AUXO: HETEROGENEITY-MITIGATING FEDERATED LEARNING VIA SCALABLE CLIENT CLUSTERING

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ABSTRACT

Federated learning (FL) is an emerging machine learning (ML) paradigm that enables heterogeneous edge devices to collaboratively train ML models without revealing their raw data to a logically centralized server. Heterogeneity across participants is a fundamental challenge in FL, both in terms of non-independent and identically distributed (Non-IID) data distributions and variations in device capabilities. Many existing works present point solutions to address issues like slow convergence, low final accuracy, and bias in FL, all stemming from the client heterogeneity.

We observe that, in a large population, there exist groups of clients with statistically similar data distributions (*cohorts*). In this paper, we propose Auxo to gradually identify cohorts among large-scale, low-participation, and resource-constrained FL populations. Auxo then adaptively determines how to train cohort-specific models in order to achieve better model performance and ensure resource efficiency. By identifying cohorts with smaller heterogeneity and performing efficient cohort-based training, our extensive evaluations show that Auxo substantially boosts the state-of-the-art solutions in terms of final accuracy, convergence time, and model bias.

1 INTRODUCTION

Federated learning (FL) enables distributed clients to collaboratively train an ML model without moving their local data to the cloud. It circumvents the systematic privacy risk and cost of data transfers in centrally collecting user data. FL is increasingly being adopted by many popular applications, such as Google's Gboard (GBoard, 2020), Apple's Siri (Paulik et al., 2021), NVIDIA's medical platform (Li et al.), Meta's Ads recommendation (Meta, 2021), and WeBank risk prediction (McMahan & Ramage, 2017), across up to millions of end-user devices.

Despite its privacy advantage over traditional ML, FL faces unique challenges due to statistical heterogeneity among user data and systems-level heterogeneity among user device capabilities. On the one hand, statistical heterogeneity makes one single global model insufficient for satisfying every client's data distributions (Li et al., 2020c; Zhao et al., 2018). Even if a personalization algorithm is used to generate individual models for each client, they may suffer from heterogeneity-borne challenges (Tang et al., 2021; Long et al., 2022). Several studies that try to mitigate the effect of statistical heterogeneity, such as FedYoGi (Reddi et al., 2021), q-FedAvg (Li et al., 2020b), FTFA (Cheng et al., 2021), have shown that their convergence depends on the degree of heterogeneity, both theoretically and empirically. On the other hand, system heterogeneity raises challenges for straggler mitigation and fault tolerance, and degrades overall system efficiency (Yang et al., 2020; Bonawitz et al., 2019; Xu et al., 2019). For example, recent studies that consider system heterogeneity, such as Oort (Lai et al., 2021), PyramidFL (Li et al., 2022), and FedProx (Li et al., 2020a), have shown that their performance also worsen with increasing heterogeneity (§2.2).

To tackle the root cause of the problems caused by heterogeneity instead of only the symptoms arising from heterogeneity, we consider *whether we can reduce heterogeneity itself during FL training instead of simply trying to address its ill effects?* Intuitively and analytically, we observe that real-world FL populations often include groups of clients with statistically similar data distributions or *cohorts* (Yuan et al., 2022) (§2.3). If a population has K cohorts, training K separate models – one for each cohort with lower statistical heterogeneity – can boost the performance of many existing FL algorithms that are orthogonal to ours and target on convergence (Reddi et al., 2021; Li et al., 2020a; Lai et al., 2021), fairness optimization (Li et al., 2020b), communication efficiency (Abdelmoniem et al., 2023; Rothchild et al., 2020) and so on.

Although some recent works that have attempted to train separate models for different client groups (Briggs et al., 2020; Ghosh et al., 2020; Long et al., 2022), how to cluster clients at scale and in the wild while respecting client privacy has received little systematic attention (§2.4). To this end, we

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propose **Auxo**, a cohort manager for efficient FL, to enable 1) scalable cohort identification to reduce intra-cohort heterogeneity under large-scale and low-participation FL scenarios; and 2) efficient cohort-based training to guarantee model convergence and facilitate most FL optimizations (e.g., fairness optimization) without extra resource cost.

