# On the Privacy of Decentralized Machine Learning

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Abstract—In this work, we carry out the first, in-depth, privacy analysis of Decentralized Learning-a collaborative machine learning framework aimed at circumventing the main limitations of federated learning. We identify the decentralized learning properties that affect users' privacy and we introduce a suite of novel attacks for both passive and active decentralized adversaries. We demonstrate that, contrary to what is claimed by decentralized learning proposers, decentralized learning does not offer any security advantages over more practical approaches such as federated learning. Rather, it tends to degrade users' privacy by increasing the attack surface and enabling any user in the system to perform powerful privacy attacks such as gradient inversion, and even gain full control over honest users' local model. We also reveal that, given the state of the art in protections, privacy-preserving configurations of decentralized learning require abandoning any possible advantage over the federated setup, completely defeating the objective of the decentralized approach.

#### I. INTRODUCTION

Collaborative machine learning is gaining traction as a way to train machine learning models while respecting the privacy of users [35]. There are two main approaches to collaborative machine learning: federated learning [35] and decentralized learning [32]. In the former, learning is orchestrated by a central parameter server that intermediates communications among users and maintains the global state of the system. The use of a unique central server brings limitations for both performance and privacy. On the communication side, the server becomes a communication bottleneck as the number of users in the system grows. On the privacy side, the server becomes a single point of trust as it has full control of the learning process and thus it can arbitrarily influence users' models [4], [12], [46], [57] and access their intermediate states [13], [70].

**Decentralized machine learning**, also known as fully-decentralized machine learning, peer-to-peer machine learning, or gossip learning, aims to address these limitations by performing the optimization learning process via peer-to-peer communication instead of a central server. Users communicate only with a subset of other users to exchange the information needed to train the model (see Figure 1). In a way, every node acts as a small parameter server that locally aggregates the received model updates and uses them to update the current local state. This process repeats until consensus in the system is achieved.

Proponents of decentralized learning argue that decentralization (1) reduces the bandwidth consumption, as there is no central aggregator, (2) provides users with control on who they communicate with, and (3) increases privacy in the system by eliminating any entity (the parameter server) that has higher

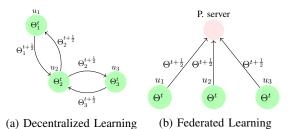


Fig. 1: Schematic representation of the decentralized learning and federated learning protocols.

influence on the system. In addition, decentralized learning also helps with other issues in federated approaches such as data and resource heterogeneity [20], [43], [54].

A large body of theoretical studies, empirical evaluations, and model extensions attest to the effectiveness and relevance of decentralized machine learning [8], [18], [21], [26], [27], [28], [30], [31], [34], [45], [47], [48], [55], [32], [60], [65], [66]. While the performance gain may be unquestionable [18], [26], [32], most decentralized learning studies do not evaluate the impact of decentralization on users' privacy. These studies either state that decentralized learning offers a higher level of privacy compared to other approaches such as federated learning without any evidence [8], [55], or do not provide any privacy argument [21], [28], [30], [31], [32], [60], [65].

In this work, we carry out the first, in-depth study of the privacy guarantees offered by decentralized collaborative machine learning against passive (honest-but-curious) and active (malicious) adversaries. We show that there is a strong relation between the underlying communication topology of the decentralized system and the level of privacy that can be achieved by any decentralized learning protocol. By introducing a series of novel passive and active attacks, we demonstrate that adversaries can exploit their direct and indirect connections in the decentralized network to carry out inference attacks on honest users. We show that current decentralized learning techniques cannot prevent all attacks simultaneously and different system configurations can only trade-off protection against one attack for vulnerability against another. Our attacks are agnostic to the concrete decentralized protocol and therefore provide a sound evaluation framework to support principled privacy analyses of collaborative machine learning systems.

The conclusion of our evaluation is that, in contrast to common belief, decentralized learning does not offer any privacy advantages over more practical approaches such as federated learning. Rather, decentralized learning inherently boosts the

capabilities of privacy attackers compared to federated settings. As a result, users in decentralized learning cannot reach the same privacy as users in federated learning neither against passive nor active adversaries. To obtain the same protection as in federated learning, decentralized learning has to be built on a fully-connected communication topology and use expensive aggregation techniques, essentially destroying any advantage of decentralization over the federated approach.

In summary, these are our contributions:

- We provide the first in-depth privacy evaluation of decentralized learning protocols. We show that the capabilities that decentralization grants to adversarial users result in high privacy risk for honest users, generally higher than in federated learning, against active and passive attackers.
- We characterize the factors that lead to privacy leakage. We show that they are deeply dependent on the connectivity of the underlying communication topology. We propose a suite of attacks that exploit these factors to learn information about the users' private training sets. We show that the solutions against these attacks are in conflict: the solutions to eliminate one factor augment the other; leaving little space to build efficient privacy-preserving decentralized systems.
- We discuss the applicability and limitations of current mitigations aimed at improving privacy in decentralized learning. We show that, in their current state, they are not sufficient to close the privacy gap between the decentralized and federated setup. Finally, we draw attention to the practical challenges that need to be addressed to deploy truly privacy-preserving decentralized learning.

Organization: We start in Section II, where we briefly survey collaborative machine learning and define the notation we use within the paper. Section III follows by formalizing our evaluation setup. In Section IV, we abstract the main sources of privacy leakage of decentralized learning protocols. In Section V, we analyze the security of the decentralized protocol against passive (honest-but-curious) adversaries. Section VI extends the analysis to active (malicious) adversaries. Section VII surveys the main, privacy-related, open problems in decentralized learning. Section VIII concludes the paper, with Appendices containing additional material. In the paper, background and analysis of previous works are provided, when necessary, within the respective sections.

#### II. COLLABORATIVE MACHINE LEARNING

Collaborative machine learning enables a set of n distributed users V to train a shared model f defined by a set of parameters  $\Theta$ . Each client  $v \in V$  that participates in the training protocol with a set of training instances  $X_v$ . This training dataset must be kept private, i.e., it must not be directly shared with any other party running the protocol. Parties involved in the training should not learn anything about each other's training set besides what can be inferred from the final model. In this paper, we limit our privacy definition to the privacy of this training set, and not other attributes that could be learned about users (e.g., location [6] or device type).

The shared model f is typically trained using a distributed version of Stochastic Gradient Descent (SGD). In this version,

information about users' training sets is iteratively propagated via *model updates*. These updates are intermediate outputs of the local optimization process e.g., gradients or parameters [35], [32] obtained after one or more local SGD steps. Users receive updates from other users via direct connections in a peer-to-peer fashion, or indirectly through other parties (typically a server). Users combine the received updates with their local state to compute their local model. Eventually, users share a generalized model capturing information from all users in V.

#### A. Decentralized Learning

In decentralized learning, users are directly connected to each other in a peer-to-peer fashion. They solve the (distributed) optimization learning problem through gossip communication. We model users' connections as an *undirected* graph G, where users are nodes and communication links are edges (Figure 1a). We refer to this graph as *communication topology* or simply *topology*. At each training step, users aggregate the model updates received from their *neighbors*, locally apply one or more optimization steps using their local training dataset, and broadcast their adjusted model parameters (Figure 1a). During these steps, **users have a local view of the current parameters different from other users**. Eventually, after a suitable number of communication rounds, users converge to a global set of parameters. When users achieve a global status, we say they achieved *consensus*.

There exists a large body of studies on decentralized learning [2], [3], [10], [11], [17], [26], [30], [31], [45], [47], [48], [51], [55], [32], [59], [63], [66], [67], [68]. These works improve different aspects of decentralized learning, among others scalability, asynchronicity and data heterogeneity.

### B. Federated Learning

In federated learning [35] users learn the model via a central *parameter server* that iteratively aggregates and synchronizes model updates (Figure 1b). At each training step, users download the global model from the server and locally apply one or more local training steps. Users then send the model updates (e.g., accumulated gradients/weights) to the server. The server aggregates the user's inputs into a single update and apply it to the global model parameters.

In federated learning, there is no direct communication among users. Thus, they do not have direct access to each other's model updates. They only receive information about other users contributions in aggregated form from the parameter server, and cannot distinguish individual contributions or their sources. Contrary to decentralized learning, in federate learning users share the same global state throughout the whole training process.

#### III. EVALUATION SETUP

Our privacy evaluation of decentralized learning is designed as a comparative analysis with federated learning. In this section, we formalize the privacy notion we evaluate in this paper. We also introduce the decentralized and federated learning protocols targeted by our analysis and describe how we parametrize them in our evaluation. We provide more details about our setup in Appendix B.

**Privacy risk.** Collaborative learning aims to keep the users' training sets private, i.e., minimize the risk that examples in this set become known to others. In this paper, we quantify the privacy risk using *Membership Inference Attacks* (MIAs).

We define a privacy metric based on the "label-informed" entropy introduced by Song et al. [53]. Given a set of model parameters  $\Theta$ , a local training set X, and a test set  $\mathcal{O}$  s.t.  $X \cap \mathcal{O} = \emptyset$  and  $|X| = |\mathcal{O}| = m$ , we estimate the privacy risk as the accuracy of the membership inference attack over the sets X and  $\mathcal{O}$ :

$$M(\Theta, X, \mathcal{O}) = \frac{1}{2 \cdot m} \sum_{i=0}^{m-1} [MIA_{\Theta}(X_i) + \neg MIA_{\Theta}(\mathcal{O}_i)]$$
(1) with  $MIA_{\Theta}(x) = \xi(f_{\theta}(x)) < \rho$ , (2)

where  $\xi$  is the label-informed entropy [53] and  $\rho$  is a threshold.

