

Blades: A Unified Benchmark Suite for Byzantine Attacks and Defenses in Federated Learning [Experiment, Analysis & Benchmark]

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ABSTRACT

Federated learning (FL) facilitates distributed training across clients, safeguarding the privacy of their data. The inherent distributed structure of FL introduces vulnerabilities, especially from adversarial (Byzantine) clients aiming to skew local updates to their advantage. Despite the plethora of research focusing on Byzantine-resilient FL, the academic community has yet to establish a comprehensive benchmark suite, pivotal for impartial assessment and comparison of different techniques.

This paper investigates existing techniques in Byzantine-resilient FL and introduces an open-source benchmark suite for convenient and fair performance comparisons. Our investigation begins with a systematic study of Byzantine attack and defense strategies. Subsequently, we present *Blades*, a scalable, extensible, and easily configurable benchmark suite that aims at supporting researchers and developers in efficiently implementing and validating novel strategies against baseline algorithms in the domain of Byzantine-resilient FL. The design of *Blades* incorporates key characteristics derived from our systematic study, encompassing the attacker’s capabilities and knowledge, defense strategy categories, and factors that influence robustness. *Blades* contains built-in implementations of representative attack and defense strategies and offers user-friendly interfaces for the seamless integration of new ideas. We maintain the source code and documents at <https://github.com/lishenghui/blades>.

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The source code, data, and/or other artifacts have been made available at <https://github.com/lishenghui/blades>.

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1 INTRODUCTION

Federated learning (FL) [32, 45] has emerged as a compelling paradigm, allowing for collaborative machine learning model construction using distributed data across a diverse range of client devices, from desktops and mobile phones to IoT devices. The FL process typically involves several iterative steps: Firstly, a central server distributes the current global model to client devices. Subsequently, the clients independently perform one or multiple local steps of stochastic gradient descent (SGD) using their local datasets and transmit the updates back to the server. The server then aggregates these local updates to generate a new global model, which serves as the basis for the next round of training. Such a paradigm allows clients to execute a significant portion of the computation without disclosing their private training data to a centralized entity or one another. Furthermore, FL exhibits improved communication efficiency compared to traditional distributed learning methods [5], as it capitalizes on multiple local update steps before transmitting the updates [33].

Due to the distributed nature of optimization, FL is vulnerable to Byzantine failures [44, 53], wherein certain participants may deviate from the prescribed update protocol and upload arbitrary parameters to the central server. In typical FL algorithms such as FedAvg [45], the server aggregates the client updates by computing their sample mean and incorporates the result into the global model. However, it is well-known that this approach can be significantly skewed, even with the presence of a single Byzantine client [39]. The server thus requires Byzantine-resilient solutions to defend against malicious clients. Depending on the adversarial goals, Byzantine attacks in FL can be classified into two categories: targeted attacks and untargeted attacks [27, 44]. Targeted attacks, such as backdoor attacks, aim to manipulate the global model to generate attacker-desired misclassifications for some particular test samples [3, 6, 60], while untargeted attacks aim to degrade the overall performance of the global model indiscriminately [18]. In this study, our attention is primarily on untargeted attacks, consistent with the majority of Byzantine-resilient research [9, 13, 30, 37, 54, 56, 64]. Henceforth, any reference to “Byzantine” will imply “untargeted Byzantine” unless explicitly stated otherwise.

In recent years, the field of FL has seen the emergence of various Byzantine-resilient approaches. These approaches aim to protect distributed optimization from Byzantine clients and assure the performance of the learned models [26, 53]. For instance, robust

aggregation rules are widely used to estimate the global update from a collection of local updates while mitigating the impact of malicious behaviors. Typical rules include `GeoMed` [13], `Krum` [9], `TrimmedMean` [64], and `Median` [64]. Similarly, different attack strategies are emerging, striving to circumvent defense strategies [7, 61]. For instance, the A Little Is Enough (ALIE) attack can bypass most robust aggregation rules by taking advantage of the empirical variance between clients’ updates if such a variance is high enough, especially when the local datasets are not independent and identically distributed (non-IID) [7, 39]. Thus, defending against adversarial attacks remains an open problem in FL [29].

Moreover, the development of a benchmark suite tailored specifically for Byzantine-resilient FL is crucial for facilitating fair performance comparisons and accelerating the evaluation of novel attack and defense mechanisms. While several open-source frameworks have been developed to enable FL simulations [16, 48, 66], a unified benchmark suite that can capture the characteristics of adversarial settings and fill the requirement of this field is still lacking.

Our work: Aiming to advance the study of Byzantine attacks and defenses in FL, we systematically investigate existing techniques and introduce an open-source benchmark suite, named `Blades`, which facilitates convenient and fair algorithmic performance comparisons. This suite enables the development of FL algorithms and encourages the exploration of novel defenses against Byzantine attacks, thereby driving progress in FL robustness. Specifically, we make the following key contributions:

A systematic study on the literature: We start by systematically studying existing Byzantine attacks and defenses in FL and its predecessor, distributed machine learning, to provide a comprehensive overview of the fundamental aspects and techniques in this domain. Specifically, attacks are classified into five levels based on the adversary’s capabilities and knowledge [56]. Defense strategies are primarily categorized into three branches: Robust Aggregation [9, 13, 30, 37, 39, 54, 64], Trust-based Strategies [11, 50, 62], and Variance-reduced Algorithms [21, 58], according to their inherent characteristics. This study enhances our understanding of the landscape surrounding Byzantine resilience and facilitates the identification of effective countermeasures in FL. It also serves as a foundation for inspiring the design of our benchmark suite.

Blades, a benchmark suite: We introduce `Blades`, an open-source benchmark suite for Byzantine-resilient federated Learning with Attacks and Defenses `Experimental Simulation`, which is specifically designed to fill the need for studying attack and defense problems in FL. `Blades` is built upon a versatile distributed framework, `Ray`, enabling effortless parallelization of single machine code across various settings, including single CPU, multi-core, multi-GPU, or multi-node, with minimal configuration requirements. This makes `Blades` efficient in terms of execution time, as client and server operations are executed in a parallel manner. In addition, `Blades` provides a wide range of attack and defense mechanisms and allows end users to plug in customized or new techniques easily. We illustrate the user-friendly nature of `Blades` through examples and validate its scalability with respect to clients and computational resources. The results highlight that `Blades` can effectively handle large client populations and computational resources.

Algorithm 1 A FedAvg-family Algorithm for FL

Input: $K, T, \mathbf{w}^0, \text{CLIENTOPT}, \text{SERVEROPT}$

- 1: **for** each global round $t \in [T]$ **do**
- 2: Select a subset S_t from K clients at random
- 3: **for** each client $k \in S_t$ **in parallel do**
- 4: $\mathbf{w}_k^t \leftarrow \mathbf{w}^t$
- 5: **for** E_l local rounds **do**
- 6: Compute an estimate $g_k(\mathbf{w}_k^t)$ of $\nabla F_k(\mathbf{w}_k^t)$
- 7: $\mathbf{w}_k^t \leftarrow \text{CLIENTOPT}(\mathbf{w}_k^t, g_k(\mathbf{w}_k^t), \eta_l, t)$
- 8: **end for**
- 9: $\Delta_k^t \leftarrow \mathbf{w}_k^t - \mathbf{w}^t$
- 10: Send Δ_k^t back to the server
- 11: **end for**
- 12: $\Delta^{t+1} \leftarrow \text{AGG}(\{\Delta_k^t\}_{k \in S_t})$
- 13: $\mathbf{w}^{t+1} \leftarrow \text{SERVEROPT}(\mathbf{w}^t, -\Delta^{t+1}, \eta_g, t)$
- 14: **end for**
- 15: **return** \mathbf{w}^T

Comprehensive experimental evaluations: Using `Blades`, we extensively examine representative defense techniques against state-of-the-art attacks. The results demonstrate that high-level attacks can inflict significant harm on defense strategies, attributable to the increased capabilities and knowledge of the adversaries compared to lower-level attacks. We also explore key factors (e.g., momentum, non-IID degree, and differential privacy (DP)) that potentially influence Byzantine resilience. The key takeaways from our experiments can be summarized as follows:

- Variance-based attacks such as ALIE pose the most substantial challenge to the robust aggregation rules.
- Hybrid defense strategies that integrate multiple techniques demonstrate greater promise than purebred defenses.
- When employed as an auxiliary technique, client momentum confers advantages in defending against ALIE attacks, whereas server momentum tends to exacerbate the vulnerability.
- Both the degree of non-IID in the training data and the budget allocated for privacy preservation considerably impact the robustness of defense mechanisms.

