TrajGDM: A New Trajectory Foundation Model for Simulating Human Mobility

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ABSTRACT

Capturing the universal movement pattern and simulating human mobility is one of the most important trajectory data-mining tasks. Most of the current mobility modeling methods are specially designed to solve a specific task, which leads to questions regarding generalizability. Aiming to construct a general trajectory foundation model to overcome this weakness, we proposed a generative Trajectory Generation framework based on Diffusion Model (TrajGDM) to capture the universal mobility pattern and simulate human mobility. It is capable of solving multiple trajectory tasks through learning the generation of the trajectory. The generation process of a trajectory is modeled as a step-by-step uncertainty reducing process. A trajectory generator network is proposed to estimate the uncertainty in each step, and a trajectory diffusion and generation process is defined to train the model to simulate the real dataset. Finally, we compared the proposed method with 5 strong baselines on 2 public trajectory datasets: T-Drive and Geo-life. By comparing 5 different evaluation metrics, the result showed that the similarity between generated and real trajectories' movements measured by Jensen-Shannon Divergence improved by at least 50.3% in both datasets. It also addresses the problem of generating diverse trajectories, which is ignored by most previous models. Then, we conducted zero-shot experiments on two trajectory tasks, trajectory prediction and reconstruction. In trajectory prediction, the accuracy of TrajGDM's zero-shot inference is up to 23.4% higher than that of the benchmark method, and the reconstruction accuracy increased by a maximum of 25.6%.

CCS CONCEPTS

• Information systems → Spatial-temporal systems.

KEYWORDS

Trajectory generation; Diffusion model; Foundation model; Geospatial AI Infrastructure

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1 Introduction

Modeling human mobility properly is essential to all trajectory tasks. Despite the fact that the mobility pattern is universal in a trajectory dataset, most of the current models are unable to learn the universal mobility pattern in a dataset and solve various related tasks. Learning to simulate trajectories is one way to capture the universal mobility pattern. A trajectory generation model aims at generating a synthesized trajectory dataset based on the mobility pattern learned from the real one [1]. Accurately simulation of trajectories requires a model to learn the generation process of trajectories, which directly reflects the universal mobility pattern. Thus, learning the universal pattern through simulating the generation process of a trajectory could provide a solution for solving most of the trajectory modeling tasks.

Currently, the majority of the traditional trajectory generation models are based on the Generative Adversarial Network (GAN) and employ a trajectory prediction model as its generator [1,2]. With the absence of the latent space, they fail to generate diverse trajectories. Moreover, their trajectory prediction models maximize the likelihood of $P(x_i|x_1, \dots, x_{i-1})$, where x_i denotes the trajectory point at time i, while it is different from modeling $P(x_1, \dots, x_i)$, which is the actual target for trajectory generation. Besides that, the training object of a GAN based model is to judge whether a generated trajectory looks real, it ignores the distribution of the trajectory dataset. All these problems lead to the geography distribution formed by all generated trajectories that cannot be promised to follow the distribution of its imitated data.

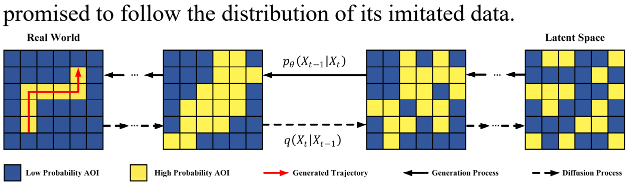

Figure 1: The intuition of the TrajGDM.

Inspired by the bloom of generative foundation models [3], in this study, we propose a generative Trajectory Generation framework based on Diffusion Model (TrajGDM). It aims at modeling the universal trajectory mobility pattern through learning the trajectory generation process. In our model, the trajectory generation process is modeled as an uncertainty reducing process shown in figure 1. X_t denotes the trajectory at step t of the trajectory generating process p, and diffusion process q. A deep learning network with parameter θ is employed to estimate the uncertainty in X_t based on X_{t-1}.