Intuitively, M measures the average margin that separates members from non-members instances. Higher values of M indicate that the model f behaves very differently for members and non-members, and thus the attacker can easily identify training set samples. Low values of M indicate that the model f behaves comparably on member and non-member inputs, hindering membership inference.

For convenience, in our evaluation we subtract the random guessing baseline (0.5) from the accuracy so that the results we report are centered in 0.

**Data:** Initial parameters:  $\Theta_v^0$ , local training set:  $X_v$ , weight matrix: w, consesus step:  $\eta$ 

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 \begin{array}{c|c} \mathbf{1} \ \mathbf{for} \ t \in [0,1,\dots] \ \mathbf{do} \\ \\ & /^* \ \operatorname{Local} \ \operatorname{optimization} \ \operatorname{step} \\ & \xi_v^t \sim X_v; \\ \mathbf{3} & \Theta_v^{t+\frac{1}{2}} = \Theta_v^t - \eta \nabla_{\Theta_v^t} (\xi_v^t, \Theta_v^t); \\ & /^* \ \operatorname{Communication} \ \operatorname{with} \ \operatorname{neighbors} \\ \mathbf{4} & \mathbf{for} \ u \in \mathbf{N}(v)/\{v\} \ \mathbf{do} \\ \\ \mathbf{5} & \operatorname{send} \ \Theta_v^{t+\frac{1}{2}} \ \operatorname{to} \ u; \\ \\ \mathbf{6} & \operatorname{receive} \ \Theta_u^{t+\frac{1}{2}} \ \operatorname{from} \ u; \\ \mathbf{7} & \mathbf{end} \\ & /^* \ \operatorname{Model} \ \operatorname{updates} \ \operatorname{aggregation} \\ & & \\ \mathbf{8} & \Theta_v^{t+1} = \frac{1}{|\mathbf{N}(v)|} \sum_{u \in \mathbf{N}(v)} \Theta_u^{t+\frac{1}{2}}; \\ \\ \end{array}
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**Algorithm 1:** Training protocol for every decentralized user  $v \in V$ .

**Decentralized learning protocol.** We target our privacy analysis on a decentralized learning protocol based on the seminal *D-PSGD* protocol by Lian et al. [32]. This protocol provides the same core functionality and properties as the bulk decentralized protocols that can be found in the literature [2], [11], [21], [26], [30], [31], [34], [51], [60], [63], [67], and thus serves as a representative abstraction of the state of the art. Additionally, it allows us to carry out a straightforward comparison with federated learning protocols.

In D-PSGD, the n users agree on a communication graph G, and on the training setup (e.g., architecture, hyperparameters, and initial parameters). Then, every user v runs Algorithm 1 in parallel. This algorithm, consists of three steps: 1. Local training. Users perform local training to update their local state. They sample a mini-batch  $\xi$  from their local training

set and apply gradient descent on their local view of the model parameters. The result is an intermediate model  $\Theta_v^{t+\frac{1}{2}}$  that we refer to as *model update*.

- 2. State Sharing. Users share their model updates  $\Theta_v^{t+\frac{1}{2}}$  with their neighbors, and receive their neighbors' updates (line 4 in Algorithm 1). Hereafter, we use the notation  $\mathbf{N}(v)$  to refer to the set of neighbors of node v. where we always consider  $v \in \mathbf{N}(v)$ .
- 3. Aggregation. Users compute their new model by aggregating all their neighbor's updates with their local one. The aggregation is the average of the model parameters.<sup>1</sup>

This algorithm repeats until nodes converge in a consensus state [32], [26]. We measure the consensus distance C among nodes as the average, pairwise discrepancy among local parameters at the time t:

$$C(t) = \frac{\sum_{v \in V} \sum_{u \in V/\{v\}} \|\Theta_v^t - \Theta_u^t\|^2}{|V|^2 - |V|}.$$
 (3)

Intuitively, large values of C indicate that there is a large discrepancy among users' local parameters. Small values of C indicate that users have similar local models. We say that the system has found consensus when  $C(t) < \epsilon$ , for a small enough  $\epsilon$ .

Following the most relevant works in decentralized learning [3], [10], [11], [17], [26], [55], [32], [63], we assume the communication graph to be fixed, i.e., the links among nodes do not change over time and users do not drop-off in the middle of a round. We also assume users to agree on the initial parameters of the local models before the training and to start with the same state  $\Theta_v^0$  [26], [32].

COMMUNICATION TOPOLOGY Within our privacy analysis, we consider three classes of communication topology:

*Torus*. In this regular topology, every user is connected with four other nodes. It represents the best-case scenario for the decentralized learning given its good mixing properties and higher spectral gap that allow for fast convergence and efficient communication [26]. We consider torus graphs with different numbers of nodes and we refer to them as *torus-n*, where *n* is the number of nodes.

Random Regular. We build graphs G in which, for a given number of nodes n and a degree d, every node has degree d. Random regular topologies enable us to analyze the impact of the density of connections (d) on the privacy of decentralized learning. We refer to these graphs as regular-(n,d).

Davis Southern women social network. This topology, used by Koloskova et al [26], simulates an unstructured, more natural communication topology such as the one generated by users in a cross-device setting. This social network has 32 users and a heterogeneous degree distribution among nodes with an average degree of 5.74. We refer to this topology as social-32.

**Federated Learning protocol.** We take the Federated Averaging (FedAVG) [35] protocol as representative of federated learning algorithms in the literature. We target FedAVG in a

<sup>&</sup>lt;sup>1</sup>We assume model updates to have equal weights, though in general the aggregation of line 8 can be expressed via a weighted sum.

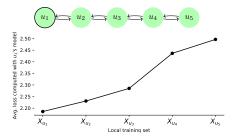


Fig. 2: Average loss of  $u_1$ 's local model computed on every local training set.

cross-silo setting, where the number of users is fixed and users cannot drop-off the protocol, which matches the functionality of D-PSGD, to be able to perform a fair comparison between the two protocols. As in Algorithm 1, we force users' local training step to be computed on a single, random batch per round. Under this configuration, algorithm 1 becomes functionally equivalent to FedAVG when the graph G is complete (i.e., when every user is connected to everyone else).

**Datasets and architecture.** In our experiments, we use the training sets CIFAR-10 and CIFAR-100 [29]. As in [26], we assume the best-case scenario for the partition of the training set among users: the local training set is uniformly distributed among nodes. We use a ResNet20 [16] as architecture, with the same hyper-parameters for both the decentralized and federated settings. We report results obtained on different architectures in Appendix D-B.

# IV. ADVERSARIAL ADVANTAGE POINTS IN DECENTRALIZED LEARNING

In this section, we identify characteristics of decentralized learning that grant more powerful capabilities to adversaries than those that adversaries can have in a federated learning scenario. In Sections V and VI, we demonstrate how adversaries can exploit these characteristics to breach the privacy of users participating in the system.

### A. Local generalization.

Generalization is pivotal to protect the privacy of the training set against attacks based on the model behavior. While well-generalized models may still leak information about the underlying training set [62], [33], it has been demonstrated that poor generalization significantly increases the privacy risk [52].

Generally speaking, good generalization in collaborative machine learning is achieved when the number of users participating in the learning protocol is maximized: the more users involved in training the machine learning model, the less information about a single individual can be retrieved from this model [41]. This holds both for intermediate models shared throughout the protocol, and for the final model obtained at the end of the training.

Federated learning maximizes generalization in this respect: the central server ensures that every state of the global model is computed using all the n available model updates, and every model update contributes equally at this computation. In the decentralized setting, every user has a different local

state. This state is a function of the models of all other users in the system, but not all users contribute equally. In fact, the contribution of user  $u_i$ 's model on user  $u_j$ 's local parameters depends on the distance between those users in the communication topology. The strength with which updates influence other users' models decays exponentially with the number of intermediary users, as they are transmitted mixed with those intermediary users' models.

This intuition is captured by the chain-like topology of Figure 2 (top) in which  $u_1$ , the first user in the chain, only has one direct neighbor and the rest of the users in the system are more than one hop away. Here, user  $u_1$  only receives the updates produced by  $u_5$  after they have been propagated through all the other users in the chain. When  $u_5$ 's update reaches  $u_1$  the strength of its signal is reduced by a factor  $\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{16}$  due to the aggregation rule (line 8 Algorithm 1). In contrast, in federated learning every pair of users is virtually separated by a single hop: the server.

This slow propagation results in practice in the local state of users being often dominated by its own training set and that of their neighbors. We illustrate this effect in Figure 2 (bottom), where we report the average loss given from  $u_1$ 's local model on the local training sets of other users. The loss increases with distance between  $u_1$  and the owner of the local training set. We refer to this phenomenon in decentralized learning as "local generalization" in contrast to "global generalization" offered by federated learning.

Due to local generalization, users' intermediate states carry more information about their own local training set than other users' training sets in the system. While this may be not a problem for the effectiveness of training, it introduces a privacy risk when local states are shared with other users in the system. The ability to access those poorly generalized models gives a substantial advantage to adversarial users. This advantage can only be reduced by reducing the average distance between each pair of users, or, more pragmatically, increasing the number of neighbors of each node, i.e., reducing the impact of local generalization. In the best case, when all nodes are connected to each other, local generalization becomes global generalization throughout the training process, equivalently to federated learning.

