predictive and generative mobility models can be greatly beneficial for several aspects of social good, from mobility in emergency

¹The online version of the tutorial and all the updated material can be found at <https://humanmobility-tutorial.github.io/>

scenarios [14] to the prevention of epidemic diffusion [9], nowcast well-being [26] and even the design of more sustainable smart cities [11]. We will discuss about present and future challenges on mobility-related problems such as ride-sharing [29], automatic discovery of urban regions [37, 42], prediction of health from human displacements [1, 5] and traffic forecasting [20, 28]. Finally, we discuss privacy issues related to the analysis of human mobility data [27].

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