Private Multi-Party Machine Learning in an Untrusted Setting

by

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Abstract

The problem of machine learning (ML) over distributed data sources arises in a variety of domains. Unfortunately, today's distributed ML systems use an unsophisticated threat model: data sources must trust a central ML process.

We propose a *brokered learning* abstraction that provides data sources with provable privacy guarantees while allowing them to contribute data towards a globally-learned model in an untrusted setting. We realize this abstraction by building on the state of the art in multi-party distributed ML and differential privacy methods to construct *TorMentor*, a system that is deployed as a hidden service over an anonymous communication protocol.

We define a new threat model by characterizing, developing and evaluating new attacks in the brokered learning setting, along with effective defenses for these attacks. We show that TorMentor effectively protects data sources against known ML attacks while providing them with a tunable trade-off between model accuracy and privacy.

We evaluate TorMentor with local and geo-distributed deployments on Azure. In an experiment with 200 clients and 14 MB of data per client our prototype trained a logistic regression model using stochastic gradient descent in 65s.

Lay Summary

The lay or public summary explains the key goals and contributions of the research/ scholarly work in terms that can be understood by the general public. It must not exceed 150 words in length.

Preface

At University of British Columbia (UBC), a preface may be required. Be sure to check the Graduate and Postdoctoral Studies (GPS) guidelines as they may have specific content to be included.

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Glossary

This glossary uses the handy `acroynym` package to automatically maintain the glossary. It uses the package's `printonlyused` option to include only those acronyms explicitly referenced in the LaTeX source.

GPS	Graduate and Postdoctoral Studies

Acknowledgments

Thank those people who helped you.

Don't forget your parents or loved ones.

You may wish to acknowledge your funding sources.

Chapter 1

Introduction

Machine learning (ML) models rely on large volumes of diverse, representative data for training and validation. However, to build multi-party models from user-generated data, users must provide and share their potentially sensitive information. Existing solutions [28, 30], even when incorporating privacy-preserving mechanisms [1], assume the presence of a trusted central entity that all users share their data and/or model updates with. For example, the Gboard service [31] uses sensitive data from Android keyboard inputs to generate better text suggestions; users who wish to train an accurate Gboard suggestion model must send their mobile keyboard data to Google.

Federated learning [32] keeps data on the client device and trains ML models by only transferring model parameters to a trusted central coordinator. In the quest for training the optimal ML model as quickly as possible, the coordinator is not incentivized to provide privacy for data providers: data is collected and is only kept on the device as a performance optimization [32].

Furthermore, federated learning is not private or secure against adversaries, who can pose as honest data providers or an honest coordinator and who use auxiliary information from the learning process to infer information about the training data of other users [21], despite data never being explicitly shared. One may consider obfuscating data labels before learning, but this is also insufficient to guarantee privacy [8]. General privacy-preserving computation models exist, but they rely on substantial amounts of additional infrastructure. These include homomorphically encrypted secure aggregation [6], secure multi-party computation [33], or trusted SGX infrastructure [38], all of which are infeasible for individuals and small organizations to deploy.

Today there is no accessible solution to collaborative multi-party machine learning that maintains privacy and anonymity in an untrusted setting. In developing this solution, we propose a novel setting called *brokered learning* that decouples the role of coordination from the role of defining the learning process. We introduce a short-lived, honest-but-curious *broker* that mediates interactions between a *curator*, who defines the shared learning task, and *clients*, who provide training data. In decoupling these roles, curators are no longer able to directly link clients to their model updates, and cannot manipulate the learning process.

Clients and curators never directly communicate: they are protected from each other by a broker that is only used to coordinate the learning task. The broker is administered by an honest-but-curious neutral party, detects and rejects anomalous behavior, and terminates when the learning objective is met. Our system design supports privacy and anonymity by building on accessible public infrastructure to minimize the cost of setting up and maintaining a broker.

We realize the brokered learning setting by designing, implementing, and evaluating *TorMentor*, a system which creates *brokers* to interface with the curator and the clients in a brokered learning process. TorMentor is implemented as a hidden Tor service, but can use any general-purpose anonymous communication service to safeguard the identities of curators and clients.

Although the model curator is removed from the learning process, a myriad of other attacks are still possible. We adapt known ML attacks to brokered learning and build on several state of the art techniques to thwart a variety of these attacks when they are mounted by clients, brokers and curators. Client-side differential privacy [12, 19] protects users from inversion attacks [16, 17], reject on negative influence (RONI) [3] and monitored client statistics [34] prevent model poisoning attacks [5, 24] and proof of work [2] mitigates sybil attacks [11].

Our evaluation of TorMentor demonstrates that these defenses protect clients and curators from each other. For example, in one experiment with 50% malicious poisoning clients, a TorMentor broker was able to convergence to an optimum after mitigating and recovering from malicious behavior through our novel adaptive proof of work mechanism. We also evaluated the performance of our prototype in a geo-distributed setting: across 200 geo-distributed clients with 14 MB of data per client, the training process in TorMentor takes 67s. By comparison the training on a similar federated learning system without Tor would take 13s. The observed overhead of TorMentor ranges from 5-10x, and depending on the level of privacy and security required, TorMentor's modular design allows users to further tune the system to meet their expected needs on the security-performance trade-off.

In summary, we make four contributions:

- ⋆ We develop a *brokered learning* setting for privacy-preserving anonymous multi-party machine learning in an untrusted setting. We define the responsibilities, interactions, and threat models for the three actors in brokered learning: curators, clients, and the broker.

- ⋆ We realize the brokered learning model in the design and implementation of *TorMentor* and evaluate TorMentor's training and classification performance on a public dataset.

- ⋆ We translate known attacks on centralized ML (poisoning [24, 37] and inversion [16, 17]) and known defenses in centralized ML (RONI [3], differential privacy [12]) to the brokered learning setting. We evaluate the privacy and utility implications of these attacks and defenses.

- ⋆ We design, implement, and evaluate three new defense mechanisms for the brokered learning setting: distributed RONI, adaptive proof of work, and thresholding the number of clients.

Chapter 2

Background

Machine Learning (ML). Many ML problems can be represented as the minimization of a loss function in a large Euclidean space. For example, a binary classification task in ML involves using features from data examples to predict discrete binary outputs; a higher loss results in more prediction errors. Given a set of training data and a proposed model, ML algorithms *train*, or iteratively find an optimal set of parameters, for the given training set. One approach is to use stochastic gradient descent (SGD) [7], an iterative algorithm which samples a batch of training examples of size *b*, uses them to compute gradients on the parameters of the current model, and takes gradient steps in the corresponding gradient direction. The algorithm then updates the model parameters and another iteration is performed (Appendix A contains all background formalisms).

Our work uses SGD as the training method. SGD is a general learning algorithm that is used to train a variety of models, including deep learning [44].

Distributed multi-party ML. To support larger models and datasets, ML training has been parallelized using a parameter server architecture [28]: the global model parameters are partitioned and stored on a parameter server. At each iteration, client machines pull the parameters, compute and apply one or more iterations, and push their updates back to the server. This can be done with a synchronous or asynchronous protocol [23, 40], both of which are supported in our work.

Federated Learning [32]. The partitioning of training data enables multi-party machine learning: data is distributed across multiple data owners and cannot be shared. Federated learning supports this setting through a protocol in which clients send gradient updates in a distributed SGD algorithm. These updates are collected and averaged by a central server, enabling training over partitioned data sources from different owners.

Attacks on ML. Our work operates under a unique and novel set of assumptions when performing ML and requires a new threat model. Despite this novel setting, the attacks are functionally analogous to state of the art ML attacks known today.

Poisoning attack. In a poisoning attack [5, 34], an adversary meticulously creates adversarial training examples and inserts them into the training data set of a target model. This may be done to degrade the accuracy of the final model (a random attack), or to increase/decrease the probability of a targeted example being predicted as a target class (a targeted attack) [24]. For example, such an attack could be mounted to avoid anomaly detectors [41] or to evade email spam filtering [37].

In federated learning, clients possess a disjoint set of the total training data; they have full control over this set, and can therefore perform poisoning attacks with minimal difficulty.

Information leakage. In an information leakage attack, such as model inversion, an adversary attempts to recover training examples from a trained model $f(x)$. Given a targeted class y, one inversion technique involves testing all possible values in a feasible feature region, given that some information about the targeted example is known. The attack then finds the most probable values of the targeted example features [16].

