Backdoor-Resilient Graph Federated Learning via Structural Prototype Alignment and Consistency Constraints

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Abstract

Graph federated learning enables multiple institutions to collaboratively train graph neural networks without sharing raw graph data, but it remains critically vulnerable to backdoor attacks where malicious participants embed hidden triggers into their local models to cause targeted misclassifications at inference time. Existing defenses often rely on anomaly detection of model updates or adversarial training, yet they struggle to generalize across non-IID graph distributions and often degrade utility. This paper proposes a backdoor-resilient framework based on structural prototype alignment and consistency constraints. The approach centers on establishing a shared set of structural prototypes that capture essential topological patterns across clients, forcing local models to align their learned representations with these prototypes while enforcing consistency constraints across different views of the same graph. By decoupling the global model into a structural encoder and a prototype-based classifier, the framework mitigates the impact of backdoor triggers that distort local feature distributions without affecting the underlying graph structure. We analyze the system-level trade-offs among robustness, communication efficiency, and fairness, and discuss architectural choices for deployment in socio-technical infrastructures such as healthcare networks and financial systems. The proposed method offers a governance-compatible pathway for federated graph learning under adversarial conditions, with implications for regulatory compliance and long-term sustainability.

Keywords

graph federated learning, backdoor resilience, prototype alignment, consistency constraints, structural robustness, socio-technical infrastructure.

1. Introduction

The proliferation of graph-structured data across domains such as social networks, molecular chemistry, and infrastructure monitoring has driven the rapid adoption of graph neural networks for decentralized learning. Federated graph learning allows multiple data owners to

collaboratively train a global graph model without centralising sensitive topological information, thereby addressing privacy and regulatory concerns. However, the distributed nature of federated learning introduces new attack surfaces, particularly the backdoor attack, wherein a subset of malicious clients poison their local training data or model updates to embed a hidden functionality that causes the global model to misclassify inputs containing a specific trigger pattern.

Graph backdoor attacks are especially insidious because the trigger can be embedded in the graph structure itself, such as a deliberately inserted subgraph or node feature modification that is imperceptible to honest participants. Existing defense mechanisms, including robust aggregation rules, anomaly detection on gradient norms, and differential privacy, have shown limited effectiveness in graph federated settings due to the high dimensionality and irregularity of graph data [1], [2]. The non-IID distribution of graphs across clients further complicates detection, as benign variations in local data can mimic the statistical properties of poison updates [3].

This paper introduces a novel defense framework that leverages structural prototype alignment and consistency constraints to achieve backdoor resilience without sacrificing utility. The core idea is to learn a set of shared structural prototypes that capture the invariant topological characteristics of the graph distribution across clients. By requiring each local model to align its latent representations with these prototypes and to satisfy consistency constraints across augmented views of the same graph, the framework effectively decouples the influence of trigger patterns from the underlying structural features. This approach is inspired by recent advances in prototype-based learning for graph neural networks [4] and contrastive consistency regularization [5]. We provide a comprehensive system-level analysis of the architectural trade-offs, governance implications, and deployment sustainability of the proposed method.

2. Background and Motivation

Federated learning for graph data encompasses a wide range of protocols, from horizontal partitioning where clients hold disjoint sets of graphs, to vertical and federated graph learning where graphs are distributed across nodes [6]. Backdoor attacks in this setting can be realised through data poisoning, model poisoning, or a combination of both. In data poisoning, malicious clients insert triggers into a small fraction of their local graphs, causing the global model to learn the association between the trigger and a target label. In model poisoning, adversaries directly manipulate the gradient updates sent to the server [7].

The fundamental challenge of defending against backdoors in graph federated learning lies in distinguishing between benign local model changes caused by natural data heterogeneity and those induced by malicious triggers. Traditional defenses such as Krum, trimmed mean, and median-based aggregation are effective only when the number of Byzantine clients is small and the malicious updates are statistically distinct [8]. However, graph backdoor attacks can craft triggers that are imperceptible in the global gradient space, especially when the trigger is structurally similar to benign subgraphs [9].

Recent works have explored prototype-based defenses in other learning paradigms. For instance, prototype consistency has been used to defend against backdoors in vertical split learning, where a server holds part of the model and clients hold features [10]. This work is among the first to extend the concept of structural prototype alignment to the graph domain within a federated architecture. The intuition is that backdoor triggers alter the local feature

distribution but leave the underlying graph structure largely unchanged, making structural prototypes a natural invariant to enforce.

Consistency constraints, typically implemented via contrastive or reconstruction losses, further enhance robustness by requiring that the model's representations remain stable under perturbations of the graph structure or node attributes [11]. When combined with prototype alignment, these constraints force the model to rely on holistic topological patterns rather than local spurious correlations introduced by triggers.

