

# Verifiable Byzantine Robust Graph Neural Networks using Federated Learning

2005090 - Tawkir Aziz Rahman

2005074 - Dipanta Kumar Roy Nobo

CSE472: Machine Learning Sessional

Department of Computer Science and Engineering  
Bangladesh University of Engineering and Technology (BUET)

December 2025

# 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

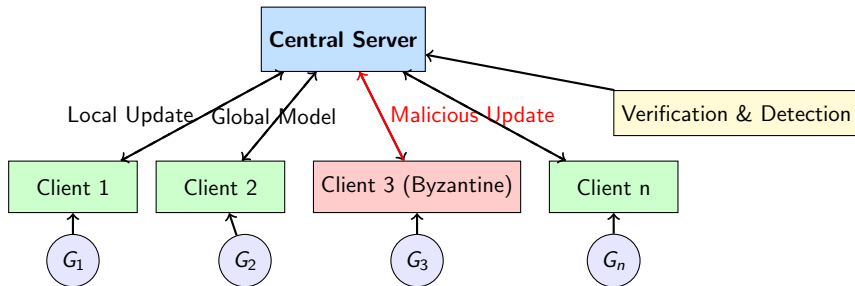
## Existing Defense Methods

- 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

### Benefits

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

## 2. Malicious Client Detection

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

### 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.