2 放宽核心联邦学习假设：新兴环境和方案的应用

2.1 完全分布式/点对点分布式学习

	联邦学习	完全分布式（点对点）学习
管理	中央管理服务器或服务可以组织训练，但从不查看原始数据。	没有集中的管理。
广域通讯	中心辐射型拓扑，中心代表的是协调服务提供商（通常不包含数据），分支连接到客户端。	对等拓扑，可能带有动态连接图。

2.1.1 算法挑战

Effect of network topology and asynchrony on decentralized SGD

Local-update decentralized SGD

Personalization, and trust mechanisms(机制)

Gradient compression and quantization(量化) methods

2.1.2 实际挑战

模拟区块链

安全聚合协议

客户端差分隐私

(更新参数分成两部分，比较这两组的准确率，准确率低的一组随机去掉一部分节点
回滚机制，如果效果不好，仍旧采取之前的参数 每次提交的时候，都附带一个准确率，准确率达到标准的的节点暂时不更新)

2.2 跨域联邦学习

现实情境：如果许多公司或组织共享激励以基于其所有数据来训练模型，但不能直接共享其数据。

数据划分(《联邦学习》主要讲的是这个跨域的部分)

```
             +--------------------+
             | Federated Learning |
             +---------+----------+
                       |
          +------------+------------+
          v                         v
+---------+------------+   +--------+----------+
| Fully Decentralized  |   | Cross-Silo         |
| / Peer-to-Peer       |   | Federated Learning |
| Distributed Learning |   +---------+----------+
| (Cross-Devices)      |             |
+----------------------+   +---------+----------+
                           v                    v
                    +------+-------+    +-------+------+
                    | partitioning |    | partitioning |
                    | by examples  |    | by features  |
                          +--------------+    +--------------+

```

安全的多方计算或同态加密

Federated transfer learning

Federated AI Technology Enabler (FATE)

IEEE P3652.1 Federated Machine Learning Working Group

激励机制

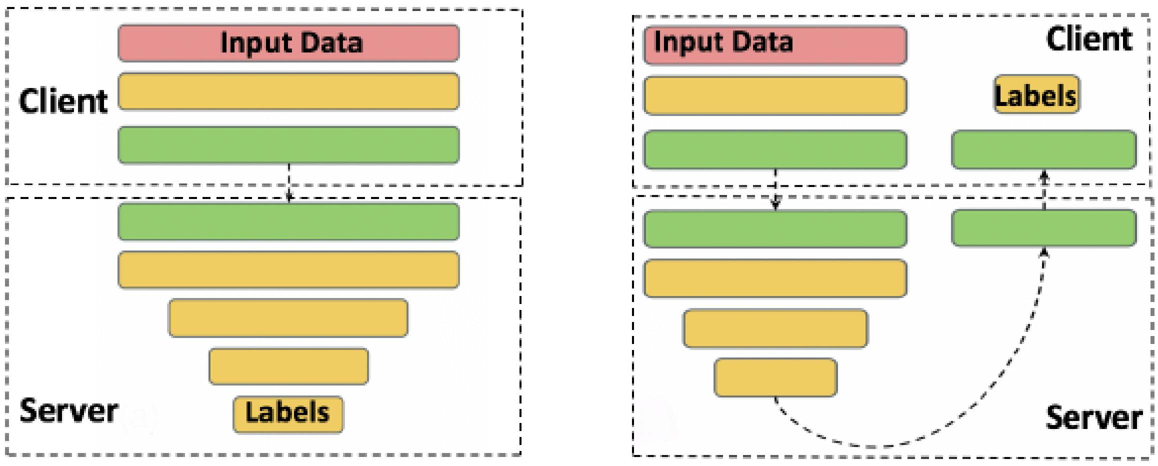
差分隐私

Tensor factorization(采用什么样的参数，中间过程的参数，最终的参数，还是。。。)

2.3 拆分学习

在客户端和服务器之间按层划分模型的执行

每个客户端计算通过深层网络到达特定层（称为切入层）的前向通过。



(a) Vanilla split learning (b) U-shaped split learning

https://splitlearning.github.io/.

3 提高效率和有效性

developing better optimization algorithms; providing different models to different clients; making ML tasks like hyperparameter search, architecture search, and debugging easier in the FL context; improving communication efficiency; and more.

开发更好的优化算法； 为不同的客户提供不同的模型； 在FL上下文中使诸如超参数搜索，架构搜索和调试之类的ML任务更容易； 提高沟通效率； 和更多。

3.1 Non-IID Data in Federated Learning

1.不相同的客户分布

- Feature distribution skew
- Label distribution skew
- Same label, different features
- Same features, different label
- Quantity skew or unbalancedness

Most empirical work on synthetic non-IID datasets (e.g. [289]) have focused on label distribution skew, where a non-IID dataset is formed by partitioning a “flat” existing dataset based on the labels.

针对不同分布类型的数据 设计不同的处理方式

2.Violations of independence

3.Dataset shift

3.1.1 Strategies for Dealing with Non-IID Data

One natural approach is to modify existing algorithms (e.g. through different hyperparameter choices)

For some applications, it may be possible to augment data in order to make the data across clients more similar.

it is no-longer clear that treating all examples equally makes sense. Alternatives include limiting the contributions of the data from any one user (which is also important for privacy, see Section 4)

利用联邦学习训练一个精度相对较好的模型，然后部署到设备上，本地训练生成一个高精度模型

In addition to addressing non-identical client distributions, using a plurality of models can also address violations of independence stemming from changes in client availability.

3.2 Optimization Algorithms for Federated Learning

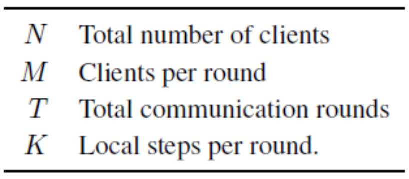
In prototypical federated learning tasks, the goal is to learn a single global model that minimizes the empirical risk function over the entire training dataset

for optimization, non-IID and unbalanced data, limited communication bandwidth, and unreliable and limited device availability are particularly salient.

