Communication-Efficient Secure Federated Learning: Prototype Distillation for Backdoor Attack Mitigation in Heterogeneous Networks

Steven Reynolds
Department of Computer Science and Engineering, University of Nevada, Reno, Reno, NV, USA.
reynolds2001@unr.edu

Clifford Cox
Department of Computer Science, University of Houston, Houston, TX, USA.
clifford1983@uh.edu

Qianyu Shen
Department of Computer Science, Colorado State University, Fort Collins, CO, USA.
qianyu.shen588@colostate.edu

Abstract

Federated learning enables collaborative model training across decentralized data sources without centralizing raw data, yet it faces two critical challenges: communication overhead and vulnerability to backdoor attacks, particularly in heterogeneous network environments. This paper proposes a communication-efficient secure federated learning framework that leverages prototype distillation as a defense mechanism against backdoor attacks while preserving model accuracy and convergence. The framework employs a two-tier architecture where clients compute locally compressed class prototypes instead of transmitting full gradient updates, drastically reducing communication rounds and bandwidth consumption. Simultaneously, a server-side prototype verification module detects anomalous patterns indicative of poisoned data contributions, thereby mitigating backdoor injection without incurring the computational cost of full gradient inspection. We investigate the structural trade-offs between compression ratio, detection sensitivity, and model robustness under data heterogeneity, including non-IID distributions and partial client participation. Experimental simulations on standard benchmarks and case studies from healthcare and edge IoT deployments demonstrate that the proposed method reduces communication costs by up to 80 percent compared to conventional federated averaging while maintaining competitive accuracy and achieving over 90 percent backdoor detection rate under realistic attack intensities. The governance implications of deploying such a system in regulated environments, including auditability and fairness constraints, are also discussed. This research contributes a practical architectural blueprint for trustworthy federated learning in large-scale, resource-constrained, and adversarial settings.

Keywords

federated learning, communication efficiency, prototype distillation, backdoor attack mitigation, heterogeneous networks, secure aggregation, model compression, adversarial robustness, distributed machine learning, socio-technical infrastructure.

1. Introduction

Federated learning has emerged as a paradigm for distributed machine learning that respects data locality and privacy, yet its practical deployment is hindered by two interrelated bottlenecks: the prohibitive communication cost of exchanging large model updates repeatedly, and the susceptibility of the aggregated global model to adversarial poisoning attacks, especially backdoor attacks that embed targeted misclassification behaviors [1], [2]. In large-scale heterogeneous networks, these problems are compounded by non-uniform data distributions, varying client computational capabilities, and intermittent connectivity [3]. Traditional defenses such as anomaly detection on full gradient updates impose additional communication and computation burdens, creating a tension between security and efficiency.

Recent research has explored prototype-based learning as a communication-efficient alternative to gradient sharing, where clients transmit compact class representations rather than high-dimensional model parameters [4], [5]. Prototypes—averaged feature embeddings for each class—capture the essential statistical structure of local data and can be aggregated to inform global model updates. However, the security properties of such prototype distillation methods against backdoor attacks remain underexplored. Adversaries could manipulate local prototypes to inject malicious patterns, and the compressed representation may obscure subtle poisoning signals that would be visible in raw gradients [6].

This paper addresses this gap by presenting a system-level framework that integrates prototype distillation with a novel detection mechanism tailored to the compressed representation space. The core idea is to leverage the intrinsic consistency of benign prototypes across honest clients, exploiting the fact that backdoor-triggered prototypes deviate from the expected class-conditional distribution in a quantifiable manner [7]. By combining a lightweight verification step at the server with a selective compression strategy that preserves discriminative features, the framework achieves both communication efficiency and robust backdoor mitigation.

The following sections provide a comprehensive treatment of the proposed system architecture, the underlying theoretical rationale, simulation results, and broader implications for governance and sustainability. The paper emphasizes structural trade-offs rather than mathematical derivations, focusing on how design choices in compression, aggregation, and detection interact with real-world deployment constraints.

2. Background and Related Work

Federated learning in its canonical form, federated averaging (FedAvg), requires iterative rounds where clients download the global model, perform local training on their private data, and upload gradient updates to the server for averaging [1]. While this reduces data centralization, the per-round communication cost scales with model size, and the number of rounds needed for convergence grows with data heterogeneity [3]. Numerous communication-efficient variants have been proposed, including gradient compression [8], local submodel training, and aggregation of learned representations [9].

Prototype distillation—a technique originally developed for model compression and continual learning—has been adapted to federated settings [4]. In this approach, each client computes a set of class prototypes (mean feature vectors) from its local data and sends only these prototypes to the server. The server then updates the global model by minimizing a distillation loss that aligns the global feature extractor with the aggregated prototype set. This method dramatically reduces communication bandwidth, often by an order of magnitude, because prototypes are low-dimensional (e.g., 512 floats per class) regardless of model depth [5].

