SHORT-PAPER

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ABSTRACT

Generating mobile traffic in urban contexts is important for network optimization. However, existing solutions show weakness in capturing complex temporal features of mobile traffic. In this paper, we propose a Knowledge-Guided Conditional Diffusion model (KG-Diff) for controllable mobile traffic generation, where a customized denoising network of diffusion model is designed to explore the temporal features of mobile traffic. Specifically, we design a frequency attention mechanism that incorporates an Urban Knowledge Graph (UKG) to adaptively capture implicit correlations between mobile traffic and urban environments in the frequency domain. This approach enables the model to generate network traffic corresponding to different environments in a controlled manner, enhancing the model's controllability. Experiments on one real-world dataset show that the proposed framework has good controllability and can improve generation fidelity with gains surpassing 19%.

CCS CONCEPTS

• **Networks** → **Network simulations**; • **Information systems** → **Spatial-temporal systems**.

KEYWORDS

Generative model; Diffusion models; Mobile traffic generation

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1 INTRODUCTION

Mobile web applications have become an integral part of people's daily lives, with online socializing platforms such as Instagram, and e-commerce sites like Alipay. As a result, a large volume of mobile traffic data is generated, providing valuable information on network status and human activity. The traffic data captures time-varying network information from different locations, which can be used by both researchers to solve within and beyond networking problems. For example, utilizing the traffic data to develop resource scheduling/optimization algorithms [4, 9] or inferring demographic patterns [3] and implementing urban planning [11]. Accessing to such data is essential for conducting research in different applications, while the data is limited to a few researchers due to the complexity and resource-intensiveness of data collection [2], as well as strict local policies and regulations [7]. Moreover, mobile traffic data contain sensitive individual or regional information. Sharing such data poses significant privacy risks and legal implications. Therefore, researchers face significant challenges in acquiring and utilizing real-world mobile traffic data for their studies.

One practical and promising solution is to synthesize mobile traffic data. The primary objective of the solution is to create high-fidelity, time-varying mobile traffic data in urban contexts, which is a conditional generation process [15]. It involves information such as populations, land uses, and Point of Interest (POI) distributions within the city to serve as conditions to control the generated data. Through the method, the generated data exhibits similar characteristics to real-world data given arbitrary contextual features, which enables researchers to produce their customized network datasets. Existing studies have made initial efforts to generate mobile traffic data. For example, Wang *et al.* [14] utilized a Generative Adversarial Network (GAN) with causal convolution to capture the temporal dependencies of network traffic data. Xu *et al.* [15] proposed a SpectraGAN framework that leverages two GANs from both time and frequency domains to generate mobile traffic data. Gong *et al.* [5] used Variational AutoEncoder (VAE) to impute mobile traffic data in a compressed manner. However, existing studies encounter two significant limitations that degrade their overall performance.

(i). Traditional generative models such as VAE and GAN struggle to generate network traffic data with high controllability. VAE compresses origin data into a latent space, which fails to capture the intricate correlation between conditions and network traffic, leading to a situation where the conditions cannot effectively control the model. GAN simultaneously trains two neural networks, which suffer from instability during the training process and the phenomenon of mode collapse. These issues result in the models only generating fixed patterns of network traffic data and failing to utilize conditional information to enhance the controllability.