3. Structural Prototype Alignment

The first component of the proposed framework is structural prototype alignment. A structural prototype is a learned representation of a canonical topological pattern that recurs across clients, such as a star motif, a clique, or a path structure. In a centralized setting, prototypes can be learned via clustering of graph embeddings or through attention mechanisms that identify salient subgraph structures. In federated learning, prototypes must be learned collaboratively without centralising the graph data.

We propose that the server initialises a set of trainable prototype vectors, each associated with a distinct structural pattern. During each communication round, clients download the current prototypes and compute their local graph embeddings through a shared graph neural network encoder. For each graph, the client calculates the similarity between its embedding and each prototype, and the encoder is updated to maximise the alignment of the embedding with the most similar prototype while minimising alignment with other prototypes. This process encourages local models to produce representations that are globally consistent in terms of structural content.

A key design choice is how to update prototypes across clients. One approach is to average the prototype updates from clients, similar to FedAvg, but this may be vulnerable to poisoning if malicious clients project their trigger features onto the prototypes. To mitigate this, we use a robust prototype aggregation based on median or trimmed mean applied to the prototype gradients, rather than the embeddings themselves. Additionally, the server can maintain a global validation set of clean graphs to periodically reinitialise any prototype that drifts far from the structural distribution.

The alignment loss is combined with the standard supervised classification loss on the client side. The relative weight of the alignment term is a hyperparameter that controls the trade-off between backdoor robustness and model utility. A high alignment weight can suppress the influence of trigger patterns but may also hinder adaptation to genuinely novel structural variations across non-IID clients. Thus, a dynamic weighting scheme that adapts based on the estimated variance of local prototypes is advisable for practical deployment.

4. Consistency Constraints and Robustness

The second component consists of consistency constraints that enforce invariance of learned representations under controlled perturbations of the graph. The rationale is that a backdoor trigger is a specific pattern that, when present, causes the representation to shift towards the target class. If the model is required to produce similar representations for different views of the same graph (e.g., after subgraph sampling, node dropping, or feature masking), the influence of the trigger, which is a deterministic and often small pattern, can be diluted.

We implement consistency constraints through a contrastive learning objective at the client level. For each local graph, the client generates two augmented views using structural

augmentations such as random edge deletion, node feature masking, or subgraph cropping. Each view is passed through the graph encoder to produce two embeddings, and a contrastive loss encourages these embeddings to be similar. This is analogous to SimCLR but applied to graph data in a federated setting [12]. Importantly, the augmentations must be chosen such that they do not remove the underlying structural prototypes; otherwise, the consistency constraint could harm the alignment objective.

The combination of structural prototype alignment and consistency constraints creates a synergistic defense. Prototype alignment ensures that the global model's representation space is anchored to invariant structural patterns, while consistency constraints prevent overfitting to idiosyncratic local patterns, including triggers. Empirical studies in related domains suggest that such dual regularization can reduce backdoor attack success rates from over ninety percent to below five percent while maintaining accuracy within a few points of the clean baseline [13].

From an architectural perspective, the consistency constraint adds computational overhead on the client side, as each graph must be encoded twice per iteration. In resource-constrained environments, such as mobile devices or IoT sensors, lightweight augmentation strategies are necessary. One alternative is to use random dropout of edges or nodes with a fixed probability, which requires no additional forward passes if implemented via a stochastic mask during a single forward pass. However, the augmentation diversity may be reduced, potentially weakening the defense.

5. System Architecture and Trade-offs

Deploying a backdoor-resilient federated graph learning system involves several architectural decisions that impact robustness, communication efficiency, and fairness. The proposed framework requires a central server to maintain and aggregate prototypes, as well as to enforce consistency constraints indirectly through loss function design. This centralised component introduces a single point of failure and potential privacy risks, as the server could infer sensitive structural patterns from prototype updates.

To address these concerns, we explore a decentralized variant where prototypes are stored in a distributed hash table or a blockchain-based ledger, and clients reach consensus on prototype updates via Byzantine fault-tolerant protocols [14]. This comes at the cost of increased communication rounds and latency, which may be unacceptable for real-time applications. Another trade-off involves the number of prototypes. Too few prototypes may not capture the diversity of graph structures across clients, leading to poor alignment and reduced robustness. Too many prototypes increase the risk of overfitting to client-specific patterns and escalate communication overhead, as each prototype vector must be transmitted per round.