Another model inversion attack uses prediction confidence scores from $f(x)$ when predicting y to perform gradient descent to train a model $\hat{f(x)}$ that closely resembles $f(x)$. The victim's features are probabilistically determined by using the model in prediction. The resulting vector x that comes from this process is one that most closely resembles an original victim training example [17].

Information leakage attacks have been extended to federated learning: instead of querying information from a fully trained model, an adversary observes changes in the shared model during the training process itself [21]. In doing so, the adversary can reconstruct training examples that belong to other clients.

Defenses for ML. *A RONI (Reject on Negative Influence)* defense [3] counters ML poisoning attacks. Given a set of untrusted training examples D_{un}, this defense trains two models, one model using all of the trusted training data D, and another model using the union dataset $D' = D \cup D_{un}$ which includes the untrusted data. If the performance of D' is significantly worse than the performance of D on a validation dataset, the data D_{un} is flagged as malicious and rejected. However, this defense relies on access to the centralized dataset, which is infeasible in the federated learning setting.

Differential privacy [12] is a privacy guarantee that ensures that, for a given dataset, when used to answer questions about a given population, that no adversary can identify individuals that are members of the dataset. Differential privacy is user-centric: the violation of a single user's privacy is considered a privacy breach. Differential privacy is parameterized by ε, which controls the privacy-utility tradeoff. In the ML context, utility equates to model performance [44]. When ε approaches 0, full privacy is ensured, but an inaccurate model is produced. When ε approaches infinity, the optimal model is produced without any privacy guarantees.

Differential privacy has been applied to several classes of ML algorithms [4, 42] in decentralized settings to theoretically guarantee that a client's privacy is not compromised when their data is used to train a model. This guarantee extends to both the training of the model and to usage of the model for predictions.

Differentially private SGD [19, 44] is a method that applies differential privacy in performing SGD. Before sending gradient updates at each iteration, clients perturb their gradient values with additive noise, which protects the privacy of the input dataset. The choice of batch size impacts the effect of the privacy parameter on the model performance. Our work uses differentially private SGD to provide the flexible privacy levels against attacks in our setting.

Anonymous communication systems. Clients are still at privacy risk when sending model updates directly to an untrusted broker, so we add an additional layer of indirection in our work. Onion routing protocols are a modern method for providing anonymity in a distributed P2P setting. When communicating with a target node, clients route traffic through a randomly selected set of relay nodes in the network, which obfuscates the source and destination nodes for each message.

Our work supports the use of any modern implementation for providing anonymous communication. We select the Tor network [10] as the system in our implementation.

Sybil attacks and proof of work. An anonymous system that allows users to join and leave may be attacked by sybils [11], in which an adversary joins a system under multiple colluding aliases. One approach to mitigate sybil attacks is to use proof of work [2], in which a user must solve a computationally expensive problem (that is easy to verify) to contribute to the system. This mechanism provides the guarantee that if at least 50% of the total computation power in the system is controlled by honest nodes, the system is resilient to sybils.

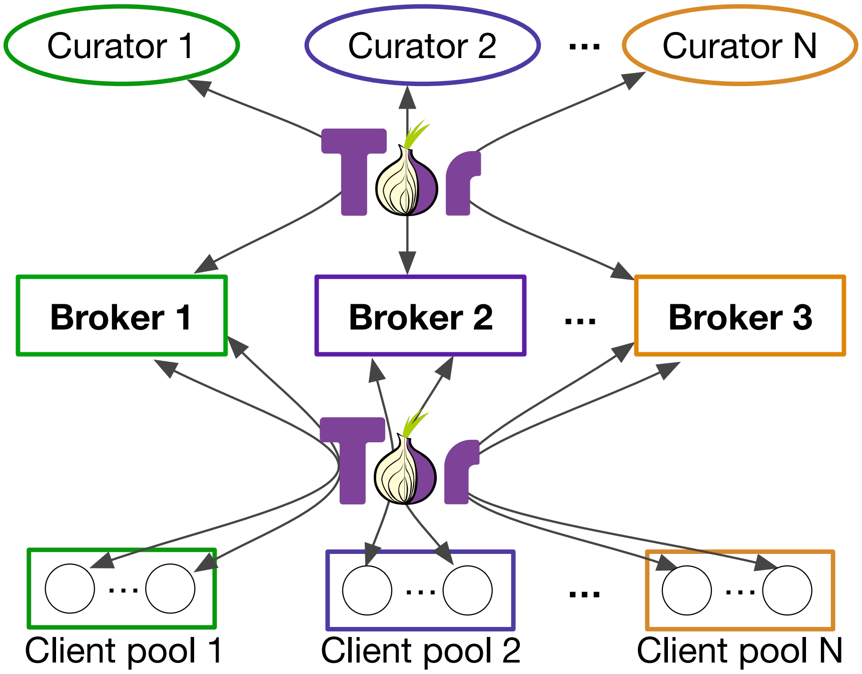


Figure 2.1: Brokered learning and TorMentor design. Brokers (implemented as hidden Tor services) mediate between curators (top) and sets of clients (bottom).

Chapter 3

Brokered Learning

In this work, we define *brokered learning*, which builds on the federated learning setting [32], but assumes no trust between clients and curators.

3.1 Decoupling federated learning

In federated learning, a central organization (such as Google) acts as the parameter server and performs two logically separate tasks: **(1)** define the data schema and the learning objective, **(2)** coordinate distributed ML. The federated learning server performs both tasks at a central service, however, there are good reasons to separate them.

Fundamentally, the goals of data privacy and model accuracy are at tension. Coordinating the ML training process in a private and secure manner compromises the model's ability to learn as much as possible from the training data. In current learning settings, the coordinator is put in a position to provide privacy, yet they are not incentivized to do so.

To take things even further, a malicious curator can observe the contributions of any individual client, creating an opportunity to perform information leakage [21] attacks on clients, such as model inversion [16, 17] or membership inference [43]. These attacks can be mitigated in federated learning with a secure aggregation protocol [6], but this solution does not handle poisoning attacks and requires several coordinated communication rounds between clients for each iteration.

Client anonymity may also be desirable when privacy preferences are shared. For example, if attempting to train a model that uses past criminal activity as a feature, one user with strong privacy preferences in a large group of users with weak privacy preferences will appear suspicious, even if their data is not revealed.

A key observation in our work is that *because data providers and model curators agree on a learning objective before performing federated learning, there is no need for the curator to also coordinate the learning.*

Brokered learning decouples the two tasks into two distinct roles and includes mechanisms for anonymity to protect data providers from the curator while orchestrating federated learning. In this setting the users in the system (model curators and data providers) do not communicate with one another, which facilitates a minimal trust model, strengthening user-level privacy and anonymity. As well, users do not reveal their personal privacy parameters to the broker, since *all privacy-preserving computation is performed on the client*.

At the same time brokered learning maintains the existing privacy features of federated learning: data providers do not need to coordinate with each other (or even be aware of each other). This is important to counter malicious clients who attack other clients [21].

3.2 Defining brokered learning

Brokered learning builds on federated learning [32] but provides additional privacy guarantees. This model introduces a **broker** to mediate the learning process.

Curators define the machine learning model. A curator has a learning task in mind, but lacks the sufficient volume or variety of data to train a quality model. Curators would like to collaborate with clients to perform the learning task and may want to remain anonymous. We provide curators with anonymity in TorMentor by deploying a broker as a Tor hidden service, and by using the broker as a point of indirection (Figure 2.1).

Curators may know the identities of clients that wish to contribute to the model or may be unaware of the clients that match their learning objectives. Brokered learning supports these and other use cases, For example, curators may know some subset of the clients, or set a restriction on the maximum number of anonymous clients who can contribute[1].

Clients contribute their data to the machine learning task and specify the criteria for their participation. Instead of fully trusting the curator as they would in federated learning, clients communicate with an honest-but-curious broker. The broker is trusted only with coordinating the learning process, and does not learn the identity nor data of any client. This threat model is similar to what was used in the secure aggregation protocol for federated learning [6].

Brokered learning allows these clients to jointly contribute to a shared global model, without being aware of nor trusting each other. Each client only needs to be concerned about its personal privacy parameters. Some clients may be more concerned with privacy than others; brokered learning supports differentially private machine learning with heterogeneous privacy levels, which has been shown to be feasible [19].