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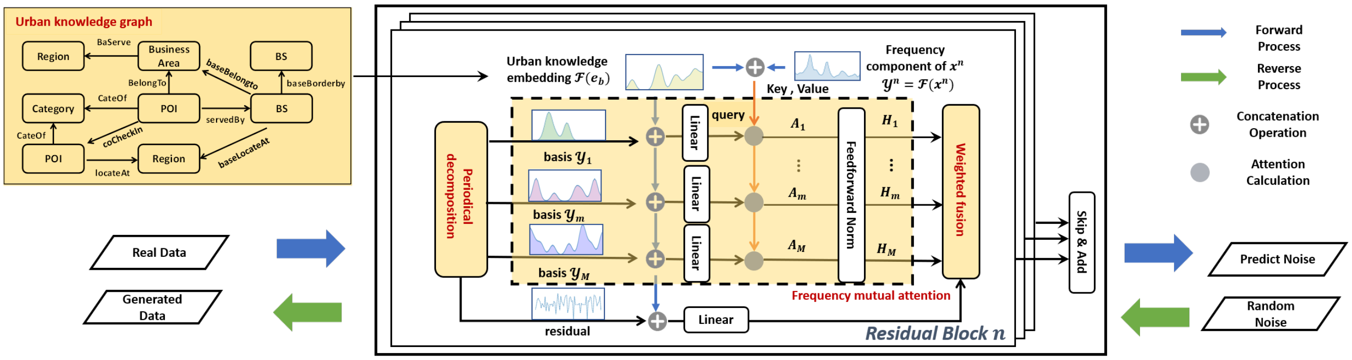


Figure 1: KG-Diff framework for urban mobile traffic generation.

(ii). Existing studies fail to model various periodic features of mobile traffic. Mobile traffic shows multi-scale periodicity in the temporal domain. To characterize the periodic patterns and aperiodic features, some works manually decompose mobile traffic with a few fixed patterns, such as daily patterns (with 24 hours) or weekly patterns [6], while the type of decomposition neglects some small-scale periods that will reduce the overall fidelity of generated data. Moreover, there exists a correlation between urban environments and network traffic. Existing research often overlooks this potential correlation, leading to a degradation of generation performance.

To mitigate the above limitations, we propose a Knowledge-Guided conditional Diffusion model (KG-Diff) with a customized denoising network for generating mobile traffic data in the urban environment. Our contributions can be summarized as:

- We propose an attention-based approach to incorporate urban contextual features extracted from an Urban Knowledge Graph (UKG) into the diffusion model. Unlike GANs/VAEs that generate data through a single forward propagation process, the attention approach is applied in each denoising step to fuse conditions with network traffic. This enhances the control of conditional information over the generation process, which tackles the first limitation.
- We further decompose network traffic into multi-scale periods in the frequency domain. Unlike manually specifying a fixed number of periods, the frequency-based decomposition adaptively explores the potential correlations between different periods of network traffic and urban contextual features, which enhances the generation fidelity and addresses the second limitation.
- We evaluate the KG-Diff on a real-world dataset. The result demonstrates the model improves generation fidelity by 19% and shows good controllability to generate desired traffic patterns.

2 PROBLEM FORMULATION AND METHOD

2.1 Mobile Traffic Generation Problem

Our article focuses primarily on downlink traffic within each BS communication area. The generation problem of mobile traffic is defined as: *Given a target BS, generating the mobile traffic sequence $\mathcal{S}$ across a period conditioning on urban contextual information C.* However, generating mobile data in an urban environment is not a straightforward task. The urban environment encompasses various information such as population, POIs, and regional functions, which is hard to comprehensively characterize. On the other hand, there exists complex correlations between urban features and mobile traffic. Effectively capturing and utilizing the correlation to guide traffic generation needs to be addressed.

2.2 KG-Diff Framework

The framework is depicted in Figure 1 which includes 4 units.

2.2.1 Urban feature construction unit. We employ Urban Knowledge Graph (UKG) [6, 8, 13], covering entities like BS, POIs, and functional regions in mobile networks, which integrates geographical and semantic relations to fully depict urban features. It includes triplets on factual knowledge as $K = \{h, t, r\}$ that denotes head entities, tail entities, and linking relations. To effectively extract context features from the UKG, we leverage a representation learning method, TuckER[16], to learn the relationships r and obtain latent embeddings of each entity, so that the embeddings can serve as condition vectors of the denoising network. Specifically, TuckER measures the plausibility scores for triplet $\{h, t, r\}$ as

$$v(h, t, r) = \mathbf{W} \times e_h \times e_t \times e_r, \tag{1}$$

where $W \in \mathbb{R}^{d \times d \times d}$ is the core tensor of the model, d and $\times_i$ represent the embedding dimension and the tensor product. The $e_h, e_t \in \mathbb{R}^d$ is the learnable vector of UKG entities. By optimizing the cross-entropy loss between positive triplets and negative triplets, we can obtain the KG Embedding (KGE) as $\mathcal{K} = \{k_b \in \mathbb{R}^d\}$ and input to the frequency mutual attention unit.