# B. System knowledge.

Unfortunately, dense topologies in which users have a large number of neighbors have negative implications for performance and security. On the performance side, dense topologies increase the communication overhead of users, defeating the fundamental objective of decentralized protocols: decreasing the overall consumed bandwidth. On the security side, dense topologies increase malicious users' visibility of the state of the system, providing them with additional information to launch privacy attacks.

When users observe individual model updates produced by their neighbors in a decentralized learning system (Figure 1a), they end up with different views of the system. Such partial view of the system allows an attacker to isolate information produced by individual users from the global state, and thus reverse the benefits of generalization on users' privacy. We call this adversarial capability unique to decentralized learning

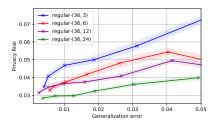


Fig. 3: Average privacy risk of model updates generated by decentralized users on regular graphs with increasing density (CIFAR-100).

"system knowledge". In Sections V-A2, V-B1 and VI-B1, we introduce attacks showing how an attacker node can exploit this capability to reduce users' privacy beyond simply exploiting the local generalization phenomenon.

We conclude that, unfortunately, generalization and system knowledge are in direct opposition. Increasing the number of users' neighbors to reduce the risks introduced by local generalization inherently increases users' capability to learn more about the system, boosting their adversarial capabilities. In this paper, we show that **this intrinsic trade-off fundamentally limits the privacy achievable by users in decentralized learning** both against passive and active adversaries.

#### V. PRIVACY AGAINST PASSIVE ADVERSARIES

In this section, we evaluate the privacy protection provided by decentralized learning against a passive (honest-but-curious) attacker who wants to infer information about private training sets of other users in the system. This attacker does not deviate from the execution described in Algorithm 1. They can only passively observe the model updates received during the normal execution of the protocol and process them in an arbitrary way. They cannot forge adversarial model updates, and cannot change the loss function of the model or tamper with their local training set. Additionally, we assume a weak adversary, who has no auxiliary information about other users or the underlying system. We evaluate users' privacy loss against *adversarial neighbors* i.e., adversaries directly connected to the victim.

**Remark:** By definition, as the communication topology is connected [26], [26], [30], [31], every user has at least one neighbor. Therefore, decentralized learning is required to guarantee privacy against adversarial neighbors as a cardinal property of the protocol. Note that the only scenario that allows decentralized users to rule out adversarial neighbors is when trust is introduced in system; that is, users assume that all their neighbors are honest.

#### A. Decentralized user vs Federated user

In this section, we first compare the adversarial capabilities of decentralized users against the ones of federated users. We then extend this comparison to the federated parameter server. 1) Inference on Received Model Updates: We now demonstrate the privacy risk inherent to sharing updates from models that suffer from local generalization (see Section IV) against a passive adversary.

Let  $\tilde{a}$  be a passive adversary with a set of neighbors  $\mathbf{N}(\tilde{a})$ . For every target user  $v \in \mathbf{N}(\tilde{a})$ ,  $\tilde{a}$  receives a model update  $\Theta_v^{t+\frac{1}{2}}$ . The received model update  $\Theta_v^{t+\frac{1}{2}}$  is a valid set of parameters for the current model f. Therefore, the attacker can directly attack  $\Theta_v^{t+\frac{1}{2}}$  to infer information about v in a whitebox setting. In Figure 4 we report the privacy risk measured on the received model updates ("Received model", red line), and the privacy risk measured on a federated leaning equivalent set up — same number of users and same local training set partition ("Global model", blue line). For federated learning we measure the privacy risk on the only state of the system observable by users: the global state of the model provided by the federated parameter server. We quantify the privacy risk (y-axis) as the normalized MIA accuracy computed via Eq 1 averaged across all the attacker's neighbors:

$$\frac{1}{|\mathbf{N}(\tilde{a})|-1} \sum_{\mathbf{N}(\tilde{a})/\tilde{a}} M(\Theta_v^{t+\frac{1}{2}}, X_v, \mathcal{O}). \tag{4}$$

The plots x-axis, represents the global generalization error  $g_{err}(t)$  of the system at iteration t i.e., the *overfitting* measured on the average of users' local parameters<sup>2</sup>. We compute  $g_{err}(t)$  as:

$$g_{err}(t) = acc(X, \Theta^t) - acc(\mathcal{O}, \Theta^t), \tag{5}$$

where,  $\Theta^t = \frac{1}{|V|} \sum_{v \in V} \Theta^t_v$  is the global state of the system,  $X = \bigcup_{v \in V} X_v$  is the union of all the local training sets, and  $\mathcal O$  is a test set completely disjointed from X.

For each combination of topology and dataset, Figure 4 shows the average results over 16 runs. In each run we select the malicious user uniformly at random. The halo around the curves captures the standard deviation. Additionally, we report the consensus distance (gray dotted line) for the decentralized learning runs, computed using Eq. 3.

As we see in the figure, in decentralized learning, the privacy risk associated with the model updates shared by users ("Received model") is a function of the generalization error and the consensus distance. Naturally, the larger the generalization error (i.e., the more overfitting), the larger the privacy risk. But this risk also increases with the consensus distance. This follows from the local generalization phenomenon (see Section IV): large consensus distance indicates that information is still not uniformly propagated in the system, thus updates carry significantly more information about the local training sets than sets from other users. More critically, this happens even when the generalization error is close to 0 (leftmost parts of the plots). Thus, even when a decentralized system has perfect generalization, sharing model updates puts the privacy of **users at risk**. As expected, at the same level of generalization error, the privacy risk approaches zero when we evaluate it on the global model in federated learning instead.

When the system reaches consensus (rightmost part of the plots), as anticipated in Section IV, the privacy risk of decentralized and federated approaches converge. This indicates that,

<sup>&</sup>lt;sup>2</sup>In federated learning, this is simply the global model as  $\forall_{v \in V} \Theta^t = \Theta^t_v$ 

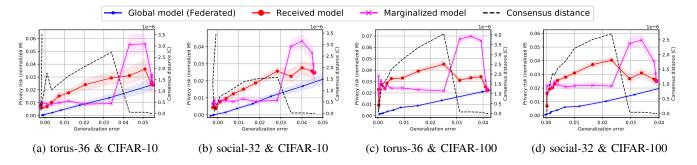


Fig. 4: Average privacy risk on four different communication topologies and datasets for decentralized and federated learning. The shaded regions represent the standard deviation over 16 runs.

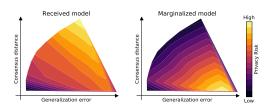


Fig. 5: Privacy risk as a function of generalization error and consensus distance for the received and marginalized model. Setup: torus-36 on CIFAR-100.

regardless of their direct or indirect connectivity, the attacker is eventually able to learn the same amount of information about all the users' private training sets in the system. We conclude that decentralized learning does not offer better privacy than federated learning even if neighbors are fully trusted by the user. Indeed, as soon as the network reaches consensus and the adversary has access to the final global model, non-neighbor adversaries can obtain the same amount of information on users as in federated learning. Moreover, once consensus is reached, global generalization error (i.e., overfitting) reaches its highest level and, therefore, the highest level of privacy risk for the global model.

As we argue in Section IV, the harmful effect of local generalization on the privacy risk can be reduced if the density of the communication topology increases. This is visible in Figure 3, where we evaluate the effect of density on the privacy risk using random regular topologies with increasing density (regular-(36, d) with  $d \in \{3, 6, 12, 24\}$ ). As the density increases, models generalize faster and the privacy risk reduces. We observe similar results when evaluating a torus-64 topology, which we show in Appendix D-A.

Next, we demonstrate how a decentralized adversary can further increase the inherent privacy risk in the shared model updates by exploiting system knowledge (see Section IV).

2) Inference on Functionally Marginalized Model Updates: A passive decentralized adversary that has access to model updates produced by different users can use these multiple views of the system to "de-noise" the information received from honest users, magnifying information leakage. To demonstrate this capability, we introduce a novel attack that we call "functional marginalization".

Functional marginalization exploits the fact that the local model of user v can be factorized into two core components:

$$\Theta_v^t \approx \mathring{\Theta}_v^t + \Theta_{V/v}^t, \tag{6}$$

where  $\overset{\circ}{\Theta}^t_v$  represents the contribution of the local training set of the node v, whereas  $\Theta^t_{V/v}$  captures the contributions of all other nodes in the system.

Having enough information about  $\Theta^t_{V/v}$ , and knowing  $\Theta^t_v$ , the adversary could marginalize the term  $\mathring{\Theta}^t_v$  in Eq 6. Exactly recovering the term  $\Theta^t_{V/v}$  is unfeasible. However, the adversary can obtain a rough approximation of it. Given a neighbor victim v, an attacker  $\tilde{a}$  can approximate the global functionality of the system  $\Theta^t_{V/v}$  from the model updates received from other neighbors. The adversary estimates the global functionality as the average of all parameters they receive, excluding the victim's:

$$\Theta_{V/v}^{t} = \frac{\sum_{u \in \mathbf{N}(\tilde{a})/v} \Theta_{u}^{t + \frac{1}{2}}}{|\mathbf{N}(\tilde{a})|}.$$
 (7)

Then, by removing the approximated global functionality component from the victim's model update,  $\tilde{a}$  isolates the victim's contribution:

$$\mathring{\Theta}_v^t = |\mathbf{N}(\tilde{a})| \cdot (\Theta_v^{t + \frac{1}{2}} - \Theta_{V/v}^t). \tag{8}$$

This process can also be seen as reversing the aggregation operation in line 8 in Algorithm 1 by pulling out the term  $\Theta_v^{t+\frac{1}{2}}$  from the averaged model  $\Theta_v^{t+1}$ .