A broker is a short-lived process that coordinates the training of a multi-party ML model. When a model that is defined by a curator in TorMentor, a single broker is created and deployed as a hidden service in an anonymous network [2]. Clients perform actions such as requesting access to the system, defining client-specific privacy parameters and sending model updates for distributed SGD. We define a precise client API in Section 5. When model training is complete, the broker publishes the model and terminates. In our vision, brokers are not intended to be long lasting, and their sole function should be to broker the agreement between users to facilitate anonymous multi-party ML. Brokers may even explicity be managed by governments or as part of a privacy enhancing business model, both of whom are incentivized to provide privacy, anonymity and fairness in distributed ML.

3.3 Example use cases

Medical Sharing Network. Hospitals store substantial patient medical data. However, due to strict regulations, they cannot share this data with each other. No individual hospital wishes to host the infrastructure for model coordination, and no

[1] We assume that the broker identifies or advertises the learning process to clients out of band, externally to TorMentor.

[2] In this paper we do not consider who is running the broker; but we do assume that it is an honest-but-curious third party that is distinct from the curator and the participating clients.

individual hospital is trusted to securely coordinate the analysis. An alternative solution is for the network of hospitals to collaborate in a brokered learning system. For this the hospitals would define the learning task, one hospital would agree to deploy the broker as a hidden service, and all other willing hospitals would join and contribute model updates, training a shared model.

Internet of Things. With the growth of the Internet of Things (IoT), and a largely heterogeneous set of device providers, there is currently no solution for privacy-preserving multi-device ML, hosted by a neutral provider. Without anonymous multi-party ML, each system device provider would need to host their own ML coordinators and would have no mechanism for sharing models across other providers.

Brokered learning allows these devices to collaborate on model training without explicitly trusting each other. Devices reap the benefits of shared trained models, without risking data privacy loss. The broker can be run by any single company, or a neutral trusted third party, neither of which have power to compromise device-level privacy.

Chapter 4

Threat model, guarantees, assumptions

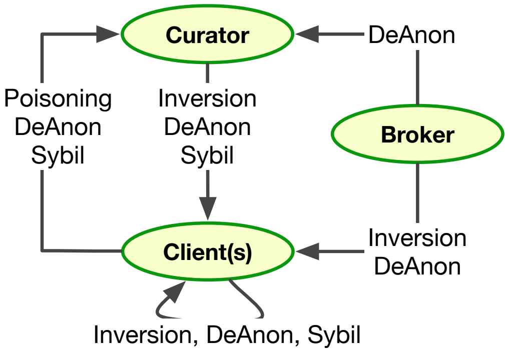
We realized brokered learning in a system called *TorMentor*, which uses differentially private distributed SGD [44] to train a model in an anonymous multi-party setting. We select Tor [10] as the anonymous communication network for TorMentor. TorMentor is designed to counter malicious curators and malicious clients who may attempt to gain additional information (information leakage) about others or negatively influence the learning process (poisoning). The honest-but-curious broker coordinates the learning process, but is *not* trusted with the identity nor the data of users.

Clients and curators do not attack the broker itself, rather they aim to attack other curators, other clients, or the outcome of the learning process. Brokers are also untrusted in the system: the client and curator APIs protect them from potential broker attacks. Figure 4.1 overviews TorMentor's threat model with attacks/defenses and who can attack who and how.

Deanonymization. For anonymous communication to and from the broker we assume a threat model similar to Tor [10]: an adversary has the ability to observe and control some, but not all of the network. Adversaries may attempt to observe Tor traffic as a client or as a broker in the network [13, 27, 35]. Adversaries can also influence traffic within Tor through their own onion router nodes, which do not necessarily need to be active TorMentor clients.

Attack	Defenses
Poisoning	Validation
Inversion	Diff-priv, bystanders
DeAnon	Tor, broker indirection
Sybil	Proof of work

(a)



(b)

Figure 4.1: (a) Attacks/defenses in TorMentor. (b) Threat model: an edge is an attack by source against target(s).

Poisoning attacks. In our threat model, poisoning attacks are performed by clients against shared models. After a curator defines a model, adversarial clients can use the defined learning objective to craft adversarial samples that oppose the objective. We assume that adversaries generate these adversarial samples using a common strategy such as label flipping [5], and join the training process and poison the model by influencing its prediction probabilities.

Inversion attacks. We assume that adversaries can target a specific client victim who they know is using the system. Inversion attacks can be executed from a variety of points: the adversary may be administering the broker, the adversary may curate a model that the victim joins, or the adversary joins model training as a client, knowing that the victim has also joined. Although the broker does not expose model confidence scores in the model prediction API, which are a key piece of information for performing inversion attacks in a black-box setting [17], our threat model grants adversaries white-box access to the model internals, which is more powerful than a traditional model inversion attack.

In TorMentor, adversarial clients have access to the global model and can infer confidence scores or gradient step values by carefully observing changes to the global model and reconstructing a copy of the victim's local model. This attack is similar to a model stealing attack [47]: after stealing an accurate approximation of a victim's local model, an adversary can mount an inversion attack on the approximation to reconstruct the victim's training examples.

Sybil attacks. Since clients and curators join the system anonymously, they can generate sybils, or multiple colluding virtual clients, to attacks the system [11]. In federated learning, all users are given an equal stake in the system, and thus sybils make poisoning and inversion attacks linearly easier to perform.

4.1 Security guarantees

TorMentor guarantees that curator and client identities remain anonymous to all parties in the system by using an anonymous communication network. Our prototype uses Tor and provides the same guarantees as Tor, however, it can use other anonymous messaging systems [9, 48]. For example, since Tor is susceptible to timing attacks, an adversary could target a client by observing its network traffic to de-anonymize its participation in the system.

TorMentor exposes a small, restrictive API to limit a user's influence on the system. TorMentor alleviates the risk of poisoning attacks and inversion attacks by allowing clients to specify *k*, the minimum number of clients required for training. When a client joins the system, they are able to specify the number of other clients required in the system, which TorMentor guarantees will be honored. Clients also locally use differential privacy to further protect their privacy. Both parameters are defined by the client, guaranteeing that clients (and not the curator) controls this accuracy-privacy tradeoff.

TorMentor prevents sybils through proof of work, similar to the Bitcoin protocol [36]. This mechanism makes it expensive, though not impossible, to mount a sybil attack. Proof of work is implemented at two points: proof of work as a prerequisite for system admission, and proof of work as a prerequisite for contributing to the model.

4.2 Assumptions

We assume that the only means to access information within the system is through the APIs defined in Section 5. A TorMentor instance and its corresponding brokers are exposed as a hidden service with a public *.onion* domain. We assume that this

.onion becomes a widely known and trusted domain[1].

We use proof of work to defend against sybils and therefore assume that the adversary does not have access to more than half of the computational power relative to the total computational power across all users in an instance of the TorMentor training process [2].

We make the same assumptions as Tor [10]; for example, we assume that an adversary does not control a large fraction of nodes within the Tor network.

[1] To build further trust the TorMentor service can use an authoritatively signed certificate.

address ← **curate**(mID, maxCli, minCli, validSet)
Curate a new model. Curator provides modelID, client count range, validation set. TorMentor returns a hidden service address for a newly specified broker.
P_{admit} ← **join**(mID)
Client joins a curated model. Client provides modelID; TorMentor returns a SHA-256 admission hash puzzle P_{admit}.
conn, M_t ← **solve**(mID, S_{admit}, minCli, schema)
Client finds the solution S_{admit} to P_{admit} and joins. Client provides modelID, solution to puzzle, min number of clients and its dataset schema; TorMentor returns a connection and global model state.
$M_{g,t+1}$, $P_{i,t+1}$ ← **gradientUpdate**(mId, $S_{i,t}$, $\Delta_{i,t}$)
Client pushes a local model update to the global model state. Client i provides modelID, solution to previous SHA-256 puzzle $S_{i,t}$ and gradient update $\Delta_{i,t}$ at iteration t; TorMentor returns new global model state $M_{g,t+1}$, and the next SHA-256 puzzle $P_{i,t+1}$.

Table 4.1: TorMentor API. The curate call (top row) is the only curator API call. The bottom three calls are for clients.