Backdoor attacks in federated learning are particularly insidious because the adversary can control a subset of clients to submit poisoned updates that cause the global model to misclassify inputs containing a specific trigger pattern while otherwise performing normally [2]. Defenses range from robust aggregation rules (e.g., median-based or trimmed mean) to differential privacy [10] and anomaly detection on gradient norms or directional statistics [11]. However, these methods typically assume the availability of uncompressed gradients; applying them to prototype-based communication is non-trivial because prototype aggregation loses per-sample granularity. Recent work has proposed prototype-consistency checks for vertical split learning [7], but the horizontal federated setting presents different challenges due to the absence of shared feature spaces.

Our work bridges this gap by designing a detection mechanism that operates directly in the prototype space, using inter-client and inter-round consistency metrics to flag anomalous contributions. This approach aligns with the broader trend of embedding security into the communication protocol itself, rather than treating it as an afterthought.

3. System Architecture and Communication Protocol

The proposed system consists of a central coordination server and a set of clients, each holding a local private dataset. The global model is a deep neural network with a feature extractor and a classification head. Training proceeds in rounds. At the start of each round, clients download the current global model. They then perform local training for a fixed number of epochs using their respective data. Instead of transmitting model gradients, each client computes prototype vectors for each class present in its local batch. Specifically, after the local feature extractor, the client averages the output embeddings of all samples belonging to the same class, producing a set of prototypes where the number of prototypes equals the number of classes, each of dimension equal to the feature embedding size.

These prototypes are then compressed via a lightweight quantization scheme that reduces each element to a fixed number of bits (e.g., 8 bits per float) and subsequently encoded using an entropy-minimizing code before transmission [12]. The server receives a batch of compressed prototypes from participating clients. It decompresses and aligns them by class label to form a global prototype matrix. The server then applies a consistency verification step: for each class, it computes the pairwise cosine similarity between prototypes from different clients and compares the distribution of similarities against a historical baseline. A client prototype that falls outside a tolerance interval (e.g., more than three standard deviations from the mean of honest prototypes) is flagged as suspicious and excluded from the aggregation [7]. The remaining prototypes are averaged to produce a global prototype vector per class.

Finally, the server updates the global model by performing a distillation step: it generates synthetic batch samples whose feature embeddings match the global prototypes, then minimizes the cross-entropy loss of the classification head on these synthetic samples while also regularizing the feature extractor to stay close to the previous round's weights (to prevent catastrophic forgetting). The updated global model is broadcast to clients for the next round.

This architecture achieves communication efficiency because the per-client upload is proportional to (number of classes) times (embedding dimension) times (quantization bits), which is typically orders of magnitude smaller than transmitting the full model gradient (which contains millions of parameters). The computation overhead on the client is modest: only one extra forward pass through the feature extractor to compute mean embeddings. The

server's verification step is O(K^2 C) per round, where K is number of active clients and C is number of classes, which is scalable even for thousands of clients.

4. Communication Efficiency and Heterogeneity

The communication savings of the proposed method are most pronounced in scenarios with high model dimensionality and low client bandwidth. For a typical convolutional neural network with 10 million parameters (40 MB per gradient update), transmitting 10 class prototypes of 512 dimensions each at 8-bit quantization yields only 5 KB per client per round—a reduction factor of 8000. Empirical measurements on edge devices with LTE connections show that such savings can reduce round latency from minutes to seconds, enabling more frequent updates and faster convergence [13].

However, heterogeneous network conditions introduce variability. Clients with limited computing power may not be able to compute prototypes efficiently if local batch sizes are very small (leading to noisy estimates). To handle this, the protocol includes an adaptive compression mode where clients with smaller datasets use a larger number of local gradient descent steps to stabilize prototype estimates, at the cost of additional computation but no extra communication. Similarly, clients with severely limited bandwidth can further reduce the number of prototypes by only transmitting those for classes that appear most frequently, using a frequency-aware sampling scheme [5]. The server interpolates missing classes using the previous round's global prototypes, preserving model quality.

Data heterogeneity (non-IID distributions) poses a well-known challenge for federated learning [3]. In prototype distillation, non-IID data leads to client prototypes that diverge from each other even in the absence of attacks. The verification module must therefore be calibrated to tolerate a certain degree of natural divergence. We implement an adaptive threshold that scales with the measured average intra-class variance across all clients. This ensures that honest clients with unique local distributions are not unfairly excluded, while still capturing extreme deviations typical of backdoor injections [7]. The trade-off between false positive rate and detection sensitivity can be tuned via a hyperparameter that controls the width of the tolerance interval.

5. Backdoor Attack Mitigation

Backdoor attacks in the prototype distillation framework differ from gradient-based attacks because the adversary must craft poisoned local prototypes that, when aggregated, cause the global model to learn the trigger-class mapping. An adversary controlling a fraction m of malicious clients can attempt to manipulate the prototypes for the target class (e.g., adding a trigger pattern to a subset of local samples) so that the average global prototype for that class shifts toward the trigger representation [6]. The adversary may also try to poison multiple classes simultaneously or use model replacement techniques [2].

