

System Optimization in Synchronous Federated Training: A Survey

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Abstract—The unprecedented demand for collaborative machine learning in a privacy-preserving manner gives rise to a novel machine learning paradigm called federated learning (FL). Given a sufficient level of privacy guarantees, the practicality of an FL system mainly depends on its time-to-accuracy performance during the training process. Despite bearing some resemblance with traditional distributed training, FL has four distinct challenges that complicate the optimization towards shorter time-to-accuracy: information deficiency, coupling for contrasting factors, client heterogeneity, and huge configuration space. Motivated by the need for inspiring related research, in this paper we survey highly relevant attempts in the FL literature and organize them by the related training phases in the standard workflow: selection, configuration, and reporting. We also review exploratory work including measurement studies and benchmarking tools to friendly support FL developers. Although a few survey articles on FL already exist, our work differs from them in terms of the focus, classification, and implications.

I. INTRODUCTION

While building high-quality machine learning (ML) models demands a massive amount of training data, the communication cost and privacy concerns impinge on the process of collecting data from diverse sources. Particularly, it is not until very recently that many governments start to strictly regulate the commercial use of data by enacting privacy-preserving legislations (e.g., GDPR [1], HIPAA [2], and CCPA [3]), the breach of which has led to fines of hundreds of millions of dollars per year [4], [5]. As such, the unprecedented desire for multiple entities (e.g., devices or silos) to collaboratively train a shared model in an efficient and privacy-preserving way ultimately gives birth to an ML paradigm called federated learning (FL) [6]. With the merits of not exposing raw data, FL has been widely adopted by leading industries with applications ranging from mobile devices [7]–[12], financial management [13], [14] to medical care [15], [16].

Apart from providing strong privacy guarantees, the key to the success of a federated training system also lies in its efficiency, which is typically measured by the time-to-accuracy performance, i.e., the wall clock time taken to train a model for reaching the target accuracy. Throughout the literature, we have witnessed a contiguous array of efforts in exploring possible optimization strategies of all kinds. Still, as of today, there is much room for further improvements due to the following distinct challenges in FL (§ II): (1) **information deficiency**: the information needed for optimally configure the system are typically outdated or unavailable due to privacy constraints and scaling issues; (2) **coupling of**

contrasting factors: statistical utility (the number of iterations taken to reach a plausible target accuracy) and system utility (the duration of an iteration), the two multiplying factor for time-to-accuracy, are typically at odds with each other; (3) **client heterogeneity**: clients cannot be treated uniformly due to the intrinsic differences in terms of resource, data, and state; and (4) **huge configuration space**: the operational dimensions for system developers are too many to explore within a reasonable amount of time. Given these challenges, it is worth summarizing existing research efforts in an organized manner so that researchers can gain a holistic view of the lessons learned so far to solicit further exploration.

To position existing research attempts in optimizing the time-to-accuracy performance in FL, we propose a layered approach that categorizes them by the training phases at which they take effect: selection, configuration, or reporting (§ III). For the **selection phase** where the server chooses clients for participation, there are mainly two lines of optimization efforts: (1) one focuses on prioritizing clients either with high statistical utility or system utility [17], [18], and (2) the other explicitly considers both utilities and works out more informed solutions in response to client dynamics in reality [19], [20]. As for the **configuration phase** where the server sends the global model to selected clients with auxiliary configuration information and clients perform local training, we sort out four lines of work: (1) the first two lines advocate mitigating the communication cost by reducing model size [21]–[34] and decreasing synchronization frequency [35]–[39]; while (2) the last two lines of minimize computational overhead by shortening training latency in a round [40]–[44] as well as bringing down the number of training rounds [45]–[50]. In terms of the **reporting phase**, we focus on the aggregation and outline two related optimizations: (1) one is to reduce the aggregation latency by adopting hierarchical methods [51]–[53] and inventing lightweight privacy-preserving methods [54]–[56], and (2) the other is to improve the long-term convergence rate through introducing adaptive optimizers to the server-end [57]–[59]. For each of the attempted optimization, our discussion includes necessary details for readers to understand the motivation, mechanism, and major results. In addition, as **grounding works** such as measurement studies [60] and benchmarking tools [61]–[66] are also indispensable in system research, we also review their status quo to provide tutorials on FL practice (§ IV).

Our work has a clear focus: the system-level efforts made in improving the time-to-accuracy performance for synchronous

federated training. Moreover, we also share some implications derived from the literature and our survey process. It thus differs from existing surveys which either have partial coverage or fail to align the materials to system researchers' interests (§ V). We thus expect it to be an initial attempt to bridge the gap of system-oriented surveys in FL literature, as well as soliciting more contributions in related research.

II. BACKGROUND, PROBLEM STATEMENT AND CHALLENGES

In this chapter, we provide a detailed introduction to the system optimization problem in federated training. We start with a quick primer on the execution workflow of federated training (Section II-A), followed by the problem statement and the scope of this survey (Section II-B). We next outline two challenges that make the problem difficult: optimality and practicality (Section II-C), which also serve as a summary of criteria in evaluating existing solutions presented thereafter.

A. Federated Training

Federated learning (FL) [6] has recently emerged as a new paradigm of collaborative machine learning (ML) that allows multiple distributed clients (e.g., mobile devices or business organizations) to collaboratively train or evaluate a model with decentralized data. Despite the same end goal as traditional distributed learning, FL mainly differs in orchestration, resource constraints, data distribution, and participation scale [67]. At its core, FL keeps private data on-premises, while introducing a central server to maintain a global model and iteratively refine it with aggregates of clients' local updates. This circumvents the communication cost and privacy risks in gathering clients' raw data. Due to the privacy merits, FL has been widely adopted by the industry in various domains. In mobile devices, Google runs FL to improve the user experience for Google Keyboard [7]–[10] and Assistant [11], while Apple deploys FL to evaluate and tune speech recognition models [12]; in the financial space, both IBM [13] and WeBank [14] independently utilize FL to detect financial misconducts; in the medical field, NVIDIA applies FL to create medical imaging AI [15] and predict patients' needs for oxygen [16].