2 BACKGROUND AND RELATED WORK

2.1 FL and Optimization

In FL, a collection of clients collaboratively learn a shared global model using their private datasets in a distributed manner, assisted by the coordination of a central server. The goal is to find a parameter vector \mathbf{w} that minimizes the following distributed optimization model:

$$\min_{\mathbf{w}} F(\mathbf{w}) := \frac{1}{K} \sum_{k \in [K]} F_k(\mathbf{w}), \quad (1)$$

where K represents the total number of clients and $F_k(\mathbf{w}) = \mathbb{E}_{\mathbf{z} \sim \mathcal{D}_k} [\ell(\mathbf{w}; \mathbf{z})]$ denotes the expected risk of the k -th client. Here, \mathcal{D}_k is the data distribution for the k -th client and $\ell(\cdot; \cdot)$ is a user-specified loss function.

The most popular algorithms in the literature that solve (1) are the FedAvg-family algorithms [28, 45, 52]. As shown in Algorithm 1, at t -th round of communication, a subset of clients S_t is selected,

typically through a random sampling process. The server then broadcasts its current global model parameters \mathbf{w}^t to each selected client. Simultaneously, the clients independently perform local optimization on their respective private data, aiming to minimize their own empirical loss. This process involves multiple local rounds, denoted as E_l , where the clients compute an estimate $g_k(\mathbf{w}_k^t)$ of the gradient $\nabla F_k(\mathbf{w}_k^t)$ using their local data. The client model’s \mathbf{w}_k^t are iteratively updated using the estimated gradient and a client-specific learning rate η_l . The computed local model updates, denoted as Δ_k^t , are then transmitted back to the server. The server aggregates these updates using an aggregation rule, often averaging aggregation [45], to generate a global update. This update represents a direction for the global optimizer, capturing the collective knowledge of the participating clients. Subsequently, the server employs the global optimizer, denoted as SERVEROPT, to update the global model’s parameters \mathbf{w}^t using the negative of the aggregated updates, denoted by $-\Delta_k^{t+1}$ (which is called “pseudo-gradient” [52]), and a global learning rate η_g . By iterating this process for multiple rounds, the FedAvg-family algorithms refine the global model by leveraging the clients’ distributed computing capabilities and decentralized datasets.

Our study adopts the full client participation paradigm in alignment with previous research [40]. As such, every client is actively engaged in each round of local training, ensuring that $|S_t| = K$ as per Algorithm 1. The rationale behind this choice is grounded in a prevailing assumption of Byzantine-resilient studies in FL, i.e., the number of malicious updates for aggregation is less than half during each round. Selecting subsets at random risks contravening this foundational assumption, given the inherent possibility of inadvertently favoring an excessive proportion of adversarial clients over their benign counterparts [39].

2.2 Byzantine Attacks and Defenses in FL

Byzantine attacks pose a significant threat to FL due to its distributed optimization nature [44, 53]. In general, the malicious clients may upload arbitrary parameters to the server to degrade the global model’s performance. Hence, in Algorithm 1, the FedAvg-family algorithm we consider in this work, Line 9 can be replaced by the following update rule:

$$\Delta_k^t \leftarrow \begin{cases} \star & \text{if } k\text{-th client is Byzantine,} \\ \mathbf{w}_k^t - \mathbf{w}^t & \text{otherwise,} \end{cases} \quad (2)$$

where \star represents arbitrary values.

As aforementioned, the focus of this work is on untargeted Byzantine attacks, where the adversary’s objective is to minimize the accuracy of the global model for any test input [7, 18, 39, 55]. Various attack strategies have been proposed to explore the security vulnerabilities of FL, taking into account different levels of the adversary’s capabilities and knowledge [7, 30, 36, 55]. For instance, with limited capabilities and knowledge and without having access to the training pipeline, the adversary can manipulate a single client’s input and output data. In more sophisticated attacks, the adversary possesses complete knowledge of the learning system and designs attack strategies to circumvent defenses. Regarding defenses, robust aggregation rules are widely employed to enable Byzantine-resilient estimation of the true updates and mitigate the influence of malicious updates [9, 13, 30, 37, 54, 64]. Furthermore, other research directions such as

trust-based strategies [11, 50, 62] and variance-reduced algorithms [21, 58] are also worth investigating. For a detailed exploration of the core techniques and aspects of Byzantine attacks and defenses in FL, we refer to Section 3.

2.3 Connecting Byzantine-resilient FL with Traditional Distributed Learning

The study of Byzantine-resilient FL has its roots in the realm of traditional distributed learning, where a central server distributes data to workers who perform gradient estimation; the gradients are then collected and aggregated by the server for model update [2, 13, 64]. FL originally emerged as an extension of distributed learning to address the limitations imposed by communication constraints and privacy concerns associated with decentralized data ownership [65]. Although FL and traditional distributed learning are employed in different application domains [35], they face similar security vulnerabilities stemming from Byzantine attacks due to the distributed nature of optimization. Furthermore, many existing techniques initially proposed for studying Byzantine-resilient distributed learning [7–9, 13, 64] have now found extensive application in the defense mechanisms utilized in FL [18, 39, 51, 55, 56]. Therefore, it is important to examine FL and traditional distributed machine learning together when it comes to Byzantine resilience.

Benefiting from the generality of Algorithm 1, obtaining traditional distributed learning algorithms is straightforward. For example, by assuming both “CLIENTOPT” and “SERVEROPT” as a gradient descent step and setting $E_l = 1$ and $\eta_l = 1$, Algorithm 1 simplifies to the naive distributed SGD with gradient aggregation [13]. In contrast, setting $\eta_g = 1$ leads to the naive FedAvg algorithm. This connection enables the generalization of traditional techniques, such as robust aggregation rules, from traditional distributed learning to suit the requirements of FL.

2.4 Existing Simulators for FL

In FL, simulators can provide a fast evaluation of a particular solution’s potential utility and help investigate novel approaches before making real deployments. Recently, several FL simulators have been proposed with different foci and scopes. For example, LEAF [10] provides open-source federated datasets and metrics for evaluation; PrivacyFL [48] and Pysyft [66] focus on the privacy guarantees of FL algorithms. FLUTE [16] is designed for optimization and high-performance simulation of FL. However, there is a lack of focus on the simulation of robustness and security concerns. To fill in this gap, we have developed BLADES.

3 SYSTEMIZATION OF BYZANTINE ATTACKS AND DEFENSES

This section provides a systematic overview of Byzantine resilience in FL, encompassing key attack and defense techniques and other factors influencing robustness.

3.1 Classification of Byzantine Attacks in FL

On the basis of previous efforts for Byzantine attacks in FL, we classify these attacks into five levels in terms of the adversary’s

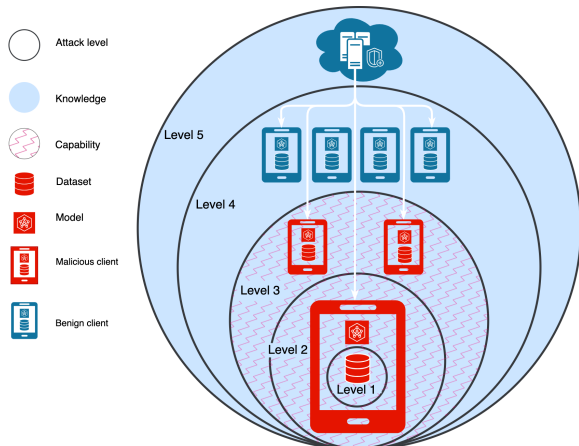


Figure 1: Overview of our classification of Byzantine attacks in FL. The diagram illustrates the relationship between different attack levels, where high-level attacks inherit the capabilities and knowledge of low-level attacks. The adversaries at Levels 1 to 5 have various degrees of knowledge and control capability over the dataset, model, and strategy of different entities in the system.

capabilities and knowledge. An overview of our classification system is illustrated in Fig. 1. Adversaries at higher levels have better knowledge and control over clients’ training data and local models. Notably, adversaries at Level 5 even have complete knowledge of the FL system, including server-side defense strategies.