2.2.2 Periodical decomposition unit. The unit is responsible for transforming the network traffic from the time domain to the frequency domain. Denote hidden features as x^n that is the concatenation of noise data and position embeddings in denosing step n, we transform x^n into frequency-domain $\mathcal{Y}^n$ via Fourier transformation and decompose $\mathcal{Y}^n$ into M frequency bases $\{\mathcal{Y}_m\}_M$ and one residual $\mathcal{Y}_r$. The decomposition process can be expressed as

$$\mathcal{Y}_m = (0, ..., \arg top(|\mathcal{Y}^n|)_{mf_0:(m+1)f_0}, ..., 0), \tag{2}$$

$$\mathcal{Y}_r = \mathcal{Y}^n - \sum_{m=1}^{M} \mathcal{Y}_m, \quad \text{where } \mathcal{Y}^n = \mathcal{F}(x^n), \tag{3}$$

where $\arg top(|\mathcal{Y}|)_{mf_0:(m+1)f_0}$ denotes selecting the maximum frequency point in the range from mf_0 to $(m+1)f_0$ based on the amplitude of $\mathcal{Y}$ and the rest frequency components of $\mathcal{Y}_m$ are set as 0, where the $\mathcal{F}$ is the Fourier transformation operation.

2.2.3 *Frequency mutual attention unit.* The unit extracts the correlations of each frequency basis $\mathcal{Y}_m$ and the urban contextual features k_b. To achieve this goal, we propose a frequency-based mutual attention mechanism that utilizes scaled dot-product attention: $Score(Q_m, K) = Softmax(\frac{Q_m K^T}{\sqrt{d}})$, $A_m = Score(Q_m, K)V$, where Q, K, V represent queries, keys, and values that can be denoted as

$$Q_m = W^Q[\mathcal{Y}_m \oplus \mathcal{F}(k_b)], K = W^K[\mathcal{Y} \oplus \mathcal{F}(k_b)], V = W^V[\mathcal{Y}^n \oplus \mathcal{F}(k_b)], \tag{4}$$

where $\oplus$ denotes the concatenation of tensors, W^Q, W^K, W^V are weights of linear projection. The frequency component of urban knowledge is passed into the attention process since we argue that contextual features not only affect mobile traffic in the temporal domain but also produce dependencies in the frequency domain.

2.2.4 *Weighted fusion unit.* After the frequency attention process, we obtain M hidden representation H_m and one residual $\mathcal{Y}_r$. To recover the features back to the time domain while maintaining the consistency of the amplitude of the original features, the unit fuses all the M bases. Meanwhile, we also integrate the KGE k_b with the residual traffic in the time domain, to capture the disturbing features. The overall fusion process can be formulated as

$$\{\alpha_m\}_{m=1:M} = Softmax(W^M|\mathcal{Y}_m| + b^M), \tag{5}$$

$$y^T = W^y[\mathcal{F}^{-1}(\sum_m \alpha_m \mathcal{H}_m) + W^r \mathcal{F}^{-1}(\mathcal{Y}_r) \oplus k_b], \tag{6}$$

where W^M, b^M, W^y, and W^r are learnable parameters. Finally, the model is optimized recurrently with the objective loss as

$$minL(\theta) = min\mathbb{E}_{x^0 \sim q(x^0), \epsilon \sim N(0,I)}[||\epsilon - \epsilon_\theta(x^n, n|k_b, y^T)||^2], \tag{7}$$

where $q(x^0)$ is the noise scheduling distribution and ϵ_θ represents the predicted noise vectors.