While both model training and evaluation play crucial roles in the development of an FL model, they have different criteria in system design. In this survey, we narrow down the scope to the **training** process, which is the most long-lasting and resource-intensive stage throughout the development of an FL model. Due to its predominance in practice, we focus on the support for the **synchronous** mode, wherein an ML model is trained across a pool of candidate clients in rounds, and in each round, the server needs to wait until a predefined deadline or receiving a sufficient number of clients' updates prior to deriving an aggregated update. In more detail, each round consists of the following three phases (Figure 1).

- **Selection.** At the beginning of each round, the server waits for a sufficient number of clients with eligible status (i.e., be charging and connected to an unmetered network) to check in. The server then selects a subset of them based on certain strategies (e.g., randomly or selectively)

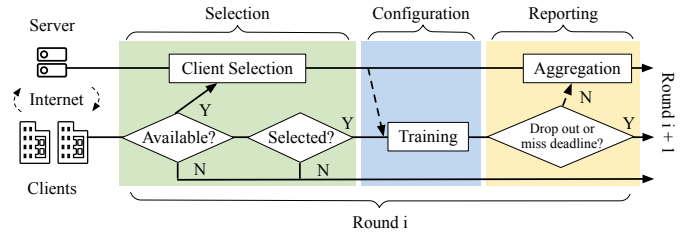


Fig. 1. Standard synchronous federated training protocol [60], [63], [68].

for participation, and responds to those not selected with instructions to reconnect later.

- **Configuration.** The server next sends the global model status and configuration profiles (e.g., the number of local epochs or the reporting deadline) to each of the selected clients. Based on the instructed configuration, the clients perform local model training independently with their private data.
- **Reporting.** The server then waits for the participating clients to report local updates until reaching the predefined deadline. The current round is aborted if there are not enough clients reporting in time. Otherwise, the server aggregates the received local updates, uses the aggregate to update the global model status, and the round is thus successfully completed.

B. System Optimization: the Problem

The primary goal of system optimization in federated training is to minimize the end-to-end resource usage of performing a task. The most common metric is the wall clock time, which is typically measured from the very beginning to a certain desirable checkpoint (e.g., convergence or reaching target accuracy). When a metered network is in use (e.g., when clients are on-demand virtual machines in a public cloud), the overall monetary cost becomes another relevant metric that deserves special attention. When uncharged devices are involved, the power consumption should also be accounted for. Because the cost and energy consumption generally grows linearly as time flies, in this survey, we are particularly interested in reducing **time-to-accuracy**, i.e., the wall clock time for achieving a preset target accuracy.

Intuitively, the time-to-accuracy performance of federated training is determined by two factors [20]: (1) **statistical utility**: the number of rounds taken to reach the target accuracy; and (2) **system utility**: the (average) duration of a training iteration, which can be attributed to the speed at which clients can perform training and communication, respectively. Thus, the effectiveness of an optimization solution critically depends on the enhancement of either type of utility, or both.

The solutions discussed here operate at the **system-level**. As a result, albeit with effectiveness on affecting the statistical or system utility, the following approaches will not be covered:

- Hardware updates, e.g., introducing programmable switches to enjoy the system efficiency brought by in-network aggregation [69], [70].

- Security mechanisms, e.g., employing robust aggregation methods to protect the statistical utility from being impaired by model poisoning attacks [71], [72].
- Paradigm innovations, e.g., adopting personalization strategies [73]–[76] where clients fit separate but related models to tackle the data heterogeneity (mentioned later).

C. What Makes it Hard: the Challenges

Despite the clear exploration direction towards optimization, it is non-trivial to work out a feasible solution due to the following two challenges.

1) *On the Optimality of a Solution:* **First, the information needed in decision making may be outdated or even unavailable.** For example, to estimate a client’s system utility, it is common to refer to its most recent response latency [20]. However, due to the dynamics over time, such information may not accurately reflect the client’s current status. There also exists a cold-start issue, where we are totally unaware of a client’s system capabilities until its first participation. As for estimating a client’s statistical utility, the amount of available information is further limited by privacy concerns. According to the recent FL literature, exploratory attacks such as property inference [77], membership inference [78], [79] and data reconstruction [80], [81] can be made possible with model updates. As such, even exposing model updates can discourage clients from participation, let alone inquiring about their data distribution or even raw data [82]–[84]. Note that the uncertainty in clients’ statistical utility and system utility can be accumulated over time.

Even given a holistic view on the environment, **the problem remains hard due to the coupled nature of statistical utility and system utility.** Intuitively, improving system utility is equivalent to minimizing the average resource consumption (e.g., time or bandwidth) per task unit. On the other hand, reducing the resources invested in a task unit inevitably downgrades the quality of the outcome (e.g., statistical utility) as long as no resource is redundant. To exemplify, by constantly picking the fastest clients in client selection, the average duration of each round indeed decreases, whereas the number of rounds taken to target accuracy may be increased as other clients’ data are under-represented in the global model. Another example can be taken from model compression. To improve communication efficiency, a client can send only an important subset of model updates by sparsification [30]–[34], or a low-bit representation of them by quantization [21]–[25]. Although the per-round communication duration can be significantly reduced by adopting a higher compression ratio, the convergence has to take more rounds to occur due to the loss of computational precision.

The problem is further complicated by client heterogeneity. Federated training involves tens to potentially millions of clients, each of which intrinsically differs from one another in the following three aspects:

- **Resource Heterogeneity.** Due to the variability in hardware specifications and system-level constraints, clients in federated training typically possess different capabilities in computation (CPU, memory, storage, and accelerators),

communication (connectivity and bandwidth) and power (battery level and lifespan) [85]. These types of heterogeneity complicate the optimization of the overall system utility. For example, merely improving the communication speed does not necessarily lead to shorter end-to-end latency, especially when the straggler is bottlenecked by the computation [63].

- **Data Heterogeneity.** As the training datasets of clients are typically generated based on their local activities and contexts, they are not independent and identically distributed (IID). More specifically, clients’ datasets mainly differ in two aspects¹: (1) sample quantity (i.e., the number of data samples), and (2) label partition (i.e., the distribution of data labels) [86]. As a result, not all of them are representative of the population distribution. In case that we do not include all the clients in the federation, optimization for statistical utility has to additionally account for such heterogeneity.
- **State Heterogeneity.** As observed from real-world traces [60], [63], the available slots of mobile device clients varies significantly in temporal distribution due to different user behaviors (e.g., screen locking or battery charging). Therefore, in each round, there can be different sets of candidate clients to choose from, as well as different client drop-out outcomes. On top of the non-IID distribution of clients’ data as mentioned above, this type of heterogeneity further complicates statistical utility optimization. Nevertheless, in the cross-silo settings, it may be less of a concern due to the stable and dedicated nature of clients’ computing power [65], [67].