Naive Data Poisoning Attacks (Level 1): At this level, the adversary possesses access to the training dataset of individual clients but lacks knowledge of the model’s architecture, parameters, and outputs [53]¹. These attacks are relatively straightforward to initiate, as they require minimal knowledge and access to the system. For example, an attacker could alter the labels of a dataset to introduce biases into the model or insert samples with subtle yet detrimental modifications [38, 41]. However, the limited knowledge and access to the system may restrict the effectiveness of attacks at this level. In addition, except for server-side defenses, it is also feasible to implement defensive measures (e.g., gradient clipping) during the local training phase on the client’s side, as the adversary cannot tamper with the training pipeline.

Naive Model Poisoning Attacks (Level 2): At this level, the adversary has complete control over a single participant, including access to the model parameters. They can manipulate the model updates transmitted to the server directly. Attacks at Level 2 and higher are referred to as “Byzantine attacks” [39] because the updates submitted by clients can be arbitrary. A straightforward Level 2 attack is to sample some random noise from a distribution (e.g., Gaussian distribution) and add it to the updates before communicating with the server [37].

Collusion Attacks (Level 3): At this level, multiple malicious entities collude to compromise an FL system. These attacks are particularly challenging to defend against because the adversaries can

¹The term “data poisoning” specifically implies that the attacker’s access is restricted to the dataset only, whereas sophisticated attacks to data such as DLF [56] are categorized as Level 2 due to their reliance on additional information for modifying the training data.

share information with each other and coordinate their actions accordingly. In some cases, a single adversary may control a group of participants, e.g., by injecting fake clients to improve their effectiveness [12]. Adversaries at Level 3 and below face a trade-off between attack effectiveness and the risk of being detected by the server. The more effective an attack is, the higher the chance of it being detected by the server, which can lead to countermeasures such as client blocking [49, 57]. On the other hand, if the adversary takes steps to reduce their detection risk, such as slowing down the attack or using more subtle methods, their attacks may not be effective. Therefore, attackers must carefully consider this trade-off when planning their strategies for collusion attacks in FL systems.

Limited Omniscient Attacks (Level 4): In addition to the knowledge of malicious clients, the adversary at Level 4 possesses extra information about the benign clients, making them more dangerous than attackers at lower levels. This extra information may include model updates or local data distributions from benign clients, which allows the adversaries to craft more effective attacks. Due to access to peer information, attackers can conceal their identities by carefully crafting their updates and thus circumventing certain defense mechanisms. For instance, A Little is Enough (ALIE) attack [7] assumes that the benign updates are expressed by a normal distribution. The attackers, therefore, can immediately take advantage of the high empirical variance between the updates of benign clients and upload a noise in a range without being detected.

Omniscient Attacks (Level 5): The adversaries are assumed to have complete knowledge of the FL system, including server-side defense strategies. Level 5 attacks are often considered impractical to achieve in real-world settings due to the significant level of access and knowledge required, as noted in [56]. Nevertheless, it is essential to examine the probable impact of Level 5 attacks to identify vulnerabilities in defense strategies and to encourage the development of more effective security measures in FL systems. Level 5 attacks are generally known as “adaptive attacks” [18]. In these attacks, adversaries develop malicious updates by solving an optimization problem aimed at maximizing the global model’s damage in each local round, given their full knowledge of the local updates and defense strategies [39, 55].

It is worth noting that several taxonomies have already been proposed in the literature to categorize FL poisoning attacks [27, 56]. In contrast, our new classification offers a few advantages for benchmarking attacks and defenses in FL. Firstly, it provides insights into the efficacy and limitations of attacks at different levels. Secondly, by categorizing attacks based on the adversary’s skills and knowledge, our classification aids in conducting a thorough assessment of the robustness of defense mechanisms against different levels of threats. In turn, the proposed benchmark suite ensures an equitable and accurate evaluation of defenses. Additionally, the abstraction of the adversarial components in our simulator could benefit from the characteristics of our proposed attack classification, as shown in Section 4.

In Table 1, we compare several representative attack strategies categorized by our classification system. For brevity and the sake of space limitation, we only choose six of them (shown in bold in Table 1) to examine in this paper. Below we introduce these selected attacks in detail.

Table 1: Example attack strategies grouped according to our classification system.

Attack	Level of Knowledge and capability				
	Level 1	Level 2	Level 3	Level 4	Level 5
LabelFlipping [30]	✓				
SignFlipping [36]		✓			
Noise [37]		✓			
MPAF [12]	✓				
ALIE [7]		✓	✓	✓	
DPA [56]	✓	✓	✓	✓	
IPM [61]			✓	✓	
MinMax [55]		✓	✓	✓	
Fang Attack [31]		✓	✓	✓	✓
AGR-tailored Attack [55]		✓	✓	✓	✓

LabelFlipping [30]: The adversary simply flips the label of each training sample [18]. Specifically, a label l is flipped as $L - l - 1$, where L is the number of classes in the classification problem and $l = 0, 1, \dots, L - 1$.

SignFlipping [36]: The adversary strives to maximize the loss via gradient ascent instead of gradient descent. Specifically, it flips the gradient’s sign during the local updating step.

Noise [37]: The adversary samples some random noise from a distribution (e.g., Gaussian distribution) and uploads it as local updates.

ALIE [7]: The adversary takes advantage of the empirical variance among benign updates and uploads a noise within a range without being detected. For each coordinate $i \in [d]$, the attackers calculate mean (μ_i) and std (δ_i) over benign updates and set malicious updates to values in the range $(\mu_i - z^{max} \delta_i, \mu_i + z^{max} \delta_i)$, where z^{max} ranges from 0 to 1, and is typically obtained from the Cumulative Standard Normal Function [7]. The i -th malicious update is then obtained by $\Delta_{k,i}^t \leftarrow \mu_i - z^{max} \mu_i$.

IPM [61]: The adversary seeks the negative inner product between the true mean of the updates and the output of the aggregation rules so that the loss will at least not descend. Assuming that the attackers know the mean of benign updates, a specific way to perform an IPM attack is

$$\Delta_1^t = \dots = \Delta_M^t = -\frac{\epsilon}{K - M} \sum_{i=M+1}^K \Delta_i^t, \quad (3)$$

where we assume that the first M clients are malicious, ϵ is a positive coefficient controlling the magnitude of malicious updates.

MinMax [55]: Similar to ALIE, the adversary strives to ensure that the malicious updates lie close to the clique of the benign updates. The difference is that MinMax re-scales z^{max} such that the maximum distance from malicious updates to any benign updates is upper-bounded by the maximum distance between any two benign updates.

3.2 Defenses

The defenses against Byzantine attacks primarily assume that only the server is trusted. Thus the defenses rely on server-side deployment. The literature has presented various directions toward mitigating the risks of Byzantine attacks in FL.

Table 2: A summary of robust aggregation rules. Those highlighted in bold will be evaluated through experiments in Section 5.