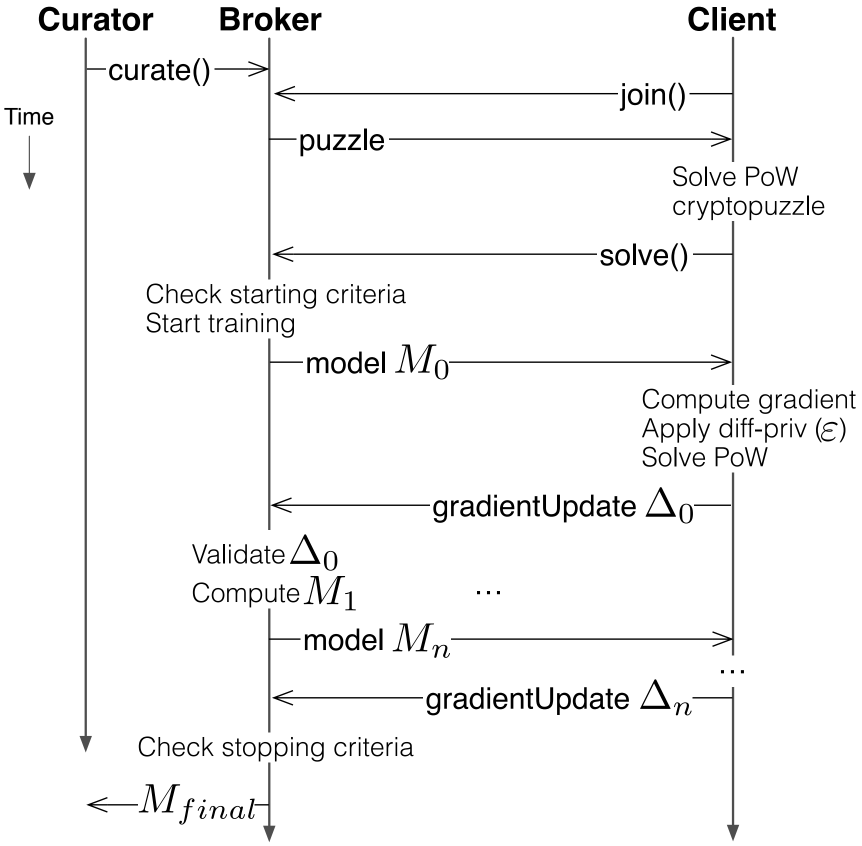


Figure 4.2: Overview of the TorMentor protocol between curator/broker/-client.

Chapter 5

TorMentor Design

TorMentor design has three goals: (1) meet the defined learning objective in a reasonable amount of time, (2) provide both anonymity and data privacy guarantees to clients and curators, and (3) flexibly support client-specific privacy requirements.

Design overview. The broker handles all communication between clients and the curator, and acts as the coordinator in an untrusted collaborative learning setting. Each TorMentor broker is deployed as a Tor hidden service with a unique and known *.onion* domain. Several clients may join a model once a curator defines it, with requirements for joining specified by both the curator and the clients. Each broker and therefore each model is associated with a pool of clients among whom the learning procedure takes place (see Figure 2.1).

Each broker runs a separate *aggregator* process and *validator* process. The aggregator serves the same purpose as a parameter server [28]: storing and distributing the parameters of the global model. The validator is a novel addition in our work that observes and validates the values of gradient updates sent by clients to the aggregator.

Next, we review the TorMentor API in Table 4.1 and the training process illustrated in Figure 4.2. We then detail how TorMentor defends against adversarial clients and curators.

5.1 Curator API

The curator uses the **curate** call to bootstrap a new model by defining a *common learning objective*: the model type, the desired training data schema and a validation dataset. These are critical to perform ML successfully (even in a local setting). We therefore expect that a curator can provide these.

Once the learning objective is defined, a Tor *.onion* address is established for the specified model, and the system waits for clients to contact the hidden service with a message to join. The validation dataset is used by the validator to reject adversaries, and to ensure that the ML training is making progress towards model convergence.

Too few clients may lead to a weak model with biased data, while a large number of clients will increase communication overhead. The curator can use the API to adjust an acceptable range for the number of clients contributing to the model.

5.2 Client API

A client uses the **join** call to join a curated model. A client's data is validated against the objective when joining. Our prototype only checks that the specified number of features matches those of the client, but more advanced automatic schema validation techniques [39] can be used.

The client uses the **solve** call to perform a proof-of-work validation, similar to that of the blockchain protocol [36], in which a cryptographic SHA-256 admission hash is inverted, the solution is verified to contain a required number of trailing '0' digits, and a new puzzle is published. Once the proof-of-work is completed, the client is accepted as a contributor to the model. Once the desired number of clients have been accepted to the model, collaborative model training is performed through the TorMentor protocol: each client computes their SGD update on the global model and pushes it to the parameter server through the **gradientUpdate** call.

Clients compute gradient updates *locally*. Clients also maintain a personal privacy level ε and a personal batch size b to tune their differentially-private updates during model training. With the privacy-utility tradeoff in mind, it is natural for clients and curators to have different preferences regarding client privacy. Some clients may value privacy more than others and thus will tune their own privacy risk, while curators want to maximize their model utility *TorMentor is the first system to support anonymous machine learning in a setting with heterogeneous user-controlled privacy goals.*

5.3 Training process

Training in TorMentor (Algorithm 1) is performed in a fashion similar to that of the parameter server [28]: each client pulls the global model, locally computes a gradient step, and applies the update to the global model. TorMentor users the differentially private SGD [44] method, which allows clients to select their own privacy parameter ε and batch size b. We assume that clients understand how to properly define these parameters and are aware of their implications on the privacy-utility tradeoff and their privacy budgets [12].

Since clients may fail or be removed from the system by the broker, bulk synchronous computation in TorMentor may be infeasible. Instead, as an alternative to the synchronous update model in federated learning [32], TorMentor also supports a total asynchronous model [23, 28], which enables parallelization but allows clients to compute gradients on stale versions of the global model, potentially compromising model convergence. A lock-free approach to parallel SGD is feasible if the the step size is tuned properly, and the corresponding global loss function meets certain strong convexity guarantees [40], which we assume is true when using the total asynchronous model in our brokered learning setting. This approach also negates the affect of stragglers in a high latency environment (see Section 7).

Clients are free to leave the training process at any time. TorMentor keeps a registry of the active clients, and checks that the minimum number of clients condition is met at each gradient update. In the case of clients leaving the system, TorMentor uses timeouts to detect the clients who drop out of the system. Such clients do not negatively impact the curator or other clients. As long as the required minimum number of clients k exists, the learning process will not halt and no work will be wasted.

```
Data: Training data $x, y$; batch size $b$; privacy parameter $\varepsilon$
Result: Returns a single gradient update on the model parameters
while IsTraining do
    Pull gradients $w_t$ from TorMentor;
    Subsample $b$ points $(x_i, y_i) \in B_t$ from training data;
    Draw noise $Z_t$ from Laplacian distribution;
    Compute gradient step through differentially private SGD;
    Push gradient to TorMentor
end
```

Algorithm 1: TorMentor differentially private SGD training algorithm.

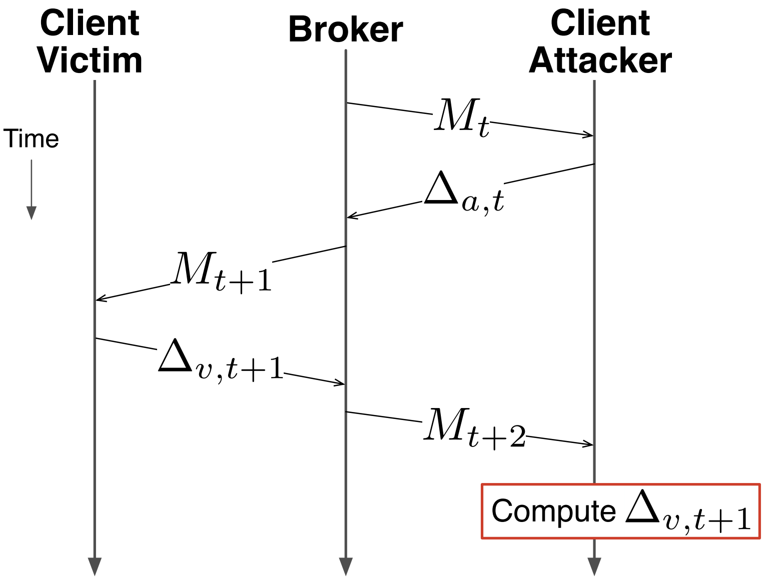


Figure 5.1: One iteration in an inversion attack in which an attacker observes the difference between M_t and M_{t+2}, and infers this difference to be $\Delta_{V,t+1}$. After many iterations, the attacker can discover M_V^*, the optimal model trained on the victim's data.