Last but not least, **it is infeasible to search through the entire configuration space for the global optimum.** On the one hand, the space is prohibitively large, as a federated training task typically spans 10^1 – 10^6 users and 10^2 – 10^4 rounds [67], wherein each phase of a round (§ II-A) has multiple configurable hyperparameters and alternative policies (e.g., client selection choices in the selection phase, or the number of local steps in configuration phase). On the other hand, most of the online decisions are made on the critical path of the task, meaning that the time spent on working out a solution is also counted towards the end-to-end runtime performance, the very objective of the optimization. As a result, it is desirable to be guided by efficient and effective heuristic algorithms, especially balancing the exploration and exploitation efforts made in the solution space.

2) *On the Practicality of a Solution:* Apart from navigating the performance-accuracy-privacy trade-off, the design process of a practical optimization solution should mitigate the accompanying side-effects on other aspects such as the loss of **robustness** to attacks and failures [67]. For example, to evaluate the statistical utility of a client, the server may require it to report the loss values generated in local training [20]. However, a malicious or free-rider client may intentionally respond with arbitrary values in the hope of messing with the orchestration or reaping the benefits of the federation without

¹A more complete categorization of non-IID scenarios can be found in § IV-B1.

making solid contributions. As such backdoors are introduced by the optimization solution, the developers should take charge of eliminating the undesirable exploitations of these security loopholes. Other possible concerns that may arise as a result of a system optimization solution including but not limited to **fairness** (e.g., whether participant bias is introduced in the solution), **generality** (e.g., whether the solution applies to diverse tasks), and **ease of deployment** (e.g., whether the solution can be implemented with moderate engineering efforts). In other words, a mature system optimization solution should not only improve the time-to-accuracy performance by enhancing statistical and system utility but also minimize the adverse impact on other aspects which federated training also values in practice.

III. RECENT OPTIMIZATION APPROACHES

In the past few years, considerable research efforts have been put into tackling the above challenges for fully unleashing the performance potential of FL training. In this chapter, we organize them by the training phases, i.e. selection (Section III-A), configuration (Section III-B), and reporting (Section III-C), as visualized in Figure 2.

A. Optimizing the Selection Phase

Due to the (potentially) large population size and the heterogeneity across clients, the effectiveness of the used participant selection algorithm plays a critical role in the time-to-accuracy performance in federated training. However, the state-of-the-practice system still relies on randomly picking participants [68], which inevitably leads to waste of resources and suboptimal convergence speed. In response, there is an array of work to guide the selection, which can be roughly categorized by the target utility that they improve upon.

1) *Partial Optimization Attempts*: This line of work does not consider the interplay between statistical utility and system utility. Instead, they mainly focus on lifting the either of utility with the other ignored or controlled to a limited extent.

- **Statistics-Oriented**. To approach the convergence rate in centralized settings where the data is IID, CSFedAvg [17] advocates that clients with a lower degree of non-IID data should participate more often. To this end, the authors propose weight divergence to capture the non-IID degree of data owned by a client. More precisely, it measures the normalized Euclidean distance between a client’s model and the reference model trained by the server with auxiliary IID data. According to the 500-client simulation over CIFAR-10 and Fashion MNIST, CSFedAvg reduces the time-to-accuracy by up to $4.0\times$ and $2.7\times$, respectively, compared to random selection.
- **System-Oriented**. In synchronous training, clients with the lowest system utility bottleneck the speed of a federation round. A straightforward way to bound the time usage is setting a deadline for randomly selected clients’ to report updates and ignoring any update submitted after the deadline. To avoid waste of computing resources, FedCS [18] takes a step further by proactively selecting a set of clients whose participation is not likely to miss the

deadline according to latency estimation. As there can be multiple eligible sets, FedCS further favors the solution with the largest scale of participation, which reduces part of the loss in statistical utility. Technically, the whole problem is formalized as a complex combinatorial one, and the authors resort to a greedy algorithm for efficient approximation. As indicated in their 1000-client simulation, FedCS outperforms FedLim (modified FedAvg with per-round deadlines imposed) by up to $1.2\times$ and $1.8\times$ in the time-to-accuracy when training over the non-IID CIFAR-10 and Fashion MNIST datasets, respectively.

2) *Co-Optimizing Statistical/System Utility*: Given the coupled nature of clients’ system utility and statistical utility, it is more practical to navigate the sweet point of jointly maximizing both of them.

- **Coarse-Grained**. TiFL [19] first considers increasing the system utility. To that end, it divides clients into different tiers based on the observed runtime performance, and at each round only selects clients from the same tier for mitigating the waste of resources due to idle waiting for stragglers. To reduce the average iteration span, it also limits the number of times a (slow) tier can be selected. On top of that, the statistical utility is respected by prioritizing tiers with lower testing accuracy whenever there is more than one electable tier. Compared with FedCS, TiFL bears some resemblance in limiting the participation of less capable clients, while being more aware of the statistical utility. As reported in a 50-client cluster with 5 client tiers, TiFL achieves an improvement over random selection by up to $3\times$ speedup in overall training time and by 6% in accuracy.
- **Fine-Grained**. Compared to TiFL, Oort [20] reconciles the demand for enhancing both system utility and statistical utility in finer granularity. Specifically, it associates each client with a continuous score and prioritizes those clients with higher scores. The score is meant to be a principled measurement of both the statistical utility, determined by the training loss, and the system utility, estimated from historical response latency. As some components of the score cannot be known in advance until the corresponding client’s first participation, or cannot be guaranteed to be stable due to the client’s runtime dynamics, the score estimation process is actually modeled as a multi-armed bandit (MAB) problem. Apart from the scoring backbone, Oort also aims to address some practical issues like staleness and robustness. Oort was evaluated on a 1300-client GPU cluster with realistic datasets and simulation on the client heterogeneity. It is reported to reduce training time by up to $14\times$ as well as improving model accuracy by up to 9.8%.