Aggregation Type	Reference	Dimension-wise	Euclidean Distance-based	Cosine Distance-based	Eigenvector	Clipping-Based	Statetful	Sign-based	Median-based
GAR	Krum [9], Multi-Krum [9]		✓						
	GeoMed [13]		✓						✓
	Median [64]	✓							✓
	Trimmedmean [64]	✓							
	SignSGD-MV [8]	✓						✓	
EGAR	SignGuard [63]					✓	✓	✓	✓
	CenteredClipping [30]					✓	✓	✓	✓
	RAGE [14]					✓	✓	✓	✓
	DnC [55]				✓				
	AutoGM [37]		✓						✓
	MAB-RFL [57]			✓				✓	
	Clustering [54]			✓				✓	
ClippedClustering [39]			✓			✓	✓	✓	
WAR	RFA [51]		✓						✓
	AFA [49]			✓			✓		

3.2.1 Robust Aggregation. The main branch of defense strategies strives to estimate the Byzantine-resilient global model update based on the local updates using robust aggregation rules [9, 13, 30, 37, 54, 64]. Table 2 provides an overview of representative state-of-the-art aggregation rules. The column shows the corresponding characteristics shared by different rules. We only highlight three core characteristics upon which the majority of aggregation rules rely, i.e., Dimension-wise, Euclidean distance-wise, and Cosine distance-wise. Specifically, these rule aggregate involves comparing and aggregating updates based on either dimension-wise values, Euclidean distances, or directions. We categorize the rules into the following three groups:

Gradient Aggregation Rules (GAR): Prior to the growing concern about Byzantine-resilient FL, the literature has already presented various directions toward making distributed machine learning robust against Byzantine or compromised nodes. The most typical techniques utilize robust aggregators to replace the average aggregation rule.

When used within certain assumptions, classic GARs (e.g., GeoMed [13], Krum [9], TrimmedMean [64], and Median [64]) guarantee convergence even in an adversarial setting. However, the convergence guarantee applies only to distributed stochastic gradient descent (SGD), where the server aggregates local gradients reported by working machines and performs a gradient descent step.

Extended Gradient Aggregation Rules (EGAR): In contrast to traditional distributed SGD, FedAvg-family algorithms differentiate themselves by performing multiple local SGD steps at the client level, aiming to enhance communication efficiency [45]. Therefore, the aggregation rules are extended to aggregate gradient-like local updates (a.k.a. pseudo-gradients [52]).

Weight Aggregation Rules (WAR): Early studies proposed the adoption of robust aggregation techniques for model weight instead of gradients and updates [49, 51]. Although this category

of techniques demonstrates a certain level of robustness in countering certain attacks, analyzing their convergence properties can be challenging. [40].

FedAvg-family algorithms often incorporate GARs [39] initially proposed for distributed SGD, even though they lack convergence guarantee for multiple steps of local updates. Nevertheless, it is possible to integrate and conduct unified research and comparison between the two approaches to explore their combined potential, considering the utilization of local updates in FedAvg-family algorithms and the application of robust aggregation rules derived from distributed SGD.

3.2.2 Trust-based Strategies. Trust-based strategies operate under the assumption that specific clients or datasets are considered trustworthy by the server [11, 18, 50, 62]. The server, thereby, can re-weight and filter the local model updates according to various metrics, including empirical loss [18], Cosine similarity [11], and entropy [50].

Compared to robust aggregation rules, trust-based strategies exhibit the potential to address the case where the majority of clients are malicious. Nonetheless, the availability of trustworthy datasets or clients for the server is not always guaranteed, primarily due to concerns regarding user data privacy.

3.2.3 Variance-reduced Algorithms. Variance reduction techniques have been recognized for their significance in improving the robustness of FL against Byzantine attacks [21]. Previous research in GAR has highlighted that the bounded variance of benign gradients plays a critical role in the Byzantine tolerance of malicious nodes [13, 64], inspiring the development of variance-reduced algorithms [21, 58].

The core idea of variance-reduced algorithms is to reduce the stochastic noise of gradient estimators used by benign clients, thereby making it easier to filter out Byzantine gradients. Byrd-SAGA, for instance, combines the celebrated SAGA method [15] with the GeoMed aggregation rule. It is noteworthy that variance-reduced algorithms act as supportive mechanisms and require concurrent utilization with robust aggregation rules to attain robustness. They are currently used exclusively in distributed SGD settings and are incompatible with multiple local steps on the client side. Such a characteristic imposes limitations on the optimization’s communication efficiency.

3.2.4 Additional Defense Techniques. In addition to the aforementioned categories, a range of supplementary defense techniques offer further enhancements to the security and robustness of FL systems. While these techniques do not fit explicitly into the previously defined categories, they are still significant in the context of FL defense.

Momentum: In the context of Byzantine-resilient FL, momentum was initially introduced to reduce the variance of local updates [30]. Recent studies have shown that distributed momentum could improve existing defenses against state-of-the-art attacks [19, 22, 46]. Specifically, each client maintains the momentum by accumulating historical gradients and uploading it for aggregation. When distributed momentum is employed, the local model optimization process considers the historical momentum accumulated from the clients themselves. As a result, the impact of Byzantine updates is

reduced because the aggregated momentum tends to smooth out the influence of malicious updates.

Clipping: Some aggregation rules enhance robustness by performing clipping (Table 2) on all the updates in advance:

$$\Delta_k^t \leftarrow \Delta_k^t \min\left(1, \frac{\tau}{\|\Delta_k^t\|}\right), \quad (4)$$

where τ is a hyper-parameter of the clipping value, which is determined by the server. The underlying intuition is to mitigate the impact of adversarial updates that could lead to substantial model deviations. In addition, it is worth noting that the risk of gradient explosion, as revealed by our experiments, could also be mitigated by clipping gradients [20]. See Section 5.1.3 for more details.

3.3 Other Factors Influencing Robustness

Apart from attack and defense strategies, there are other factors that influence the robustness of the optimization process, such as differential privacy and data heterogeneity.

Noise-adding for Differential Privacy (DP): One of the most common approaches to building a DP-based mechanism is to use Gaussian noise injection [4, 17]. According to prior art [17], the noisy updates

$$\tilde{\Delta}_k^t \leftarrow \Delta_k^t + \mathbf{y}_k^t, \quad (5)$$

with $\mathbf{y}_k^t \sim N(0, I_d \times s^2)$ where $s = \frac{2G_{\max} \sqrt{2 \log(1.25/\delta)}}{b\epsilon}$, sent by client k is (ϵ, δ) -differential private. Given a privacy budget (ϵ, δ) , the privacy guarantees of the overall learning procedure can be determined by leveraging the composition property of DP. The robustness guarantee of robust aggregation rules depends on the low variance of client stochastic gradients. However, the Gaussian DP mechanism adds random noise to the gradients, which can increase the variance especially when the DP budget is low (e.g., when ϵ and δ approach 0), making it more difficult to satisfy the robustness conditions [64].

Data Heterogeneity: As noted in prior studies [18, 31, 39], the presence of data heterogeneity imposes additional challenges on the exclusion of the influence of malicious updates in FL. Higher levels of data heterogeneity result in increased diversity in the local updates, making it more challenging to identify and exclude the effects of malicious updates.

4 THE DESIGN OF BLADES

In this section, we introduce the `Blades` suite that is designed for researchers and developers to benchmark adversarial FL training and evaluate performance efficiently.

4.1 Design Goals

`Blades` is a unified benchmark suite designed for simulating various Byzantine attacks and defense strategies in FL. The architecture of `Blades` is carefully designed to address the following key objectives:

Specificity: Different from existing FL simulators [16, 48, 66], `Blades` is specifically designed to simulate attacks and defenses. Thus, we should provide built-in implementations of representative attack strategies and robust aggregation schemes so that end users

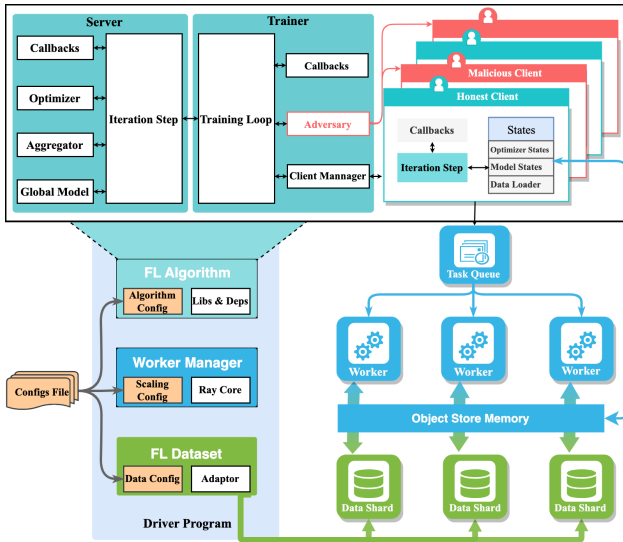


Figure 2: Illustration of our three-layer architecture for `BLades`. The application layer facilitates specific FL algorithms with attacks and defenses implementation. The execution layer provides a scalable backend for distributed training. The data layer manages training data retrieval and preprocessing operations.

can efficiently validate their approaches and compare them with existing solutions.

