

Network Structures as an Attack Surface

Topology-Based Privacy Leakage in Federated Learning

Murtaza Rangwala, Richard O. Sinnott and Rajkumar Buyya

Cloud Computing and Distributed Systems (CLOUDS) Lab School of Computing and Information Systems The University of Melbourne







What we're protecting against...

Gradient Inversion Attacks Reconstructing training data from shared updates

Model Extraction Stealing model parameters and behaviour

Membership Inference Identifying if data was used in training









Current Defenses

Differential Privacy Noise Addition

Homomorphic Encryption Computation on Encrypted Data

Secure Aggregation Cryptographic Parameter Combination



Statistical Topology Knowledge **Complete Topology Knowledge**



What is also exposed...

Network Topology Knowledge Structure and communication patterns

Organizational Relationships Institutional connections and hierarchies

Communication Metadata Frequency, timing, and routing information











Organizational Structure Knowledge

Current Defenses

No protection for structural information

Observable coordination patterns

Persistent vulnerabilities despite strong content protection

Attack Vector 1 Communication Pattern Analysis

How it works:

- Nodes with similar data distributions converge faster
- Requires fewer communication rounds in later training phases
- Creates observable frequency patterns in message exchanges

What Adversaries Learn:

- Which nodes have similar data characteristics
- Clustering of participants based on convergence behavior
- Group-level data distribution patterns

Attack Vector 2 Parameter Magnitude Profiling

How it works:

- Data heterogeneity systematically affects parameter update magnitudes
- Rare classes produce larger, less stable gradient norms
- Homogeneous data leads to smoother optimization trajectories

What Adversaries Learn:

- Nodes training on rare or sensitive classes
- Statistical signatures of data imbalance
- Convergence stability patterns



Attack Vector 3 Structural Position Correlation

How it works:

- Real deployments correlate network position with data characteristics
- Geographic proximity reflects demographic similarities
- Organizational hierarchies determine data access patterns

What Adversaries Learn:

- Systematic assignment patterns
- Institutional data clustering
- Position-based sensitive group identification

Through a systematic evaluation of 4,720 attack instances across 520 network configurations, we analyzed 6 distinct adversarial knowledge scenarios.

Knowledge Scenario	Communication Pattern	Parameter Magnitude Profiling	Topology Position Correlation	Overall Status	Attack Success Threshold: 30%
Complete Knowledge	84.1%	65.0%	47.2%	Worst-Case Upper Bound	
1-hop Neighborhood	68.8%	47.2%	47.8%	Fully Effective	
2-hop Neighborhood	76.5%	62.3%	47.9%	Fully Effective	
Statistical Knowledge	86.0%	65.4%	1 27.6%	Partially Effective	
Organizational (3-groups)	31.7%	42.5%	74.1%	Fully Effective	
Organizational (5-groups)	53.3%	61.4%	53.6%	Fully Effective	









...and across varied privacy scenarios

(30% clients, 60% data) (20% clients, 50% data) (50% clients, 80% data) Subsampling Scenario

Network scale does not impact attack effectiveness





Potential Research Directions



Topology-Aware Privacy Mechanisms

- Extend differential privacy to account for network structure correlations
- Develop privacy definitions that bound inference advantages from topology knowledge
- Create structural noise injection techniques for communication patterns



Dynamic Network Reconfiguration

- Periodic topology changes to mask timing analysis
- Randomized communication scheduling with bandwidth normalization
- Decoupling of network positioning from organizational relationships





Privacy Amplification from Correlated Participants

	 Account for topology-induced
	correlations in privacy accounting
g	 Develop participant sampling strategies
	that minimize structural leakage
า	 Balance coordination efficiency with
	structural information protection



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