The proposed KG-Diff embraces two advantages. First, we construct an UKG that incorporates multiple semantic relations such as geographical proximity and functional similarity, which can fully characterize urban complex features. Second, the frequency attention mechanism decomposes the origin network traffic into multiple periodic bases, adaptively capturing the implicit correlations between urban context and various periods of network traffic.

3 EVALUATION

We perform experiments on real mobile datasets to evaluate the fidelity and controllability of the proposed KG-Diff framework.

Dataset. We collect mobile datasets from Beijing, a large city in China, The dataset covers mobile traffic data from surpassing 19,000 BSs serving over 200,000 users during a week in October 2021. The dataset has 4 typical types of traffic patterns (pattern 0∼3).

Baselines. We choose the following 6 baselines to evaluate the effectiveness of our proposed method, which covers traffic generation models of both GAN-based and diffusion-based methods. (1). tcnGAN is a manually coded GAN network with Temporal Convolutional Networks (TCNs) [1] as generator and discriminator. (2). ADAPTIVE [16] is a transfer learning generative framework via GAN, which utilizes the UKG to align BS embeddings from one city to another. (3). spectraGAN [15] utilizes two separate GAN networks in time and frequency domains to capture periodic patterns. (4). CSDI is a conditional diffusion model that is trained for time series imputation and prediction [12]. (5). keCSDI is a manually coded generative model based on CSDI, where we expand the side information with urban knowledge k_g learned from the UKG. (6). The Knowledge-Enhanced GAN (keGAN) [6] is a hierarchical GAN framework that divides urban mobile traffic into daily patterns and weekly patterns, conditioning on the concatenation of UKG embeddings and input noise vectors.

Table 1: Mobile traffic generation results. Bold numbers denote the best and _underline_ numbers denote the second-best. Δ represents an improvement from second-best to best.

Datasets	Beijing			
Metrics	JSD	JSD-FO	MAE	CRPS
tcnGAN	0.2689 ± 0.00312	0.1646 ± 0.00047	0.1028 ± 0.00153	0.5435 ± 0.01745
spectraGAN	0.2582 ± 0.00481	0.2007 ± 0.00041	0.1192 ± 0.00106	0.5655 ± 0.01613
CSDI	0.3055 ± 0.00367	0.1716 ± 0.00049	0.1166 ± 0.00154	0.6918 ± 0.01699
ADAPTIVE	0.2486 ± 0.00295	0.2003 ± 0.00057	0.1139 ± 0.00122	0.4913 ± 0.01232
keCSDI	0.2998 ± 0.00267	0.1670 ± 0.00079	0.1119 ± 0.00153	0.6734 ± 0.01703
keGAN	_0.2070 ± 0.00379_	_0.1587 ± 0.00072_	_0.1025 ± 0.00044_	_0.4702 ± 0.015648_
KG-Diff (Ours)	**0.1956 ± 0.00435**	**0.1455 ± 0.00069**	**0.0855 ± 0.00190**	**0.4315 ± 0.01535**
Δ	5.83%	9.07%	19.88%	8.97%

Metrics. We choose Jensen–Shannon Divergence (JSD) and Continuous Ranked Probability Score (CRPS) [10] to assess the distribution fidelity. The first-order of JSD (JSD-FO) [6] is utilized to evaluate the model's stability. Besides, we select Mean Absolute Error (MAE) as the metric to investigate the generation accuracy.

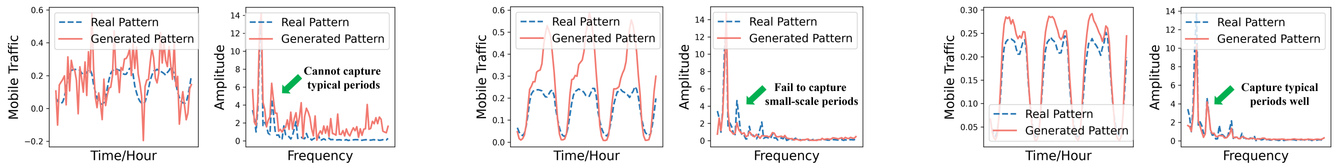
3.1 Mobile Traffic Generation

Table 1 shows the experimental result of the proposed method and all other baselines. KG-Diff achieves the best performance with a maximum improvement of 19.88%. Generally speaking, keGAN performs the second-best in the temporal domain, since it specifies a priori knowledge about the periods with daily and weekly patterns and generates mobile traffic by utilizing the identified patterns.