5.4 Defending against inversion attacks

Although a direct inversion attack in federated learning has not been realized yet, we envision a novel potential attack in this scenario. Figure 5.1 shows the proposed ideal situation for an attacker performing an inversion attack: a two client TorMentor system, one of whom is the adversary.

In this scenario the victim V and attacker A alternate in sending gradient updates to the broker. Since the global model parameters are sent to the adversary at each iteration, it can ideally observe the difference in the global model between iterations. As the attacker knows their contribution to the global model at the previous iteration, they are able to exactly compute the victim's update by calculating:

$$M_{t+2} = M_t + \Delta_{v,t+1} + \Delta_{a,t}$$
$$\Delta_{v,t+1} = M_{t+1} - M_t - \Delta_{a,t}$$

By saving and applying $\Delta_{v,t}$ at each iteration to a hidden, shadow model, the adversary can compute an approximation to M_V, the optimal model trained with only the victim's data, similar to a model stealing attack [47]. The adversary can then perform a model inversion attack [16, 17] and reconstruct the victim's training data elements in X_V. In the case that the broker carries out the inversion attack, the attack is even stronger: the broker can isolate all updates sent to it through a single connection.

Differential privacy offers a natural defense against attacks from a broker or another client by perturbing the victim's updates $\Delta_{V,t}$ that are sent to the broker. An adversary will find it difficult to recover M_V and X_V when the privacy parameter ε is closer to 0. An adversary could choose to send any vector as their $\Delta_{a,t}$ update, which allows them to curate specific gradients that elicit revealing responses from the victim [21].

In the case of attacks from other clients, the effectiveness of the differentially private SGD protocol is also contingent on a setting in which multiple clients are simultaneously performing updates. When an adversarial client receives a new copy of the global model in TorMentor, it has no mechanism to discover which clients contributed to the model since the last update, making it difficult to derive knowledge about specific clients in the system.

Thus, TorMentor exposes a privacy parameter k to clients, which clients use to express the minimum number of clients that must be in the system before training can begin. Our differentially private SGD only begins when n clients, each with a parameter $k \leq n$ exist in the system. Effectively, this means that for an adversarial client to perform the ideal model inversion against a victim with parameter k the adversary needs to create $k-1$ sybil clients.

5.5 Defending against poisoning attacks

In adding the validator process, we propose an *active parameter server* alternative to the assumed passive parameter server in current attacks [21]. The parameter server validates each client's contribution to the model health and penalizes updates from suspicious connections.

We develop a distributed RONI defense that uses sets of gradient updates, instead of datasets, and independently evaluates the influence that each gradient update has on the performance of a trusted global model. Validation (Algorithm 2) executes within the parameter server in TorMentor and validates that iterations performed by clients have a positive impact. Validation is parameterized by two variables: the validation rate at which validations are performed, and the RONI threshold [3] required before a client is flagged.

To ensure that validations are performed in a fair manner, we benchmark all clients against the same candidate model. The validator intersperses validation iterations within the gradient updates requests in distributed SGD. A validation round is triggered through a periodic Bernoulli test, with the probability parameterized by a validation rate. During a validation round, the current model state is snapshotted, and a copy of this model is sent to all active clients. The clients' gradient responses are collected and the RONI value is calculated and accumulated.

In addition to the proof of work required to join the system, we implement an adaptive proof of work mechanism to mitigate sybils in poisoning attacks. A SHA-256 proof of work puzzle that must be solved on each iteration before an update to the global model is accepted by the broker. When a client's RONI score exceeds a defined negative threshold, the broker increases the required trailing number of 0's by one, increasing the difficulty of the puzzle for that client. The difficulty of this puzzle is client- and iteration-specific, making it more expensive for malicious clients to poison the model and decreasing their influence relative to honest clients.

When the rate of validation is increased, the broker discovers poisoning clients more quickly, but with a performance overhead. When the RONI threshold is increased, the broker is more likely to detect adversaries, but the false positive rate

```
Data: Stream of gradient updates from each client $i$, over $t$ iterations $\Delta_{i,t}$
Result: Reject a client if their updates oppose the defined learning
        objective
while IsTraining do
    Draw Bernoulli value $v$;
    if $v > VALIDATION\_RATE$ then
        Set current model $M_t$ to be snapshot model $M_s$;
        Wait for client responses;
    end
    if Client c contacts TorMentor then
        Send $M_s$ instead of $M_t$;
        Save response $\Delta_{c,s}$
    end
    if All clients responded then
        Find RONI $r_c$: $r_c = err(M_s, X_{val}) - err(M_s + \Delta_{c,s}, X_{val})$;
        $total_c = total_c + r_c$;
        if $total_c > THRESHOLD$ then
            penalize $c$;
        end
    end
end
```

Algorithm 2: RONI validation algorithm.

of flagging honest nodes increases as well.

An important design detail is that a validation request looks just like a gradient update request. Therefore, adversaries cannot trick the validator by appearing benign during validation rounds while poisoning the true model. If the snapshot model M_s is taken close enough to the current model state M_t, it becomes more difficult for adversaries to distinguish whether the updates they are receiving are genuine gradient requests or not.

5.6 Modular design

To summarize, TorMentor includes several mechanisms to provide various levels of client and curator privacy and security. These include:

⋆ Using Tor to provide anonymous communication for all users (clients and the curator).

- Using proof of work as a form of admission control.
- A validator process that uses RONI and adaptive proof of work to mitigate poisoning attacks and sybils.
- Differentially private SGD and minimum client enforcement to provide client privacy and to defend against inversion attacks.

Each of these components operates independently, and if brokered learning is deployed in a setting where some of the described attacks are out of scope, these components can be independently disabled.

Chapter 6

TorMentor Implementation

We implemented a TorMentor prototype in 600 LOC in Python 2.7 and 1,500 LOC in Go 1.8. All the communication primitives are developed in Go, while the vector computation and ML are in Python. We implement differentially-private SGD [44] in Numpy 1.12. For our noise function, we use a multivariate isotropic Laplace distribution. As a performance operation, we draw random samples from this distribution prior to training by using *emcee*, an MIT licensed Monte Carlo (MCMC) ensemble sampler [15].

In our evaluation we deploy the TorMentor curator and clients on Azure by using bash scripts consisting of 371 LOC. These bootstrap VMs with a TorMentor installation, launch clients, and orchestrate experiments.

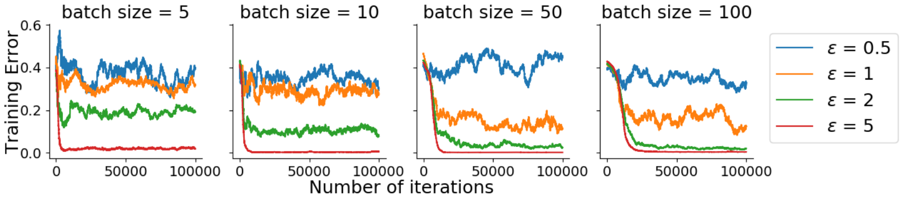


Figure 6.1: Effects of differential privacy and batch size on training loss over time. As ε and b decrease, model convergence is slower and may not be guaranteed.

Chapter 7

Evaluation

We evaluated our TorMentor design by carrying out several local and wide-area experiments with the TorMentor prototype. Specifically, we answer the following four research questions:

1. What are the effects of the privacy parameter ε and batch size b on model convergence? (Section 7.2)

2. What is TorMentor's overhead as compared to the baseline alternative? (Section 7.3)

3. How effective are the privacy parameters ε and minimum number of clients k in defending against inversion attacks? (Section 7.4)

4. How effective is validation in defending against poisoning attacks, and what are the effects of its parameters? (Section 7.5)

Next we describe the methodology behind our experiments and then answer each of the questions above.

7.1 Methodology

Credit card dataset. In our experiments we envision multiple credit card companies collaborating to train a better model that predicts defaults of credit card payments. However, the information in the dataset is private, both to the credit card companies and to their customers. In this context, any individual company can act as the curator, the broker is a commercial trusted service provider, and clients are the credit card companies with private datasets.

To evaluate this use-case we used a credit card dataset [49] from the UCI machine learning repository [29]. The dataset has 30,000 examples and 24 features. The features represent information about customers, including their age, gender and education level, along with information about the customer's payments over the last 6 months. The dataset also contains information about whether or not the given customer managed to pay their next credit card bill, which is used as the prediction for the model.