In addition to the challenges faced by state-of-the-art clustering mechanisms (Sattler et al., 2021; Duan et al., 2021), Auxo addresses the following practical challenges toward real FL deployment (§4). First, most existing clustering strategies require a complete pass of all clients, visibility to client data, or additional on-device training for every participant and over time, which is not only expensive and risky to privacy, but also can be impractical as clients can be unavailable over time. Instead, Auxo allows sporadic client availability, and respects client resource constraints and privacy. It automatically spawns new cohorts and selects the right cohort even for unseen clients while exploring a large population. Second, unlike expensive and ad-hoc hyper-parameter tuning stages used in existing solutions, Auxo finds a sweet spot between creating too many or too few cohorts. It also determines when to derive new cohorts to jointly optimize the model performance and the overall training resources.[1] Moreover, Auxo delivers such efficient cohort clustering and training while being robust to uncertainties (e.g., failure tolerance and unfavorable settings) at scale (§3).

We have implemented (§5) and evaluated (§6) Auxo on a wide variety of real-world FL datasets, tasks, and algorithms at scale. Compared to existing solutions, Auxo improves the performance for various FL algorithms, such as better test accuracy (2.1%–8.2%) and convergence speed (up to 2.2×) and smaller bias of model accuracy (5%–116%).

Overall, we make the following contributions in this paper:

- We propose a systematic clustering mechanism to identify cohorts for the practical large-scale, low-participation and resource-constrained FL setting.
- We identify a sweet spot for jointly optimizing model convergence and training cost, and provide analytical insights to ensure good model performance.
- We implement and evaluate Auxo at scale, showing the improvement of final accuracy, convergence time, and model fairness over the state-of-the-art.

2 BACKGROUND AND MOTIVATION

We start with a brief introduction of federated learning (§2.1), followed by the challenges it faces due to heterogeneity in real-world settings (§2.2) . Next, we describe some opportunities to improve FL that motivates our work (§2.3). Finally, we explain the limitations in related works that motivate our algorithm and system design (§2.4). More discussion about related works can be found in Appendix D.

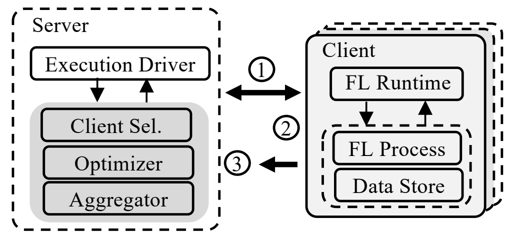


Figure 1. Traditional FL overview. The server first selects from available clients and sends out model weights. Clients train the updated model on their local dataset. After training is finished, clients report their model gradient to the server.

2.1 Federated Learning

A typical cross-device FL system consists of two primary components (Figure 1): A logically centralized cloud *server* that maintains a single global model and many distributed *clients* with private local data. The overall lifecycle of an FL training round can be divided into three broad stages.

① **Selection stage:** Clients check in with the server continuously to announce their availability for FL computation. The server selects a number of *participants* for that round based on its client selection strategy.

② **Execution stage:** The selected participants download the current model from the server and perform server-specified computation on their local data.

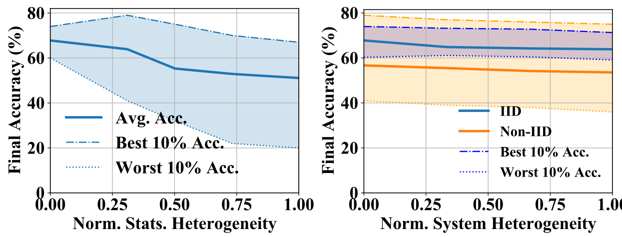
③ **Aggregation stage:** Participants that successfully complete the execution stage send model updates back to the server. The server aggregates the updates to finalize an updated model for the next round.

2.2 Heterogeneity Challenges in FL

Unlike centralized ML, FL faces unique challenges in terms of statistical and system heterogeneity. The former refers to the diversity of data distribution across clients, which hinders model convergence; the latter refers to variations in system characteristics among participants' devices, which results in large differences in training performance. Increasing heterogeneity in either dimension leads to poor performance.

Impact of statistical heterogeneity. Under large statistical heterogeneity, poor model accuracy, convergence and fairness can be observed by individual clients as the model is validated on their local data but is trained over all the clients. Existing works that address statistical heterogeneity in FL assume bounded heterogeneity (Li et al., 2020c; Zhao

[1] We refer to the number of participants that contribute to a round of FL training as training resource throughout this paper.