FL settings where the total number of devices is huge (e.g. across mobile devices) necessitate algorithms that only require a handful of clients to participate per round (client sampling). Further, each device is likely
to participate no more than once in the training of a given model, so stateless algorithms are necessary. This rules out the direct application of a variety of approaches that are quite effective in the datacenter context.

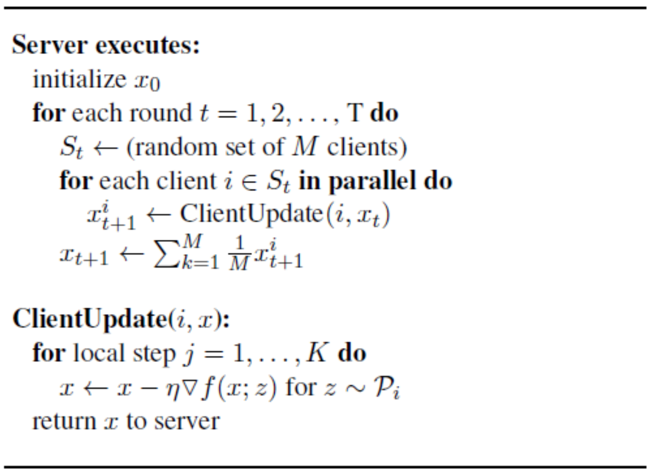
composability with other techniques.

combined with other techniques like cryptographic secure aggregation protocols (Section 4.2.1), differential privacy (DP) (Section 4.2.2), and model and update compression (Section 3.5).



N	Total number of clients
M	Clients per round
T	Total communication rounds
K	Local steps per round.

Table 4: Notation for the discussion of FL algorithms including Federated Averaging.



```
Server executes:
  initialize $x_0$
  for each round $t = 1, 2, \ldots,$ T do
    $S_t \leftarrow$ (random set of $M$ clients)
    for each client $i \in S_t$ in parallel do
      $x^i_{t+1} \leftarrow \text{ClientUpdate}(i, x_t)$
    $x_{t+1} \leftarrow \sum_{k=1}^{M} \frac{1}{M} x^i_{t+1}$

ClientUpdate($i, x$):
  for local step $j = 1, \ldots, K$ do
    $x \leftarrow x - \eta \nabla f(x; z)$ for $z \sim \mathcal{P}_i$
  return $x$ to server
```

Algorithm 1: Federated Averaging (local SGD), when all clients have the same amount of data.

Federated Averaging algorithm, an adaption of local-update or parallel SGD.

3.2.1 Optimization Algorithms and Convergence Rates for IID Datasets

the most basic split is between assuming IID and non-IID data

H-Lipschitz 数学证明

performing more local updates saves significant communication cost and reduces the time spent per iteration

several gaps between upper and lower bounds for optimization relevant
to the federated learning setting

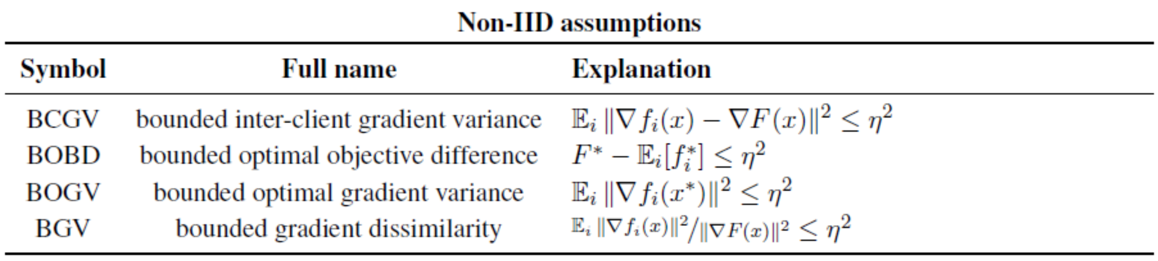
if any one client unpredictably slows down or fails.

asynchronous approaches may be difficult to combine with complimentary techniques like differential privacy or secure aggregation

3.2.2 Optimization Algorithms and Convergence Rates for Non-IID Datasets

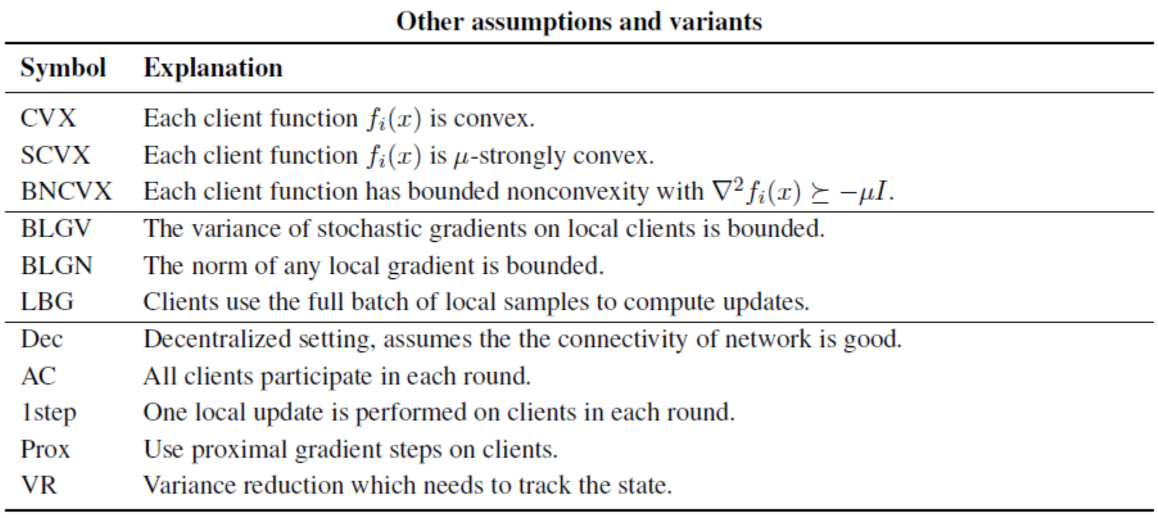
federated learning uses local data from end user devices, leading to many
varieties of non-IID data

