Early Forecast of Traffic Accident Impact Based on a Single-Snapshot Observation (Student Abstract)

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Abstract

Predicting and quantifying the impact of traffic accidents is necessary and critical to Intelligent Transport Systems (ITS). As a state-of-the-art technique in graph learning, current graph neural networks heavily rely on graph Fourier transform, assuming homophily among the neighborhood. However, the homophily assumption makes it challenging to characterize abrupt signals such as traffic accidents. Our paper proposes an abrupt graph wavelet network (AGWN) to model traffic accidents and predict their time durations using only one single snapshot.

Introduction

One minute reduction in the duration of traffic accidents produces a gain of $65 US dollars per accident (Adler, van Ommeren, and Rietveld 2013). Traffic accidents generally cause slower speeds, longer trip times, and increased vehicular queuing. In this paper, we focus on the **early forecast of traffic accident impact using a single snapshot**. Specifically, we predict the time duration of a traffic accident right after it happens. However, current studies suffer from several shortcomings: **(1)** Existing graph Fourier-based methods can hardly handle abrupt signal. **(2)** Current graph wavelets neural networks fail to incorporate the abrupt signals with spatial dependency. **(3)** Theoretical and empirical support for graph wavelet design on abrupt graph signals is missing. In this paper, we propose to use graph wavelet (GW), which has theoretical superiority over graph Fourier (GF) for accident signal modeling and shows significant advantages in predicting real-world traffic impact. (The code is available at https://github.com/gm3g11/AGWN)

Method: AGWN

Problem Setup

The task *Early Forecast of Traffic Accidents with a Signal Snapshot* is defined as:

$$\mathbf{Y} = f(\mathbf{G}, \mathbf{X}), \tag{1}$$

where $\mathbf{G}$ is the graph structure, $\mathbf{X} \in R^{N \times F}$ represent the graph signal in a single snapshot right after the accident, including traffic information (e.g., speed or occupancy rate). F denotes the feature dimension of each node, and $\mathbf{Y}$ means the duration time of traffic accidents, i.e., from when a traffic accident happens to when it is cleared. f is the function to learn.

The Proposed Model

We analyze the difference of graph Fourier and graph wavelet in terms of linear separability in accident traffic as an abrupt signal:

(1) Linear separability of graph Fourier is smaller than that of graph wavelet transform:

Theorem 1 *Let* $\mathbf{X}$ *be an abrupt graph signal, and J be the linear separability by Fisher score of* $\mathbf{X}$*, then we have:*

$$J^{GW} > J^{GF},$$

where J^{GW} *and* J^{GF} *are Fisher score of graph wavelet and graph Fourier transform of* $\mathbf{X}$ *respectively.*

(2) As a conclusion, we propose to employ a Mexican hat kernel in graph wavelet that allows the model to detect an abrupt signal. This is achieved by ensuring that its integral is zero , which is different from existing graph neural networks with N-AGW (e.g., exponential function) (Xu et al. 2019; Donnat et al. 2018). There are two reasons that support this design: Reason 1: Sensitive for Abrupt Signal. Reason 2: Guarantee for Accurate Recovering. In the classical Continuous Wavelet Transform (CWT), the admissibility condition is a key that determines whether the CWT can be inverted. Therefore, it ensures that a signal can be decomposed and recovered without any information loss.

Figure 1 depicts the multi-scale architecture of AGWN . The input layer is responsible for managing a single snapshot observation. The multi-scale wavelets equipped with the Mexican hat kernel initiate and transform the input at the middle layer. The output layer is responsible for predicting the duration using the intermediate representations.

Evaluation on Real-world Data

Our experiments are conducted on real-world data compiled with Caltrans Performance Measurement System (PeMS), Topologically Integrated Geographic Encoding and Referencing (TIGER) by U.S. Census Bureau's Master Address File, and 8574 traffic accident records are collected from

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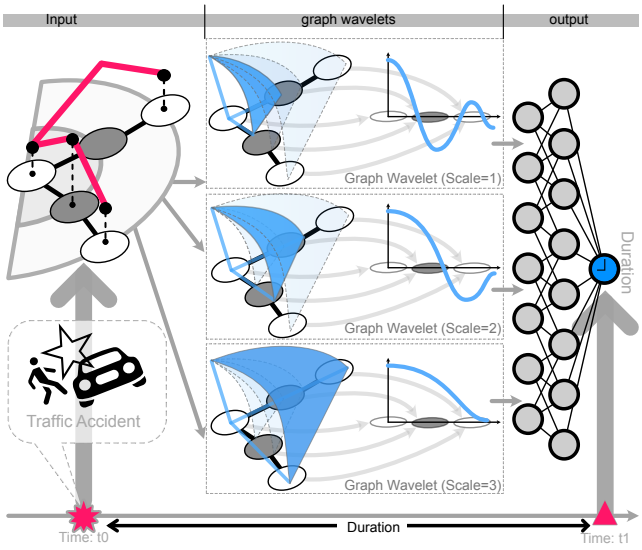

