STGGAN: Spatial-temporal Graph Generation

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ABSTRACT

This work addresses research on spatial-temporal graph generation and introduces a new model called "Spatial-temporal Graph Generative Adversarial Network" (STGGAN), which uses a newly developed variable-length Long Short Term Memory network via spatial-temporal random walks.

CCS CONCEPTS

• **Information systems** → **Spatial-temporal systems**; • **Computing methodologies** → **Deep belief networks**.

KEYWORDS

spatial-temporal graph, generative model, urban mobility

ACM Reference Format:
Liming Zhang . 2019. STGGAN: Spatial-temporal Graph Generation. In *27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (SIGSPATIAL '19), November 5–8, 2019, Chicago, IL, USA.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3347146.3363462

1 PROBLEM AND MOTIVATION

Modeling data by means of a graph is a frequent approach adopted in many domains including spatial-temporal systems. Understanding the stochastic nature and latent representation of graphs has been important. For spatial-temporal applications, a specific type of *dynamic graph* is Spatial-Temporal Graph (STG) . STGs have temporal and/or spatial attributes associated with its nodes, edges, or both. Nodes and edges change dynamically with time and location.

An example STG application is modeling user behavior in a metro transit systems. Here, each metro station is treated as a node in a transport graph of a metro system. A temporal edge is a trip from one station to another at a point in time. All trips of a user can be modeled by an STG. Figure 1 depicts such an example. Temporal dynamics and spatial randomness are observed across three days. For the case of a typical commuting pattern. the respective edges in a transport graph do hardly change (same routine). However, different types of trips (tourism) or even parts of the overall commuting pattern could see frequent changes in trips and as such the overall graph portion that is explored. Another stochastic behavior is attributed to the spatial dimension. In many high-density urban areas, several metro stations are within walking distance of any given location and a person could choose any of those stations.

Background and Related works: Among all the previous works, *graph generation* is an important upstream task. The models for graph generation are referred to as *generative models*. The immediate goal of such models is to generate synthetic graphs with similar properties to the original graphs. They are fundamental to a range of downstream tasks such as data augmentation [1], anomaly detection [3], recommender systems [9], or privacy protection [2].

So far *prescribed* models have been used for graph generation. They capture some predefined properties of a graph, e.g., degree distribution, structure of community, clustering patterns. Relevant extensions are developed for dynamic graphs, e.g., temporal stochastic block model, link-node memory models, self-exciting point processes (cf. survey papers [5, 6]). In contrast to prescribed models, *unprescribed* models adopt a deep belief network, which does not rely on predefined assumptions. These recent models include for example GraphVAE [7], GraphRNN [8], and NetGAN [4]. However, those approaches use static graphs and it is not possible to apply them to STGs like our transportation graph example.

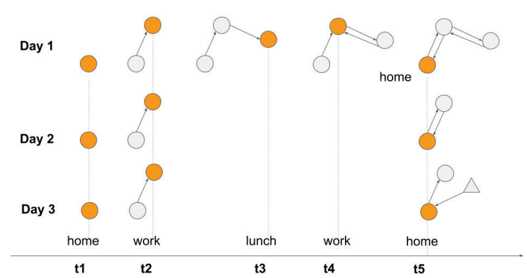

Figure 1: Three days of metro trip - (i) commuting times t_2 and t_5 - no change, (ii) lunch t_3 - change is observed, (iii) Day 3 work station change to other stations (walking distance).

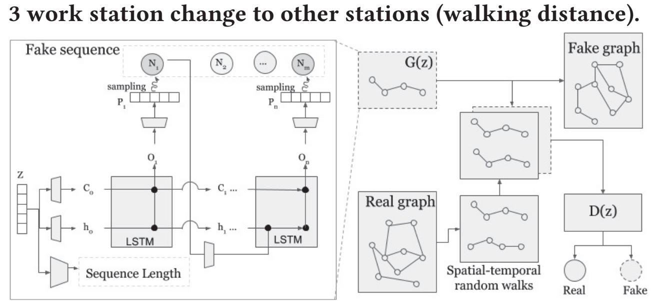

Figure 2: STGGAN with variable-length LSTM

SIGSPATIAL '19, November 5–8, 2019, Chicago, IL, USA

ACM ISBN 978-1-4503-6909-1/19/11…$15.00
https://doi.org/10.1145/3347146.3363462

Motivation and contribution: The coupled spatial and temporal randomness and regularities create complex dynamic structures, which require novel deep generative models. Here we propose a model called "Spatio-temporal Graph Adversarial Network" (STGGAN) which has the following advantages: (i) a more powerful and universal approach - demonstrated by a downstream task of movement trajectory prediction when comparing to a baseline model, (ii) accomplishes other tasks beyond prediction, such as probabilistic inference, anomaly detection, and privacy protection, (iii) allows for faster deployment to different domains.

Data: We utilize anonymized smartcard trip data from the Washington Metro system. It consists of tens of millions of records of timestamped station entries and exits. The graph has a total of 91 station nodes. The geographic locations of the stations are known.

