Poster Abstract: Generative Modeling of Post-Disaster POI Visits Recovery

Han Li[1*], Yan Zhuo[1*], Chenlong Wang[1], Huandong Wang[2,3], Xinlei Chen[1,4,5†]
[1]Shenzhen International Graduate School, [2]Department of Electronic Engineering, [3]BNRist, Tsinghua University;
[4]Pengcheng Laboratory; [5]RISC-V International Open Source Laboratory
Shenzhen[1,4,5], Beijing[2,3], China

ABSTRACT

The development of Internet of Things (IoT) systems has enabled disaster perception and prediction to be highly accurate. On this basis, high-quality post-disaster Point of Interest (POI) visit data can help city decision-makers develop more sophisticated recovery plans to minimize the cost of recovery. This work focuses on the problem of POI visits generation in post-disaster recovery scenarios, utilizing diffusion model to generate visit recovery curves base on the data from sensor networks. We take the disaster severity as condition and propose a disaster mapping method to map the sensor data to each POI.

1 INTRODUCTION

Smart cities utilize tools such as Geographic Information Systems (GIS) and IoT sensor networks for real-time monitoring of natural disasters[5]. Analyzing this data allows for early warnings and quick response[8], reducing the losses caused by disasters. As sensor networks continue to improve thier data collection capabilities[10][7], there is still a lack of grasp of the patterns and details of post-disaster recovery, which support the deployment of many post-disaster rescue and resource dispatch methods[3][9][2]. Different areas of the disaster-stricken region, due to various severity levels, should adopt different disaster response measures. The model proposed in [4] simply models the post-disaster recovery process and proposes that the degree to which a location is affected by a disaster depends on the time and distance from the disaster point, but that's not enough to get precise data about the recovery process. The model in [11] utilize deep learning methods to generate POI visits mainly focuses on learning regular patterns in daily situations, while there is little research on the changing patterns of POI under specific situations, such as various disasters. By generating the post-disaster visitation curve of each POI within the disaster area, it is possible to grasp in advance the expected disaster situation in each area before the disaster occurs, thus refining disaster defense deployment[3].

In this work, we propose a post-disaster visitation generation model (DiffusionPOI). DiffusionPOI can generate the visitation volume of each POI within the disaster area during the post-disaster recovery process based on the intensity of the disaster before it occurs. The main contributions of this work include:

- A novel generative framework to model the post-disaster visitation recovery process, enabling IoT-based disaster response systems to guide the entire process from pre-disaster prediction to post-disaster resource allocation.
- We propose an attention-based disaster mapping method that accurately map the severity of disasters from sensor networks to POIs. Additionally, the knowledge-enhanced denoising process thoroughly considers the geographical and functional correlations among POIs.

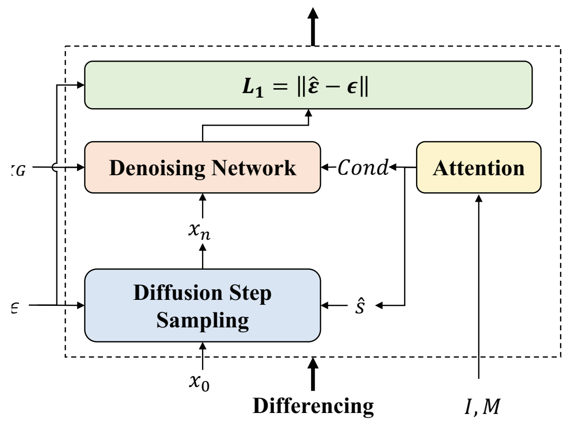

Figure 1: The framework of our model.

2 METHOD

Based on the diffusion model and knowledge graph, we propose a generation model shown in Figure 1. An attention-based disaster mapping mechanism performs as the condition to guide the generation process of the diffusion model. During the post-disaster recovery process, we input differential data into the model so that the gradual decay process of the difference between the number of visits and the steady state can be better modeled. In addition, we use knowledge graphs to extract geographical and functional relationships between POIs.