FedProx algorithm



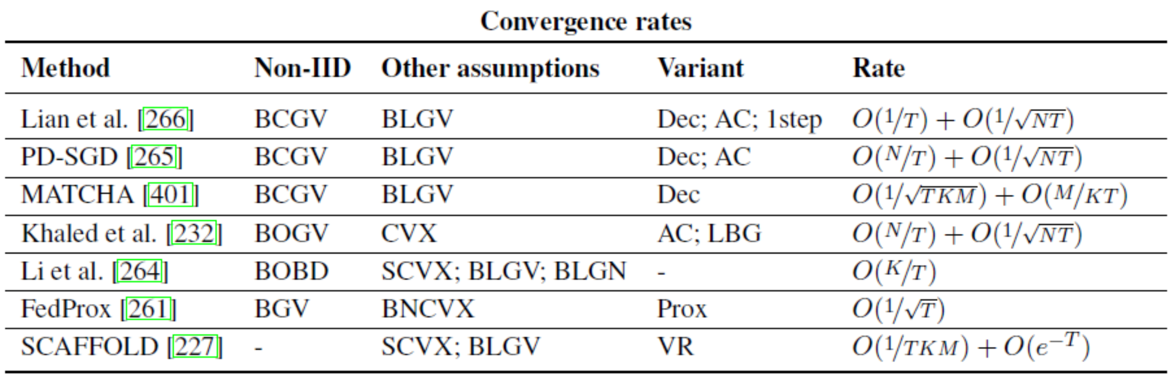
Non-IID assumptions

Symbol	Full name	Explanation
BCGV	bounded inter-client gradient variance	$\mathbb{E}_i \|\nabla f_i(x) - \nabla F(x)\|^2 \leq \eta^2$
BOBD	bounded optimal objective difference	$F^* - \mathbb{E}_i[f_i^*] \leq \eta^2$
BOGV	bounded optimal gradient variance	$\mathbb{E}_i \|\nabla f_i(x^*)\|^2 \leq \eta^2$
BGV	bounded gradient dissimilarity	$\mathbb{E}_i \|\nabla f_i(x)\|^2 / \|\nabla F(x)\|^2 \leq \eta^2$



Other assumptions and variants

Symbol	Explanation
CVX	Each client function $f_i(x)$ is convex.
SCVX	Each client function $f_i(x)$ is μ-strongly convex.
BNCVX	Each client function has bounded nonconvexity with $\nabla^2 f_i(x) \succeq -\mu I$.
BLGV	The variance of stochastic gradients on local clients is bounded.
BLGN	The norm of any local gradient is bounded.
LBG	Clients use the full batch of local samples to compute updates.
Dec	Decentralized setting, assumes the the connectivity of network is good.
AC	All clients participate in each round.
1step	One local update is performed on clients in each round.
Prox	Use proximal gradient steps on clients.
VR	Variance reduction which needs to track the state.



Convergence rates

Method	Non-IID	Other assumptions	Variant	Rate
Lian et al. [266]	BCGV	BLGV	Dec; AC; 1step	$O(1/T) + O(1/\sqrt{NT})$
PD-SGD [265]	BCGV	BLGV	Dec; AC	$O(N/T) + O(1/\sqrt{NT})$
MATCHA [401]	BCGV	BLGV	Dec	$O(1/\sqrt{TKM}) + O(M/KT)$
Khaled et al. [232]	BOGV	CVX	AC; LBG	$O(N/T) + O(1/\sqrt{NT})$
Li et al. [264]	BOBD	SCVX; BLGV; BLGN	-	$O(K/T)$
FedProx [261]	BGV	BNCVX	Prox	$O(1/\sqrt{T})$
SCAFFOLD [227]	-	SCVX; BLGV	VR	$O(1/TKM) + O(e^{-T})$

Federated Learning Algorithm

PD-SGD MATCHA

Acceleration and variance reduction techniques

Connections to decentralized optimization

there is still no consensus on how to incorporate momentum or variance-reduction techniques into local SGD and Federated Averaging

3.3 Multi-Task Learning, Personalization, and Meta-Learning

3.3.1 Personalization via Featurization

3.3.2 Multi-Task Learning

cross-silo与cross-device的区别：连接是否稳定

reconsider the relationship between clients (local datasets) and learning tasks (models to be trained)

3.3.3 Local Fine Tuning and Meta-Learning

meta-learning

model-agnostic meta-learning   MAML algorithms

differential privacy

FL problems, modeled by existing datasets used for simulated FL experiments (Appendix A), can serve as realistic benchmark problems for MAML algorithms.

none of the existing works clearly formulates what would be comprehensive metrics for measuring personalized performance

Can non-parameter transfer LTL algorithms, such as ProtoNets, be of use for FL?

3.3.4 When is a Global FL-trained Model Better?

a natural theoretical question is to determine under what conditions the shared global model is better than independent per-device models.

Can we guarantee that the model hFL learned via federated learning is at least as accurate as hk when used for client k? Can we quantify how much improvement can be expected via federated leaning? And can we develop personalization strategies with theoretical guarantees that at least match the performance of both natural baselines (hk and hFL)?

3.4 Adapting ML Workflows for Federated Learning

3.4.1 Hyperparameter Tuning

Hyperparameter optimization (HPO) has a long history under the framework of AutoML, but it mainly concerns how to improve the model accuracy rather than communication and computing efficacy for mobile devices.