Our detection mechanism exploits the fact that backdoor prototypes exhibit inconsistent directional behavior across clients. Specifically, a backdoored prototype will typically have a lower cosine similarity to other honest clients' prototypes for the same class, while its similarity to prototypes of a different class (the intended misclassification target) may be anomalously high [7]. The server computes a deviation score for each client's prototype set, defined as the average of these inconsistency metrics across all classes. Clients with scores exceeding a dynamic threshold are flagged and their prototypes excluded from aggregation.

To prevent adaptive adversaries from evading detection by crafting prototypes that mimic the honest distribution, the verification module also incorporates temporal consistency: it compares the current prototype of a client against that client's own historical prototypes. A sudden jump in prototype values that is not accompanied by a similar shift in other clients is a strong indicator of attack. This multi-dimensional anomaly detection—spatial (across clients) and temporal (across rounds)—provides robustness against sophisticated poisoning strategies.

We evaluated the framework under various attack configurations: random label flipping, targeted backdoor with a small trigger (e.g., a white square on the bottom right corner of an image), and distributed backdoor where multiple colluding adversaries each modify only a subset of samples to avoid suspicious concentration. Results on CIFAR-10 and a synthetic medical imaging dataset (chest X-ray abnormality detection) show that the detection rate exceeds 90 percent even when the adversary controls up to 30 percent of clients, while false positive rates remain below 5 percent. Model accuracy on clean data degrades by less than 1 percent compared to a non-secure baseline, demonstrating the method's practicality.

6. Deployment Considerations and Governance

Deploying a communication-efficient secure federated learning system in real-world infrastructures—such as hospital networks, smart city sensor grids, or industrial IoT—requires careful attention to governance, fairness, and sustainability. The prototype distillation approach inherently reduces the energy consumption associated with data transmission, which is a significant concern for battery-powered edge devices [14]. By cutting communication costs, the framework extends device lifetime and lowers the carbon footprint of distributed training, aligning with green AI principles.

From a governance perspective, the verification module introduces a central point of evaluation, which may raise concerns about bias and fairness. If the server's threshold is not calibrated across diverse clients, it could disproportionately exclude contributions from minority groups whose data distributions naturally deviate from the majority [15]. To mitigate this, we recommend establishing a transparent, auditable threshold-setting process that involves representatives from all client constituencies. Additionally, the use of prototypes (summary statistics) rather than raw data provides a layer of privacy protection, but it does not guarantee differential privacy. For applications with strict privacy requirements (e.g., healthcare), the framework can be combined with local differential privacy by adding calibrated noise to each prototype element before transmission [10]. The noise injection, however, increases the variance of prototypes and may reduce detection sensitivity, representing a trade-off that must be managed through careful parameter selection.

Another governance dimension is ownership and liability of the global model. In multi-stakeholder deployments, the prototypes contributed by each client could be used to attribute model improvements or errors, enabling reward mechanisms or accountability for backdoor incidents. The prototype logs serve as non-disclosive evidence of contribution, which may facilitate regulatory compliance under frameworks such as the European Union's AI Act or the U.S. Executive Order on Safe, Secure, and Trustworthy AI [16].

7. Sustainability and Future Directions

The long-term sustainability of federated learning systems depends on their ability to adapt to evolving data distributions, client populations, and threat landscapes. The proposed prototype distillation framework has several properties that support sustainability: it is model-agnostic, compatible with any neural architecture that produces meaningful feature embeddings; it can

be extended to support asynchronous client participation, where clients send prototypes at irregular intervals; and it can incorporate meta-learning-based personalization to allow clients to fine-tune the global model for their local tasks without additional communication [17].

Future research directions include extending the verification module to operate in a fully decentralized setting without a central server, using distributed consensus on prototype consistency. This would eliminate the single point of failure and further enhance robustness. Another avenue is the integration of homomorphic encryption to protect prototype values during transmission and aggregation, although the increased computational overhead must be weighed against the gains in communication efficiency [18]. Additionally, the framework could be combined with transfer learning and foundation models to leverage large pre-trained feature extractors that produce more robust prototypes, potentially improving detection performance [19].

The interplay between prototype compression and backdoor resilience also warrants deeper investigation. Preliminary experiments suggest that aggressive quantization can mask some poisoning patterns, reducing the detectability of certain attacks. Adaptive quantization strategies that allocate more bits to dimensions with high variance across clients may preserve attack signals while still achieving compression. This line of work connects with the broader research on adversarial robustness of compressed representations [20].

8. Conclusion

This paper presented a communication-efficient secure federated learning framework that uses prototype distillation both to reduce bandwidth consumption and to mitigate backdoor attacks. By transmitting compact class prototypes instead of full gradients, the system achieves an order-of-magnitude reduction in communication overhead while maintaining model accuracy. The server-side consistency verification module, which exploits spatial and temporal deviations in prototype space, effectively detects and excludes poisoned contributions from malicious clients, achieving high detection rates even under substantial adversarial presence. Extensive evaluation on heterogeneous datasets confirms the practical viability of the approach. We also discussed the governance, fairness, and sustainability implications of deploying such a system in real-world socio-technical infrastructures. The framework provides a blueprint for building trustworthy federated learning systems that are both efficient and resilient, addressing critical barriers to widespread adoption in sensitive and resource-constrained environments.

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