As the recovered "functionally marginalized model"  $\Theta_v^t$  is a function of just the local training set of v, the adversary can use it to obtain better results than when attacking  $\Theta_v^{t+\frac{1}{2}}$ , which has contributions from other users. We show this improvement in Figure 4 ("Marginalized model", purple line).

The improvement, however, is not consistent. Recall that the privacy risk is a function of the global generalization error and the consensus distance. When the consensus distance is high (leftmost part of the plots), the information received is not an accurate representation of the global functionality  $\Theta^t_{V/v}$ . Thus, the marginalized model  $\mathring{\Theta}^t_v$  may not be a good representation of the victim's local training set and the attack performs worse than on the received model. As the consensus distance C decreases (rightmost part of the plots), the privacy

risk abruptly increases, reaching its highest value. This is because when the consensus distance is low,  $\Theta^t_{V/v}$  is a good representation of the global state and the marginalization in Eq. 8 is a model that well represents the victim's local dataset. Of course, when the consensus distance C approaches zero, and all users have the same view, marginalization has no effect as there is no victim's contribution to be isolated. Indeed, when  $C(t)\!=\!0$ , Eq. 8 results in  $\mathring{\Theta}^t_v\!=\!\Theta^{t+\frac{1}{2}}_v$  and the privacy risk is the same as when the received model is attacked directly.

Attacks on the received model update or its functionally marginalized version are complementary: the former succeeds when the consensus distance is high, the latter succeeds when consensus distance is low. We compare these two attacks in Figure 5, along three dimensions: generalization error (xaxis), consensus distance (y-axis), and privacy risk (heat map). While privacy risk is proportional to generalization error for both cases, the received model maximizes leakage when consensus distance is maximized (top center), marginalized model, instead, maximizes it when the consensus distance is approaching its minimum (bottom left). Eventually, privacy risk declines for both models when consensus distance is minimized (i.e., C(t)=0 in the rightmost edge of the plots). This means that the adversary can maximize their effectiveness by choosing the best attack after evaluating the consensus distance on the received model updates.

The results in this section prove that, when the topology is non-complete, decentralized users are exposed to greater privacy risks than in federated learning against an adversarial user that only exploiting information available from an honest execution of the decentralized protocol. In Section V-B1, we show that this claim holds also for the complete topology.

#### B. Decentralized user vs Federated Server

We now compare the adversarial capabilities of passive users in decentralized learning against a passive parameter server in federated learning.

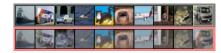
The parameter server is in a privileged position to run privacy attacks in federated learning. Unlike users, who only receive aggregate models and updates, the parameter server is able to access individual model updates, and the intermediate states of the user's local optimization processes, e.g., gradients (i.e., FedSGD) or pseudo-gradients (i.e., FedAVG). This advantageous position enables the parameter server to perform powerful privacy attacks such as gradient inversion [13], [23], [44], [64], [69], [70] and accurate inference attacks [41].

In particular, gradient inversion attacks exploit the fact that the gradient produced by one or more SGD iterations is just a smooth function of the data used to compute it. Thus, the gradient can be inverted to recover the underlying input. Typically, this is achieved by searching for a set of input instances that generates a gradient similar to the one produced by the user. Thanks to the inherent smoothness of the neural model, this search can be solved as a second-order optimization [13], [23], [64], [70] or via other analytic approaches [44], [69].

In order to perform gradient inversion, the attacker necessitates of two pieces of information: (1) the gradient computed on the victim's data  $\nabla_{\Theta_v^t} \mathbf{L}(\xi_v^t)$ , and (2) the parameters of the



(a) MNIST



(b) CIFAR-10

Fig. 6: Examples of reconstruction (red panels) obtained via gradient inversion attacks on the node v (see Figure 7) using [13].

network used to compute the gradient  $\Theta_v^t$ . While these two components are always available to the parameter server in federated learning, they may not be accessible to decentralized learning users.

A model update  $\Theta_v^{t+\frac{1}{2}}$  shared by a neighbor v of an attacker  $\tilde{a}$  in decentralized learning is defined as:

$$\Theta_v^{t+\frac{1}{2}} = \Theta_v^t - \eta \nabla_{\Theta_v^t} \mathbf{L}(\xi_v^t). \tag{9}$$

To obtain the gradient  $\nabla_{\Theta_v^t} \mathbf{L}(\xi_v^t)$ ,  $\tilde{a}$  needs to learn  $\Theta_v^t$ . However, the exact value  $\Theta_v^t$  is not available to the attacker as it is a function of the model updates generated by v's neighbors. In principle, this should preclude decentralized users from performing gradient inversion attacks. However, as we show below a passive decentralized user can recover a suitable gradient signal by exploiting system knowledge and use it to complete the attack.

1) Gradient inversion in decentralized learning: There are several situations in which a decentralized attacker can perfectly recover the individual gradient of their neighbors. First, we have two trivial cases that result on  $\Theta^t_v = \Theta^t_{\tilde{a}}$ : the first training iteration  $t\!=\!0$ , and when users  $\tilde{a}$  and v achieve consensus (i.e., C(t)=0). In both cases, the attacker can recover the victim's gradient as  $\frac{1}{\eta}(\Theta^{t+\frac{1}{2}}_v - \Theta^t_{\tilde{a}})$ .

Gradient recovery at  $t\!=\!0$  can be easily prevented, e.g., users could choose different initial parameters  $\Theta^0$ , but it is not clear how this modification would impact the learning process. However, reaching consensus is the goal property of decentralized learning protocols. Thus, eventually, the second trivial case happens and the attacker can always recover a gradient suitable to implement inversion. Even when consensus is not achieved, an attacker can obtain a noisy gradient as long as C(t) is close to 0, by approximating the model of the victim as:

$$\nabla_{\Theta_v^t} \mathbf{L}(\xi_v^t) = \lim_{C(t) \to 0} \frac{1}{\eta} (\Theta_v^{t + \frac{1}{2}} - \Theta_{\tilde{a}}^t). \tag{10}$$

Here, the quality of the recovered gradient would be inversely proportional to the consensus distance C(t). However, even when C(t) is arbitrary large, having system knowledge (see Section IV) enables the adversary to unconditionally recover neighbors' gradients.

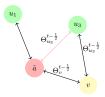


Fig. 7: The attacker node  $\tilde{a}$  is capable of accessing the gradient of the victim node v thanks to its connection with the honest node  $u_3$ .

As already introduced, in order to recover the gradient produced by v, an attacker  $\tilde{a}$  needs to subtract the unknown set of parameters  $\Theta^t_v$  from the received model update  $\Theta^{t+\frac{1}{2}}_v$ , where the former is defined as:

$$\Theta_v^t = \frac{1}{|\mathbf{N}(v)|} \sum_{u \in \mathbf{N}(v)} \Theta_u^{t - \frac{1}{2}}.$$
(11)

Here,  $\Theta_u^{t-\frac{1}{2}}$  is the model broadcasted by user u to all its neighbors during the previous training iteration (t-1). If the set of attacker's neighbors  $\mathbf{N}(\tilde{a})$  is a super-set of the victim's neighbors set  $\mathbf{N}(v)$ , then the attacker can perfectly recover  $\Theta_v^t$  using the neighbors' models updates received at time t-1. In other words, if the adversary has enough knowledge of the system (i.e., a sufficient number of neighbors), the latter can be used to recompute the unknown local state of the victim.

Figure 7 illustrates the issue for a random graph. The local model of the victim v (in yellow) is defined as  $\Theta^t_v = \frac{1}{3}(\Theta^{t-\frac{1}{2}}_v + \Theta^{t-\frac{1}{2}}_{\tilde{a}} + \Theta^{t-\frac{1}{2}}_{u_3})$ , where  $\Theta^{t-\frac{1}{2}}_{u_3}$  is a model update produced by another user who is not under the control of the attacker (i.e.,  $u_3$ ). However, if the attacker  $\tilde{a}$  (in red) also has access to  $u_3$  updates (i.e.,  $\mathbf{N}(v) \subset \mathbf{N}(\tilde{a})$ ), this can recompute the local state  $\Theta^t_v$ , and, so, recover the gradient signal from v's model updates.

Once the adversary has v's gradient,  $\tilde{a}$  can run the inversion attack. Figure 6 shows a sample of images reconstructed via gradient inversion for the topology in Figure 7 obtained using the optimization-based method proposed in [13]. The effectiveness of this attack is independent from the number of nodes in the system as well as the number of the victim's neighbors. The quality of the reconstruction only depends on the size of the batch used to compute the gradient, the number of parameters in the network, and the possible transformations applied on the model updates e.g., compression or local differential privacy [22].