Scalability: A benchmark suite for FL must exhibit scalability in terms of both clients and computing resources. Scalability with clients refers to the ability to accommodate a large and diverse set of clients participating in the learning process. Scalability with computing resources entails efficiently utilizing and adapting to different computational setups.

Extensibility: `BLades` should support FL configurations of different models, datasets, and optimizers, including standardized implementations such as `FedSGD` and `FedAvg`. The `PyTorch` framework has been selected as the preferred choice for implementing the models. `BLades` should also allow end users to easily incorporate new types of attacks, defenses, and optimization algorithms.

4.2 Core Framework Architecture

To achieve the design goals, especially regarding scalability and extensibility, we decompose the system into three distinct layers: the Application layer, Execution layer, and Data layer. An overview of the architecture of `BLades` is illustrated in Fig. 2. The rationale behind this design is to separate the design goals and foster a modular architecture, thereby enabling optimizations tailored to the specific requirements of each goal. The Application layer focuses on providing extensibility, allowing for easy configuration and integration of various FL-related functionalities and features. The Execution layer ensures the system’s scalability, efficiently handling large workloads and resources. Furthermore, the Data layer functions as an auxiliary component, aiming at enhancing data loading and pre-processing in the distributed environment.

```

1  stop: training_round: 2000
2
3  config:
4    global_model: resnet
5    num_malicious_clients:
6      grid_search: [0, 3, 6, 9, 12]
7
8    client_config:
9      lr: 1.0
10
11   server_config:
12     aggregator:
13       grid_search: [Mean, Median, GeoMed]
14
15   optimizer:
16     type: SGD
17     lr_schedule: [[0, 0.1], [1500, 0.1]]
18     momentum: grid_search: [0.0, 0.5, 0.9]
19
20   adversary_config:
21     grid_search:
22       - type: LabelFlipAdversary
23       - type: IPMAdversary
24       alpha: 0.1

```

Figure 3: An example configuration file for simulating the LableFlipping attack [39] and IPM attack [7]. `BLades` is fully configurable and allows grid search for hyperparameter tuning.

4.2.1 Application Layer. It is the top layer of `BLades` and provides a user-friendly interface for designing and deploying FL algorithms. The main abstractions in this layer include:

Server: A server is an object that aggregates model updates from multiple clients and performs global optimization. Once a local training round is finished, it gathers the model updates and takes one iteration step. Defense strategies, such as robust aggregations, are usually applied here to eliminate the impact of malicious updates.

Trainer: The trainer encapsulates the optimization process for a particular FL algorithm. A trainer manages key aspects of the training loop, including interactions with the server, client group management, and state synchronization between the server and clients. Each trainer corresponds to a specific FL algorithm, such as `FedAvg`, and can be configured with various hyperparameters to control the local training process. It also allows customization with callbacks invoked at specific points during training, such as after each local training round or server optimization step. The “Adversary” component in the Trainer can control a subset of clients to perform malicious operations.

Client: The client acts as a participant in the FL process. We provide the client-oriented programming design pattern [23] to program the local optimization of clients during their involvement in training or coordination within the FL algorithm. This pattern allows end users to specify and execute certain types of attacks easily. Other than that, users can also customize the behaviors of Byzantine clients using the interface we provide.

The application layer has several dependencies that provide a variety of functionalities. Particularly, we adopt the `Tune` library² [42] for experiment configuration and hyperparameter tuning at any scale. As an example, Fig. 3 shows a configuration file for simulating the LableFlipping [39] and IPM [7] attack with different hyperparameter settings. With the help of `Tune`, `BLades` reads the file and parses

²<https://docs.ray.io/en/latest/tune>

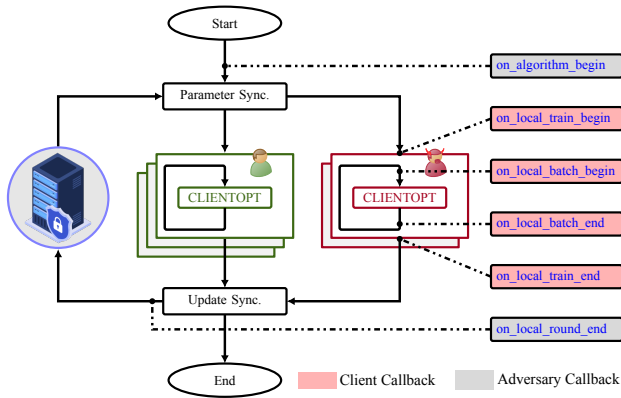


Figure 4: The pipeline for implementing attacks using `Blades`. We define some time points when users can register executable methods to perform customized attacks. At specific time points, client callbacks and adversary callbacks are triggered to invoke the registered methods.

the configurations to generate a series of experimental trials. The trials are then scheduled to execute on the execution layer. Notably, the “`grid_search`” keyword allows for the different combinations of hyperparameters and configurations in the grid, containing “`num_malicious_clients`”, “`server_config`”, and “`adversary_config`” in this example, which results in 90 trails at once.

4.2.2 Execution Layer. The execution backend is built upon a scalable framework Ray³ [47] for training and resource allocation. Ray provides two key advantages for `Blades`: 1) It allows users to customize computing resources (e.g., CPUs and GPUs) to clients and servers conveniently; 2) It enables `Blades` to easily adapt to in-cluster large-scale distributed training, benefiting from the capabilities of the Ray cluster. The core abstractions in the execution layer are:

By decoupling the execution layer from the application layer, clients remain unaware of the specific implementation details of the backend. As a result, users can concentrate solely on the application layer for implementing FL algorithms and submitting client training pipelines to the worker group.

4.2.3 Data Layer. The data layer facilitates data pre-processing and loading for distributed training with the execution backend. It supports both IID and non-IID partitions for studying homogeneous and heterogeneous scenarios, respectively. At the beginning of the training, the dataset is separated into multiple shards and pre-allocated to workers’ memory to allow fast data loading. In addition, we provide adapters to import datasets from well-known 3rd-party benchmarks in FL, such as LEAF [10], FedML [23], and TensorFlow Federated [1].

4.3 Implementation of Attacks and Defenses

4.3.1 Implementing Attacks. We note that adversarial attackers may perform some self-defined manipulation before or after

specific time points. For instance, LabelFlipping [30] attacks are typically executed at the beginning of batch forward propagation, while SignFlipping [36] attacks are carried out immediately after back-propagation. To address this, we have designed a unified pipeline integrated with a callback mechanism, which enables actions to be performed at various stages of training, as depicted in Fig. 4. A callback or callback method is any reference to executable code that is passed as an argument to another piece of executing code. The callback method is expected to execute at some defined time points.

This design offers extensibility to facilitate customization, where the minimal pipeline focuses on repetitive local training and server-side optimization while the malicious behaviors are defined through the callback mechanism. Users only need to override specific callback methods to execute a custom attack without modifying the pre-defined logic.

The pipeline consists of two levels of callbacks: client level and adversary level. Since the attacks at Levels 1 & 2 only have access to local model parameters and datasets, they can be easily implemented by registering behaviors to the client objects and hereby can be executed in parallel on multiple nodes or cores. As an illustrative instance, the upper panel of Fig. 5 shows a code snippet that exemplifies the implementation of a LabelFlipping attack on a classification task encompassing 10 distinct classes. Through a straightforward customization of the “`on_batch_begin()`” callback method, the user can effortlessly modify the labels from class i to $9 - i$ during local training.

For attacks at Level 3 and above, clients in the distributed environment need to exchange data, coordinate actions, and synchronize their activities for making decisions regarding malicious actions. A straightforward solution to simulate such attacks is allowing inter-client communication using the remote function mechanism in Ray. However, this will make the simulation more complex and limit the scalability of the system. One possible consequence is the occurrence of deadlocks [25], i.e., when two or more clients are waiting for each other to release a resource or respond to a communication, none of them can proceed.