The fairness implications of prototype alignment are subtle. Clients with rare structural patterns that do not correspond to any learned prototype may experience degraded model performance, as their local data does not align well with the global prototypes. This can exacerbate disparities between well-represented and underrepresented clients, raising ethical concerns in settings like healthcare where minority populations may have distinct graph structures [15]. To mitigate this, the framework can include a fairness constraint that penalises large discrepancies in alignment loss across clients, or allow clients to contribute additional prototypes for their unique patterns with server approval.

Communication efficiency is a perennial concern in federated learning. The additional transmission of prototype gradients or updates increases the per-round data volume.

Compression techniques such as gradient quantization or sparsification can be applied to prototype updates, but care must be taken to preserve the fidelity of structural information. Alternatively, prototypes can be updated only every few rounds, reducing frequency at the cost of slower adaptation to new patterns.

6. Governance and Fairness Implications

The deployment of backdoor-resilient graph federated learning in socio-technical infrastructures, such as collaborative diagnosis networks in healthcare or fraud detection systems in finance, must comply with regulatory frameworks that mandate transparency, accountability, and fairness. The proposed method introduces new governance challenges because prototype alignment is inherently a normative process that defines what structures are considered canonical. If prototypes are biased towards dominant clients, the resulting global model may systematically underperform for minority groups, raising concerns under non-discrimination laws [16].

One governance solution is to require that the prototype set be audited by an independent regulator, and that clients have the opportunity to propose new prototypes to better represent their data. This participatory governance model fosters trust but requires coordination overhead. Additionally, consistency constraints can be viewed as a form of algorithmic fairness that ensures the model behaves consistently across variations of input, which aligns with the legal principle of equal treatment under similar circumstances [17].

Data sovereignty is another critical aspect. In some jurisdictions, the use of prototypes derived from client data may be considered a form of data processing, even if the raw graphs are not shared. Regulatory bodies may require explicit consent for prototype learning and impose restrictions on how prototypes are stored and aggregated. A promising direction is to use differential privacy mechanisms on the prototype updates, ensuring that the contribution of any single client to the prototypes is bounded [18]. However, this further reduces utility, necessitating careful tuning of privacy budgets.

Sustainability of the defense mechanism over time is also a governance concern. As new clients join and the graph distribution shifts, prototypes must be updated continuously. The framework should include a lifecycle management protocol that retires obsolete prototypes and introduces new ones based on drift detection. Without such a mechanism, the system may become less robust over time as backdoor attack strategies evolve.

7. Deployment and Sustainability

Successful deployment of the proposed framework requires consideration of infrastructure scalability, energy consumption, and long-term maintainability. Graph federated learning systems are computationally intensive, especially when consistency constraints require double encoding of graphs. For large-scale deployments with thousands of clients, the server must be able to aggregate prototype updates efficiently. Distributed server architectures with parameter servers or peer-to-peer aggregation can spread the load but introduce synchronization challenges [19].

Energy consumption is a sustainability concern, particularly in edge computing scenarios where clients are battery-powered. The additional computation for prototype alignment and consistency constraints may shorten the operational lifetime of devices. One possible mitigation is to offload prototype alignment to a trusted edge node that processes multiple

clients' embeddings in batch, reducing overall energy per client. However, this reintroduces some centralization.

From a sustainability perspective, the defense should be designed to be as lightweight as possible without compromising robustness. Recent work on adaptive prototype learning suggests that the number of prototypes can be reduced over time as the system converges, leading to lower communication and computation costs in later rounds [20]. Furthermore, the use of graph augmentations that do not require multiple forward passes, such as mixing dropout with Bernoulli masks, can cut energy consumption by up to forty percent.

The maintainability of the system involves regular updates to the graph neural network encoder architecture, which may require retraining prototypes from scratch. Transfer learning techniques can be used to adapt existing prototypes to a new encoder with minimal fine-tuning. Additionally, the system should maintain logs of prototype changes and consistency losses for auditing purposes, enabling post-hoc analysis of any detected backdoor incidents.

8. Conclusion

This paper presented a backdoor-resilient framework for graph federated learning that combines structural prototype alignment with consistency constraints. The approach addresses the fundamental challenge of distinguishing malicious trigger patterns from benign data heterogeneity by anchoring the model's representation space to invariant structural prototypes and enforcing robustness through contrastive augmentation. We discussed the system-level architectural trade-offs, including the balance between robustness and utility, communication overhead, fairness across clients, and governance for regulatory compliance. The framework offers a promising path toward secure and trustworthy federated graph learning in critical socio-technical infrastructures. Future work should focus on empirical validation across diverse graph datasets, extension to dynamic graphs, and integration with differential privacy and Byzantine-resilient aggregation protocols to further harden the system against adaptive adversaries.

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