B. Optimizing the Configuration Phase

In the configuration phase, there are mainly two processes that are responsible for the time-to-accuracy performance. One is downlink (i.e., server-to-client) model transmission and the other is local model training. Thus, both aspects can be reinvented for system optimization. As for communication

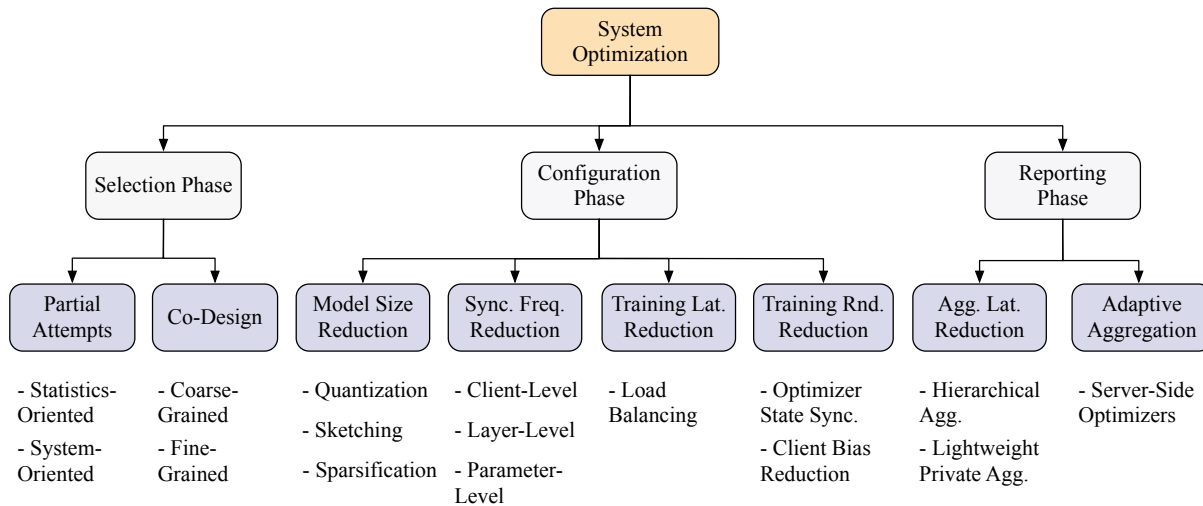


Fig. 2. Taxonomy of the approaches discussed in § III.

overhead reduction, one can reduce the size of model updates (Section III-B1) and decrease the synchronization frequency (Section III-B2). To lower computational overhead, one can shorten the training latency by balancing the workload across clients (Section III-B3), as well as reducing the number of rounds taken to converge by adopting heterogeneity-aware training algorithms (Section III-B4). As the uplink model submission (i.e., client-to-server) that takes place in the later mentioned reporting phase shares the same operational space as the downlink one, we combine the discussion on both of them in this section for brevity.

1) *Model Update Size Reduction*: Prior arts of model update size reduction mainly fall into three camps: quantization, sketching, and sparsification. Ahead of the emergence of FL, the exploration of these directions has already been initiated in the context of traditional distributed learning. While their communication merits are mostly reproducible in FL, they also face new challenges due to the privacy regulations and client heterogeneity, which we will also point out hereafter.

- **Quantization.** Quantization converts each scalar in a model update to its low-bit representation which takes up less space. While quantization has already gained its fame in traditional distributed learning and we refer the readers to dedicated surveys like [87] for more details, here we only introduce the most representative work. As the first quantization work in model training with rigorous convergence proof, QSGD [21] performs unbiased quantization with standard random dithering, a technique borrowed from image processing. After its birth, related works emerged with more aggressive quantization bit-widths set and more appealing empirical performance obtained. For example, TernGrad [22] advocates using only ternary values (0, ± 1) in the uplink direction, while signSGD [23] can use only binary signs (\pm) in both uplink and downlink communication. It is worth mentioning that a popular technique in tackling the precision loss brought by quantization is error feedback, whose basic idea is to accumulate the previous quantization errors

and compensate for them in the current round. Leveraging this technique, ECQ-SGD [24] performs consistently better than QSD in terms of both convergence speed and accuracy, while EF-SGD [25] has achieved a narrower generalization gap from centralized training compared to standard signSGD.

Despite their generality, there are some practical concerns on applying these general quantization strategies to FL due to the privacy constraints and client heterogeneity. For example, determining the clipping threshold for quantization needs to exploit the knowledge about its input (i.e., local model updates) for reducing the induced error as in dACIQ [88]. However, an FL client does neither possess a priori knowledge on others' model updates, nor can it require the precise values of them. To work out a globally applicable clipping threshold, we may need to share some less sensitive information (e.g., the maximum and minimum values in local updates) across clients for threshold estimation as in BatchCrypt [55]. Still, whether such a circumvention guarantees accurate estimation and immunity to privacy attacks remains an open question.

- **Sketching.** Existing quantization approaches assume the input values follow a certain distribution (e.g., a uniform or bell-shaped one), which may not always be the case in model updates [26]. To be more general, some researchers introduce sketching methods where some memory-saving data structure is used to approximate the exact distribution of model update values in a single pass over the values. For example, SketchML [26] utilizes a quantile sketch method to generate a non-uniform mapping from gradient values to low-bit integers. SketchML achieves empirical success such as decreasing the gradient size by around $7\times$ and is the first effort to introduce sketching for compressing model updates in ML training. Similar to quantization, sketch algorithms can also make use of error feedback techniques to efficiently amend the errors induced by the approximation, as in SketchedSGD [27] and FetchSGD [28]. There are also sketching practice that

compresses auxiliary variables apart from model updates, such as sketching clients' momenta and per-coordinate learning rates as in [29].

- **Sparsification.** While quantization and sketching operate at the level of precision in terms of model size reduction, sparsification operates at the coordinate level. Specifically, sparsification allows each client to transmit only a sparse subset of its model updates, while the rest are accumulated and incorporated into future training. Technically, the sparsified gradient is obtained by first performing element-wise multiplication on the original gradient with some 0/1 mask and then discarding zero elements. The masks are typically randomly generated as in [30], while another commonly used variant is the top $s\%$ scheme where 1 is given to the coordinates that rank top $s\%$ in absolute magnitude and 0 otherwise [31]–[34]. The top $s\%$ method can reduce the traffic amount by up to three orders of magnitude, while still preserving model quality with no significant extension of communication rounds [31], [32].

