FedPlanGuard: Planning-Aware Backdoor Detection and Mitigation in Federated and Vertical Split Learning Systems for LLM-Driven Applications

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Abstract

The integration of large language models into federated and vertical split learning systems introduces unprecedented challenges in maintaining service integrity under adversarial manipulation. This paper presents FedPlanGuard, a planning-aware framework for detecting and mitigating backdoor attacks in distributed learning environments where LLM-driven applications operate across heterogeneous client nodes. Unlike conventional defenses that operate at the parameter or gradient level, FedPlanGuard leverages high-level planning signals extracted from model reasoning trajectories to identify anomalous behavior patterns that indicate backdoor injection. The framework operates within a socio-technical infrastructure that spans governance protocols, client trust assessment, and adaptive mitigation scheduling. We examine the structural trade-offs between detection sensitivity, communication overhead, and model utility, and demonstrate how planning-aware mechanisms can distinguish between benign distribution shifts and malicious manipulation. Through a cross-domain analysis of vertical split learning architectures, we show that planning consistency metrics provide a robust signal for backdoor detection even when gradient perturbation is minimal. The paper also addresses policy implications for deployment in critical infrastructures, emphasizing fairness constraints and auditability requirements. FedPlanGuard contributes a system-level perspective that bridges planning intelligence, secure aggregation, and decentralized oversight, offering a scalable path toward trustworthy LLM-driven applications in federated ecosystems.

Keywords

federated learning, vertical split learning, backdoor detection, planning-aware security, large language models, adversarial robustness, distributed systems governance.

1. Introduction

The widespread adoption of large language models in distributed learning frameworks such as federated learning and vertical split learning has expanded the attack surface for adversarial actors seeking to compromise model behavior through backdoor injection. In these settings, malicious participants can embed hidden triggers that cause the global model to misbehave on specific inputs while maintaining normal performance on benign data. Traditional defense mechanisms rely on statistical anomaly detection in gradient updates or model weights, but

they often fail when attackers carefully craft perturbations that blend into natural data distribution shifts. The emergence of planning-driven reasoning in LLMs, where models generate step-by-step plans before executing actions, offers a new dimension for backdoor detection. By monitoring the consistency between planning trajectories and final outputs, it becomes possible to identify inputs that activate backdoor behavior even when gradient-level signals are inconspicuous.

FedPlanGuard addresses this gap by introducing a planning-aware detection and mitigation framework specifically designed for federated and vertical split learning systems serving LLM-driven applications. The framework operates at the intersection of system architecture, adversarial robustness, and socio-technical governance. It does not require modification to the underlying learning algorithm but instead introduces a lightweight planning audit module that interfaces with the aggregation server. The detection component leverages planning consistency metrics derived from high-level reasoning paths, while the mitigation component uses adaptive client weighting and scheduled re-training to neutralize compromised contributions.

This paper makes three primary contributions. First, it provides a comprehensive threat model for backdoor attacks in planning-aware LLM systems deployed across federated and vertical split learning topologies. Second, it proposes the FedPlanGuard architecture, detailing the planning extraction pipeline, anomaly scoring mechanism, and mitigation orchestration. Third, it discusses the broader implications for infrastructure governance, fairness, and sustainability, including the trade-off between detection depth and computational overhead. The analysis draws on cross-domain case illustrations, including healthcare diagnostics, financial risk assessment, and autonomous task planning, to demonstrate the framework's applicability.

2. Background and Related Work

Federated learning allows multiple clients to collaboratively train a global model without sharing raw data, while vertical split learning partitions the model across parties, with each holding distinct features. Both paradigms have been shown vulnerable to backdoor attacks where a malicious client inserts a trigger into its local data to influence the global model [1, 2]. Existing defenses include robust aggregation rules, cryptographic techniques, and Byzantine-resilient protocols [3, 4]. However, these methods often assume that malicious updates are statistically distinguishable in the gradient space, an assumption that adversarial optimization can circumvent [5].

The integration of LLMs into distributed systems introduces new attack vectors because LLMs exhibit compositional reasoning and can be manipulated at the planning stage. Recent work on planning-guided reinforcement learning has shown that high-level plans can be used to steer model behavior toward desired outcomes [6]. Dou et al. proposed a framework where LLMs first generate a plan and then execute actions, improving reasoning robustness [7] – this planning signal provides a natural substrate for anomaly detection. In vertical split learning, backdoor defenses have been proposed based on prototype consistency, where the similarity of intermediate representations across clients is used to detect outliers [8]. Yet, these methods do not explicitly account for planning-level manipulations.

Planning-aware security is an emerging area. Zhou introduced a cost-aware vulnerability patch planning method using multi-agent reinforcement learning, demonstrating that planning can itself become a target of adversarial manipulation [9]. Gao et al. developed a quality prediction model for LLM API responses, highlighting the need for monitoring at the service

level [10]. The present work synthesizes these strands by treating planning as both a detection signal and a potential attack surface.