Prior to performing the training, we normalized, permuted, and partitioned the datasets into a 70% training and 30% testing shard. For each experiment, the training set is further sub-sampled to create a client dataset, and the testing shard is used as the curator-provided validation set. Training error, the primary metric used in evaluation, is calculated as the error when classifying the entire 70% training shard. In brokered learning, no single client would have access to the entire training dataset, so this serves as a hypothetical metric.

Wide-area deployment on Azure. We evaluated TorMentor at scale by deploying a geo-distributed set of 25 Azure VMs, each running in a separate data center, spanning 6 continents. Each VM was deployed using Azure's default Ubuntu 16.06 resource allocation. Each VM was provisioned with a single core Intel Xeon E5-2673 v3 2.40GHz CPU, and 4 GB of RAM. Tor's default `stretch` distribution was installed on each client. We deployed the broker at our home institution as a hidden service on Tor. The median ping latency (without using Tor) from the client VMs to the broker was 133.9ms with a standard deviation (SD) of 61.9ms. With Tor, the median ping latency increased to 715.9ms with a SD of 181.8ms.

In our wide-area experiments we evenly distribute a varying number of clients across the 25 VMs and measure the training error over time. Each client joins the system with a bootstrapped sample of the original training set (n = 21,000 and sampled with replacement), and proceeds to participate in asynchronous model training.

7.2 Model convergence

We evaluate the effect of the privacy parameter ε and the batch size b when performing learning over TorMentor. Figure 6.1 shows training error over time with a single client performing differentially private SGD [44] to train a logistic regression model using the entire training shard.

We found that models converge faster and more reliably when the batch size is higher and when ε is higher (less privacy). These results are expected as they are confirmations of the utility-privacy tradeoff. In settings with a low ε (more privacy) and a low batch size we observed that the effect of differential privacy is so strong and the magnitude of the additive noise is so large that the model itself does not converge, rendering the output of the model useless. Based on these results, the experiments in the remainder of the paper use a batch size of 10.

7.3 Scalability and overhead

We also evaluated TorMentor's scalability by varying the number of participating clients. We evaluate the overhead of Tor and the wide-area in TorMentor by running TorMentor experiments with and without Tor. All nodes were honest, held a subsample of the original dataset, and performed asynchronous SGD.

Figure 7.1 shows that, when updating asynchronously, the model convergences at a faster rate as we increase the number of clients.

We also compared the convergence time on TorMentor with a baseline WAN parameter server. For the WAN parameter server we used the same clients deployment, but bypassed Tor, thereby sacrificing anonymity.

The results in Table 7.1 show that on average, the overhead incurred from using Tor ranges from 5-10x. However, as the number of clients increases, the training time in both deployments drops, while the central deployment slows down.

7.4 Inversion defenses evaluation

We first set up the inversion attack by carefully partitioning the dataset. Of the 30,000 examples in the credit dataset, 9,000 (30%) examples were partitioned into X_{test}, a test dataset. The remaining 21,000 examples were evenly partitioned across

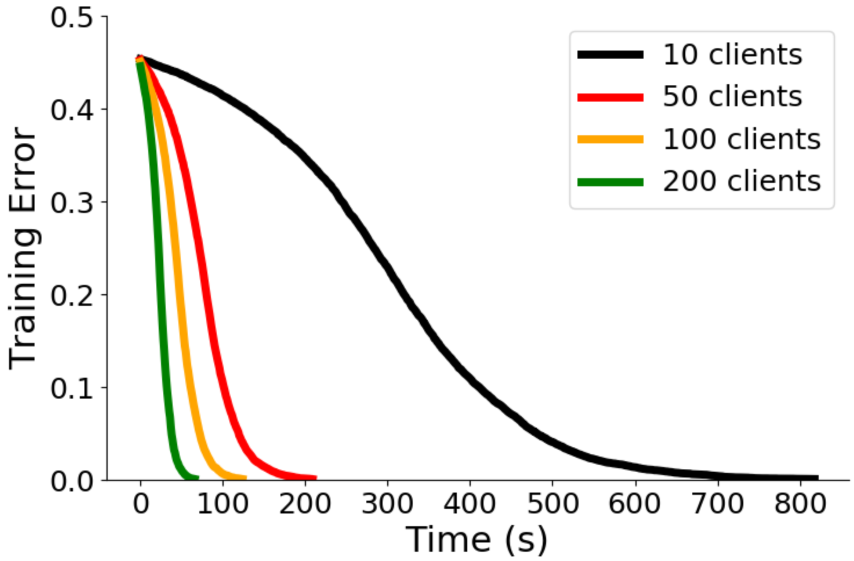


Figure 7.1: TorMentor model convergence in deployments with 10, 50, 100, and 200 clients.

# of Clients	TorMentor	w/o Tor
10	819 s	210 s
50	210 s	34 s
100	135 s	18 s
200	67 s	13 s

Table 7.1: Time to train the model with TorMentor, with and without Tor, over a varying number of clients.

clients. The victim's dataset X_v was one of these partitions, with all the y_i prediction values flipped. This was done to sufficiently separate the victim model from the globally trained model[1]. With this victim dataset, a globally trained model achieved an error of 95.4% when attempting to reconstruct the victim model, and predicting on the test set.

[1] We originally attempted the inversion with one of the training data shards as the victim dataset, but we found that even naively comparing the final global model M_g^* to the optimal victim model M_v^* resulted in a low reconstruction error of 4.4%. Thus, separating the victim model in a way that makes it distinguishable is necessary.

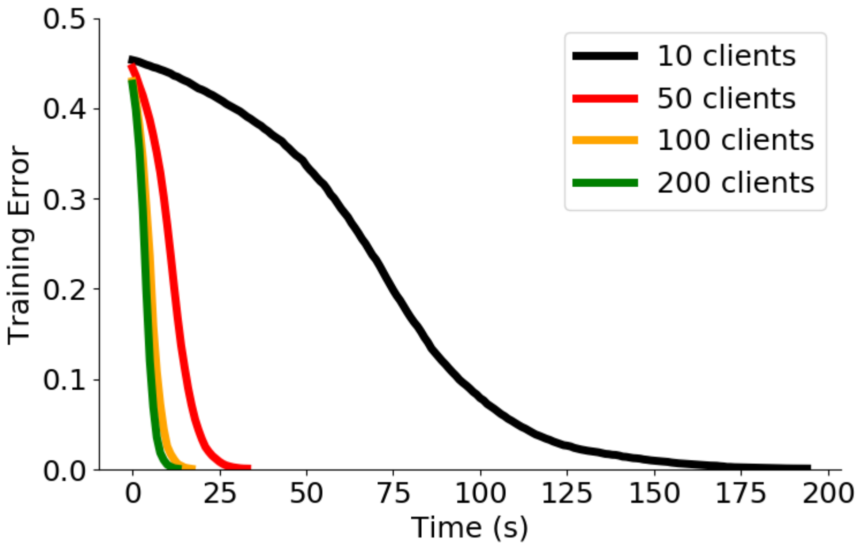


Figure 7.2: TorMentor without Tor model convergence in deployments with 10, 50, 100, and 200 clients.

With this setup we carried out the attack described in Figure 5.1. Each attack was executed for 4,000 gradient iterations, which was long enough for the global model to reach convergence in the baseline case. We then calculated the reconstruction error by comparing the resulting inversion model to the true victim model, a model trained with only the victim's data, by comparing predictions on the test set. That is, if the inversion model and true victim model classify all test examples identically, the reconstruction error is 0. The reconstruction error would also serve as the error when an attacker uses outputs from $\hat{M}_v$ to infer the training examples in X_v [17, 47].

Since the inversion attack is passively performed, it is defended by a client carefully tuning the privacy parameters ε and the minimum number of clients k. We evaluate the effects of these parameters in Figures 7.3 and 7.4.

Figure 7.3 shows the effect of the privacy parameter ε on the reconstruction error, as ε is varied from 0.5 to 5, plotting the median and standard deviation over 5 executions.