While similar cost savings are shown to be transferable to plaintext FL, it is unclear whether sparsification can be further compatible with cryptographic techniques that are widely adopted for privacy enforcement in FL. For example, apart from the uplink model updates, it is also desirable to sparsify the downlink global update for fully releasing the potential of communication improvement. However, implementing the downlink sparsification may not be feasible when the server is not aware of the plaintext values of the aggregated update as a result of the applied Secure Multi-Party Computation (SMPC) [54], [89]–[91] or Homomorphic Encryption (HE) [55], [92]–[94] techniques.

It is noteworthy that as quantization (or sketching) and sparsification are orthogonal to each other, they can be combined to reap the most benefits in model size reduction [95], [96].

2) *Synchronization Frequency Reduction:* At its core, the reduction in the synchronization frequency is achieved by identifying and precluding redundant synchronization efforts. This can be operated at different granularity ranging from clients, layers to individual parameters in a model update. We discuss hereafter each of these categories in detail.

- **Client-Level.** In the literature, the importance of an entire model update is usually measured by some numerical features. In the most intuitive form, a model update in Gaia [35] is considered significant if its magnitude relative to the current value $|\frac{Update}{Value}|$ exceeds a specific threshold such as 1%. While the magnitude may serve as a good indicator for data center learning performed, it may not work in FL where determining an appropriate threshold is hard due to clients' heterogeneity in FL. Given this intuition, some researchers propose to involve the comparison with some reference points for a more robust measurement of the importance. For example, [36] observes the Euclidean distance between the local model and a reference model, while CMFL [37] focuses on the number of values with the same sign in the local model

and the most recent global model.

- **Layer-Level.** Apart from considering a model update as a whole, there also exists work that tries to reduce the synchronization frequency on a layer basis. A representative work done in this direction is TWAFL [38] where model aggregation is conducted layer-wise. As observations made in deep neural network (DNN) fine-tuning [97], shallow layers in a DNN learn general features across different datasets while deep layers learn ad hoc ones. TWAFL hence proposes to update shallow layers more frequently than deep layers as they are more responsible for the overall performance of the global model.
- **Parameter-Level.** Some industrial practitioners also consider whether to synchronize for each round at the level of individual parameters. Noticing that each parameter usually evolves in a transient-then-stable manner, i.e., it first varies drastically and then settles down around a certain value with slight oscillation, APF [39] proposes to stop synchronizing those parameters whose evolution moves to their stationary phase.

3) *Training Latency Reduction:* A client's training latency is determined by both its computational workload and resource capabilities. While the latter cannot be altered, the former still leaves room for optimization innovations. We discuss one major line of such efforts.

- **Load Balancing.** Given the variations in computing power and data volume, clients may not finish the training process at the same time. To mitigate the resulting straggler effects, [40], [41] suggest balancing the amount of training data across clients. Specifically, they turn to reinforcement learning (RL) techniques for determining the optimal number of data units used in an iteration for each device client. While such approaches achieve shorter end-to-end latency compared with normal strategy (that always consumes all data in clients), whether partial data involvement still converges to a comparative accuracy as full coverage remains unknown.

Instead of using different amounts of data, FedProx [42] balances the system load across clients by formulating an inexact learning problem and allowing variable steps of local solvers. FedProx also respects data heterogeneity by regularizing the Euclidean distance between local models and the global ones. A similar approach to FedProx is FedDANE [43], which formulates another inexact learning problem that is inspired by Distributed Approximate Newton (DANE) method [98]. Despite the encouraging theoretical results, FedDANE underperforms FedProx in the presence of data heterogeneity and low participation rate, suggesting a discrepancy between theory and practice which needs further investigation.

Last but not least, load balancing can also be achieved by varying the complexity of local models. For example, HeteroFL [44] assigns sub-models with different widths of hidden channels to clients so that clients with fewer capabilities can train smaller sub-models. All sub-models share the same model architecture, and thus normal model aggregation is still possible. The authors empirically

show that the quality of the global model trained with heterogeneous sub-models is comparative to that trained with full local models.

4) *Training Round Reduction*: In the settings with heterogeneous data, more local computation in a communication round does not necessarily lead to fewer numbers of rounds for reaching satisfying optima [50]. Thus, adopting heterogeneity-aware techniques such as adaptive optimization and bias reduction can help remedy the convergence speed in FL practice.

- **Optimizer State Synchronization**. It is common practice for first-order moment optimization to apply momentum to dampen oscillations [99], [100]. However, in the federated settings, if the clients' momenta are separately updated, they may deviate from each other due to non-IID data distributions. Thus, there are researchers proposing optimizer state synchronization frameworks where clients' optimizer states are synchronized by the server periodically. PR-SGD-Momentum [45] is aligned with this direction and also gives proof on the linear speedup of convergence w.r.t. the number of workers. FedAC [46] also applies momentum at clients with periodic synchronization, while it is proven to obtain the same linear speedup property with asymptotically fewer rounds of synchronization. MFL [47] is another similar idea with theoretical guarantees, but it focuses on accelerating deterministic gradient descent (DGD) instead of SGD, unlike the previous two studies.
- **Client Bias Reduction**. Due to data heterogeneity, clients' model updates can be biased towards the minima of local objectives, known as "client drift" as in the literature [101], which hinders the convergence of the global model. To reduce the variance across clients, SCAFFOLD [48] advocates the use of control variates. Specifically, each of the clients and the server maintains a control variate, and at each local step, a client de-biases its local updates with two control variates: one of its own and the other broadcast by the server. SCAFFOLD converges provably faster than FedAvg [6] without any assumption made on the client selection or data heterogeneity. Mime [49] considers a similar idea but makes different choices on the specific definitions of control variates. While the use of control variates requires persistent client states, there exists another line of work that works for stateless clients: posterior averaging. Instead of approaching FL as optimization, this line of work formulates the problem as a posterior inference one. Compared to traditional federated optimization, posterior inference can benefit from an increased amount of local computation without risking stagnating at inferior optima. FedPA [50] instantiates this idea with an efficient algorithm to conduct federated posterior inference with linear computation and communication costs.