Figure 1: Illustration of AGWN's Architecture

the Regional Integrated Transportation Information System (RITIS). Baselines include popular graph neural networks such as GCN (Kipf and Welling 2017), ChebNet (Defferrard, Bresson, and Vandergheynst 2016), GAT (Veličković et al. 2018), GraphSAGE (Hamilton, Ying, and Leskovec 2017), Graph Isomorphism Network (GIN) (Hu et al. 2019), Simplifying GCN (SGC) (Wu et al. 2019). Graph Wavelet Neural Network (GWNN) (Xu et al. 2019) is also included for showing the advantage of AGWN over non-AGWN. The following two Tables 1 and 2 record the experiment errors on two random subgraphs.

Experimental Results Analysis. Table 1 and the table 2 show 5-fold experiment results.

Method	MAE	RMSE	MAPE
GAT	10.60 ± 3.38	8.37 ± 1.91	$24.02\% \pm 12.79\%$
SGC	7.61 ± 2.87	8.05 ± 1.97	$21.77\% \pm 17.79\%$
GIN	11.85 ± 2.61	9.9 ± 2.01	$18.02\% \pm 14.26\%$
GWNN	11.79 ± 3.14	9.25 ± 2.45	$19.34\% \pm 7.30\%$
GCN	7.54 ± 3.27	7.98 ± 1.94	$20.65\% \pm 16.67\%$
GraphSAGE	10.6 ± 3.38	8.37 ± 1.91	$24.02\% \pm 12.79\%$
ChebNet	7.51 ± 3.3	6.94 ± 1.97	$19.36\% \pm 18.09\%$
AGWN	$\mathbf{6.37 \pm 2.41}$	$\mathbf{5.70 \pm 1.11}$	$\mathbf{14.64\% \pm 5.41\%}$

Table 1: Accident impact prediction the first subgraph

Method	MAE	RMSE	MAPE
GAT	11.26 ± 3.42	7.45 ± 2.5	$25.77\% \pm 13.54\%$
SGC	7.04 ± 3.6	7.79 ± 2.59	$11.52\% \pm 14.15\%$
GIN	15.10 ± 3.84	10.76 ± 2.81	$21.22\% \pm 10.56\%$
GWNN	13.81 ± 4.05	10.38 ± 2.85	$22.00\% \pm 6.70\%$
GCN	7.54 ± 3.56	7.93 ± 2.43	$16.99\% \pm 13.11\%$
GraphSAGE	7.19 ± 3.58	5.66 ± 2.46	$13.37\% \pm 13.79\%$
ChebNet	7.37 ± 3.61	6.94 ± 2.55	$15.93\% \pm 13.60\%$
AGWN	$\mathbf{6.97 \pm 2.98}$	$\mathbf{4.64 \pm 2.12}$	$\mathbf{6.64\% \pm 2.78\%}$

Table 2: Accident impact prediction the second subgraph

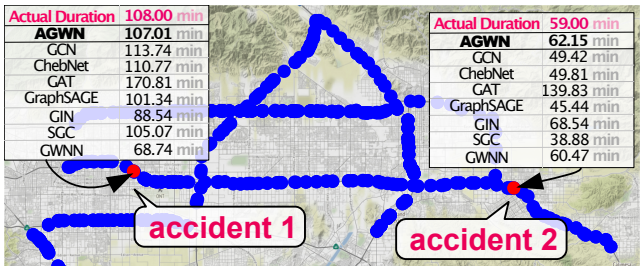

Figure 2: Case study: **(Accident 1)** and **(Accident 2)**

Case Study. Figure 2 depict two accident cases accident 1 (latitude/longitude is 34.078035/-117.62377) and accident 2 (34.061758/-117.179004) happened in the first subgraph. AGWN has a great balance between robust and accurate.

Conclusions

This article aimed to investigate the early forecasting of traffic accident impact using graph learning and a single snapshot. We quantified the linear separability of main graph learning techniques such as graph Fourier and graph wavelet and determined the ideal configuration for graph wavelet. As such, we developed an end-to-end graph neural network, AGWN , to characterize traffic incidents. Promising results and a detailed study using real-world data confirmed the algorithm's usefulness and efficiency in predicting the impact of traffic accidents early on.

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