3.4.2 Neural Architecture Design

neural architecture search (NAS)

There are three major methods for NAS, which utilize evolutionary algorithms, reinforcement learning, or gradient descent to search for optimal architectures for a specific task on a specific dataset.

Weight Agnostic Neural Networks

3.4.3 Debugging and Interpretability for FL

Augenstein et al. [32] proposed the use of differentially private
generative models (including GANs), trained with federated learning.

whether any of these methods or their combinations can come close to providing optimal trade-offs between communication and accuracy in federated learning.

it is difficult to deduce concrete insights from these theoretical works for communication bandwidth reduction in practice as they typically ignore the impact of the optimization algorithm.

3.5 Communication and Compression

Compression objectives

- Gradient compression – reduce the size of the object communicated from clients to server, which is used to update the global model.
- Model broadcast compression – reduce the size of the model broadcast from server to clients, from which the clients start local training.
- Local computation reduction – any modification to the overall training algorithm such that the local training procedure is computationally more efficient.

broader ML community

facebook 开放了一个差分隐私库

Compatibility with differential privacy and secure aggregation

Secure Aggregation and mechanisms of adding noise to achieve differential privacy

模仿网络层来设计联邦学习

Joint design of compression methods that are compatible with Secure Aggregation, or for which differential privacy guarantees can be obtained, is thus a valuable open problem.

Wireless-FL co-design

Potential
solutions to address this challenge include federated distillation (FD), in which workers exchange their model output parameters (logits) as opposed to the model parameters (gradients and/weights), and optimizing workers' scheduling policy with appropriate communication and computing resources.

3.6 Application To More Types of Machine Learning Problems and Models

Bayesian neural networks

4 Preserving the Privacy of User Data

we advocate a strategy wherein the overall system is composed of modular units which can be studied and improved relatively independently, while also reminding ourselves that we must, in the end, measure the privacy properties of the complete system against our ideal privacy goals set out above.

4.1 Actors, Threat Models, and Privacy in Depth

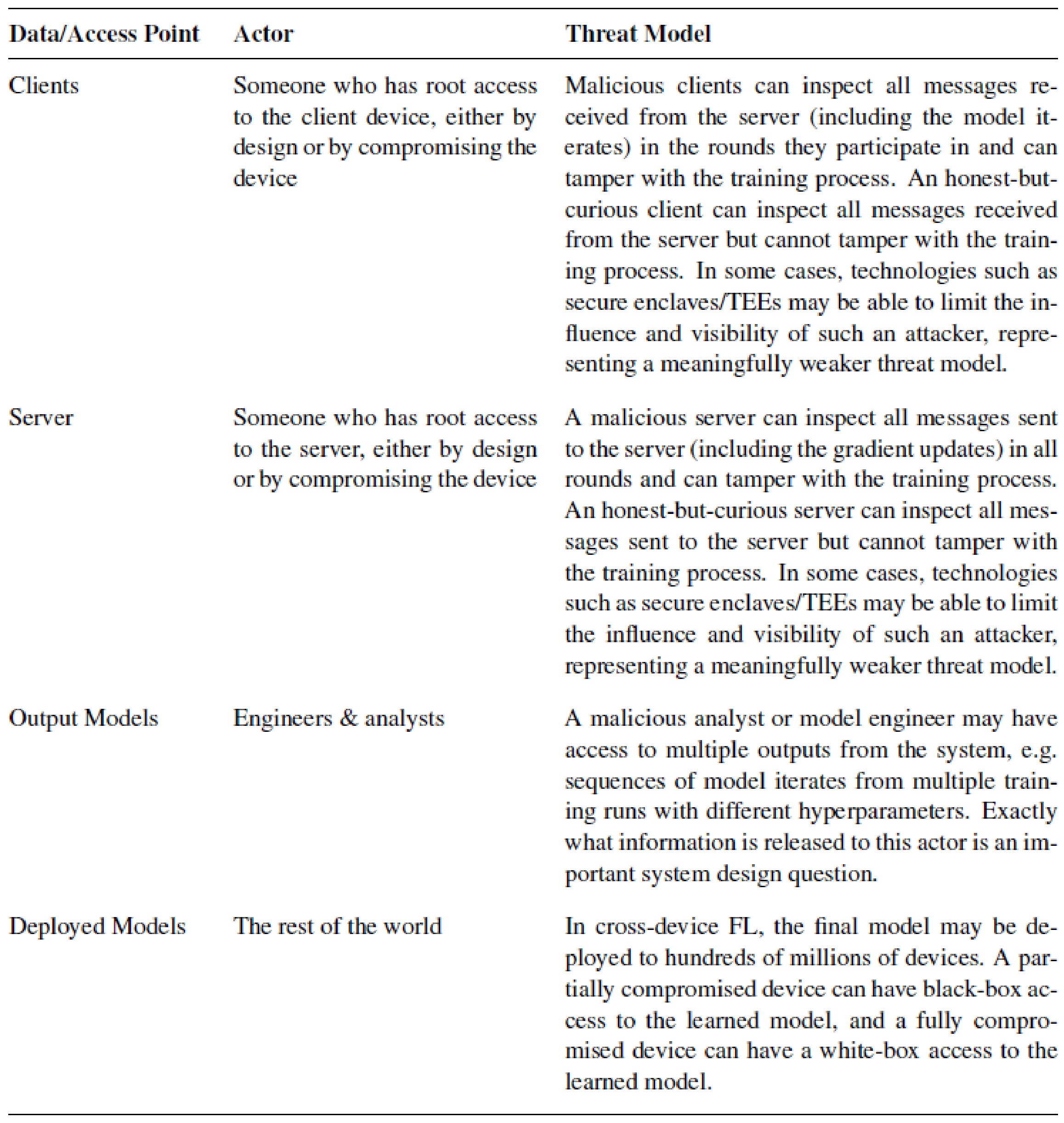
Secure Multi-Party Computation (MPC) protocol

Trusted Execution Environment (TEE)

Private Disclosure techniques

4.2 Tools and Technologies

First, we need to consider how f is computed and what is the information flow of intermediate results in the process, which primarily influences the susceptibility to malicious client, server, and admin actors.