We then test the quality of generated mobile traffic and the ability to capture the small-scale periods, as shown in Figure 2. From a microscopic perspective, the spectraGAN and keGAN fail to capture the small-scale periods of traffic data while the KG-Diff can well depict the small-scale periods. The spetralGAN generated data without knowledge guidance, causing the algorithm unable to capture the typical periods of traffic data. The keGAN artificially selected fixed periods, which fails to capture "small-scale" periods in the frequency domain. The KG-Diff utilizes the frequency attention mechanism, which not only captures a fixed 24-hour period but also adaptively captures small-scale network traffic periods.

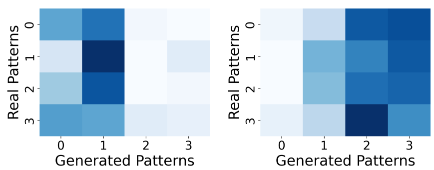
3.2 Control on Mobile Pattern Generation

We then investigate the model's controllability. After the training process converges, we input pattern-wise urban knowledge into the model as test data. For example, in our dataset, the mobile traffic of BS indexed $\{381, 746\}$ have the corresponding pattern of 0. We input the corresponding KG embeddings into the model and analyze whether the generated samples belong to pattern 0. We select four well-trained models: CSDI, keGAN, keCSDI, and KG-Diff, where the results are depicted in Figure 3. It can be observed that CSDI cannot accurately generate traffic data aligned with the target pattern without urban knowledge. For keGAN, although the model inputs urban knowledge as a condition, the model suffers

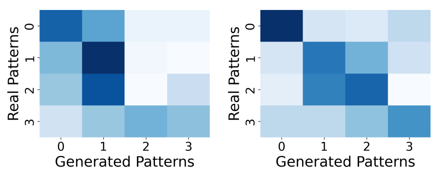


(a) Generated samples of spectraGAN. **(b) Generated samples of keGAN** **(c) Generated samples of KG-Diff**

Figure 2: Comparison of mobile traffic generation. KG-Diff can capture both daily and small-scale patterns of mobile traffic.



(a) Samples of CSDI **(b) Samples of keGAN**



(c) Samples of keCSDI **(d) Samples of KG-Diff**

Figure 3: Controllability of generating patterns. Each row with 4 squares represents the quantity of each generated pattern after inputting a real pattern. The darker the color of the square, the greater the number of generated patterns. KG-Diff can generate corresponding patterns that are consistent with real patterns.

from a mode collapse issue that only learns patterns 2 and 3. For diffusion model-based methods, they exhibit strong controllability under the conditions: as shown in Figure 3 (c), (d), they are capable of generating patterns 0, 1, and 3. While keCSDI can't generate pattern 2 since it only captures periodic features in the temporal domain, struggling to capture the long-term correlations between different time points solely via the temporal domain. In contrast, the proposed KG-Diff conveys KGE in both the temporal and frequency domains. Through frequency domain attention mechanisms, it can better extract the correlations among different periods, enhancing the model's controllability.

4 CONCLUSION

In this paper, we propose the KG-Diff framework to generate urban mobile traffic. We design a denoising network with a frequency attention mechanism conditioning on the environment features that id constructed via the UKG. The framework adaptively captures the correlations between urban contextual features and different periods of network traffic. Our evaluation of a real-world dataset shows our scheme surpasses generation baselines by up to 19.88%. Additionally, KG-Diff successfully captures the correlation between urban contexts and mobile traffic, allowing for controllable generation of traffic patterns with different environmental data.

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