

Efficient Unlearning for Spatio-temporal Graph (Student Abstract)

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Abstract

Machine unlearning is becoming increasingly important as deep models become more prevalent, particularly when there are frequent requests to remove the influence of specific training data due to privacy concerns or erroneous sensing signals. Spatial-temporal Graph Neural Networks, in particular, have been widely adopted in real-world applications that demand efficient unlearning, yet research in this area remains in its early stages. In this paper, we introduce STEPS, a framework specifically designed to address the challenges of spatio-temporal graph unlearning. Our results demonstrate that STEPS not only ensures data continuity and integrity but also significantly reduces the time required for unlearning, while minimizing the accuracy loss in the new model compared to a model with 0% unlearning.

Introduction

Regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) endow individuals with the right to demand the complete removal of their personal data from deep models. Conventional machine unlearning methods like data poisoning, which often reduce partial influences, are inadequate for complete unlearning. Unlearning methods are also needed to support the proactive removal of poor-quality or missing data points, which are common in training datasets, making efficient unlearning methods essential.

Spatio-temporal graph neural networks are widely used in environmental applications like weather forecasting, where maintaining model accuracy may require removing outdated data. Location-based services such as navigation apps, travel planners, and recommendation systems often raise privacy concerns, highlighting the need for efficient unlearning techniques.

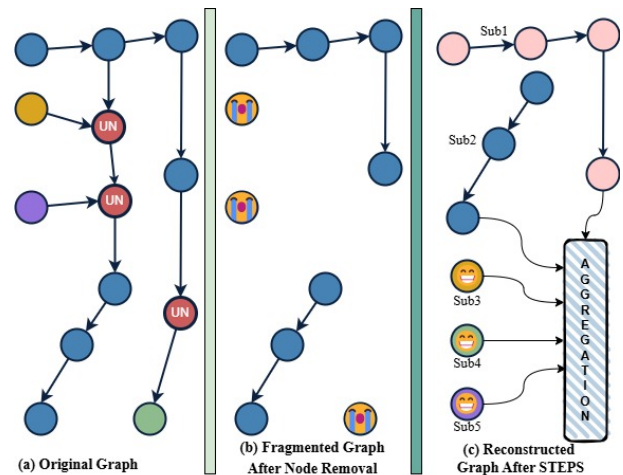
The challenges of graph unlearning for spatio-temporal graphs lie in maintaining data continuity and integrity. Inappropriate methods may lead to a significant loss of valuable information, resulting in misinterpretation of the predicted spatio-temporal systems. However, research on unlearning is mainly focused on machine unlearning (Bourtole et al. 2021), and graph unlearning (Chen et al. 2022) is still in its early stages. It does not yet support the unlearning of

spatio-temporal graphs, which remains an unexplored area of research.

To address these challenges, we propose an efficient unlearning framework, called **STEPS**. Our framework is experimentally ascertained with two real-world datasets, including a real-time urban water system dataset and a traffic dataset.

STEPS Unlearning Framework

STEPS is an acronym for the unlearning framework's implementation, which includes: **S**patio-**T**emporal graph complexity **E**valuation, determining the number of shards, establishing the **P**artition-**A**ggregation strategy, and defining the **S**ub-model scale, as illustrated in Figure 1.



Note: (a) UN nodes must be removed from the graph. Orange, purple, and green nodes represent key nodes. (b) UN removal fragments the graph. (c) STEPS uses spectral partitioning to split the graph into subgraphs (sub1, sub2, etc.), aggregates them via weighted averaging to preserve spatio-temporal information, enabling fast model shard unlearning with good accuracy.

Figure 1: STEPS Unlearning Framework

The core principle of STEPS lies in striking a balance between maintaining model accuracy post-unlearning and accelerating the unlearning process through graph partitioning. This approach aims to optimize the trade-off between preserving spatio-temporal graph information and reducing

Dataset	Node Removal %	Louvain				Metis				Spectral			
		Mean	Median	MLP	Wtd. Avg	Mean	Median	MLP	Wtd. Avg	Mean	Median	MLP	Wtd. Avg
RWW	0%	0.611	0.779	0.810	0.643	0.609	0.779	0.849	0.617	0.612	0.779	0.748	0.585
	5%	0.609	0.771	0.795	0.642	0.612	0.789	0.846	0.612	0.610	0.776	0.820	0.584
	10%	0.613	0.774	0.806	0.656	0.603	0.780	0.767	0.646	0.600	0.790	0.851	0.585
	15%	0.641	0.785	0.825	0.672	0.603	0.769	0.802	0.636	0.604	0.753	0.828	0.590
PEMS08	0%	0.918	0.996	0.837	0.907	0.768	0.996	0.792	0.767	0.762	0.995	0.779	0.679
	5%	0.918	0.996	0.792	0.906	0.766	0.996	0.780	0.762	0.763	0.995	0.855	0.679
	10%	0.922	0.996	0.805	0.908	0.774	0.996	0.845	0.776	0.776	0.996	0.887	0.698
	15%	0.928	0.995	0.852	0.916	0.808	0.996	0.765	0.797	0.800	0.996	0.785	0.734

