Verifiable Byzantine Robust Graph Neural Networks using Federated Learning

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Problem & Motivation

Problem Statement

Training AI models on graph data across multiple organizations is challenging due to security threats and privacy concerns.

Key Challenges:

- **Privacy**: Organizations can't share sensitive data
- **Security**: Malicious participants can corrupt the model
- **Trust**: Hard to verify if participants are honest

Real-World Applications:

- Healthcare: Disease networks across hospitals
- Finance: Fraud detection across banks
- Social Networks: Privacy-preserving analysis
- Cybersecurity: Distributed threat detection

Our Goal

Develop a secure and verifiable system for collaborative graph-based machine learning.

Background & Related Work

Foundation: RUNG (NeurIPS 2024)

- Robust method for handling graph data
- Reduces bias in predictions
- Strong performance guarantees

Why RUNG?

- State-of-the-art robustness
- Handles noisy connections effectively
- Proven theoretical guarantees

Collaborative Learning Challenges

- **Malicious Participants**: Some clients may be dishonest
- **Data Diversity**: Different data distributions across clients
- **Efficiency**: Need to minimize communication overhead

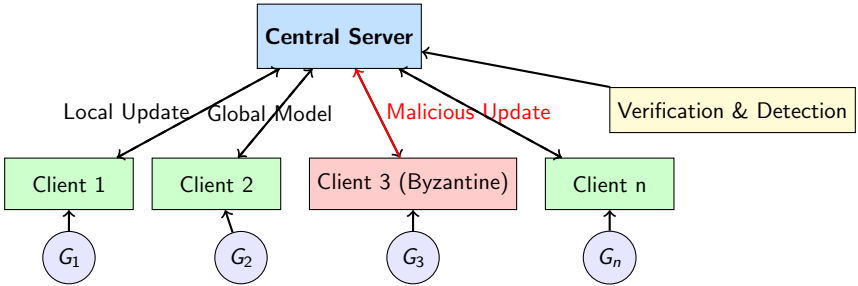
Existing Defense Methods

- Distance-based filtering
- Statistical aggregation
- Averaging techniques

Limitation

Current methods don't work well with graph data and lack verification.

Proposed Approach: System Architecture



Key Components

1. **Local Training**: Each client trains RUNG on local graph G_i
2. **Verifiable Aggregation**: Cryptographic proofs ensure correct local computation
3. **Byzantine Detection**: Statistical tests identify malicious clients
4. **Robust Update**: Weighted aggregation down-weights suspicious updates

Proposed Approach: Key Innovations

1. Verifiable Training

- Each client provides cryptographic proof of honest computation
- Server can verify correctness without accessing private data
- Fast and efficient verification process

2. Malicious Client Detection

- Compare updates from different clients
- Identify suspicious or outlier behavior
- Automatically down-weight malicious contributions

Benefits

- Ensures data privacy
- Detects dishonest behavior
- Low computational overhead

Aggregation Strategy

- Trusted clients get higher weight
- Suspicious clients are excluded
- Adaptive to attack patterns

Guarantee

Our system remains accurate even when up to 30% of participants are malicious.

Experimental Plan

Benchmark Datasets

- Cora - Small academic citation network
- CiteSeer - Medium citation network
- PubMed - Large biomedical network
- ogbn-arxiv - Very large academic network

Testing Scenarios

- Vary number of clients (10 to 50)
- Test with different malicious ratios (0% to 40%)
- Simulate realistic data distributions

Comparison Methods

- Standard federated learning
- Existing robust methods
- Centralized training (ideal case)

What We'll Measure

- Prediction accuracy under attacks
- Ability to detect malicious clients
- Communication efficiency
- Training speed and convergence

Additional Analysis

We will study the impact of verification overhead and detection sensitivity.

Expected Contributions

Expected Outcomes

1. A novel secure training system
2. Strong performance guarantees
3. Comprehensive experimental validation
4. Open-source code release

Publication Target

NeurIPS 2026

Impact

Enables secure collaboration for sensitive graph data across organizations.