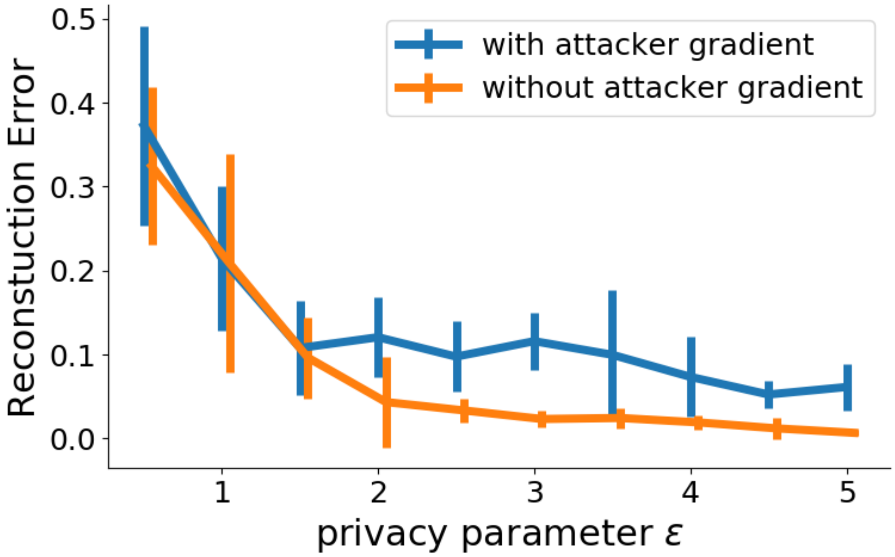


Figure 7.3: Model agreement between victim model and inverted estimate in the ideal setting (Fig. 5.1), with varying ε.

In the baseline case the client and curator are alternating gradient updates as in Figure 5.1, and there is no differential privacy. As ε decreases (increasing privacy), the reconstruction error of the inversion attack increases. When $\varepsilon = 1$, the reconstruction error is consistently above 10%.

When the attacker sends a vector of zeros as their gradient update, the inversion attack is most effective, as this completely isolates the updates on the global model to those performed by the victim. Figure 7.3 shows the same experiment performed when the attack contributes nothing to the global model. As ε increases beyond 2 (decreasing privacy), the attack performed without sending any gradients consistently outperforms the attack when performing gradient updates. This behavior, however, is suspicious and a well designed validator would detect and blacklist such an attacker. Therefore, this case is a worst case scenario as the attacker must attempt to participate in the model training process.

Inversion attacks are made more difficult when randomness in the ordering of gradient updates is increases. Two methods for increasing this randomness include (1) adding random latencies at the broker, and (2) introducing bystanders: clients

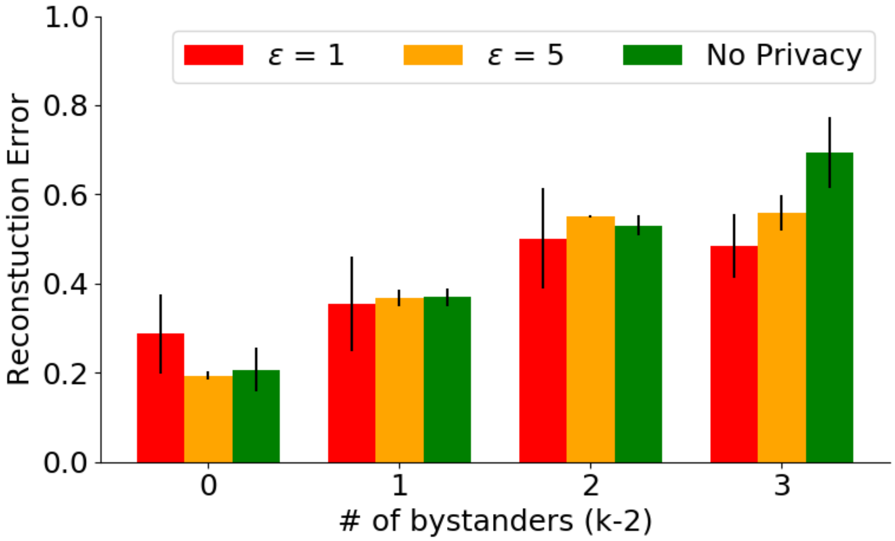


Figure 7.4: Reconstruction error between victim model and inverted model estimate, with varying privacy parameters: the number of bystanders and the privacy parameter ε.

other than the attacker and victim. In Figure 7.4, we evaluate both of these methods by asynchronously training a model on TorMentor with one victim, one attacker (using the same datasets as in Figure 7.3), and a varying number of bystanders. When replying to a client response, we sample a random sleep duration uniformly from 0-500ms at the server before returning a message. All clients choose the same value for parameter k and the actual number of clients in the system is equal to k. Thus, in the framework consisting of one victim and one attacker, the number of bystanders equals $k-2$.

Introducing even just one bystander ($k = 3$) into the system increases the reconstruction error during an inversion attack from about 20% to 40%. As k grows, a model inversion attack becomes more difficult to mount.

Figure 7.4 also illustrates that differential privacy defends client privacy when the number of bystanders is low. When there are no bystanders in the system, decreasing the privacy parameter ε (more private) increases the reconstruction error. The effects of a low ε value in a model inversion setting have a higher variance

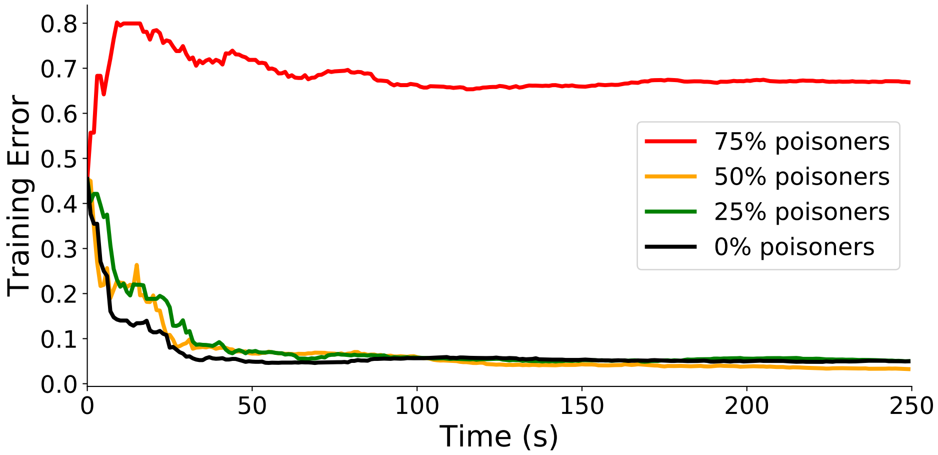


Figure 7.5: Model training loss over time, when attacked by a varying proportion of poisoners. RONI threshold is maintained at 2%.

than in executions with higher ε values. Another mechanism that helps to mitigate inversion attacks is the adaptive proof of work mechanism that counters sybils (an attacker could spawn $k-1$ sybils as an alternative way to isolate the victim).

7.5 Poisoning defenses evaluation

We evaluate the effect of our proof of work on poisoning attacks. To do this, we deployed TorMentor in an setting without differential privacy or Tor in a total asynchronous setting with 8 clients. We then varied the proportion of poisoners and the RONI threshold. Figure 7.5 shows the training error for the first 250 seconds for a RONI threshold of 2%, while varying the proportion of poisoning attackers from 25% to 75%, with a validation rate of 0.1.

As the number of poisoners increases, different effects can be observed. When the number of poisoners is low (below 25%), the model still converges, albeit at a slower rate than normal. With 50% poisoning, the model begins to move away from the optimum, but is successfully defended by the validator, which increases the proof of work required for all of the poisoners within 30 seconds. From this point, the poisoners struggle to outpace the honest nodes, and the model continues on a path to convergence. Lastly, when the proportion of poisoners is 75%, the increase

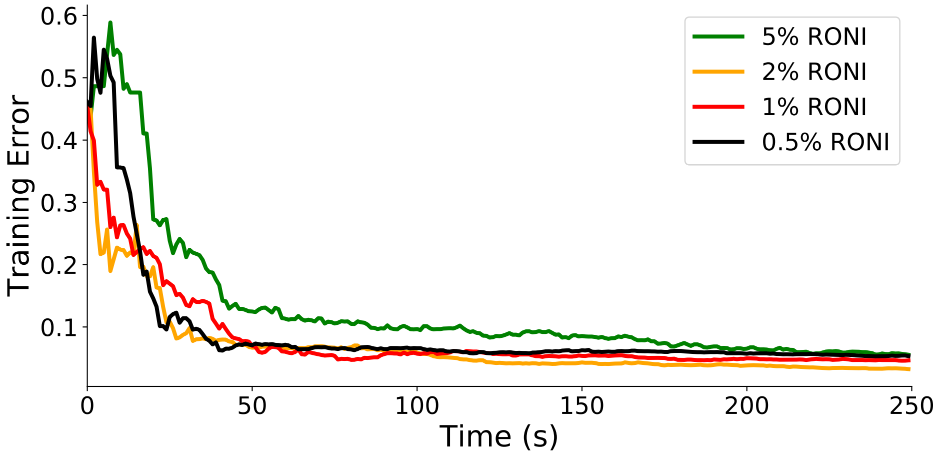


Figure 7.6: Model training loss over time, when attacked by 50% poisoners. RONI threshold is varied from 0.5% to 5%.

in proof of work is too slow to react; the model accuracy is greatly compromised within 20 seconds and struggles to recover.