Table 1: Algorithm Performance at Different Node Removal Rates (RMSE)

sub-model scale for efficient unlearning. Excessive partitioning may lead to a significant loss of graph information, while insufficient partitioning could negate the benefits of unlearning. Consequently, a critical step in STEPS involves evaluating the optimal partition granularity based on the complexity of the spatio-temporal graph (as shown in Equation (1)).

$$C = \alpha \cdot \frac{|E|}{|V|} \cdot \log(|V|) + \beta \cdot T + \gamma \cdot F \cdot \log(F) \quad (1)$$

V is the number of nodes in the graph; E is the number of edges; T is the number of time steps in the time series data; F is the number of features per node; α , β , and γ are weighting parameters for structural, temporal, and feature complexity respectively. In practice, we conduct empirical testing on specific datasets to determine the complexity, which subsequently guides the selection of exact partitioning numbers and sub-model scales. Next, the STEPS framework employs spectral partitioning and a weighted average aggregation method by default. The former exploits the eigenstructure of the graph Laplacian to potentially reflect spatial and temporal dependencies in the data, while the latter processes data across temporal points or spatial regions. Then the unlearning time can be succinctly determined:

$$\text{Unlearning Time} = f(P, C, M_p, M_a, \xi) \quad (2)$$

where P denotes partition size, C the count of partitions, M_p the partitioning method, M_a the aggregation method, and ξ the overall complexity.

Experiments

To validate the applicability of our STEPS unlearning framework to spatio-temporal graphs, we conducted experiments using two datasets: a real-world water system dataset (RWW dataset) we collected over four months from an urban water system, and the established PEMS08 traffic dataset. Our framework accommodates various unlearning proportions; we specifically tested node removal rates of 5%, 10%, and 15%. For partitioning, we compared the Louvain(Blondel et al. 2008) and Metis(Karypis and Kumar 1997) methods, while for aggregation, we evaluated Mean, Median, and multilayer perceptron (MLP) strategies. We employed the well-established Spatio-Temporal Graph Convolutional Networks (STGCN) (Yu, Yin, and Zhu 2017). The primary evaluation metrics were changes in accuracy and unlearning time efficiency.

As shown in Table 11, the default Spectral partitioning and Weighted Average aggregation configurations exhibit superior performance. Across different initial partition settings and node removal rates (5%, 10%, 15%), our framework consistently achieves the best accuracy. Regarding unlearning time efficiency, Figure 2 illustrates that our STEPS framework significantly reduces sub-model update time compared to both full model retraining and alternative methods, for both 4 and 10 shards. The efficiency of our chosen aggregation methods is evident in Table 2. Notably, while aggregation consumes a minimal portion of the total unlearning time, different methods show marked accuracy variations in Table 1. This suggests that exploring advanced aggregation techniques could substantially enhance unlearning accuracy without significantly increasing computational time.

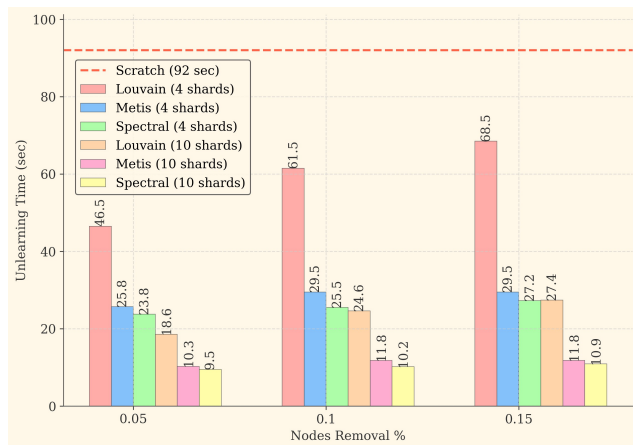


Figure 2: Unlearning Time Comparison

Method	Mean	Median	MLP	Wtd. Avg
Time (ms)	1.469	4.228	2.06	1.642

Table 2: Aggregation Time Comparison

Conclusion

To our knowledge, this study is the first to explore unlearning for spatio-temporal graphs. Moving forward, we aim to develop specialized techniques tailored to this domain.

Acknowledgments

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Ethics Statement

In this research, we developed the STEPS framework to address efficient unlearning in spatio-temporal graph neural networks. Our experiments utilized two datasets: the publicly available PEMS08 traffic dataset and a real-world water system dataset that we collected with proper permissions. The data used contain no personally identifiable information, and all privacy considerations have been duly addressed.

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