The neighbors-discovery trick: Interestingly, the attacker does not need to know  $\mathbf{N}(v)$  to recover the gradient. The attacker can exploit its system knowledge to discover  $\mathbf{N}(v)$  from  $\mathbf{N}(\tilde{a})$  when  $\mathbf{N}(v) \subseteq \mathbf{N}(\tilde{a})$ , by searching for  $Q \subseteq \mathbf{N}(\tilde{a})$  such that E(Q) = 0, where E is defined as:

$$E(Q) = \Theta_v^{t + \frac{1}{2}} - (\tilde{\Theta}_Q + \tilde{\nabla}_Q) \quad \text{with}$$
 (12)

$$\tilde{\Theta}_Q = \frac{1}{|Q|} \sum_{u \in Q} \Theta_u^{t - \frac{1}{2}} \quad \text{and} \quad \tilde{\nabla}_Q = \Theta_v^{t + \frac{1}{2}} - \tilde{\Theta}_Q \tag{13}$$

For the correct set  $Q = \mathbf{N}(v)$ , we have  $\tilde{\Theta}_Q + \tilde{\nabla}_Q = \Theta_v^{t+\frac{1}{2}}$  and the subtraction in Eq. 12 is equal to 0. Intuitively, this

process searches for the model updates of the previous round that explain the model update received at the current time step. When there is no  $Q \subseteq \mathbf{N}(\tilde{a})$  s.t. E(Q) = 0, the attacker learns that it is not connected to all the victim's neighbors. In Appendix A, we empirically demonstrate the effectiveness of this approach. Additionally, note that Eq. 12 is linear and can be solved via linear/dynamic programming.

To maximize the chances to effectively execute gradient inversion on a victim, the best strategy for an adversary is to maximize their number of neighbors and then use Eq. 12 to determine the victims' local connections. Since decentralized learning does not typically assume any limitation on the ability of a node to choose arbitrary communication patterns, this strategy is in reach for any adversary and gradient inversion should be a significant privacy concern for decentralized users. We note that, even if the protocol would prevent users from incrementing their number of neighbors, attackers can always expand the number of observable model updates by colluding with other nodes in the system. In this case, the higher the density of the topology, the lower the number of nodes the attacker has to collude with in order to get a full view of the system and be back in an advantageous position to run gradient inversion attacks. In Section VI, we show that maximizing the number of neighbors remains an optimal strategy for the attacker also in the malicious setting for different classes of attacks.

Finally, we note that while we have shown gradient inversion is possible in the context of D-PSGD [32], the attack would be effective when other update rules are employed. As long as the attacker can access the same sources of information available to the victim (e.g., model updates), the attacker can isolate the victim's contribution from the current state of the system.

Summing up, a passive adversarial user in decentralized learning can be as powerful as a passive server in the federated setup. When the decentralized adversary is fullyconnected, this is obvious. In both cases, the adversary (1) can observe all the individual model updates produced by every user in the system and (2) can isolate the individual gradients produced by all the users regardless of their local communication patterns (by exploiting Eq. 12). Even if the adversary is not fully-connected, a decentralized adversary  $\tilde{a}$  is as powerful as a parameter server for any other user v in the system for which  $N(v) \subseteq N(\tilde{a})$ . This translates into decentralized settings bringing much higher privacy risks for users: while in federated learning there is a single adversarial server, in decentralized learning there may be multiple, separate adversarial users with equivalent power. Thus, the power of the adversary, and the privacy risk, is multiplied rather than being diluted by decentralization.

#### C. Defenses

Next, we discuss defensive techniques that could be used to prevent the passive attacks introduced in this section.

**Topology Changes.** Reducing the leakage of model updates originated from local generalization requires increasing the density of the communication topology underlying the decentralized learning network (Section V-A1). Ideally, the topology

would be complete, minimizing local learning effects and thus leakage. Yet, such a decision is in conflict with the conclusions of Section V-B, which show that increasing connectivity enhances the adversary's capability to collect knowledge of the system which results in even more significant inferences about other honest users' training sets. Indeed, with a complete topology, every user would reach the same adversarial capabilities of a passive parameter server in federated learning. We discuss in Section VII future steps to alleviate problems associated to how the communication topology is built.

**Secure Aggregation.** A way for decentralized learning to evade the local generalization vs. system-knowledge minimization trade-off is to rely on secure aggregation protocols (SA) [5]. In these protocols, every node implements the aggregation in line 8 of Algorithm 1 in a privacy-preserving way, i.e., without revealing the values of their updates in the clear. Intuitively, preventing the attacker from accessing individual model updates would eliminating attacks relying on system knowledge such as gradient recovery and functional marginalization; although gradient recovery would unavoidably succeed when  $\mathbf{N}(v) = \{\tilde{a}\}$  (always) or  $\mathbf{N}(\tilde{a}) = \{v\}$  (when C approaches zero).

Thus, when SA is applied, decentralized learning can grant users the same level of privacy against passive adversaries as federated learning by relying on a complete topology to achieve global generalization. While this may seem a suitable solution, every user in this setup has the same communication complexity as a parameter server in federated learning in addition to the overhead imposed by the cryptographic operations needed for secure aggregation. At such point, deploying secure aggregation-based decentralized learning results on a massive overhead with respect to federated learning at no gain in privacy. This essentially contradicts the premises behind the development of decentralized learning protocols, casting doubt on their utility.

Other mitigations. An alternative solution to reduce the effect of local generalization could be the decentralized learning protocol proposed by Vogels et al. to handle data heterogeneity [55]. In this protocol, users propagate the *exact* model updates of other users. This approach effectively creates phantom/virtual edges between users routing model updates through non-neighbors nodes, and thus it does not solve the underlying problem. In fact, this setup only increases the power of active adversaries that now can not only influence others with their own updates, but also by manipulating other users' updates (see Section VI-A).

A second alternative would be to rely on *model inconsistency* [46] to counter gradient recovery. With this technique, users distribute different versions of the same model to their neighbors (e.g., using differentially-private noise independently sampled for each neighbor). This approach would indeed prevent perfect gradient recovery, but would have a nonnegligible impact on the convergence rate of the system. More research is needed to understand whether there is an operation point in which attacks can be thwarted to a large extent while still obtaining a performance that improves the trade-offs in federated learning.

Finally, we acknowledge that approaches such as gradient compression [26] and local/distributed differential privacy [24],

[7] would reduce the amount of information in the shared model updates, and thus would decrease the privacy risk [22]. We note, however, that these same techniques can be applied in federated learning and thus do not result in any meaningful advantage for the decentralized setting.

#### VI. PRIVACY AGAINST ACTIVE ADVERSARIES

In this section, we assume active (malicious) adversaries who can deviate from Algorithm 1: they can forge and send arbitrary model updates to their neighbors and actively influence the system. As before, we evaluate users' privacy loss against adversarial neighbors, under the assumption that the adversary has no auxiliary information about the system or participants.

#### A. Decentralized user vs Federated user

As demonstrated in the federated setting, the effectiveness of malicious users is proportional to their capability of influencing the state (model parameters) of their victim [19], [37], [38]. The intuition is that the model updates used by the adversaries to learn information about the victim are a function of the victim's local model parameters and private data. Influencing the local model parameters means controlling this function, and, hence, how much information about the private training set is leaked by a model update [4], [12], [19], [38], [46], [57].

In both federated and decentralized learning, the local model parameters of a user  $\boldsymbol{v}$  are computed as the aggregation of the model updates produced by themselves and other users in the system:

$$\Theta_v^{t+1} = \frac{1}{m} \Theta_v^{t+\frac{1}{2}} + \frac{1}{m} \Theta_{u_1}^{t+\frac{1}{2}} + \dots + \frac{1}{m} \Theta_{u_{m-1}}^{t+\frac{1}{2}}, \qquad (14)$$

where m is the number of users participating in the aggregation (all users in federated learning, and the neighbors of v in decentralized learning). Assuming bounded model updates, this means that every user can influence at most a fraction  $\frac{1}{m}$  of v's model. See Figure 8 for an illustration. The larger m is, the smaller the influence a single adversarial user can have on v's model. In the federated setting, the influence is minimized as, by definition, m is maximal (m = n, the number of users in the system). In the decentralized setting, however, every user has a different number of neighbors m. In sparse topologies, those that bring significant cost advantage with respect to federated learning, it is always the case that m << n. Therefore, a malicious user in a decentralized setting always has higher **influence** over their neighbor's local model parameters than a equivalent malicious user in federated learning.

In order to reduce the influence of potential malicious neighbors, users can only increase m. When m is at its maximum, users are connected to all nodes in the system, effectively maximizing generalization, e.g., node  $u_2$  in Figure 8, While increasing the number of neighbors reduces the adversary's capability to influence the victim's model, an attacker also increases this influence by propagating malicious updates through other honest users. For instance, in Figure 8,  $u_2$  has additional influence on  $u_3$  through  $u_4$ . Therefore, to further boost the influence on the victim user, the attacker can create redundant connections in the communication topology. This

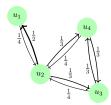


Fig. 8: Figure describing the **direct** influence factor (edge thickness and label) of each node on neighbors's local models for a given topology composed of four users.

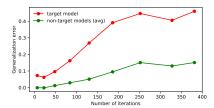


Fig. 9: Generalization errors for the target user of the echo attack and the non-target ones during the protocol for the setup: torus-36, ResNet20 and CIFAR-100.

is another instance of conflicting connectivity requirements: to reduce the impact of active attacks users must be densely connected, but they must be prevented from being densely connected in order to reduce their global influence on the system (e.g., creating redundant paths).