Alternatively, our `Blades` facilitates the implementation of sophisticated attacks by incorporating supplementary callbacks tailored for adversary entities. Distinguished from client callbacks, these adversary callbacks are executed within the driver program and allow convenient access to various system components and their states. As a result, this design simplifies the process of acquiring knowledge for high-level attacks. Fig. 4 also shows two of the most essential adversary callbacks, specifically “`on_algorithm_begin()`” and “`on_local_round_end()`”. The former is triggered at the start of the algorithm and serves the purpose of initializing the adversary and setting up client callbacks. The latter is triggered upon the completion of a local round and allows for the modification of collected updates from malicious clients before proceeding to server-side optimization and defense operations. During the “`on_local_round_end()`” callback, one can potentially access honest updates and other system states in a read-only manner to launch omniscient attacks (Levels 4 & 5). The lower panel of Fig. 5 shows an example of implementing the ALIE [7] attack using the proposed callback method.

³<https://www.ray.io>


```

1 from blades.clients import ClientCallback
2
3 class LabelFlipCallback(ClientCallback):
4     def on_batch_begin(self, data, target):
5         # This method returns original input data with
6         # flipped labels for the current batch (assuming
7         # 10 labels).
8         return data, 9 - target
9
10
11 from blades.adversary import AdversaryCallback
12
13 class ALIECallback(AdversaryCallback):
14     def on_local_round_end(self, trainer):
15         # This method computes the dimensional mean
16         # and std over client updates, then sets the
17         # malicious updates within the range of std.
18         updates = trainer.get_updates()
19         mean = updates.mean(dim=0)
20         std = updates.std(dim=0)
21
22         updates_m = mean + std
23         trainer.save_malicious_updates(updates_m)

```

Figure 5: Illustration of our callback mechanism used to simulate the Label Flipping attack (upper) [39] and ALIE attack (lower) [7]. The design’s flexibility enables easy customization by overriding methods associated with both client and adversary callbacks.

4.3.2 Implementing Defenses. As emphasized in Section 3.2, defenses in the context of our study stem from multiple facets, posing challenges to the establishment of a standardized pipeline akin to the one employed for attacks. Nevertheless, certain indispensable steps are involved in this process, namely update aggregation and global model optimization, although the specific methodology for each step may vary. The update aggregation step combines the locally collected updates, while the global model optimization step performs an optimization procedure based on the aggregated result.

As such, *Blades* introduces a foundational abstraction of the server entity, encompassing essential components such as a global model, an aggregator, and an optimizer. This architecture permits the extension of functionalities through the utilization of sub-classing, thereby facilitating the integration of advanced features. It is noteworthy to mention that even in the minimal server implementation, we offer a configurable SGD optimizer and a variety of pre-defined robust aggregation rules. Furthermore, all the components are modularized and inheritable, allowing plug-and-play of different configurations. We believe our designs can simplify the process of generating benchmark results with minimal effort.

5 EXPERIMENTS

In this section, we present the experimental results pertaining to *Blades*. Specifically, we commence by evaluating representative built-in attack and defense mechanisms, offering comprehensive perspectives on their respective advantages and limitations. Furthermore, we assess the scalability of *Blades*, focusing on its adaptability to increasing client counts and computational resources.

5.1 Attacks and Defenses Simulation

5.1.1 Experimental Setup. We simulate an FL system with one server and 60 clients, employing two popular image classification datasets: Fashion MNIST and CIFAR10. Fashion MNIST [59] consists of 50,000 gray-scale training samples and 10,000 test samples.

It encompasses 10 different categories of clothing items, such as shoes, T-shirts, and dresses. The images in Fashion MNIST are of size 28×28 . CIFAR10, introduced by Krizhevsky et al. [34], contains 50,000 color training samples and 10,000 test samples. It comprises color images of various objects classified into 10 categories, including airplanes and automobiles. The images in CIFAR10 have dimensions of $32 \times 32 \times 3$. For Fashion MNIST, we use a five-layer convolutional neural network (CNN). For CIFAR10, we use a lightweight ResNet architecture [24].

We partitioned each dataset into 60 distinct subsets, utilizing both IID (independently and identically distributed) and non-IID strategies. For the IID approach, we assumed homogeneity in data points, with each subset representing a random sampling of the entire dataset, ensuring statistical consistency. For the non-IID partition, we follow prior work [39, 43] and model the non-IID data distributions with a Dirichlet distribution $p_l \sim \text{Dir}_K(\alpha)$, in which a smaller α indicates a stronger divergence from IID. Then we allocate a $p_{l,k}$ proportion of the training samples of class l to client k .

By default, we repeat each experiment five times with different random seeds for model initialization and evaluate the accuracy of the learned model with a clean test set.

5.1.2 Robust Aggregation. Without loss of generality, we first evaluate the robustness of different aggregation rules using one step of local update, i.e., $E_l = 1$. Fig. 6 depicts the overall comparison of the robust aggregation rules with respect to test accuracy under different types of attacks. The results clearly show that the robustness of examined aggregation rules varies depending on the dataset and attack type. Notably, when utilizing the Fashion MNIST dataset, robust aggregation rules maintain higher accuracy compared to CIFAR10, which can be attributed to the relatively lower complexity and diversity of the Fashion MNIST classification task.

Regarding the examined attacks, low-level attacks such as LabelFlipping [30] and Signflipping [36] demonstrate limited effectiveness against most aggregation rules. Conversely, high-level attacks such as ALIE [7] and MinMax [55] lead to substantial performance degradation across various scenarios, particularly with an increased proportion of malicious clients. It should be noted that both ALIE and MinMax leverage the variance of benign updates. However, MinMax typically amplifies the magnitudes to larger values, thereby presenting a mixed set of advantages and disadvantages. On the one hand, larger magnitudes have the potential to push the global model further away if they are not filtered out by the aggregation rules. On the other hand, these amplified magnitudes are more easily detectable by certain defense mechanisms, such as the DnC rule employed in our experiments.

Moving to defenses, traditional GARs (i.e., Median [64], Trimmed-Mean [64], and GeoMed [51]) show vulnerabilities to multiple attack types. As already illustrated in Table 2, these methods rely on either filtering at the dimensional level or optimization based on Euclidean distance, both of which have been deemed insufficient in previous studies [39, 55]. In contrast, advanced EGARs such as DnC, ClippedClustering, and SignGuard exhibit superior resilience against most attacks. These advanced approaches typically employ hybrid mechanisms incorporating multiple techniques, enhancing their effectiveness in defending against various attack scenarios.

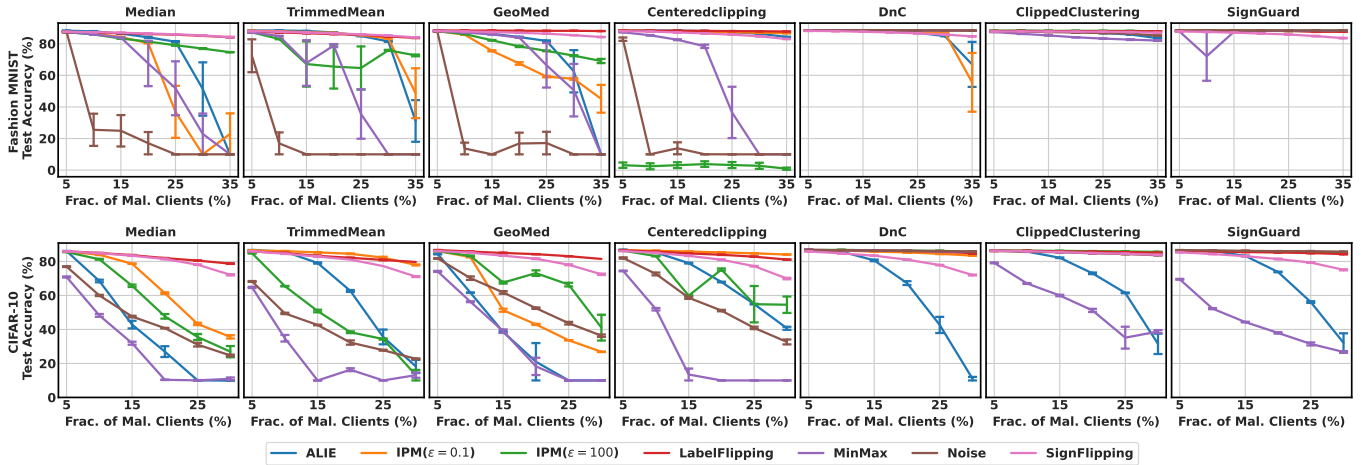


Figure 6: Comparing aggregation rules under various attacks with IID partition. Low-level attacks like LabelFlipping [30] and Signflipping [36] are ineffective against most of the aggregation rules, while high-level attacks such as ALIE [7] and MinMax [55] result in significant performance degradation across most settings, particularly as the fraction of malicious clients increases. Noticeably, traditional GARs (i.e., Median [64], TrimmedMean [64], and GeoMed [51]) exhibit vulnerabilities to several attacks, whereas advanced EGARs display greater resilience.

