ENCODING URBAN TRAJECTORY AS A SENTENCE: DEEP LEARNING INSIGHTS FOR HUMAN MOBILITY PATTERN *

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Abstract

Rapid advancements in deep learning technology have shown great promise in helping us better understand the spatio-temporal characteristics of human mobility in urban areas. [1, 2] There exist two main approaches to spatial deep learning models for urban space - a convolutional neural network (CNN) which originated from visual data like satellite image [3], and a graph convolutional network (GCN) which is based on the urban topologies such as road network and regional boundaries [4]. However, compared to language-based models that have recently achieved notable success, deep learning models for urban space still need further development. In this study, we propose a novel approach that addresses the trajectories of a trip as sentences of a language and adapts techniques like

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word embedding*[5] from natural language processing to gain insights into human mobility patterns in urban areas.

Our approach involves processing sequences of spatial units that are generated by a human agent's trajectory, treating them as akin to word sequences in a language. Specifically, we represent individual trajectories as sequences of spatial vector units using 50×50 meters grid cells to divide the urban area. This representation captures the spatio-temporal changes of the trip, and enables us to employ natural language processing techniques, such as word embeddings and attention mechanisms, to analyze the urban trajectory sequences. Additionally, we leverage word embedding models from language processing to acquire compressed representations of the trajectory. These compressed representations contain richer information about the features, while minimizing the computational load.

To evaluate the effectiveness of our approach, we are designing an experiment to validate that our urban areal embedding can be used to infer a mobile phone-assessed travel pattern. We represent trajectories based on the travel log and apply our language-like deep learning model to analyze and predict the spatio-temporal human mobility pattern in urban areas. It will be compared with the results of existing baseline models for human mobility prediction.

Our approach offers several contributions to urban planning. By leveraging the techniques of natural language processing, it can easily input the spatial information of trajectories into a deep learning model. The development of a deep learning model for urban planning can provide new insights into the underlying mechanisms and relationships between the built environment, socio-economic demographics, and travel behaviors. Combining with the existing urban big data, the deep learning model can assist to inform decisions regarding the prediction of human mobility, the design of public spaces and streets, and evidence-based urban planning.

In summary, our novel approach of encoding urban trajectories as sentences in a language, and adapting natural language processing techniques, offers a new perspective on understanding and predicting spatio-temporal patterns of human mobility in urban areas. We anticipate that our results will demonstrate the advantages of this language-based approach and provide new insights into the underlying mechanisms and relationships between various factors that influence human mobility patterns.

Keywords: human mobility, urban trajectory, deep learning model, natural language processing

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*In this abstract, we use the terms "representation" and "embedding" interchangeably.

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