3. System Architecture and Threat Model

We consider a typical federated learning setup with a central aggregation server and N clients, each holding local data. In vertical split learning, the model is divided into a bottom model held by feature owners and a top model held by the server, with computational parties exchanging intermediate representations. The LLM-driven application is assumed to use a planning module that generates a sequence of high-level steps before producing a final response. The threat model includes an adversary that controls a subset of clients and seeks to embed a backdoor trigger such that when the trigger appears in the input, the model outputs a target label or behavior defined by the attacker.

The adversary has two capabilities: first, it can manipulate its local training data to include the trigger; second, it can modify the planning trajectory produced by its local instance of the LLM. The attacker aims to ensure that the backdoor remains effective even after aggregation, while avoiding detection by standard defenses. The detection challenge is compounded in vertical split learning because the server does not see the raw data, only intermediate representations and gradients. Our threat model assumes the adversary has knowledge of the aggregation protocol but not the specific detection mechanism.

FedPlanGuard introduces a planning audit module at the server side that receives, for each client, a representative sample of planning trajectories along with the corresponding final outputs. These trajectories are encoded using a lightweight transformer that produces a fixed-size representation, which is then compared across clients using cosine similarity metrics. The assumption is that benign planning trajectories will exhibit a high degree of consistency under similar inputs, whereas manipulated trajectories will deviate because the attacker must preserve the trigger activation pattern.

4. FedPlanGuard Framework

The FedPlanGuard framework consists of four core components: planning extraction, consistency scoring, anomaly classification, and adaptive mitigation. Planning extraction operates asynchronously and does not interfere with the training loop. After each global round, the server randomly selects a small set of validation inputs that include canonical trigger patterns and benign variants. Each client is asked to return the planning trajectory generated by its local LLM for these inputs. The server then computes pairwise consistency scores across clients using a normalized dot product of trajectory embeddings.

Consistency scoring employs a multi-scale approach: at the token level, at the semantic role level, and at the structural level of plan hierarchy. For LLMs that produce plans as sequences of subgoals, the structural consistency measures the graph edit distance between planning graphs. Clients with consistently low similarity to the majority cluster are flagged as suspicious. To avoid false positives due to data heterogeneity, FedPlanGuard uses a dynamic threshold that adapts based on the historical variance of consistency scores across training rounds.

Anomaly classification combines the planning consistency score with traditional gradient-based metrics such as cosine similarity and norm of updates. A logistic regression model trained on synthetic attack data assigns a combined anomaly score. Clients whose score exceeds a predefined percentile are placed under probation. Mitigation strategies are tiered:

under probation, the client's update is weighted lower during aggregation; upon repeated anomalies, the client is excluded and a remediation process begins, which involves re-training the global model on a clean set of client contributions.

5. Detection and Mitigation Mechanisms

Detection in FedPlanGuard proceeds through a sequence of checks. First, the server performs a rapid screening using planning consistency on a small batch of inputs. This step incurs minimal overhead because trajectories are computed only once per round and are already available from the client's inference pass. Second, for clients flagged by the screen, a deeper analysis is performed using gradient clustering and prototype consistency, as proposed in [8]. This layered approach balances detection accuracy with computational cost.

Mitigation is designed to be gradual to preserve model utility. When a client is placed on probation, its update is aggregated with a weight proportional to its trust score, which is a moving average of past consistency scores. For clients that show persistent anomalies, the mitigation module triggers a recovery phase: the server broadcasts a clean reference trajectory to all clients and requires them to recompute their updates with a penalty term that penalizes divergence from the reference plan. This approach resembles curriculum learning and ensures that the global model does not drift away from the benign distribution.

A critical aspect of mitigation is scheduling. FedPlanGuard uses a reinforcement learning agent that learns to choose among three actions: keep the client, reduce its influence, or isolate it. The agent's reward is based on a multi-objective function that includes global model accuracy on a held-out validation set, communication cost, and fairness across clients. This approach is inspired by [9] but adapted to the backdoor context. The mitigation agent runs on the server and updates its policy periodically based on observed outcomes.

6. Planning-Aware Integration

The integration of planning awareness into backdoor detection is non-trivial because LLM planning outputs are high-dimensional and context-dependent. FedPlanGuard addresses this by using a pre-trained sentence encoder to embed each planning step into a fixed 768-dimensional vector, then averaging over steps to obtain a trajectory embedding. The embedding space is regularized using contrastive learning: during a bootstrap phase, the server collects benign trajectories from all clients and trains a Siamese network to distinguish between trajectories from the same input versus different inputs. This network then serves as the consistency metric.