From this evaluation, we note that, if a poisoner was able to detect this defense, and attempt to leave and rejoin the model, an optimal proof of work admission puzzle should require enough time such that this strategy becomes infeasible.

Figure 7.6 shows the execution of model training with 50% poisoning clients for different RONI validation thresholds. As the threshold decreases, adversaries are removed from the system more quickly, allowing the model to recover from the poisoning damage.

Setting the RONI threshold too low is also dangerous as it increases the effect of false positives. In Figure 7.6, we observe that the model initially performs poorly, this is due to incorrectly penalizing honest clients. The effect of a low RONI is especially noticed in combination with differential privacy. To confirm this, we performed two additional experiments in which the validator had a RONI threshold of 0.5% (the highest threshold from Figure 7.6), and a full set of honest clients with differential privacy parameter ε joined the model. When ε was set to 5, the model converged to an optimal point in 480 seconds. When ε was set to 1, the validator flagged all of the honest clients, and the model did not reach convergence.

The difference between model convergence, model divergence, and a privacy violation all rely on a careful interplay between ε, the minimum number of clients k, the RONI threshold, the proof of work difficulty, and the anticipated attacks that TorMentor expects to deter. Determining the optimal parameters for a deployment depends on the anticipated workloads, data distribution, and attack severity. Given the large scope of potential attacks and attack scenarios in this space [24], we leave the exploration of such parameter selection to future work.

Chapter 8

Discussion

User incentives. Although TorMentor demonstrates that privacy-preserving, untrusted collaborative ML is technically feasible, social feasibility remains an open question [45]. That is, are there application domains in which data providers are incentivized to contribute to models from anonymous curators? And do these incentives depend on the type of data, protections offered by a brokered learning setting, or something else? Regarding curators, are there cases in which curators would be comfortable using a model trained on data from anonymous users? We believe that such application domains exist, partly because of the widespread usage of federated learning [18] and a growing concern over data privacy [14].

Usability of privacy parameters. Allowing clients and curators to define their own privacy parameters ε and k allows for more expressive privacy policies, but these parameters, and their implications, are difficult for users to understand. Furthermore, privacy budgets, a fundamental element in safely implementing and using differential privacy, are complex and difficult to understand [14], as evidenced by Apple's recent struggles in implementing such a system [46].

Machine learning and Tor latency. Table 7.1 shows that Tor adds significant latency to the machine learning process. On the one hand this (unpredictable) latency can make it more difficult to mount an attack; for example, the success of the inversion attack partly depends on predictable timing. On the other hand, it would be desirable to shorten training time.

At the moment Tor's latency is paid at each iteration, indicating that methods with a lower iteration complexity would perform better. One solution to this problem is to locally aggregate gradients [6, 23, 32] over many iterations before sending them to the broker, trading off potential model staleness for reduced communication costs.

Outside of aggregating gradients, several iterative alternatives to SGD exist, such as the Newton-Raphson method [25] or other quasi-Newton methods [20], which involve computing the second-order Hessian. This provides convergence with a lower iteration complexity, but with a higher computational cost per iteration. A differentially-private version of the Newton-Raphson method has also been developed [26].

TorMentor can be extended to generally support iterative ML update methods. For models and learning objectives where Newton-Raphson is applicable, we expect that Newton-Raphson will complete faster than SGD when accounting for the overhead of Tor.

Data-free gradient validation. While we demonstrated that our active validation approach defends against attacks (e.g., Figure 7.5), it relies on the curator, who defines the learning objective, to provide the ground truth to determine if an update is beneficial or not. This approach is not only prone to bias but also opens up a new avenue for attack from the curator; an adversarial curator could submit a junk validation set to attack clients.

It is possible to mitigate these risks by using a data-free solution. An open question is whether or not it is possible to achieve the same effect without an explicit ground truth. We believe that the use of a statistical outlier detection method [22] to detect and remove anomalous gradient updates may bring the best of both worlds. This would alleviate the need for and risk of a curator-provided validation dataset, and this technique would also eliminate the computational overhead of performing explicit validation rounds. Another alternative would require the use of robust ML methods that are known to handle poisoning attacks [3, 34], but these methods are only applicable with stronger assumptions about the curator who now must specify a ground truth model.

Chapter 9

Conclusion

We introduced a novel multi-party machine learning setting called *brokered learning*, in which data providers and model curators do not trust one another and interoperate through a third party brokering service. All parties define their privacy requirements, and the broker orchestrates the distributed machine learning process while satisfying these requirements. To demonstrate that this proposal is practical, we developed TorMentor, a system for anonymous, privacy-preserving ML in the brokered learning setting. TorMentor uses differentially private model training methods to provide the strongest known defenses against attacks in this setting [24] and to support heterogeneous privacy levels for data owners. We also developed and evaluated novel ML attacks and defenses for the brokered learning setting.

Using a Tor hidden service as the broker to aggregate and validate client gradient updates, TorMentor collaboratively trains a model across 200 geo-distributed clients, without ever directly accessing the raw data or de-anonymizing any of the users. We define a realistic threat model for brokered learning and show that in contrast to existing solutions for distributed ML, such as Gaia [23] and federated learning [32], TorMentor's defenses successfully counter recently developed poisoning and inversion attacks on ML.

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Appendix A: SGD and differential privacy

Stochastic gradient descent (SGD). In SGD at each iteration t, the model parameters w are updated as follows:

$$w_{t+1} = w_t - \eta_t(\lambda w_t + \frac{1}{b} \sum_{(x_i,y_i)\in B_t} \nabla l(w_t, x_i, y_i)) \tag{1}$$

where η_t represents a degrading learning rate, λ is a regularization parameter that prevents over-fitting, B_t represents a gradient batch of training data examples (x_i, y_i) of size b and ∇l represents the gradient of the loss function.

As the number of iterations increases, the effect of each gradient step becomes smaller, indicating convergence to a global minimum of the loss function. A typical heuristic involves running SGD for a fixed number of iterations or halting when the magnitude of the gradient falls below a threshold. When this occurs, model training is complete and the parameters w_t are returned as the optimal model w^*.

Distributed SGD. In parallelized ML training with a parameter server [28], the global model parameters w_g are partitioned and stored on a parameter server. At each iteration, client machines, which house horizontal partitions of the data, pull the global model parameters $w_{g,t}$, compute and apply one or more iterations, and push their update $\Delta_{i,t}$ back to the parameter server:

$$\begin{aligned} \Delta_{i,t} &= -\eta_t(\lambda w_{g,t} + \frac{1}{b} \sum_{(x_i,y_i)\in B_t} \nabla l(w_{g,t}, x_i, y_i)) \\ w_{g,t+1} &= w_{g,t} + \sum_i \Delta_{i,t} \end{aligned} \tag{2}$$

Differential privacy and SGD. ε*-differential privacy* states that: given a function f and two neighboring datasets D and D' which differ in only one example, the probability of the output prediction changes by at most a multiplicative factor of e^{ε}. Formally, a mechanism $f : D \rightarrow R$ is ε-differentially private for any subset of outputs $S \subseteq R$ if

$$Pr[f(D) \in S] \leq e^{\varepsilon} Pr[f(D') \in S].$$

In differentially private SGD [44] the SGD update is redefined to be the same as in Equation (2), except with the addition of noise:

$$\Delta_{i,t} = -\eta_t(\lambda w_{g,t} + \sum_{(x_i,y_i)\in B_t} \frac{\nabla l(w_{g,t}, x_i, y_i) + Z_t}{b}) \tag{3}$$

where Z_t is a noise vector drawn independently from a distribution:

$$p(z) \propto e^{(\alpha/2)||z||}$$