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 propose 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 6 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’ movement character measured by Jensen-Shannon Divergence (JSD) 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. Moreover, we applied zero-shot inferences on two basic trajectory tasks: trajectory prediction and trajectory reconstruction. The zero-shot prediction accuracy of our model is up to 23.4% higher than the benchmark, and the reconstruction accuracy improves by a maximum of 25.6%.

CCS CONCEPTS
• Information systems • Information systems applications • Spatial-temporal systems • Location based services

KEYWORDS
Trajectory generation; Diffusion model; Foundation model

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ACM Reference format:

1 Introduction
Modeling human mobility plays a central role in a wide range of applications. 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 most of the trajectory modeling tasks.

Currently, the majority of the 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 \( P(x_t|x_1, ..., x_{t-1}) \), where \( x_t \) denotes the trajectory point at time \( t \), while it is different from modeling \( P(x_1, ..., x_t) \), 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 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 $\theta$ 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 processes 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 specifically designed Transformer based 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, such as trajectories recorded in location indexes, 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 by JSD to measure their similarity with the real one. The result shows that, in the metric used for evaluating individual mobility performance JSD decreased by at least 50.3%, and 25.9% in the metric evaluating trajectories’ geography distribution. The generation diversity of TrajGDM also outperforms all SOTA methods without any suspense. The minimum repetition rate for trajectories generated by other SOTA methods 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 GAN based models.

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

4 Conclusions

In this work, we proposed a generative trajectory generation model. 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 future work, we will further explore its ability in other trajectory tasks and introduce time into the model.

REFERENCES