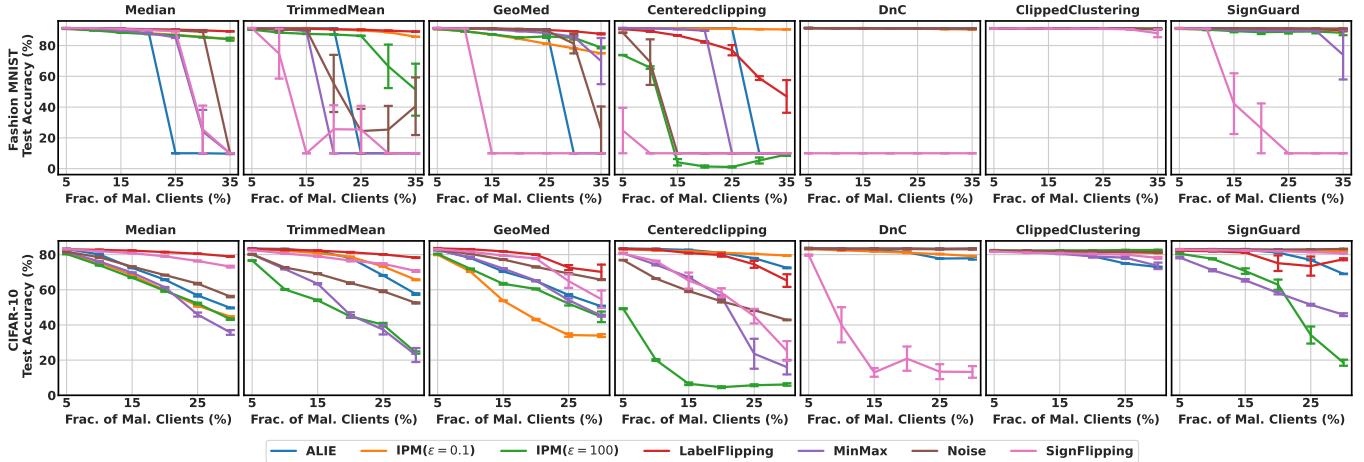


Figure 7: Evaluation of aggregation rules while utilizing 20 steps for local updates (i.e., $E_l = 20$). Traditional GARs consistently show increased susceptibility to these attacks, whereas advanced EGARs demonstrate enhanced robustness. Notably, ClippedClustering exhibits effective defense against all examined attacks with minimal performance loss, while other methods display distinct vulnerabilities depending on the attack type.

Figure 7 shows the results of aggregation rules using 20 steps of local updates, i.e., $E_l = 20$. Similarly, traditional GARs (i.e., Median [64], TrimmedMean [64], and GeoMed [51]) still exhibit greater vulnerabilities to attacks compared to EGARs. However, Figure 7 reveals a greater diversity in the robustness of aggregation rules when utilizing the Fashion MNIST dataset. Particularly, the SignFlipping attack causes a significant accuracy drop to most defenses

when down to 15% of the clients are malicious. Notably, ClippedClustering exhibits effective defense against all examined attacks without substantial degradation in performance, whereas other aggregation rules manifest vulnerabilities to specific attack types.

(Takeaway) 1) Different aggregation rules can offer protection against specific types of attacks but concurrently exhibit vulnerabilities to others; 2) For gradient aggregation, variance-based attacks pose the most substantial challenge to the established robust aggregation rules; 3) Hybrid strategies that integrate multiple techniques demonstrate greater promise than purebred defense strategies.

5.1.3 The Risk of Gradient Explosion. Another interesting observation in Fig. 6 is that four robust aggregation rules fail to handle Noise attacks on Fashion MNIST even when only 10% of the clients

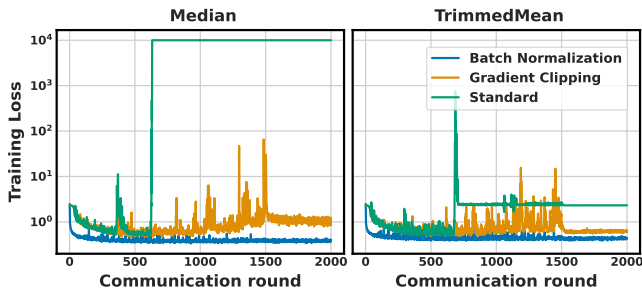


Figure 8: Training loss on Fashion MNIST with noise attacks where 20% of clients are malicious. The loss values are clamped to $[0, 10^4]$. The attacks lead to gradient explosions, which are mitigated by gradient clipping and batch normalization.

are malicious. Upon closer examination of the gradients and loss values, we observe significant gradient explosions among the benign clients, which prevent the model from converging to the optimal solution. We believe that the decline in performance is attributed not only to substantial deviations but also to the potential detrimental impact of gradient explosions caused by malicious attacks.

To validate our findings, we employ two measures to mitigate gradient explosions, i.e., gradient clipping and batch normalization, and show the comparison in Fig. 8. When no measures are taken, the training loss shows sudden spikes and ends up with a large value, indicating that the model cannot converge to an appropriate solution. With gradient clipping and batch normalization, the training process becomes more stable. Batch normalization not only prevents gradient explosions but also accelerates the training process, facilitating faster convergence.

(Takeaway) Malicious updates could increase the vulnerability of global models to gradient explosions. Consequently, it is imperative to apply effective mechanisms (e.g., clipping and batch normalization) to address this issue.

5.1.4 Impact of the degree of non-IID in datasets. Figure 9 illustrates the test accuracy results of the ALIE attack on CIFAR10, varying the levels of non-IID partitioning. It can be observed that the effectiveness of the attack increases significantly when the dataset is highly non-IID (e.g., $\alpha = 0.1$). This observation is consistent with prior studies [18, 39, 55]. A commonly proposed explanation is that as the local data distributions become significantly different, the model updates diversify, thereby posing an additional challenge for the aggregation rules to perform a proper aggregation.

(Takeaway) The presence of diverse local data distributions poses a greater challenge for robust aggregation.

5.1.5 Impact of noise-adding for DP. Next, we assess the influence of introducing Gaussian noise for DP on the resilience of defenses utilizing Fashion MNIST. Figure 10 illustrates that as the privacy budget diminishes, the test accuracy across all aggregation rules declines more rapidly as the number of malicious increases. With a high budget (e.g., $\epsilon = 100.0$), all aggregation rules result in comparable accuracy levels to those without the incorporation of DP noise. In contrast, when the privacy parameter ϵ equals 1.0, the

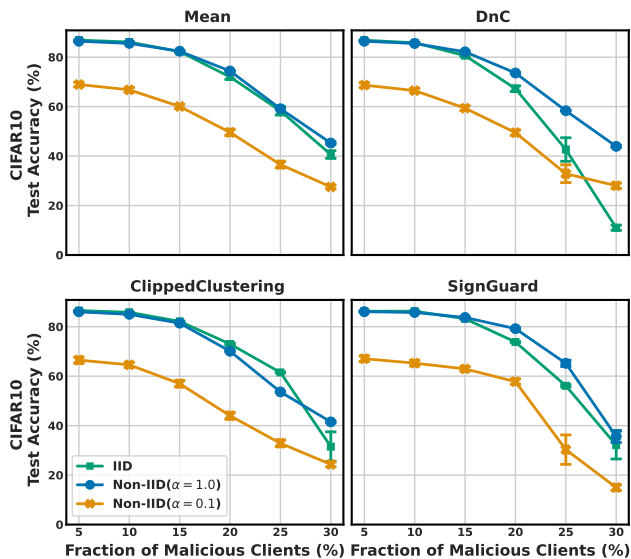


Figure 9: Impact of various degrees of non-IID on the robustness of aggregation schemes against ALIE attack. A lower α value indicates a higher degree of non-IID.