(a) Statistical heterogeneity. (b) System heterogeneity.

Figure 2. The impact of heterogeneity on final accuracy.

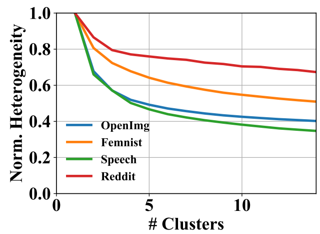


Figure 3. Intra-cluster heterogeneity in real datasets.

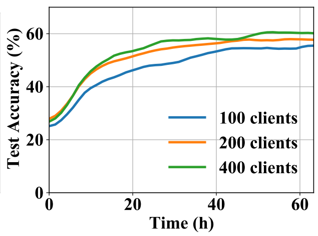


Figure 4. Diminishing return by adding more participants.

et al., 2018; Reddi et al., 2021; Li et al., 2020a). Thus, they are fragile to larger statistical heterogeneity.[2] For example, our analysis of FedYoGi (Reddi et al., 2021) (a state-of-the-art FL algorithm) on OpenImage (OpenImg, 2018) (an FL image dataset), in Figure 2a shows that the model accuracy and its fairness across clients worsens with increasing statistical heterogeneity. To reach the same model performance with larger heterogeneity, more communication and/or computation costs are needed. This is true for personalization algorithms as well (Tang et al., 2021).

Impact of system heterogeneity. Heterogeneity of system-level characteristics raise challenges such as fault tolerance and straggler mitigation (Li et al., 2020a; Huba et al., 2022). Over-commitment (Bonawitz et al., 2019), which discards updates from slowest-responding participants, is commonly used to reduce the impact of stragglers, but it may lead to participation bias against slow devices. Figure 2b shows the final accuracy of the OpenImage task under different degrees of system heterogeneity (variance of system speed). For each experiment, we control the round duration and the number of successful participants to be the same; as a result, participation bias exacerbates with increasing system heterogeneity. Since participation bias may enhance statistical heterogeneity in another form, the final accuracy decreases with increasing system heterogeneity (albeit at a slower rate than statistical heterogeneity).

[2] In this experiment, we measure the statistical heterogeneity among a set of clients using the popular L2 distance on their data distributions (Lai et al., 2021).

	CFL	FL+HC	FlexCFL	IFCA	Auxo
Partial part.	×	✓	✓	✓	✓
Low avail.	×	×	✓	✓	✓
Res. constraint	×	×	×	×	✓
Training perf.	×	×	×	×	✓

Table 1. Comparing Auxo with existing Clustered FL.

2.3 Opportunities

The opportunity for improving FL training performance, therefore, lies in decreasing heterogeneity especially the statistical heterogeneity. By identifying statistically homogeneous groups and performing FL within each group, we may be able to boost model performance of most FL algorithms that are suffered by the heterogeneity.

Despite large statistical heterogeneity across the entire FL client population, there exist groups of statistically similar clients in most large populations. Figure 3 shows that for four representative FL workloads (Lai et al., 2022) in the real world. We use K-means clustering (with increasing values of K) on clients' data distribution by their L2-distance metric. As the number of clusters increases from one (i.e., traditional FL with one global model) to larger values, we observe a small number of statistically similar groups emerge for most datasets.

However, training K models to converge may need more training resources compared to training one model. As shown in Figure 4, increasing training resources has diminishing returns on the model convergence, which presents the primary opportunity leveraged in this work: *instead of letting all available clients contribute to a single global model, it may be more beneficial to partition them into several cohorts, each with smaller heterogeneity.*

2.4 Limitations of Existing Clustered FL Solutions

Recent efforts in the ML community have (theoretically) explored to create smaller groups of statistically similar clients. Yet, existing clustered FL algorithms often fall short across multiple dimensions in practical deployments (Table 1), which motivates us to design systems support for efficient cohort identification and training. We empirically show the superior performance of Auxo over them too (§6.2).

