論 文 の 内 容 の 要 旨

論文題目　Citywide Human Mobility Estimation using Deep Learning
(深層学習を利用した都市スケールでの人々のモビリティ推定)

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With the progress of urbanization, more and more people are now living in urban areas with very high population density. The agglomeration of population and industries has improved the cities' production efficiency as well as provided many conveniences for the people living there. However, at the same time, dense urban areas have also emerged many new challenges due to the concentration of population and industries. In order to find possible solutions to these challenges, many different types of data sources have been collected from cities via different sensors. We divide the collected data into two kinds: data with the static feature, and data with the dynamic feature, according to what kind of information they contained. For example, road networks, street maps, et al., mainly reflect the static characteristics of the city. In contrast, surveillance videos, GPS positioning data, et al. mainly reflect on the dynamic characteristics of the town. These continuously collected urban data gave birth to the concept of urban computing. In recent years, many studies use these data with the dynamic characteristics of cities to solve different problems in cities, such as traffic forecasting, urban planning, et al. However, we must admit that urban sensing and data acquisition are still a significant challenge. Given the two main problems existing in GPS trajectory data that simulate citywide human mobility: 1) privacy protection, 2) sampling deviation and noise, we hope to use deep learning-based methods for human mobility estimation.

In Chapter 2, we first briefly introduced the concept of generative models and the reasons for using generative models for human mobility estimation. We first define the problem of citywide human mobility estimation as a Bayesian inference problem. We assume that no matter how complex a human mobility trajectory is, we can always find a probability distribution in the hidden space to characterize the information contained in this complex trajectory. Hence, the key to human mobility estimation is finding the posterior distribution of this hypothetical hidden space distribution when the actual trajectory is observed. We hope to solve this problem because the hidden space distribution contains the necessary information for each complex trajectory. At the same time, we can avoid the possibility of privacy violation when using the trajectory directly. Furthermore, suppose we can find the joint distribution of the hidden space distribution and the actually observed trajectory. In that case, we can also sample from the hidden space distribution to reduce the sampling bias of the collected trajectory data. This chapter uses the framework of variational inference to solve this inference problem and uses LSTM as Encoder and Decoder to complete the conversion between trajectory data and hidden space distribution. The experimental results show that our method can achieve our goal. Nevertheless, at the same time, we also discovered the limitation that the newly generated virtual trajectory does not comply with the constraints of geographic information.

Chapter 3 considered the advantages and limitations of directly using the generative model for human mobility estimation and considered improving two of these limitations. The first limitation is that when we generate new virtual data directly using the generative model, the newly generated trajectory data does not comply with geographic information constraints. That is, the car could appear in an area outside the road network. The second limitation is that it is difficult for us to quantitatively measure the authenticity of the newly generated virtual trajectory data. We naturally think that we can use map matching to match the newly generated trajectory to the road network regarding the first limitation. However, we have noticed that such post-processing will change the citywide human mobility pattern. Therefore, we first used the shortest distance with the map matching method to conduct a simple experiment to measure the change of the citywide human mobility pattern of the post-processing virtual trajectory. The experimental results show that the citywide human mobility pattern represented by the post-processing trajectory data has probably changed by more than 20%. Then, from the perspective of trajectory similarity, we use the retrieval idea to construct a retrieval-based human mobility estimation model. In this way, we can avoid the human mobility pattern change brought by map matching as post-processing and avoid the problem of quantifying the authenticity of the newly generated virtual trajectory. We first use the deep learning model to convert complex trajectories into hidden space distributions. We then use the distance between the hidden space distributions corresponding to different trajectories to complete a quick search with the k-d tree technique. In the experiment, we compared the deep learning model with the traditional trajectory similarity method. We found that the deep learning model, especially based on the two-way LSTM and VAE model, obtained the best results. The limitation of the retrieval-based model is that we need a vast historical trajectory database, and we do not know how to estimate the appropriate weight of each observed trajectory in citywide human mobility.

Chapter 4 proposed a differentiable projection method to construct a deep learning model with linear constraints. This problem is worth studying because in some scenarios where we can get some simple prior knowledge, constrained deep learning always gives better results than conventional deep learning models as a pure data-driven algorithm. In this chapter, we give the theoretical derivation as a piece of evidence for the above conclusions. In our understanding, prior knowledge and constraints are synonymous, so that we can treat the information provided by some heterogeneous data as constraints. This chapter provides a theoretical basis and implementation method for the work of the next chapter 5. As long as the information provided can be written in a linear form, we can use the method of this chapter to model. We start from a linear equality constraint conditions problem. We could give a projection method for solving this linear equality constrained problem if the constrained conditions are independent. However, there is no straightforward way to use the projection method to solve the linear inequality constrained problems. However, fortunately, we can use a partial projection algorithm to make the projected points closer to the constrained region than the original points. Then we propose a differentiable projection method for deep learning based on this theorem. At the same time, we also used some synthetic data to conduct experiments to verify the effectiveness of this method.

In Chapter 5, we made a simple application of the constrained network model proposed in Chapter 4 in human mobility estimation. The framework proposed in this chapter is an improvement to the limitations of Chapter 3. We hope to estimate the individual human mobility trajectory while also estimating the weight of this trajectory in citywide human mobility. To this end, we used simulated heterogeneous OD data to construct our constraint information. First, we convert the trajectory data into a Gaussian mixture of hidden space distribution. Then our Encoder also needs to output the weight of this trajectory to construct citywide human mobility. Since we use constrained deep learning as our Encoder, the weight of each output can satisfy the constraint information, which makes our results better than the conventional deep learning model. The experimental results show that the proposed constrained human trajectory generation model has the best results in estimating citywide human mobility without losing the ability to express individual trajectories.

In Chapter 6, we show the work we have done so far, summarize our contributions, and discuss the limitations of the current work. In the future, a possible direction is to carry out a systematic integration of all current work. Besides, it is worth trying to use more kinds of data under the current framework for citywide human mobility estimation. At the same time, we believe that data fusion is also the direction that this research can extend in the future. Because through our current work, we find that the current method has proposed a way to solve privacy infringement when using human mobility data directly. However, a limitation lies in that although our current work reduces the problem of data sampling bias to a certain extent, it is still limited to the use of a single data source, so the final performance still has much room for improvement. In the future, we think we still need to mine more practical information from more different data sets by fusing different data sources to complete human mobility estimation with minor sampling bias.