Data/Access Point	Actor	Threat Model
Clients	Someone who has root access to the client device, either by design or by compromising the device	Malicious clients can inspect all messages received from the server (including the model iterates) in the rounds they participate in and can tamper with the training process. An honest-but-curious client can inspect all messages received from the server but cannot tamper with the training process. In some cases, technologies such as secure enclaves/TEEs may be able to limit the influence and visibility of such an attacker, representing a meaningfully weaker threat model.
Server	Someone who has root access to the server, either by design or by compromising the device	A malicious server can inspect all messages sent to the server (including the gradient updates) in all rounds and can tamper with the training process. An honest-but-curious server can inspect all messages sent to the server but cannot tamper with the training process. In some cases, technologies such as secure enclaves/TEEs may be able to limit the influence and visibility of such an attacker, representing a meaningfully weaker threat model.
Output Models	Engineers & analysts	A malicious analyst or model engineer may have access to multiple outputs from the system, e.g. sequences of model iterates from multiple training runs with different hyperparameters. Exactly what information is released to this actor is an important system design question.
Deployed Models	The rest of the world	In cross-device FL, the final model may be deployed to hundreds of millions of devices. A partially compromised device can have black-box access to the learned model, and a fully compromised device can have a white-box access to the learned model.

Table 7: Various threat models for different adversarial actors.

Second, we have to consider what is computed.

Finally, there is the problem of verifiability, which pertains to the ability of a client or the server to prove to others in the system that they have executed the desired behavior faithfully, without revealing the potentially private data upon which they were acting.