We conclude that, given that existing active attacks performed by federated users remain applicable in the decentralized setting [19], [37], [38], and that malicious decentralized users can always have greater influence on their victims than malicious users in federated learning, a malicious user in decentralized learning is more powerful than an equivalent malicious user in federated learning. In other words, decentralized learning offers less protection against active privacy attacks than an equivalent federated setup for any noncomplete topology. In Section VI-B1, we show that this result holds also for the complete topology.

In the next section, we introduce an active attack tailored for decentralized attackers that exploits all the adversarial properties enabled by the system and that cannot be replicated by a malicious federated user.

**Algorithm 2:** *echo* attack for an active attacker node  $\tilde{a}$ .

1) Echo attacks: Echo attacks exploit the high influence factor of a decentralized attacker to force the local state of a chosen neighbor victim to leak information about its private training set. The aim of the attacker is driving the victim's local model towards severe "overfitting", forcing it to memorize the local training set beyond what would be memorized in a honest execution. This amplifies the information leakage stemming from local generalization and system knowledge, worsening the impact of the attacks presented in the previous sections.

To carry out an echo attack, at the broadcast step, instead of their own model, the adversary broadcasts echos of the victim's updates at the current or previous round. Such *echo* updates artificially increase the relevance of the victim's local training set in the victim's local model. This diminishes the influence of other users in the system on the victim's model, augmenting local generalization. Malicious users in federated learning cannot replicate echo attacks as they cannot isolate other users' individual contributions from the observable global state of the system and thus cannot broadcast echo updates.

We formalize echo attacks in Algorithm 9. The attacker starts by collecting the neighbors' model updates and uses them to craft the echo update  $\Theta$ . In particular, the attacker uses the functionally marginalized version (Section V-A2) of the victim model update (i.e.,  $\tilde{\Theta} = \tilde{\Theta}_{v}^{t}$ ) which approximately captures the isolated contribution of the victim. The adversary broadcasts  $\Theta$  to all the attacker's neighbors including the victim, increasing overfitting at the next step of the victim's honest execution (line 8 Algorithm 1). The effect of echo attacks is magnified by the iterative interaction between the attacker and the victim and by the "echo chamber effect" that results from the neighbors of the attacker also propagating the malicious echo update to the victim via second order interactions. Echo attacks are extremely efficient and easy to carry: the adversary does not require a local training set or any information on the learning task and they have very low computational, as it does not need to train a local model but only post-process the received updates.

While conceptually simple, echo attacks are extremely effective in practice. Figure 9 compares the generalization error of the victim's model against other non-target users in the system at different training iterations during the echo attack. While this gap is larger at the start of the training, on average, the generalization error of the target is about 10 times more than the non-targets'. As seen in the previous section, the increase in the generalization error creates a massive privacy risk for the target node.

We show the effectiveness of the echo attack in Figure 10 on various configurations (green lines) and compare them to the results obtained with the passive inference attacks of Section V-A (dashed lines). Even when the system finds consensus, the privacy risk for the target remains high. This is because the attacker's echo updates have actively influenced the global state of the system (not only the victims's one) by artificially increasing the relevance of the victims's contribution. For the *social-32* topologies, we observe a large standard deviation. This is because the impact of the attack depends on the connectivity of the victim. Recall that the strength of an active attack is proportional to the influence factor of the attacker, which is inversely proportional to the number of neighbors of the victim (see Section VI-A). We illustrate this

phenomenon in Figure 11, where we evaluate the effect of the echo attack on targets with different number of neighbors on regular graphs with an increasing density. We keep the degree of the attacker fixed to 3 in order to isolate the impact of the victim's connectivity on the privacy risk. We see that, as we predicted in Section VI-A, low degree boosts the impact of active attacks on users.

Also, attackers can improve their effectiveness by choosing their position in the communication topology to maximize their influence on the system. Like for gradient inversion, the best strategy is to maximize their number of neighbors. If this is not possible, attackers can also aim to be in a position that maximizes the closeness centrality (or other centrality metrics) with the victim to strengthen the "echo chamber effect". However, adversaries can only use this strategy if they know the global topology. Finally, we note that if the attacker has the victim as sole neighbor or the marginalized model cannot be computed, the adversarial model update can be set to  $\tilde{\Theta} = \Theta_v^{t+\frac{1}{2}}$  (i.e., victim's model update), obtaining inferior but comparable performance; we show this in Figure 15 in Appendix D.

Echo attack on robust aggregation. One common approach to reduce the adversarial influence of active attackers in both the federated and decentralized setting is to use robust aggregation methods [25]. An example for the decentralized setup is the work of He et al. [17]. This work proposes to hamper the influence of byzantine nodes by using self-centered clipping regularization. Nodes clip the received model updates in the  $\tau$ -sphere around their current local model before aggregating them:

$$\Theta_v^{t+1} = \sum_{u \in \mathbf{N}(v)/v} \left[ w_{i,j} \cdot (\Theta_v^{t+\frac{1}{2}} + \text{CLIP}(\Theta_u^{t+\frac{1}{2}} - \Theta_v^{t+\frac{1}{2}}, \tau)) \right], \tag{15}$$

where  $CLIP(x,\tau) = min(1,\tau/||x||) \cdot x$ .

This approach hides a trade-off between generalization and robustness. The clipping procedure simply degrades the information provided by the other users in the system in favor of the local one. This successfully reduces the effectiveness of general active attacks. However, it also reduces the generalization of the users' local models, magnifying the harmful effect of local generalization. Because there is less information from others, the local model updates retain more information about the local training set of the user.

Eventually, self-centered clipping produces a very similar effect than an echo attack: the influence of local parameters is magnified. Therefore, this defense does not prevent this kind of attacks, but rather it tends to amplify them. We show this effect in Figure 12, where we compare the performance of echo attacks on systems with and without self-centered-clipping [17]. Of course, when  $\tau$  gets closer to 0, the system degenerates to non-collaborative learning (every node trains its model locally). Then, active adversaries become as effective as passive ones, and the echo attack would not offer any advantage.

#### B. Decentralized user vs Federated server

We now compare the adversarial capabilities of active adversarial users in decentralized learning against an adversarial

malicious parameter server in federated learning.

A malicious parameter server is the strongest active attacker possible. It has maximum influence on the users' models: it can arbitrarily choose the local state of a user within a single iteration, performing extremely effective attacks with little effort [4], [12], [46], [57]. Such degree of influence is hard to achieve by malicious users in the decentralized setup. In principle, even when the attacker is the only neighbor of the victim, the influence of the attacker is at most  $\frac{1}{2}$  since the victim aggregates their contribution with their own local information (see edge  $(u_2, u_1)$  in Figure 8). Thus, attacks such as [4], [12], [46], [57] cannot be easily performed by decentralized adversaries within a limited number of rounds. Yet, an adversaries can achieve a similar effect using time coupled attacks, where they influence the local state of the victim over multiple iterations [1]. However, next, we demonstrate that actually decentralized users can achieve the same direct influence of a malicious server on victims (i.e., 1) by exploiting their system knowledge.

1) State-override attack: In Section V-B1, we show that system knowledge enables the attacker to cancel the effect of generalization and isolate victims' gradients. We now introduce the "state-override attack", in which adversaries can use very similar techniques to cancel the contributions of other neighbor users and artificially achieve maximal influence on the victim's model. In particular, with this technique, attackers are able to override the result of the local model aggregation computed by the victim at line 8 of Algorithm 1.

Formally, given a target v and an adversary  $\tilde{a}$  such that  $\mathbf{N}(v) \subseteq \mathbf{N}(\tilde{a})$ , the adversary can forge and distribute a model update:

$$\Theta_{\tilde{a}}^{t+\frac{1}{2}} = -\left(\sum_{u \in \mathbf{N}(v)/\tilde{a}} \Theta_{u}^{t+\frac{1}{2}}\right) + |\mathbf{N}(v)| \cdot \tilde{\Theta},\tag{16}$$

that overrides the state of the victim with parameters of the adversary's choice:  $\tilde{\Theta}$ . Upon receiving the model updates, the victim v computes the following local aggregation:

$$\Theta_{v}^{t+1} = \frac{1}{|\mathbf{N}(v)|} \sum_{u \in \mathbf{N}(v)} \Theta_{u}^{t+\frac{1}{2}} = \frac{\left(\sum_{u \in \mathbf{N}(v)/\tilde{a}} \Theta_{u}^{t+\frac{1}{2}}\right) + \Theta_{\tilde{a}}^{t+\frac{1}{2}}\right]}{|\mathbf{N}(v)|} = \tilde{\Theta}. \quad (17)$$

Here, the contribution of the model updates from users  $\mathbf{N}(v)/\tilde{a}$  in Eq. 17 is canceled out by the adversarial update which contains the negated, partial aggregation in Eq. 16, leaving the "payload"  $\Theta$  as the result of the aggregation. This attack results in complete control of the victim's parameters regardless the number of the victim's neighbors. It enables a decentralized attacker to perform attacks such as [4], [12], [46], [57] within two iterations: one to override the model and one to learn the result.<sup>3</sup> To perform this attack, the adversary must be the last in broadcasting their model updates. If the adversary cannot do this (e.g., if the system has a broadcast schedule),  $\tilde{a}$  can use previously received model updates to achieve comparable results, as we show in Appendix C.