Scalability. FL in practice often involves millions of clients, and only a small fraction, ∼5% (Bonawitz et al., 2019; Lai et al., 2022), are available to participate in during a time window. Such low availability and partial participation limit the available information for the clustering algorithms. This, however, is ignored by CFL (Sattler et al., 2021), multi-center (Long et al., 2022) and FL+HC (Briggs et al., 2020), and makes the deployment impractical as they requires a complete pass over the entire population to identify clus-

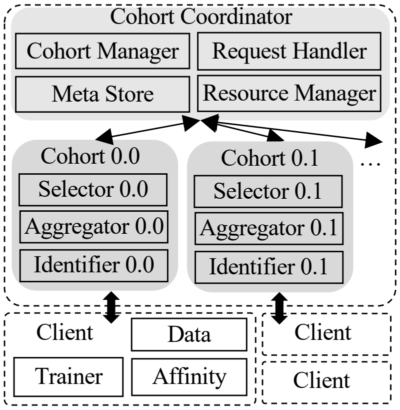


Figure 5. Auxo architecture. Auxo server guides Auxo clients to train on their best-fit cohorts.

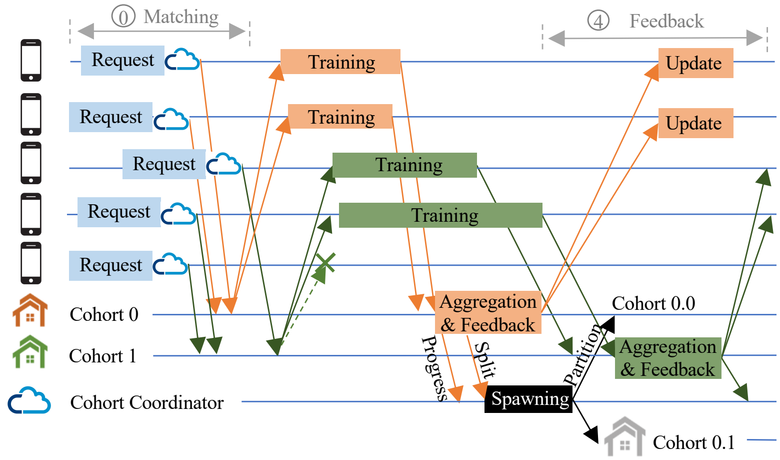


Figure 6. Auxo lifecycle. Clients first submit their affinity requests, which are then forwarded to the matched cohorts. Then each cohort conducts traditional FL training independently. Finally, each cohort reports back the results to guide clients' cohort selection.

ters. Furthermore, clients usually have limited on-board resources, but IFCA (Ghosh et al., 2020), FlexCFL (Duan et al., 2021), and FL+HC require extra computation to for *every* client and/or over time to assign them to a cluster, which incurs large computation and communication overhead. For example, IFCA initiates multiple global models and broadcasts all models for each participant to choose from in each round; and FlexCFL and FL+HC require pre-training for every client to identify their clusters.

Efficiency. In addition to the challenge of identifying statistically similar groups at scale, how to leverage those similar groups to improve model performance introduces new trade-offs in deciding the right number of cohorts and time to partition. Given a fixed amount of resources, generating more cohorts results in smaller heterogeneity; but it divides up the fixed training resource and unique training data per cohort, which hurts model convergence and generalizability. Moreover, partitioning clients too early can lead to model bias as the model is not generalized well by training on various clients, while partitioning too late can result in model variance over high heterogeneity. Unfortunately, most existing clustered FL algorithms are unaware of these tradeoffs, and rely on ad-hoc hyper-parameter tuning, which is prohibitively expensive as FL training can take many days and consume large amount of resources.

3 AUXO OVERVIEW

Auxo progressively reduces the intra-group heterogeneity and improves the model performance through cohort identification and cohort-based training toward practical FL. In this section, we introduce the cohort abstraction, provide an overview of how Auxo manages cohorts in a distributed fashion and fits into the FL life cycle.

3.1 Cohort Abstraction

Instead of training only one global model, Auxo trains a model separately for each group of FL clients that shares similar statistical data and model characteristics. We refer to each of these groups, which can perform independent FL training over more homogeneous clients than the overall population, as a *cohort* $C_m (m \in [1, M])$ with two associated properties:

- A cohort should hold a specialized model that targets data distribution with smaller intra-cohort heterogeneity.
- A cohort should have enough members $|C_m|$ to form a meaningful group and deliver the benefit of partition.

Traditional (i.e., cohort-agnostic) FL training has a single cohort with unbounded heterogeneity among the members.