C. Optimizing the Reporting Phase

In this phase, the operation room for system optimization is limited to either model uploading or model aggregation. As the former has already been combined in the last section, we

hereafter focus on optimizing the aggregation process with two main directions explored in the literature: (1) directly reducing the aggregation latency at each round (Section III-C1), and (2) expediting the convergence rate in the long run through conducting adaptive aggregation (Section III-C2).

1) *Aggregation Latency Reduction*: Compared to local training in the configuration phase, model aggregation involves less intensive computation. However, its latency can still be salient because (1) large-scale participation can put pressure on the communication, and (2) the deployment of security methods can complicate computation. We hereafter introduce the respective optimization efforts in the literature.

- **Hierarchical Aggregation**. The downsides of the traditional two-layer (server-clients) FL system involve (1) instability: the remote link to the server may be slow or even unpredictable especially in public network and/or under geo-distributed settings; (2) risk of scalability: the cloud server may suffer from network congestion when concurrently receiving too many local updates; (3) heterogeneity: the straggler effects could be exacerbated in the presence of imbalance network bandwidth. To address these issues, some researchers resort to a hierarchical design of model aggregation by introducing an extra level of edge servers, each of which is typically responsible for a small number of clients with proximity. For instance, in HierFAVG [51], after a fixed number of local updates on clients, each edge server aggregates its own clients' models. Subsequently, after another fixed interval of edge aggregation, the cloud server aggregates all the edge servers' models. It is proven that HierFAVG still guarantees convergence, and empirical studies with synthetic FL datasets show that it reduces the time-to-accuracy by up to $2.7\times$ in a simulated cloud-edge-client environment. A concurrent work HFL [52] also considers a similar design, while it does not attach theoretical analysis on its convergence behaviors. HybridFL [53] further extends this primary design with two ideas: (1) quota-triggered edge-level aggregation: edge nodes stop waiting for more local updates once receiving a sufficient number of them; and (2) immediate cloud aggregation: cloud-level aggregation is conducted right after the edge-level one is completed. This decouples each pair of interactions (i.e., cloud-edge and edge-client), thereby further mitigating the impact of client drop-out and stragglers.
- **Lightweight Private Aggregation**. As mentioned in Section II-C1, uploading model updates in the clear may be vulnerable to exploratory attacks which plague clients' privacy. Therefore, model aggregation is preferably safeguarded by cryptographic techniques, which inevitably induces extra computation and communication overhead. For instance, Secure Aggregation (SA) [90] can perform aggregation without leaking the individual model updates to the server at the cost of quadratic communication overhead ($O(N^2)$ w.r.t. population size N). To drag down the cost bound to $O(N \log N)$, Turbo-Aggregate [54] devises a multi-group circular variant of SA. Specifically, it divides clients into multiple groups and at each round, clients belong to one group transmit both (1) the aggreg-

gated model obtained from the previous group and (2) the aggregated model calculated within the current group to the next group. Besides SA, Homomorphic Encryption (HE) is another commonly used privacy-preserving aggregation technique that comes with prohibitively high message inflation and runtime overhead. In response, BatchCrypt [55] implements an end-to-end solution for batching multiple plaintexts into one large plaintext so that HE-related operations can be performed in a data-parallel manner. BatchCrypt is shown to speed up the training by $23\times$ - $93\times$ compared to plain Paillier [102] (a prevalent variant of HEs), but it still leaves the message inflation suboptimal and is incompatible with top $s\%$ sparsification approaches [56]. Instead of optimizing traditional HE schemes by batching, FLASH [56] proposes a lightweight HE scheme that is tailored for cross-silo FL. It induces negligible ($\leq 6\%$) computational overhead and no network communication overhead compared to plaintext FL for staying symmetric.

2) *Adaptive Aggregation*: In FedAvg [6], the *de facto* standard aggregation method, local model updates simply get weighted by the corresponding numbers of training samples and then added up. While it guarantees convergence when even dealing with non-convex empirical risk functions in IID data settings [48], [103], it is observed to yield unstable convergence behavior or even divergence when it faces models trained with arbitrarily non-IID data. There are thus rising interests on whether the aggregation can be more adaptive w.r.t. the data heterogeneity across clients.

- **Server-Side Optimizers.** Other than accelerating convergence with local momentum (§ III-B4), there are also exploration efforts on server-side momentum. As there is originally no optimizer at the server in FL, these methods first need to generalize the existing aggregation algorithm. Specifically, at each round, instead of collecting local model weights, the server instead collects their changes and treats these changes as the “pseudo-gradient” for the server, with which the server can use to update the global model with adaptive optimizers. FedAvgM [57] initiates the empirical studies with the simplest form of momentum applied at the server, while SlowMo [58] independently proposes a similar scheme and also attaches the theoretical analysis for its convergence behaviors. A recent work [59] makes more sophisticated use of momentum such as adopting AdaGrad [104], Adam [105] and YOGI [106] optimizers (which correspond to FedAdaGrad, FedAdam, and FedYOGI, respectively). It is shown that FedYOGI consistently outperforms FedAvgM in terms of validation performance for both sparse- and dense-gradient FL tasks. Server-side momentum methods feature no need for persistent states or computational complexity at the client-end, which are preferable for cross-device scenarios.

IV. MEASUREMENT AND BENCHMARKING TOOLS

Aside from innovating optimization solutions, there are also researchers contributing with cornerstone works that benefit

the community with informative insights from systematical measurement studies (Section IV-A) and grounding benchmarking tools (Section IV-B), as visualized in Figure 3.

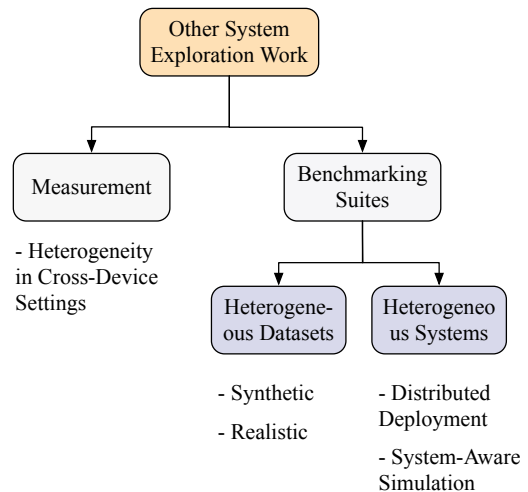


Fig. 3. Taxonomy of the work introduced in § IV.