<sup>&</sup>lt;sup>3</sup>Which is equivalent to a single round of federated learning.

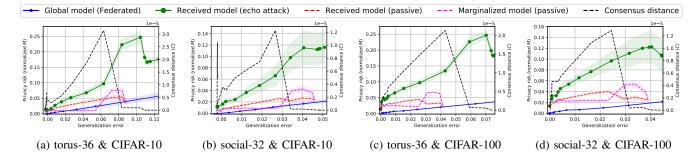


Fig. 10: Estimated privacy risk for the *echo* attack on four different combinations of communication topologies and training sets for decentralized and federated learning. The halo surrounding the curves reports the standard deviation over the multiple runs.

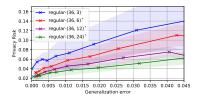


Fig. 11: Effect of different numbers of neighbors for the target of the echo attack using CIFAR-100 as training set.

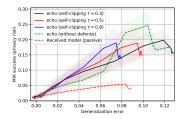


Fig. 12: Effect of the self-centered clipping robust aggregation on the echo attack for *torus-36* and *CIFAR-10*.

Summing up, like in the honest-but-curious setting, every malicious user in decentralized learning can be as powerful as a malicious parameter server in federated learning as long as the underlying topology provides them with enough system knowledge, or they can create enough connections to other users to gain this knowledge.

# C. Defenses

Next, we discuss defensive techniques that could be used to prevent the active attacks introduced in this section.

**Topology Changes.** Adversarial influence is enabled by the same decentralized learning characteristics as local generalization. Therefore, the same defenses apply: the best way to reduce the influence power of an active attacker is to increase the number of neighbors of each node, diluting the influence of malicious neighbors. But increasing the topology density puts malicious neighbors in an advantage position to collect information about the global state of the system, enabling them to run *state-override* attacks (Section VI-B1).

Secure Aggregation. Secure aggregation can prevent system-

knowledge-based attacks such as the echo and state override attacks. However, SA does not solve the root problem with active decentralized adversaries—the higher influence factor induced by sparse communication topologies.

**Robust aggregation.** Robust aggregation methods [25] are neither a good defense against privacy attacks (see the effect of echo attacks on self-centering clipping [17] in Section 9). In general, robust aggregation techniques can only trade privacy for robustness and *viceversa* as they either magnify the influence of external sources of information (i.e., model updates provided by neighbors) or internal ones (i.e., the current state of the model).

We acknowledge that robust aggregations can hamper attacks such as the state-override attack. However, robust aggregation protocols also apply to federated settings (see Appendix E for a detailed discussion). Therefore, this defense does not offer a particular advantage when decentralizing the learning process, as at most one ends up with the same protection as in federated learning.

## VII. OPEN PROBLEMS IN DECENTRALIZED LEARNING

In the previous sections, we presented a series of novel attacks which show that current decentralized learning systems do not fulfill their promise of protecting the privacy of users while reducing the cost of learning with respect to federated settings. We now discuss the main challenges that future research must address in order enable the deployment of decentralized learning with strong privacy guarantees.

Constraining the communication topology: Most of the attacks we introduce rely on leakage that is related to users' connectivity. We demonstrated how, in both the passive and active adversarial models, allowing users to choose their neighbors tremendously boosts the adversary's capabilities.

To address this issue, the communication topology underlying decentralized learning must be carefully designed to determine which attacks are possible, and therefore what level of privacy users can enjoy. This means that systems in which users join the network without constraints are undesirable, as individual decisions are unlikely to match any pre-defined topology. In fact, it is actually hard to enforce constraints without a central orchestrator that has a global knowledge of the system as years of research on peer-to-peer anonymous

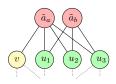


Fig. 13: Minimal example of secure aggregation evasion for an aggregation threshold of 3 users. The attacker controls the nodes  $\tilde{a}_a$  and  $\tilde{a}_b$  and recovers the exact model update produced by v.

communications highlight [14], [39], [50], [49], [56]. Yet, introducing such as a powerful central entity in the system would enable new security threats if this entity is malicious. Assuming a malicious central orchestrator who can arbitrary choose the communication topology is equivalent to assuming a malicious parameter server in federated learning. Trivially, the orchestrator can maliciously design the topology in order to grant full adversarial capability to itself (and carry the attacks in Sections V-B and VI-B).

More research is needed to create decentralized systems with secure joining processes that constraint users' positioning in the network to mitigate the attacks introduced in this paper.

Applying Secure aggregation: Secure aggregation (SA), which hides users individual updates from other users, is pivotal to reduce the power of adversaries in the decentralized setting. However, just applying SA does not guarantee privacy. Even forcing every node to have a minimum number of neighbors k participating in the aggregation [5], an attacker would be always able to recover the model update of a single user if they can impersonate or compromise an additional node in the system. Indeed, the attacker can recover the model update of a node v by simply computing the difference of two aggregated values that differ only by v's model update. More formally, given  $\tilde{a}_a$  and  $\tilde{a}_b$  the nodes under the control of the attacker  $\tilde{a}$  and a victim node v,  $\tilde{a}$  can recover  $\Theta_v^t$  for every t, by choosing  $\mathbf{N}(\tilde{a}_b) = \mathbf{N}(\tilde{a}_a)/v$ . Once the attacker nodes received the aggregated values, these can recover v's model update by computing:  $\Theta_v^t = \mathrm{SA}(\sum_u^{\mathbf{N}(\tilde{a}_a)}) - \mathrm{SA}(\sum_u^{\mathbf{N}(\tilde{a}_b)})$ . An example of this configuration is depicted in Figure 13. This approach does not require any auxiliary knowledge on the victim, and  $\mathbf{N}(\tilde{a}_a)$  can be chosen arbitrarily by the attacker. We remark that this simple SA-evasion technique is independent from the employed aggregation protocol and they would work even under verifiable SA or SA performed via Trusted Execution Environment (TEE) [42].

Assuming fault resilient SA [5] (which is necessary under real-world deployments), this strategy would work also in a complete topology, where  $\mathbf{N}(\tilde{a}_a) = \mathbf{N}(\tilde{a}_b)$ . It is enough for  $\tilde{a}_b$  to simulate the drop-off of the victim. In the general case, this technique would be remain applicable as long as the threshold for SA is greater equal to  $|\mathbf{N}(\tilde{a}_b)|-1$ .

Additionally, the security offered by secure aggregation scales with the number of participants in the protocol: the more model updates are aggregated, the less information can be inferred about a single user's update. Thus, sparse topologies reduce the effectiveness of SA and for non-complete communication topologies, decentralized secure aggregation will always

offer less privacy to users compared to federated learning. That is, a sparsely connected decentralized user always learns more information about their neighbors' model updates than a federated server.

In summary, while decentralized learning requires SA to achieve a meaningful level of security (see Section V), it is not clear how (or even if) SA can be configured to achieve strong privacy. More research is needed to find effective and reliable topology-aware SA in decentralized learning.

Achieving Differential Privacy: Applying differential privacy (DP) techniques in decentralized learning is no more trivial than implementing secure aggregation. The lack of a trusted, centralized curator (role taken by the parameter server in federated learning) prevents the use of global-DP, leaving local-DP has the only option. Local-DP results in a consistently worse trade-off between privacy and utility compared to global-DP [24], [40].

The only way to improve this trade-off is assuming the existence of an effective SA protocol that would only reveal the noisy sum of the local model updates to the aggregator i.e., distributed-DP [7], [24]. This allows to tune the local noise proportionally to the number of users m participating at the aggregation ( $\sim \frac{1}{m}$ ). Unfortunately, this approach success also depend on the density of the topology. The lower is the number of neighbors of a user, the less participants in the aggregation, and the more noise that users have to add locally to achieve a desired level of privacy. Increasing the number of neighbors would solve this issue, but would also increase the communication overhead, suppressing the advantage of decentralized learning over the federated approach. Indeed, as for secure aggregation, distributed-DP matches the utility of federated learning only when the topology is complete.

With the current DP techniques available, the lack of a centralized curator and the need to keep its communication overhead advantage prevent decentralized learning from matching the utility/privacy trade-off of the federated setting. This gap may be closed if future research develops differentially-private techniques tailored to decentralized learning. The community already started moving in this direction [8], [9], [58], achieving only limited results.

#### VIII. CONCLUSION

In the present work, we have shown that privacy in decentralized learning depends on the connectivity of users which determines how much users rely on their own data versus how much an adversary can learn about the global state of the system. Ultimately, this inherent trade-off tells us that decentralized users cannot achieve the same level of privacy granted to federated users against both passive and active adversaries. This follows from two facts:

**I:** Every non-complete topology induces local generalization on users' models, increasing the information leaked by shared model updates and boosting active adversaries influence on honest users' models. On the other end of the spectrum, dense topologies grant system knowledge to attackers, enabling even more effective privacy attacks. Between the two extremes, every topology grants superior adversarial capabilities to de-

centralized users compared to the ones achievable by federated users for the same setup.

**II:** Decentralized learning protocols allow adversarial users in the system to reach the same adversarial capabilities of a parameter server in federated learning.