3.2 Auxo Architecture

Auxo server consists of two primary components (Figure 5):

- A logically centralized **cohort coordinator** performs three main functions. First, it manages existing cohorts for fault tolerance. Second, it matches clients to their best-fit cohorts. Finally, it monitors the progress of cohort training and identification in order to decide cohort partition when it observes an opportunity for better model convergence .
- A set of **cohorts** each performs independent FL training. Each cohort contains traditional FL components such as aggregator and client selector. On top of traditional FL training activities, each cohort continuously identifies

its internal composition, reports its progress to the coordinator and waits for the partition instruction from the coordinator.

FL Lifecycle in Auxo As shown in Figure 6, following the traditional FL stages in Section 2.1, Auxo adds a matching stage ⓪ and a feedback stage ④ before and after the traditional round.

⓪ **Matching stage:** When checking in, clients using Auxo optionally include an affinity request (a hint about their cohort preference) to the cohort coordinator. If it took part in the training of one or more cohorts in the past, its preference is dependent on previous feedback. Otherwise, it has no preference. The cohort coordinator forwards the affinity request to the corresponding cohort based on its search algorithm and client's request.

① - ③ **Traditional FL stages:** Each cohort starts a traditional FL training round independently after continuously receiving its client requests from the cohort coordinator. These traditional stages include client selection, training execution, server aggregation, and so on.

④ **Feedback stage:** After the traditional FL round finishes, each cohort updates the affinity feedback for its current participants based on the Auxo clustering algorithm (§4). Then, each participant receives an affinity feedback – w.r.t. the cohort it trained with — and updates the corresponding affinity record for submitting requests in a future round of FL training. During this stage, each cohort also reports its training and identification progress to the cohort coordinator.

More details of systems implementation and distributed protocols are in Appendix B.

Resource management. Auxo jointly maximizes model convergence and resource efficiency in two ways. First, its scalable cohort identification algorithm does not require extra on-device computation and uses the same amount of resources as traditional FL algorithms(§4.1- §4.3). Second, it carefully chooses the number of cohorts and time to partition to theoretically guarantee better model convergence and generalizability despite each cohort having less training resources than the previous global model (§4.4).

Scalability and fault tolerance. Cohort management over a large scale population would incur tremendous storage, fault tolerance, and response time overhead. Thus, Auxo designs a soft-state server that offloads cohort-related information to individual clients in order to enable fate sharing – a failed client will only lose its own information. If the soft-state server fails, a restarted server only needs to load meta data from disk and receive all necessary information from the clients. We elaborate the design in Appendix B.1-B.3.

Threat model and robustness. Similar to the state-of-the-art production FL systems (Bonawitz et al., 2019; Huba et al., 2022), Auxo considers an *honest-but-curious* centralized server for aggregation, which can infer any information without interfering with the FL training. Auxo also assumes that most clients are honest, and only a small fraction can act maliciously under the control of a bad actor (Shejwalkar et al., 2021). We elaborate on how Auxo can provide robustness under this threat model along with some experiment results in Appendix B.3-B.4.

4 AUXO CLUSTERING

In this section, we present the core clustering algorithm used in Auxo to identify cohorts (§4.1- §4.3). Then, we discuss the techniques of cohort-based training to boost model performance under realistic constraints (§4.4).

4.1 Problem Formulation and Overview

Auxo's primary objective is to accurately cluster clients by their statistical heterogeneity into appropriate cohorts under the following real-world FL constraints: *a*) The participants $\mathcal{P}^r$ in each round are only a small fraction of all clients (N), i.e., $|\mathcal{P}^r| \ll N$, and *b*) The information available to today's FL central server is limited to gradients transferred by the existing FL algorithms.

The *input* to the server is a list of participants along with their gradients collected over training rounds based on these two constraints. Since the gradient of client i relies on its local dataset x_i and the received model weights (unique for the round r and cohort m), we formulate the *input* of the clustering algorithm in each round r as $\{\{g^r_m(x_i)\}_{i\in\mathcal{P}^r_m}\}_{m\in[1,M_r]}$, where $g^r_m(x_i)$ is the gradient of participant i , $\mathcal{P}^r_m$ is the participants list, and M_r is the number of cohorts.