2 APPROACH AND UNIQUENESS

In this section, we introduce the architecture of our STGGAN . It extends current unprescribed models towards the modeling dynamic STGs. Its fundamental concept lies in learning a deep generative model via spatial-temporal random walks.

Preliminaries: Given a directed graph $G = (V, E, T)$ with N nodes, $T = [0, t^+] \subseteq \mathbb{R}^+$ is a set of positive continuous values on time. V is the set of nodes. A node v has spatial coordinates (x_v, y_v). The set of *edges* $E = \{e = (v, u, t) | v, u \in V; t \in T\}$, and $|E| = |T|$. One common way to represent a graph is an adjacency matrix A. For STGs, $A^t \in \{0, 1\}^{|V| \times |V| \times 1}$ is a matrix with only binary values at time t, where $A^t_{v,u} = \mathbb{1}[(v, u, t) \in E]$. For the example of transportation graph, A^t, which consists of rows for origin stations and columns for destination stations, captures a trip from station v to station u at time t. We ignore trip duration. By definition, $A^t \sim \mathcal{F}(G)$, where A^t is just a sample from $\mathcal{F}$ distribution. Also, a subset of STGs during time $\mathcal{W}$ is a conditional distribution: $\mathcal{F}^{\mathcal{W}} = \mathcal{F}(G|\mathcal{W})$. Back to the transport graph example, a probability inference $p_{\mathcal{F}^{\mathcal{W}}}(A^t_{v,u}) = 0.98, \exists \mathcal{W} = weekdays, t = 8am$, means that the probability is 0.98 for observing a $8am$ trip on typical weekdays. $\mathcal{F}$ is approximated by deep generator $\mathcal{G}$ in STGGAN.

Deep generative model: The first part of STGGAN is composed of *Spatial-temporal Random Walks (STW)* algorithm: $f_{\mathcal{S}}$, which creates a set of short truncated random walks $\mathcal{S}$ with respect to temporal and spatial randomness and regularities of walkers traverse the graph: $\mathcal{S} = f_{\mathcal{S}}(G, L, M) = \{\mathcal{S}_1, ..., \mathcal{S}_M\} \sim \mathcal{F}$ where $\mathcal{S}_i = \langle e_1, \ldots, e_L \rangle$ is one walk, L is maximum length of walks, M is the total number of walkers (or size of a sampling batch). We set $L \ll |E|$, so that the problem is feasible for our model. $\mathcal{S} \sim \mathcal{F}$ means that STW is actually sampled from previous representation distribution $\mathcal{F}(G)$. More details including proves and benefits of such sampling process will be shown in a full publication.

Model architecture: Like any typical GAN architecture, STGGAN consists of two main components, a generator $\mathcal{G}$ and a discriminator $\mathcal{D}$ in a Min-max game (cf. Fig. 2). The role of generator $\mathcal{G}$ is to create synthetic data with similar properties to observed real data. The discriminator $\mathcal{D}$ helps the generator to improve its output by judging real from synthetic data. If synthetic data can fool the discriminator successfully, it indicates that the generator adequately models the distribution of the real dataset. Both $\mathcal{G}$ and $\mathcal{D}$ are trained using different Long-short Term Memory (LSTM) neural networks with back-propagation. However, the sequence length information is incorporated as an input to LSTM for $\mathcal{D}$, while $\mathcal{G}$ utilizes a separate Multiple-Layer-Perceptron (MLP) structure to generate the sequence length.

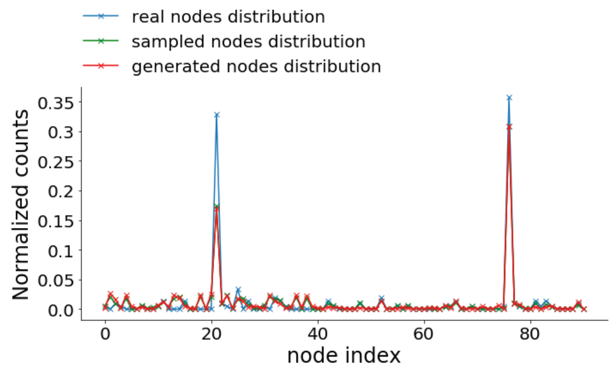

Figure 3: Training and generated results - node frequency distribution for real, sampled, and generated walks.

Initial Results: The initial experiments were done using single metro user movements. Users in the selected subset of the data have each 130 trips during a three-month period and exhibit a strong commuting behavior. Figure 3 compares node frequency distributions. It is observed that STGGAN consistently mimics known patterns. For example, the two peaks are a pair of commuting stations. The left peak is probably a work station inside the high-density (of stations) city center, resulting in a loss of passengers to other stations within walking distance. More thorough experiments with different data will be conducted for and presented in a forthcoming publication.

Acknowledgments: The author and his work are supported by GMU Presidential Scholarship and the National Science Foundation Grant CCF-1637541. I thank Dr. Pfoser Dieter and Dr. Zhao Liang as advisors, and Shan Qin at GMU for her support.

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