remote attestation and zero-knowledge proofs

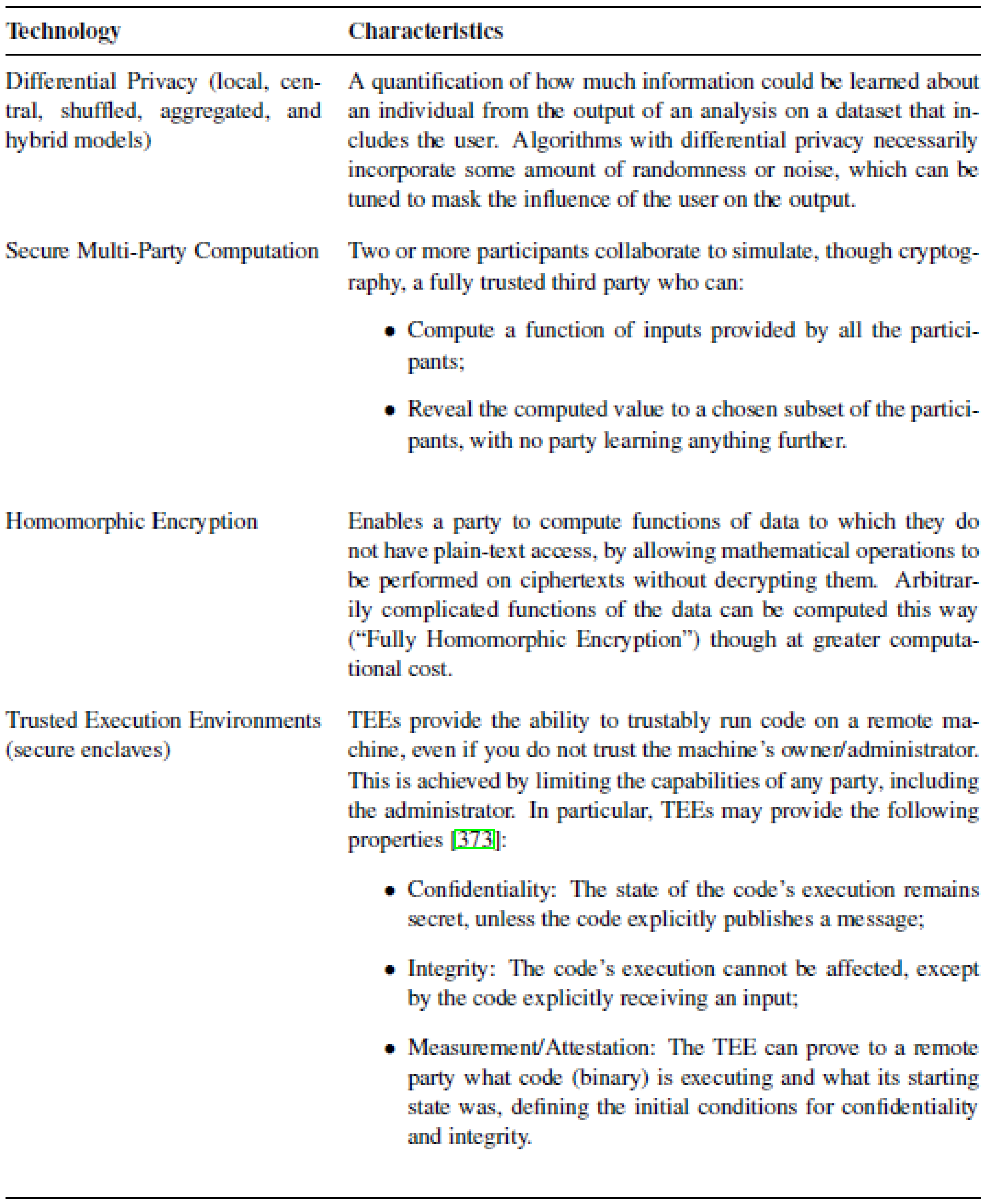
4.2.1 Secure Computations

Secure multi-party computation

Homomorphic encryption

同态加密使用格密码 椭圆曲线方案

Trusted execution environments



Technology	Characteristics
Differential Privacy (local, central, shuffled, aggregated, and hybrid models)	A quantification of how much information could be learned about an individual from the output of an analysis on a dataset that includes the user. Algorithms with differential privacy necessarily incorporate some amount of randomness or noise, which can be tuned to mask the influence of the user on the output.
Secure Multi-Party Computation	Two or more participants collaborate to simulate, though cryptography, a fully trusted third party who can: • Compute a function of inputs provided by all the participants; • Reveal the computed value to a chosen subset of the participants, with no party learning anything further.
Homomorphic Encryption	Enables a party to compute functions of data to which they do not have plain-text access, by allowing mathematical operations to be performed on ciphertexts without decrypting them. Arbitrarily complicated functions of the data can be computed this way ("Fully Homomorphic Encryption") though at greater computational cost.
Trusted Execution Environments (secure enclaves)	TEEs provide the ability to trustably run code on a remote machine, even if you do not trust the machine's owner/administrator. This is achieved by limiting the capabilities of any party, including the administrator. In particular, TEEs may provide the following properties [373]: • Confidentiality: The state of the code's execution remains secret, unless the code explicitly publishes a message; • Integrity: The code's execution cannot be affected, except by the code explicitly receiving an input; • Measurement/Attestation: The TEE can prove to a remote party what code (binary) is executing and what its starting state was, defining the initial conditions for confidentiality and integrity.

Table 8: Various technologies along with their characteristics.

Trusted execution environments

Secure computation problems of interest

Secure aggregation

Secure shuffling

Private information retrieval

Recent results on PIR have shown dramatic reductions in the computational cost through the use of lattice-based cryptosystems

4.2.2 Privacy-Preserving Disclosures

Local differential privacy

Thus, there is a need for a model of differential privacy that interpolates between purely central and purely local DP. This can be achieved through distributed differential privacy, or the hybrid model, as discussed below.

Distributed differential privacy

Distributed DP via secure aggregation

Distributed DP via secure shuffling

Encode-Shuffle-Analyze (ESA) framework   Prochlo system

Hybrid differential privacy

This construction can be directly applied in the federated learning setting

4.2.3 Verifiability

Multiple techniques can be useful to provide verifiability: zero-knowledge proofs (ZKPs), trusted execution environments (TEEs), or remote attestation.

Zero-knowledge proofs (ZKPs)

Succinct non-interactive zero-knowledge proofs   libsnark Libra

Using interactive ZKP systems and NIZKs efficiently in the context of FL remains a challenging open question.

In the setting where the verifier is the client, it
will be challenging to create a trustworthy statement to verify as it involves input from other clients.

In the setting where the verifier is the client, it will be challenging to create a trustworthy statement to verify as it involves input from other clients. Of
interest in this setting, recent work enables to handle the case where the multiple verifiers have shares of the statement

Trusted execution environment and remote attestation

4.3 Protections Against External Malicious Actors

4.3.1 Auditing the Iterates and Final Model

worst-case upper-bound

An interesting emerging area of research in this space examines the theoretic conditions (on the audited model and attacks) under which an unsuccessful attempt to identify privacy violations by a simulated attack implies that no stronger attacks can succeed at such a task.

it may be possible to design new tractable methods for quantifying a model's average-case or worst-case attack susceptibility.

4.3.2 Training with Central Differential Privacy

the server clips the L2 norm of individual updates, aggregates the clipped updates, and then adds Gaussian noise to the aggregate.

To track the overall privacy budget across rounds, advanced composition theorems [148, 221] or the analytical moments accountant method developed in [7, 297, 299, 405] can be used.

The moments accountant method works particularly well with the uniformly subsampled Gaussian mechanism.

figuring out how to adaptively bound the contributions of users and clip the model parameters remains an interesting research direction.

Privacy amplification for non-uniform device sampling procedures

quantifying the privacy amplification gains in cross-device FL is an interesting open problem.

Sources of randomness

Auditing differential privacy implementations

4.3.3 Concealing the Iterates

the MPC model

4.3.4 Repeated Analyses over Evolving Data

Specific open questions include: P51

4.3.5 Preventing Model Theft and Misuse

Protecting a deployed model during inference is closely related to the challenge of concealing the model iterates from clients during training

4.4 Protections Against an Adversarial Server

4.4.1 Challenges: Communication Channels, Sybil Attacks, and Selection

In the cross-device FL setting, we have a server with significant computational resources and a large number of clients that (i) can only communicate with the server (as in a star network topology), and (ii) may be
limited in connectivity and bandwidth.

An actively malicious adversary controlling the server could simulate a large number of fake client devices (a “Sybil attack” [140]) or could preferentially select previously compromised devices from the pool of available devices.

4.4.2 Limitations of Existing Solutions

This involves formally defining (a) what is the view of the clients data revealed to the server as a result of an FL execution, and (b) what is the privacy leakage of such a view.

outline some of the weaknesses of these methods

Local differential privacy

LDP assumes that a user’s privacy comes solely from that user’s addition of their own randomness; thus, a user’s privacy guarantee is independent of the additional randomness incorporated by all other users.

Part of this difficulty is attributed to the fact that the magnitude of the random noise introduced must be comparable to the magnitude of the signal in the data, which may require combining reports between clients.

Therefore, obtaining utility with LDP comparable to that in the central setting thus requires a relatively larger user-base or larger choice of " parameter.

Hybrid differential privacy

it does not provide privacy amplification of users’ locally-added noise.

it is unclear which application areas and algorithms can best utilize hybrid trust model data

Current work on the hybrid model typically assumes that regardless of the user trust preference, their data comes from the same distribution

The shuffle model

The first is the requirement of a trusted intermediary首先是可信中介的要求

The second drawback is that the shuffle model's differential privacy guarantee degrades in proportion to the number of adversarial users participating in the computation

Secure aggregation

this approach has several limitations: (a) it assumes a semi-honest server (only in the private key infrastructure phase), (b) it allows the server to see the per-round aggregates (which may still leak information), (c) it is not efficient for sparse vector aggregation, and (d) it lacks the ability to enforce well-formedness of client inputs.