2.1 Disaster Conditioned Denoising Process

In order to extract the severity and features of POIs, we designed a conditional module to guide the generation process of visit volume, as shown in Figure 1. The calculation of POIs' severity of disaster involves a mapping from sensors to POIs. For each POI i, its severity of impact PI_i can be determined based on the data from all sensors. According to the model proposed in [4], the disaster severity of a POI mainly depends on the distance to the dsaster, formalized as the distance relation matrix M. To improve the accuracy of this mapping, we introduce an attention mechanism, modeling the disaster mapping as a learnable process to better capture information

*Both authors contributed equally to this research.
†Corresponding author.

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from core disaster area collection points. Formally, we first derive the disaster mapping matrix M' based on the disaster information set I and the distance relation matrix, as follows:

$$M' = \text{Softmax}\big(\text{Attention}(I, M, M)\big). \tag{1}$$

Here, I, M, and M represent the Q, K, V of the attention module, respectively.

Then, based on the disaster mapping matrix, we implement the mapping from data collection points to the severity of disaster impact on POIs, obtaining the severity of impact PI for each POI:

$$PI_i = \sum_{j \in C} M'_{ij} \cdot I_j. \tag{2}$$

Next, PI and the POI features $c \in \mathbb{R}^{N_{POI} \times d_{fea}}$ are fed into a two-layer feedforward neural network with Leaky ReLU as the activation function, with $f_\theta(PI, c)$ serving as the estimated post-disaster visit volume to guide the generation process of visit volume. Overall, the conditional module can be represented as $F_\psi(I, M, c)$. Based on this, the forward diffusion process is formalized as:

$$q\big(x_n | x_0, F_\psi(I, M, c)\big) = \mathcal{N}\big(x_n; \sqrt{\alpha_n} x_0 + (1 - \sqrt{\alpha_n}) F_\psi(I, M, c), (1 - \alpha_n) I\big). \tag{3}$$

In the backward denoising process, the posterior is defined as:

$$q(x_{n-1} | x_n, x_0, I, M, c) = \mathcal{N}\Big(x_{n-1}; \tilde{\mu}\big(x_n, x_0, F_\psi(I, M, c)\big), \tilde{\beta}_n I\Big). \tag{4}$$

The training of the conditional module is considered a subtask and is optimized using MSE Loss. During training, $F_\psi(I, M, c)$ is pre-trained first, followed by the training of the entire diffusion model and $F_\psi(I, M, c)$.

2.2 Differential-Based Recovery Information Extraction

The recovery of visit volumes to POIs presents a process that gradually approaches a steady state, with the rate of change in visit volumes decreasing over time. To capture more features during this change process, our model does not directly generate POI visit volumes, but generates the change in visit volumes compared to the previous time point, denoted by $\{\Delta v_1, \Delta v_2, \ldots, \Delta v_T\}$. Then, based on the current visit volume data v_0, we obtain the sequence of visit volumes $V = \{v_1, v_2, \ldots, v_T\} = \{v_0 + \Delta v_1, v_1 + \Delta v_2, \ldots, v_{T-1} + \Delta v_T\}$.

2.3 POI Knowledge Graph Enhanced Network

Inspired by the previous work[6], we construct a POI knowledge graph. Since POIs that are near each other or share the same function tend to exhibit similar patterns in visit volume changes, we represent POIs as entities, with *NearBy* and *SameFunc* as relationships. To more effectively extract information from the knowledge graph, we employ the TuckER model[1], which utilizes Tucker decomposition as the scoring function for the knowledge graph.

3 PRELIMINARY EVALUATION

We conduct experiments using meteorological and POI access datasets from Safegraph. Disaster data comes from the sensor network of weather stations. For hurricanes, we select precipitation (PRCP) and wind speed (WSF2) as disaster intensity measures. As show in Table 1, the experiment on Hurricane Dorian in Florida shows the superiority of our model in post-disaster visit generation problems.

Table 1: Performance of our model with baselines.

	MAE	RMSE	SMAPE	MMD
Our Model	88.40	136.07	0.44	4.82
RCGAN	139.34	204.15	0.96	7.90
CVAE	107.14	157.26	0.56	5.60

We train the model within a specific area in Florida and applied it to generate visitation volumes in another area, achieving results that surpass current representative generative models. The training and generation overhead for our model at the scale of a state can be contained within the computational power and memory capacity of a single RTX A6000 graphics card.

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