A. Measurement-Based Research

Due to the complicated interplay between statistical utility and system utility, there are a few measurement studies which dedicate to providing thorough insights and actionable implications for interested researchers.

- **FLASH [60]:** FLASH particularly studies the impacts that heterogeneity has on both the statistical utility and system utility. To that end, it first collects device hardware specifications (indicating computational and communication capacities) and state changes (related to device check-in and drop-out) of 136k smartphones. It then builds a system-aware simulation framework where the trace data are randomly assigned to each client. It also respects the data heterogeneity by plugging realistic datasets including Reddit, FEMNIST, CelebA and M-Type. FLASH has systematically extracted a set of observations on the impacts of heterogeneity and possible factors for these impacts, wherein some non-trivial findings include: (1) gradient compression methods (e.g., Gradient Dropping [31] and SignSGD [23]) can hardly shorten the convergence time under heterogeneous cross-device settings; (2) advanced aggregation algorithms that overlook some aspects of heterogeneity will be less effective in realistic settings. We encourage the readers to refer to the paper for more details.

B. Benchmarking Suites

Realistic benchmark suites are necessary for enabling fair, insightful, and reproducible evaluation of the effectiveness of system optimization efforts. As the time-to-accuracy performance relies on both the statistical utility and system utility (§ II-B), in the following summary of existing benchmarking tools, we aim to cover diverse aspects of simulating practical FL: data characteristics, client capabilities, and availability.

1) *Training Datasets*: There are two prevalent categories of training datasets used in FL research. One line of work is **derived from conventional ML datasets** (e.g., CIFAR [107], MNIST [108], and Fashion-MNIST [109]). To synthesize the non-IID nature as in real FL scenarios, the data partitions in these datasets are typically formed by restricting the number of data classes each client has (e.g., partitioning by shard-based methods as in [6] or latent Dirichlet allocation (LDA) processes as in [110], [111]). Although the data generated in such a manner are indeed non-IID, they may not perfectly represent the real-world characteristics. For instance, besides the label distribution skew, in reality, non-IID data may also involve feature distribution skew (e.g., same words with different stroke width), same labels with different features (e.g., images of clothing vary due to regional differences) and same features with different labels (e.g., the same context mapped to different next words due to personal variation) [67], [86].

In contrast, the other type of datasets is **collected in real distributed scenarios** and thus naturally captures the FL features. We briefly introduce existing open-source attempts in curating such datasets as follows.

- **LEAF** [61]. LEAF is an actively maintained project, which currently consists of 6 datasets spanning multiple applications such as computer vision (CV) (FEMNIST and CelebA) and natural language processing (NLP) (Shakespeare, Reddit, and Sentiment140). Each dataset is generally formed by splitting the corresponding public dataset by the original contributors of the data samples. In other words, the non-IID nature comes from the unique behavior style of each contributor.
- **FedScale** [63]. Similar to LEAF, FedScale also collects realistic datasets and partition them with unique client identification. FedScale currently includes 18 datasets (including iNature, OpenImage, Google Landmark etc.) which span 10 FL tasks. Apart from the comprehensive coverage of tasks, FedScale has further made four contributions to the community: (1) it has the training, validation, and testing set well established; (2) it streamlines different datasets into a unified format; (3) it accounts for various participation scale from hundreds to millions of clients; and (4) it provides handy APIs for the developer to customize their datasets.
- **OARF** [62]. For a specific FL task, OARF assembles real-world datasets from different sources to realize data heterogeneity. For example, for sentiment analysis, it combines both the IMDB Movie Review and Amazon Movie Review datasets. On training, datasets belonging to different sources are distributed to different parties. As such, the data are split in a dataset-wise manner instead of a sample-wise one. OARF currently covers 9 tasks in CV and NLP.

Apart from the above systematic data collection efforts, we also have realistic datasets that are separately maintained, such as Stackoverflow [112] and PERSONA-CHAT [113].

2) *Production Systems and Simulation Platforms*: In addition to setting up data heterogeneity, we also need to incorporate system heterogeneity in realistic benchmarking. The most straightforward way to study FL designs with system

utility borne in mind is to deploy in **production-oriented systems**. Such systems not only embed the ML backbone but also address practical problems like authentication, communication, encryption, and deployment to physical distributed environments. We sketch the open-source representatives of them.

- **FATE** [64]. FATE is an FL framework that can be deployed in distributed environments. In addition to its flexible ML pipeline, FATE also features in several aspects which further facilitate the research on various goals of practical FL: (1) it supports privacy-preserving computation by implementing cryptographic algorithms such as the Diffie-Hellman key agreement [114] and homomorphic encryption [102]; (2) it covers different training architectures including horizontal FL, vertical FL, and federated transfer learning; and (3) it allows a certain degree of customization on the FL pipeline such as the aggregation step. Given its heaviness in resource consumption, FATE is currently more preferable in powering cross-silo applications instead of cross-device ones.
- **FedML** [65]. FedML is also a secure and versatile FL framework that supports distributed mode. Compared to FATE, FedML is more flexible in communication engineering due to the ease of customizing message flow and topology definitions. It is also more lightweight and can thus accommodate training on mobile or IoT devices. Moreover, it can be accelerated with GPUs, while FATE is currently not compatible with hardware accelerators.
- **Flower** [66]. Flower is a concurrent work with FedML, and it concentrates on providing a unified approach for FL with mobile devices. Similar to FedML, Flower bears in mind the goals of being (1) lightweight, (2) extensible, (3) scalable, and (4) compatible with diverse mobile platforms (e.g., Android and iOS) and ML-frameworks (e.g., PyTorch [115] and Tensorflow [116]). The main drawback of Flower is that it does not implement privacy-related algorithms, as opposed to FATE and FedML.