Point II is particularly relevant in practice. Current real-world deployments of federated learning [15], [36], [61] rely on the assumption of an honest-but-curious parameter server to guarantee a meaningful level of privacy to users [4], [12], [46]. However, applying this same trust model on decentralized learning, and, so, achieving comparable security, results in a consistently stronger assumption: Rather than trusting a single and clearly defined central server which is typically run by a well-established entity [15], [61], decentralized users must trust all their (likely unknown) neighbors.

In conclusion, while decentralization is in general a suitable approach to reduce the need for trust to increase users' privacy, the naive design of current decentralized learning protocols do not succeed at materializing the advantages of not relying on a central server. Thus, they do not offer any benefit over current, more practical federated solutions.

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#### APPENDIX A

# ADVERSARIAL NEIGHBORS DISCOVERY & TOPOLOGY MAPPING

Under deployment, weights are computed in finite precision. Then, due to floating-point arithmetic, Eq. 12 does not always result in a precise 0. For the practical case, it is enough to search for:

$$\underset{Q \in \mathbf{N}(\tilde{a})}{arg \, min} |\Theta_v^{t+\frac{1}{2}} - (\tilde{\Theta}_Q + \tilde{\nabla}_Q)|, \tag{18}$$

obtaining almost perfect accuracy (see Eq. 12). To validate this claim, we use the torus topology, the worst-case for the

adversary given its intrinsic regularity. Concretely, we consider a torus-16 topology where the attacker is fully connected and wants to enumerate the local connections of all the other users in the system. We train a ResNet20 architecture on CIFAR-10 for 10 rounds. We then use the model updates received by the attacker to recover other users' neighbors using Eq. 18. For efficiency reasons, we assume a maximum degree of 10 for honest users (while the actual maximum degree is 5). We repeat the experiment 32 times. Eq. 18 finds the exact set of neighbors for every node 98.7% of the time.

Yet, it is possible that due to finite precision arithmetic a subset  $\dot{Q} \neq \mathbf{N}(v)$  such that  $E(\dot{Q}) \leq E(\mathbf{N}(v))$  exists (see Eq. 12). To reduce this probability, it is enough to run Eq. 18 when the consensus distance is high. In the malicious case, the attacker can force large consensus distance by introducing disagreement among users, e.g., sending different model updates to different neighbors within the same round. In the passive case, the adversary can compute Eq. 18 on different rounds and take the Q that minimizes E(Q) over the multiple rounds.

# APPENDIX B DETAILS ON MODEL TRAINING

In this section, we detail the training procedure of decentralized models. The code is available.<sup>4</sup>

- Training set partition: The training set is uniformly partitioned among users. Given a training set X: every user gets a disjointed sample from X of size  $\frac{|X|}{n}$ , where n is number of users in the system. No data augmentation is performed.
- **Optimizer:** We use SGD with momentum ( $\alpha = 0.9$ ).
- Learning rate: We anneal the learning rate during the training to speed up consensus for the decentralized systems. The initial learning rate is set to 0.1, then we scale it by 0.1 at iterations 200, 350 and 450 during the training. We do not schedule the learning for federated learning.
- **Batch size:** 256.
- **Stop condition:** We train the models with *early-stopping*. We stop the training when the accuracy of the average of the local models on the validation set stops improving (with a *patience* of 3).

### APPENDIX C

STATE-OVERRIDE ATTACK WITH INEXACT INFORMATION

When the users are forced to send their updates synchronously in the decentralized protocol, an attacker can rely on the model updates of the previous time step to carry out the state-override attack. Of course, this results in an inexact suppression of the current state of the victim. In this case, the error is proportional to the average of the gradient signals of the target's neighbors and the target one. This error diminishes as the training proceeds. We show this in Figure 14, where the state-override attack with inexact information is carried out on the topology described in Figure 7, where node v is the target

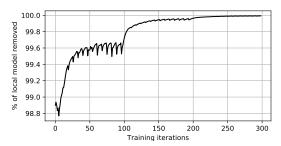


Fig. 14: Percentage of local state erased using the stateoverride attack with inexact information for the topology in Figure 7.

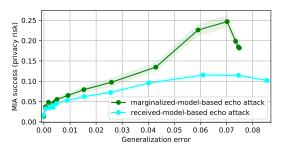


Fig. 15: Comparison between echo attack based on marginalized model (green) and received model (cyan) for CIFAR-100, *torus-36* and ResNet20.

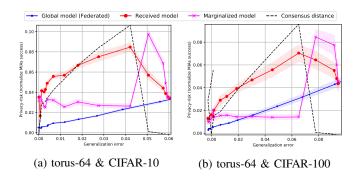


Fig. 16: Average, estimated privacy risk on two different combinations of communication topologies and training sets for distributed and federated learning (ResNet20 architecture).

and  $\tilde{a}$  is the attacker. In the worst-case, earlier in the training, the attacker suppresses 98.7% of the local state of the target. At the end of the training, it approaches values close to 100%. We conclude that the state-override attack is effective even when adversaries cannot choose when to send their updates.

# APPENDIX D ADDITIONAL RESULTS

In this section we present additional results for configurations different from the one reported in the main body of the paper

<sup>&</sup>lt;sup>4</sup>https://github.com/spring-epfl/PrivacyDecentralizedLearning

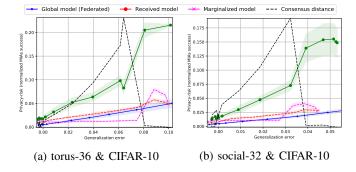


Fig. 17: Estimated privacy risk for both passive and active attacks (*echo* attack) on two combinations of communication topologies and training sets for distributed and federated learning (Shallow CNN architecture).

#### A. Scaling-up number of users

Figure 16 reports privacy risk for the received model updates and the functionally marginalized version for a *torus-64* topology. Comparing these results to the ones obtained on *torus-36* (Figure 4), it is evident that the sparsity of the topology affects privacy risk for the received model updates. Increasing the number of users while keeping the number of edges fixed<sup>5</sup> increases the average distance between users. As discussed in Section IV, this boosts the local generalization phenomenon and, therefore, increases the inherent privacy risk of the shared model updates. This result reinforces our claims: sparse topologies reduce individual user's privacy; and to keep privacy risk constant, the topology density must increase whenever new users join the protocol. This fact negates the claimed scalability property of the decentralized learning systems: growing comes at a cost.

### B. Shallower architectures

In Figure 17 we report privacy risk for a shallow Convolution Neural Network (CNN) of 225,000 parameters for both the passive and active attacks. While the privacy risk for the received model tends to be lower, the attacks behave congruently with what observed with the deeper ResNet20 model.

# APPENDIX E USER-SIDE ROBUST AGGREGATION FOR FEDERATED LEARNING

As we discuss in Section VI-B, a malicious central server in federated learning can arbitrarily decide the parameters of users' models. This is a byproduct of the stateless nature of users in federated learning. This is because federated learning is designed for users to join and drop the protocol at any given moment, and thus they must be able to immediately obtain a suitable state. To achieve this property, the parameter server effectively acts as a repository for the global state of the models.

```
1 Function server():
2
         for t \in [0, 1, ...] do
               /* Collect gradient
              for v \in V do
 3
                   \Delta_v^t \leftarrow \text{receive}(v);
 4
 5
              /* Gradient aggregation
              \Delta^t = \frac{1}{|V|} \sum_{v \in |V|} \Delta_v^t;
 6
               /* Send aggregated gradient
              for v \in V do
 7
 8
                  \operatorname{send}(v, \Delta^t);
9
         end
10
   Function client (\Theta^0, X):
11
         for t \in [0, 1, \dots] do
12
               /* Compute gradient
              \xi^t \sim X:
13
              \dot{\Delta}^t = \nabla_{\Theta^t}(\xi^t, \Theta^t);
14
              send(server, \Delta^{t});
15
               /* Receive aggregated gradient
              \Delta^t \leftarrow \text{receive(server)};
16
              /* Update current local state
              \Theta^{t+1} = \Theta^t - \eta \Delta^t;
         end
18
```

**Algorithm 3:** Example of *Stateful Federated Learning*.

As opposed to the churn-aware nature of federated users, the decentralized learning protocol we model assumes a static-topology in which users are always online and participate in all the training rounds [26], [32]. This ensures that users maintain a consistent local state during the training process. If we would make the same assumption in federated learning, then it would be possible to reduce the influence of the server on users. We show an example implementation in Algorithm 3, in which the server has limited influence, and it is possible to enhance line 17 in Algorithm 3 with robust aggregation (e.g., gradient-clipping:  $\Theta^{t+1} = \Theta^t - \text{clip}(\Delta^t, \tau)$  to bound on the influence of the server on the state of users).

On the opposite side, if we abandon the static-topology assumption in decentralized learning and users need to become stateless, decentralized learning faces similar problems as federated learning. For instance, when a new node joins the protocol at  $t \neq 0$  this node must somehow initialize its local state to a value coherent with the state of the network, as otherwise every addition of a user with arbitrary parameters would significantly affect convergence and consensus. Two solutions are possible: adding a trusted repository for initializing the model – which brings back the problems associated to the parameter server in federated learning; and inheriting the parameters from neighbors – which grants neighbors the same capability of the parameter server to determine the new user's state.

 $<sup>^5\</sup>mathrm{In}$  the torus topology, every node has 4 neighbors regardless the number of users in the system