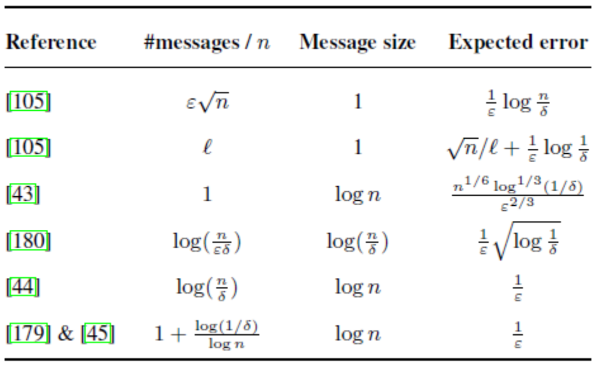
4.4.3 Training with Distributed Differential Privacy

Communication, privacy, and accuracy trade-offs under distributed DP

Trade-offs for secure shuffling

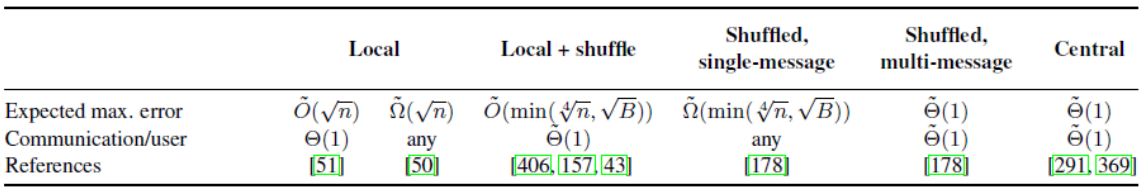
Two notable open questions are (i) to study pure differential privacy in the shuffled model, and (ii) to determine the optimal privacy, accuracy and communication trade-off for variable selection in the multimessage setup

Trade-offs for secure aggregation



Reference	#messages / n	Message size	Expected error
[105]	$\varepsilon\sqrt{n}$	1	$\frac{1}{\varepsilon}\log\frac{n}{\delta}$
[105]	ℓ	1	$\sqrt{n}/\ell + \frac{1}{\varepsilon}\log\frac{1}{\delta}$
[43]	1	$\log n$	$\frac{n^{1/6}\log^{1/3}(1/\delta)}{\varepsilon^{2/3}}$
[180]	$\log(\frac{n}{\varepsilon\delta})$	$\log(\frac{n}{\delta})$	$\frac{1}{\varepsilon}\sqrt{\log\frac{1}{\delta}}$
[44]	$\log(\frac{n}{\delta})$	$\log n$	$\frac{1}{\varepsilon}$
[179] & [45]	$1 + \frac{\log(1/\delta)}{\log n}$	$\log n$	$\frac{1}{\varepsilon}$

Table 9: Comparison of differentially private *aggregation* protocols in the multi-message shuffled model with (ε, δ)-differential privacy. The number of parties is n, and ℓ is an integer parameter. Message sizes are in bits. For readability, we assume that $\varepsilon \leq O(1)$, and asymptotic notations are suppressed.



	Local		Local + shuffle	Shuffled, single-message	Shuffled, multi-message	Central
Expected max. error	$\tilde{O}(\sqrt{n})$	$\tilde{\Omega}(\sqrt{n})$	$\tilde{O}(\min(\sqrt[4]{n}, \sqrt{B}))$	$\tilde{\Omega}(\min(\sqrt[4]{n}, \sqrt{B}))$	$\tilde{\Theta}(1)$	$\tilde{\Theta}(1)$
Communication/user	$\Theta(1)$	any	$\tilde{\Theta}(1)$	any	$\tilde{\Theta}(1)$	$\tilde{\Theta}(1)$
References	[51]	[50]	[406, 157, 43]	[178]	[178]	[291, 369]

Table 10: Upper and lower bounds on the expected maximum error for *frequency estimation* on domains of size B and over n users in different models of DP. The bounds are stated for fixed, positive privacy parameters ε and δ, and $\tilde{\Theta}/\tilde{O}/\tilde{\Omega}$ asymptotic notation suppresses factors that are polylogarithmic in B and n. The communication per user is in terms of the total number of bits sent. In all upper bounds, the protocol is symmetric with respect to the users, and no public randomness is needed. References are to the first results we are aware of that imply the stated bounds.

Privacy accounting

Handling client dropouts

More generally, the problem of operating at scale when clients are likely to be intermittently available has not been systematically addressed yet in the literature.

New trust models

Can this be leveraged to enact a trust model where the server's behavior is trusted-but-verified, i.e. wherein the server is not prevented from deviating from the desired protocol, but is extremely likely to be detected if it does (thereby damaging the trust, reputation, and potentially financial or legal status of the hosting organization)?

4.4.4 Preserving Privacy While Training Sub-Models

Open problems in this area include characterizing the sparsity regimes associated with sub-model training problems of practical interest and developing of sparse secure aggregation techniques that are communication efficient in these sparsity regimes.

Some forms of local and distributed differential privacy also pose challenges here, in that noise is often added to all elements of the vector, even those that are zero

4.5 User Perception

While the previous sections focused on rigorous quantification of privacy
against precise threat models, this section focuses on challenges around the users' perception and needs.

4.5.1 Understanding Privacy Needs for Particular Analysis Tasks

This approach is formalized in the Pufferfish framework of privacy [235], which allows the analyst to specify a class of protected predicates that must be learned subject to the guarantees of differential privacy, and all other predicates can be learned without differential privacy.

4.5.2 Behavioral Research to Elicit Privacy Preferences

educational component and preference measurement

5 Robustness to Attacks and Failures

5.1 Adversarial Attacks on Model Performance

Examples of adversarial attacks include data poisoning, model update poisoning, and model evasion attacks

These attacks can be broadly classified into training-time attacks (poisoning
attacks) and inference-time attacks (evasion attacks).

