Graph Attention Networks vs. Graph Inference Learning Under Gradient-Based Attacks on Traffic Prediction

Assignee Research

June 2, 2026

Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: What is the difference in inference efficiency and robustness degradation between Graph Attention Networks and Graph Inference Learning models under iterative gradient-based attacks on traffic. Real-time traffic prediction models play a pivotal role in smart mobility systems and have been widely used in route guidance, emerging mobility services, and advanced traffic management systems. With the availability of massive traffic data, neural network-based deep learning. 15 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Adversarial Diffusion Attacks on Graph-based Traffic Prediction Models. Research question: What is the difference in inference efficiency and robustness degradation between Graph Attention Networks and Graph Inference Learning models under iterative gradient-based attacks on traffic prediction datasets?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.8/10.

3 Results

13 papers retrieved. 15 claims extracted; 0 independently verified. Quality review score: 2.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Szegedy et al. (2013) discovered that adversarial samples are low-probability but densely distributed in deep neural net	×	0.06
Goodfellow et al. showed that generating adversarial samples is sufficient when DNNs demonstrate linear behaviors in hig	×	0.04
An experiment involving 99 smartphones moving slowly on a handcart caused Google Maps to identify an empty street as a c	×	0.01
Mobile phone-based mapping services such as Google Maps and AutoNavi make traffic state estimation and prediction based	×	0.05
Traffic prediction tasks include traffic state prediction, demand prediction, and trajectory prediction.	×	0.10
Traffic state prediction includes the prediction of traffic flow, speed, and travel time.	×	0.06
Traffic demand prediction aims to predict the number of users and traffic demand, such as taxi requests, subway inflow/o	×	0.04
Trajectory prediction tasks are used for dynamic positioning and resource allocation.	×	0.03
Traffic data is closely associated with the topological structure of road networks and is represented in non-Euclidean s	×	0.03
Conventional machine learning methods like multi-layer perceptrons overlook the graph-based inter-relationships in traff	×	0.09
The ST-GCN model achieved a value of 5.46 on the LA dataset according to Table (p9).	×	0.05
The A3T-GCN model achieved a value of 12.74 on the LA dataset according to Table (p9).	×	0.04
The ST-GCN model showed an 8.32% metric on the LA dataset according to Table (p12).	×	0.05
The A3T-GCN model showed a 22.77% metric on the LA dataset according to Table (p12).	×	0.04
The A3T-GCN model achieved a value of 230.85% on the HK dataset in one of the reported metrics in Table (p12).	×	0.04

References

- http://arxiv.org/abs/2210.02447v1
- http://arxiv.org/abs/2307.02055v1
- http://arxiv.org/abs/2104.09369v1