2 Methodology

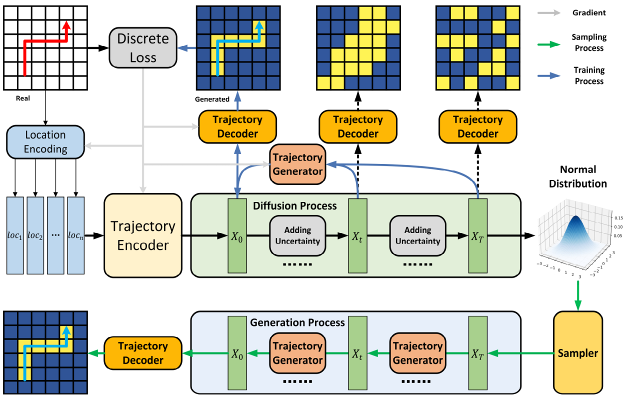

Figure 2: Structure of the TrajGDM framework.

According to figure 2, there are two important parts in TrajGDM, the diffusion process and the generation process. The generation process models the generation of a trajectory as an uncertainty removing process. We estimate the uncertainty with a deep learning network named trajectory generator. To train this trajectory generator and other structures, we construct a diffusion process based on a Markov chain. In the diffusion process, gaussian noise is added step by step, for T steps in total, to simulate the uncertainty in the trajectory.

We design a trainable location encoding method, combined with a trajectory encoder, so a discretely represented trajectory can be mapped into the feature space. This allows the diffusion process and the generation process to add and remove uncertainty in the trajectory with a numeric function. Likewise, we also design a trajectory decoder to decode the trajectory from its representation in feature space.

3 Results

For trajectory generation, we compared TrajGDM with 5 state-of-the-art baselines, including TrajVAE [4], MoveSim [1] and SeqGAN [2]. The generated trajectory datasets are evaluated from 5 aspects to measure their similarity with the real one. The comparison results show that, our model achieves significant improvement for at least 57.2% in simulating individual mobility and 25.9% in simulating trajectories' geography distribution. The generation diversity of TrajGDM also outperforms all SOTA methods without any suspense. The minimum repetition rate for trajectories generated by the SOTA method reached 27.8% in the Geo-life dataset, while the rate is only 2.2% for TrajGDM. As one of few real generative trajectory generation models, the performance of our model surpassed the GAN based models.

We conduct zero-shot trajectory prediction and reconstruction experiments with our model. In trajectory prediction, the accuracy of TrajGDM's zero-shot inference is even 23.4% higher than that of the benchmark method in the T-Drive dataset and is only slightly lower than that in the Geo-life dataset. In trajectory reconstruction, our method also shows great improvement for a maximum of 25.6% in the accuracy of trajectory reconstruction than that of traditional methods. Moreover, the flexibility of TrajGDM allows it to reconstruct a trajectory with multiple missing points, which is not capable for most others.

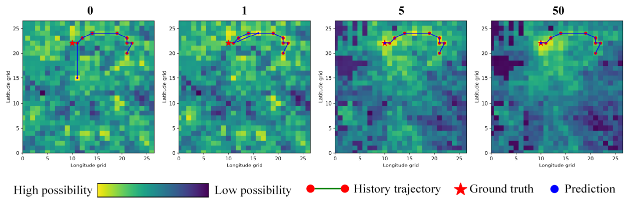

Figure 3: Possibility distributions and prediction results of different steps in the generation process of zero-shot prediction.

3 Conclusions

In this work, we proposed a generative trajectory generation model. As one of the few real generative models for trajectory generation, it shows significant improvement in simulating the mobility of an individual trajectory and the geography distribution of trajectories. Its ability to generate diverse and realistic trajectories is unique. It learns the universal mobility pattern in the trajectory dataset and is able to solve multiple trajectory tasks without extra training. To the best of our knowledge, there are few trajectory models that are able to generate, predict, reconstruct trajectories at one time. TrajGDM shows flexibility in modeling human mobility, and it has shown great potential to become a trajectory foundation model. In the future, we will further explore its ability in other trajectory tasks and try to understand the relationship between the model's latent feature space and reality.

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