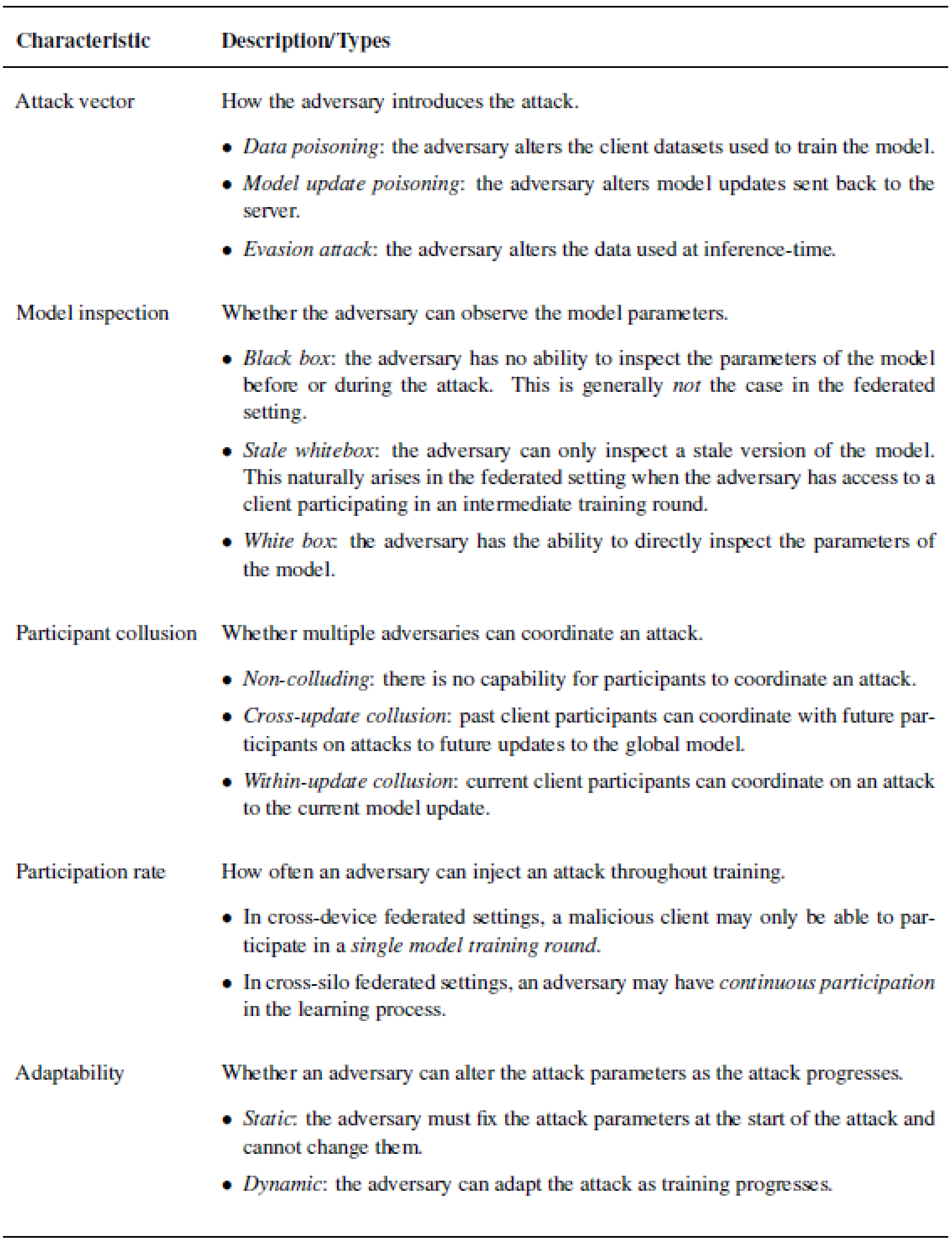
we will discuss inference-time attacks below because (a) attacks on the training phase can be used as a stepping stone towards inference-time attacks, and (b) many defenses against inference-time attacks are implemented during training.

5.1.1 Goals and Capabilities of an Adversary

Goals

1. untargeted attacks, or model downgrade attacks, which aim to reduce the model's global accuracy, or "fully break" the global model
2. targeted attacks, or backdoor attacks, which aim to alter the model's behavior on a minority of examples while maintaining good overall accuracy on all other examples

Capabilities



Characteristic	Description/Types
Attack vector	How the adversary introduces the attack. • *Data poisoning*: the adversary alters the client datasets used to train the model. • *Model update poisoning*: the adversary alters model updates sent back to the server. • *Evasion attack*: the adversary alters the data used at inference-time.
Model inspection	Whether the adversary can observe the model parameters. • *Black box*: the adversary has no ability to inspect the parameters of the model before or during the attack. This is generally *not* the case in the federated setting. • *Stale whitebox*: the adversary can only inspect a stale version of the model. This naturally arises in the federated setting when the adversary has access to a client participating in an intermediate training round. • *White box*: the adversary has the ability to directly inspect the parameters of the model.
Participant collusion	Whether multiple adversaries can coordinate an attack. • *Non-colluding*: there is no capability for participants to coordinate an attack. • *Cross-update collusion*: past client participants can coordinate with future participants on attacks to future updates to the global model. • *Within-update collusion*: current client participants can coordinate on an attack to the current model update.
Participation rate	How often an adversary can inject an attack throughout training. • In cross-device federated settings, a malicious client may only be able to participate in a *single model training round*. • In cross-silo federated settings, an adversary may have *continuous participation* in the learning process.
Adaptability	Whether an adversary can alter the attack parameters as the attack progresses. • *Static*: the adversary must fix the attack parameters at the start of the attack and cannot change them. • *Dynamic*: the adversary can adapt the attack as training progresses.

Table 11: Characteristics of an adversary's capabilities in federated settings.