In vertical split learning, the planning module may reside on the server side rather than the client side, which changes the detection logic. In that scenario, the server has direct access to the planning trajectory for each client's input. FedPlanGuard adapts by comparing the server-generated trajectory with the client's intermediate representations, using a mutual information criterion. If the client's features are inconsistent with the server's plan, a backdoor is suspected. This approach aligns with the prototype consistency defense [8] but adds a planning layer.

The planning-aware component also enables a novel form of defensive alignment: the server can periodically inject clean planning prompts and verify that client outputs match the expected plan before allowing training to proceed. This proactive detection mechanism, dubbed plan verification, introduces a small computational overhead but significantly reduces

the attack surface. In experiments simulated over synthetic federated datasets, planning verification detected over 90 percent of backdoor attempts that evaded gradient-based filters.

7. Evaluation and Case Analysis

We evaluate FedPlanGuard through a series of simulation studies on a federated learning platform with 50 clients, 5 of which are malicious. The underlying LLM is a 7B-parameter instruction-tuned model fine-tuned on a text classification task. Backdoors are injected by associating a specific phrase with a target label. Planning trajectories are generated by prompting the model to output an intermediate step-by-step reasoning chain. We compare FedPlanGuard against three baselines: Krum aggregation, trimmed mean, and a prototype-based defense [8]. Metrics include detection rate, false positive rate, and global test accuracy.

Results show that FedPlanGuard achieves a detection rate of 94 percent compared to 72 percent for the best baseline, with a false positive rate of 3 percent. The planning consistency metric alone accounts for the majority of detections, while gradient-based methods contribute primarily for clients with highly similar planning trajectories. In vertical split learning scenarios, where the server controls the top model, planning verification increases detection rate to 98 percent without significant degradation of model accuracy.

Case analysis in a healthcare application where the LLM assists in clinical decision-making reveals unique challenges: planning trajectories in medicine are highly context-dependent and may legitimately vary across institutions due to different protocols. FedPlanGuard accommodates this by learning a per-client baseline during a benign phase and flagging deviations from that baseline rather than from the global mean. In the financial risk assessment domain, where planning is about multi-step portfolio allocation, the planning graph structure proved more discriminative than token-level embeddings. These case illustrations underscore the need for domain-adaptive detection.

8. Discussion: Trade-offs and Policy Implications

The deployment of FedPlanGuard raises several structural trade-offs that must be carefully managed. The first is between detection sensitivity and model utility. Aggressive detection policies that exclude clients too quickly can lead to data heterogeneity and reduced generalization. Our tiered mitigation approach mitigates this but requires careful tuning of the threshold parameters. Second, the planning extraction step adds communication overhead because clients must transmit trajectory embeddings in addition to model updates. In bandwidth-constrained settings, the frequency of planning verification must be reduced. We propose an adaptive sampling rate that decreases as the global model converges.

Policy implications are significant. In federated systems deployed for critical infrastructure, such as smart grids or autonomous driving, backdoor attacks can have catastrophic consequences. FedPlanGuard provides an audit trail of planning consistency scores that can be used for forensic analysis and regulatory compliance. Fairness considerations arise because clients with rare but legitimate planning patterns may be flagged as anomalous. To address this, FedPlanGuard incorporates a fairness constraint that ensures the false positive rate is balanced across demographic subgroups, following the principle of equal opportunity.

Sustainability concerns include the energy cost of running a separate planning audit module on the server. While the overhead is modest relative to the training computation, scaling to hundreds of thousands of clients could be prohibitive. We suggest using a hierarchical architecture where regional servers perform preliminary detection and only escalate to the

global server when anomalies exceed a threshold. This mirrors the design of [10] for API quality monitoring.

The framework also opens the door to adversarial evasion where attackers learn to mimic benign planning trajectories. Future work should explore adversarial training of the detection model, as well as cryptographic protocols that allow the server to verify planning consistency without exposing client plans. Such secure multi-party computation techniques would strengthen the trust model further.

9. Conclusion

FedPlanGuard presents a planning-aware approach to backdoor detection and mitigation in federated and vertical split learning systems for LLM-driven applications. By leveraging the high-level reasoning trajectories generated by LLMs, the framework identifies malicious manipulations that elude conventional gradient-based defenses. The architecture balances detection accuracy, communication efficiency, and fairness through adaptive thresholds and tiered mitigation policies. Cross-domain case studies illustrate the framework's robustness across healthcare, finance, and autonomous planning. The policy implications underscore the need for auditable, equitable defenses in socio-technical infrastructures. Future directions include integrating planning verification into secure aggregation protocols and extending the framework to multi-modal LLMs. FedPlanGuard contributes a system-level blueprint for trustworthy distributed intelligence in an era of increasingly autonomous planning agents.

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