Although using production systems yields the most realistic insights, it may not be practical for researchers with limited resources and time budgets. To meet the growing demand for conducting agile FL research, several platforms **that enable system-aware simulation** have been developed. As opposed to system-unaware simulators (e.g., Tensorflow Federated [117], PySyft [118], LEAF [61], OARF [62], FedEval [119], and Plato [120]), these platforms respect the impact of client system heterogeneity by associating each client with her computation and communication speed, as well as availability dynamics, which are either set manually by developers or by replaying realistic traces. In addition, these platforms also excel in producing comprehensive metrics needed in performance analysis. Compared to real deployment, on the other hand, these systems allow researchers to make fast-forward progress without being blocked by real-world bottlenecks in computation and communication.

- **Flower** [66]. Besides deployment on real mobile devices as just mentioned, Flower also supports simulation in the cloud with configurable system-level parameters such

as bandwidth constraints and computational capabilities. With that, researchers can experiment with larger and more compute-intensive FL workloads that cannot be run on today’s mobile devices.

- **FedScale** [63]. Aside from curating real-world datasets (§ IV-B1), FedScale also builds an automated runtime to simulate FL in realistic settings. By design, FedScale integrates AI Benchmark and MobiPerf Measurements system traces to simulate clients’ heterogeneous training speed and network throughput, respectively. It also incorporates a large-scale user behavior dataset that was formulated in [60] to emulate clients’ availability dynamics. Compared to Flower, it lacks support for deployment on real distributed devices. Still, it broadly simulates realistic cross-device heterogeneity and can embrace new behavior traces with its APIs.

V. RELATED WORK AND CONCLUDING REMARKS

A. Related Surveys

The motivation for this survey stems from three observations. First, **few in-depth surveys focus on system optimization for FL**. As FL features strict compliance to privacy regulations as opposed to traditional distributed learning, many survey efforts are directed to the unique challenges such as enforcing data privacy and system robustness [121]–[125], while the system optimization issues receive less attention in dedicated surveys.

In terms of the common system optimization issues shared by FL and traditional distributed learning, there do exist extensive surveys with detailed discussion on related topics such as communication efficiency [87], [126], [127]. However, their scope is not narrowed down to FL, and thus **does not fully capture all the system optimization problems and solutions that are unique in FL**. For example, FL has in its standard workflow the selection phase which needs particular investigation due to client heterogeneity, while traditional distributed learning does not even have the notion of client selection.

Last but not least, we notice that there are comprehensive surveys such as [67], [101], [128], [129] which cover a wide range of aspects in FL including runtime performance. However, as they are not intended to have a special focus on system optimization, **their presented context may not be deep enough**. In contrast, this survey aims to provide a succinct yet complete view of the literature of system optimization in synchronous federated training.

B. Future Research Directions

The primary goal of this survey is to help researchers design future optimization solutions. To stimulate more directives for FL practitioners, we discuss in the following some possible future directions that we derive from the literature as well as our development practice.

- **Selection Phase.** (1) The state-of-the-art client selection strategies (e.g., Oort [20]) are basically evaluated on some system-aware simulators, which still risks the loss of generality. In other words, it remains unclear whether their

simulation is realistic enough or how these methods can outperform their counterparts in emulated environments or industrial practice. (2) Moreover, existing algorithms all limit the participation scale to hundreds, because involving more clients in a round is observed to have marginal benefits under primary aggregation methods (e.g., FedAvg [6]). However, according to our observations, the number of available clients at each minute can be as many as thousands in the cross-device practice. Thus, it is still desirable to carefully involve more available clients for gaining non-trivial improvement in time-to-accuracy.

- **Configuration Phase.** (1) Complied with the observations in the literature [63], most prior arts configure different clients in a consistent manner, for example, using the same learning rate or compression ratio. Although there exist some heterogeneity-aware efforts like load balancing (§ III-B3), we anticipate that there is still much room for more effective heterogeneity-aware client configuration. (2) As aforementioned (§ III-B1), it is also valuable future work to realize downlink (i.e., server-to-client) sparsification when privacy-preserving aggregation (e.g., HE or SMPC) are enforced for fully unleashing the potential of communication efficiency in the federation.
- **Reporting Phase.** (1) As the system bottleneck is usually assumed to locate at clients instead of the server, most of the existing optimization efforts focus on improving the utility (system and statistical) of clients. It is thus interesting to investigate whether such an assumption holds in all FL practices, especially when the scalability of the server is restricted due to rigid capabilities or limited budgets. (2) Existing lightweight privacy-preserving aggregation methods are not able to accommodate the need for inspecting plaintext local updates for robustness enforcement [67]. Thus, the question of how to navigate the sweet point of jointly maximizing accuracy, performance, privacy, and robustness still remains open.

C. Discussion on the Coverage

- **Cross-Device FL v.s. Cross-Silo FL.** FL applications are often categorized as either cross-device scenarios (where the participants are a mass of less capable mobile or IoT devices) or cross-silo scenarios (where the participants are 2-100 organizational entities) [67]. While the FL workflow that we base on throughout this survey is primarily proposed for cross-device FL [60], [63], [68], it also generalizes to cross-silo settings. Hence, the scope of this survey does not preclude cross-silo FL, and hence many practical methods mentioned here should apply to both settings. For those techniques that are suitable for merely one setting, we have put an emphasis on their limitations and stated the practical reasons behind them.
- **Horizontal FL v.s. Vertical FL.** From the perspective of data partition manner, FL applications can also be classified as either horizontal FL (where data are sample-partitioned) or vertical FL (where data are feature-partitioned) [128]. Much discussion in this survey is biased towards horizontal FL because (1) extensive research

attention has been drawn to horizontal settings for its wide applications, whereas (2) there are few consensus achieved even on the training workflow of vertical FL. However, some of the optimization directions, such as the quantization and sketching (§ III-B1), should also apply to certain plaintext variants of vertical FL such as [130].

D. Conclusion

In this survey, we focus on system optimization in synchronous federated training and propose a natural taxonomy that categorizes existing solutions based on both the training phase and the type of utility at which they target. Apart from problem-driven attempts, we also include related cornerstone efforts including measurement studies and benchmarking suites. We expect this manuscript to be a **useful guideline** for the design and implementation of federated learning systems.

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