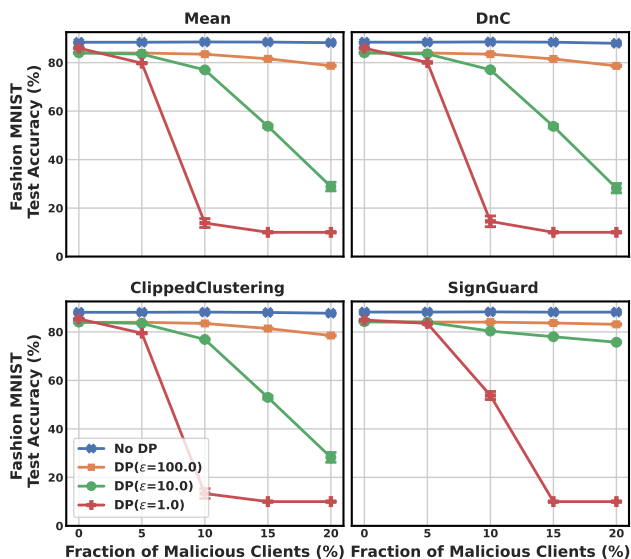


Figure 10: Impact of various DP levels on the robustness of aggregation schemes against ALIE attack. A lower ϵ value indicates a lower budget for DP. All aggregation rules become more vulnerable to adversarial attacks with a lower privacy budget.

aggregation rules yield extremely low accuracy (nearly the same as random guessing) when 10% of the clients are malicious.

(Takeaway) A low budget for DP limits the robustness of robust aggregation rules. This suggests the need for careful consideration and trade-offs between the demands of DP and Byzantine resilience in the practice of FL.

Table 3: Test accuracy of CIFAR10 on different momentum settings. The numbers with the highest accuracy are in bold. Client momentum significantly improves the robustness.

Aggregator	10% malicious clients			15% malicious clients			20% malicious clients		
	No Momentum	Server Momentum	Client Momentum	No Momentum	Server Momentum	Client Momentum	No Momentum	Server Momentum	Client Momentum
Mean [45]	86.05 (0.20)	88.46 (0.24)	89.51 (0.22)	82.89 (0.46)	80.72 (0.53)	88.18 (0.34)	73.50 (0.91)	59.92 (1.36)	85.88 (0.22)
DnC [55]	85.84 (0.19)	87.92 (0.45)	89.40 (0.15)	81.45 (0.29)	76.58 (0.08)	87.89 (0.45)	68.63 (0.40)	50.04 (3.88)	83.60 (0.40)
Median [64]	69.38 (0.58)	48.39 (2.41)	83.95 (0.31)	45.95 (3.05)	27.52 (3.97)	68.20 (0.63)	27.85 (10.7)	14.29 (6.23)	52.22 (3.73)
TrimmedMean [64]	85.98 (0.29)	87.81 (0.14)	89.57 (0.18)	79.98 (0.47)	72.40 (0.49)	87.47 (0.12)	66.69 (0.47)	41.32 (4.75)	81.72 (0.44)
ClippedClustering [39]	85.76 (0.16)	87.86 (0.19)	89.47 (0.20)	82.25 (0.25)	73.23 (1.23)	87.94 (0.36)	73.19 (0.98)	41.52 (5.63)	83.06 (0.62)

5.1.6 Impact of Momentum. As indicated in Section 3.2.4, momentum is considered a supplementary technique aiming at bolstering the robustness of Byzantine-resilient FL. To evaluate its effectiveness, we conducted experiments by training a ResNet on CIFAR10 under the ALIE attack. The obtained results are presented in Table 3. Surprisingly, the integration of server momentum demonstrates minimal enhancement in the robustness of the aggregation rules, particularly in extremely limited scenarios, while yielding even lower accuracy in other scenarios. In contrast, the aggregation rules consistently exhibit significant improvements when client momentum is employed.

(Takeaway) When employed as an auxiliary technique, client momentum confers advantages in defending against ALIE attacks, whereas server momentum exacerbates the vulnerability.

5.2 Scalability Evaluation

We evaluate the scalability of `Blades` along two lines: First, we evaluate the training time for a global round with an increasing number of clients and computing resources. Second, we evaluate the training time per round with an increasing number of GPUs.

To assess the scalability with respect to the number of clients, we conduct simulations with a fixed set of resources and vary the number of clients. As shown in Table 4, the number of clients increases from 16 to 512, which greatly outnumbers the available CPUs and GPUs. The results show that with a linear increase in the number of clients, the average training time of each global round increases linearly with little standard deviation, indicating the stable and efficient communication and task distribution implementation in `Blades`.

Table 4: Experiment for client scalability - average and standard deviation of training time per global round with increasing numbers of clients.

# Clients	16	32	64	128	256	512
Avg (seconds)	1.41	2.48	4.51	9.10	17.58	34.53
Std (seconds)	0.05	0.07	0.11	0.18	0.38	0.73

To evaluate the resource scalability of `Blades`, we design a simulation task involving 480 clients to be executed on GPUs. Fig. 11 shows the time cost of each global round with different numbers of GPUs and the associated speedups. The time cost for each global round reduces from 82.5s to 49.5s when the number of GPUs increases from 1 to 2, and the time cost reduces more if more GPUs are added. The speedup achieved does not align precisely with the number of GPUs utilized, primarily because FL is not an entirely

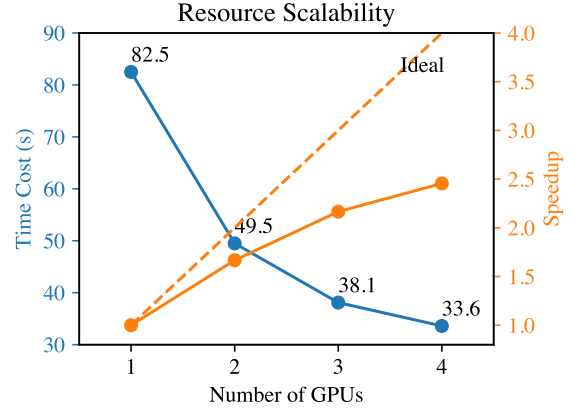


Figure 11: Resource scalability of `Blades`. Blue: Average time cost per global round decreases with the increase in the number of GPUs. Orange: The speedup increases with the increase in the number of GPUs.

parallelizable algorithm. Consequently, a substantial portion of serial work, such as the communication of local updates and model aggregation, hinders the potential speedup. Nonetheless, it can be concluded that the increase in computing resources significantly reduces the time cost of the simulation, and `Blades` is scalable with computing resources.

6 CONCLUSION AND FUTURE WORK

In this paper, we first investigated the existing methodologies employed in Byzantine-resilient FL. Then we introduced an open-source benchmark suite to address the research gap concerning attack and defense problems in FL. The `Blades` framework offers scalability, integration of cutting-edge attack and defense strategies, and adaptable interfaces that facilitate the implementation and expansion of novel attack and defense techniques. By utilizing `Blades`, we conducted a comprehensive evaluation of prominent defense techniques against state-of-the-art attacks, yielding insightful findings regarding the resilience of Byzantine-resilient FL. Furthermore, we validated `Blades` and showed that `Blades` is scalable in terms of both the number of clients and computing resources. We will continue our efforts to address new challenges with our new releases of `Blades`. We encourage the research community to explore new research using `Blades` and invite contributions to the public source repository.

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