The *output* is the cohort membership $\{S_i \in [1, M]\}$ for each client $i \in [1, N]$ with the *objective* to minimize the average intra-cohort heterogeneity:

$$J = \sum_{m=1}^{M} \frac{1}{2|\{x|S_x = m\}|} \sum_{S_i,S_j=m} ||x_i - x_j||^2. \tag{1}$$

Intuitively, we can model it as a clustering problem $\{x_1, ..., x_N\} \rightarrow \{S_1, ..., S_N\}$, whereas doing so encounters new challenges. *a*) How to derive client data similarity without direct access to data and without iterating all but part of the clustering objects every round. *b*) How to assign new incoming clients to the best-fit cohort without prior information.

Following this problem definition and challenge, Algorithm 1 illustrates the overview of Auxo clustering mechanism, which consists of an online cluster algorithm to cluster clients at scale (§4.2) and the cohort selection for individual

Algorithm 1 Auxo Clustering Algorithm

1: **Input:** Participants list $\mathcal{P}$, Exploration factor ϵ
2: **Output:** Client-cohort membership list $S_{\mathcal{D}}$
3: $M \leftarrow 1$; ▷ Initialize the number of cohorts.
4: $S_{\mathcal{D}} \leftarrow 0$; ▷ Initialize client-cohort membership.
5: $R_{\mathcal{D},M} \leftarrow 0$; ▷ Initialize client-cohort reward.
6: $L_{\mathcal{D},M} \leftarrow N/A$. ▷ Initialize client-cohort cluster id.
7: **for** each round $r = 1, 2, ...$ **do**
8: $\quad \mathcal{P}_m^r = \{i | S_i = m, i \in \mathcal{P}^r\}$
9: $\quad$ **for** each cohort $m = 1, ..., M$ in parallel **do**
10: $\quad\quad$ `Auxo-Clustering` $(\mathcal{P}_m^r)$
11: $\quad S_{\mathcal{D}} = \texttt{CohortSelection}(R_{\mathcal{D}}, \epsilon, r)$
12: **return** $S_{\mathcal{D}}$

Function `Auxo-Clustering`(Participants list$\mathcal{P}_m^r$)
▷ Identify clusters on the fly.
13: **if** $r == 1$ **then**
14: $\quad L_{\mathcal{P}_m^r, m} = \texttt{Kmeans}(g_m^r(x_{\mathcal{P}_m^r}), K)$.
15: **else**
16: $\quad \mathcal{P}_0 = \{i | L_{i,m} = 0, i \in \mathcal{P}_m^r\}$
17: $\quad \mathcal{P}_1 = \{i | L_{i,m} = 1, i \in \mathcal{P}_m^r\}$
18: $\quad C_0 = avg(g_m^r(x_{\mathcal{P}_0})), C_1 = avg(g_m^r(x_{\mathcal{P}_1}))$
19: $\quad L_{\mathcal{P}_m^r, m} = arg\min_k ||g_m^r(x_{\mathcal{P}_m^r}) - C_k||_2$
▷ Decide partitioning to start separate training.
20: **if** `PartitionCriteria`(m) **then**
21: $\quad M = M + 1$
22: $\quad R_{\mathcal{D},m} = R_{\mathcal{D},m} + 0.1 * \mathbb{1}(L_{\mathcal{D},m} == 0)$
23: $\quad R_{\mathcal{D},M} = R_{\mathcal{D},m} + 0.1 * \mathbb{1}(L_{\mathcal{D},m} == 1)$
▷ Update rewards for cohort selection.
24: **if** $M > 1$ **then**
25: $\quad R_{\mathcal{P}_m^r, m} = \texttt{ExploitReward}(R_{\mathcal{P}_m^r, m}, x_{\mathcal{P}_m^r})$
26: $\quad R_{\mathcal{P}_m^r, m'}$=`ExploreReward`$(R_{\mathcal{P}_m^r}, m')$, $\forall m \neq m'$

FL clients (§4.3).

4.2 Online Clustering

To derive client data similarity without direct access, Auxo leverages client gradient similarity to derive the client data similarity based on the theoretical insights from related works (Sattler et al., 2021; Sener & Savarese, 2018) under certain assumptions. Intuitively, gradient divergence can be attributed to data heterogeneity (Li et al., 2020a) and similar clients would have smaller gradient divergence, based on the *same* initial model weight. We leverage this observation and measure the gradient divergence by the widely-used cosine similarity (Xue et al., 2021) among the input batch of gradients $g_m^r(x_i), i \in \mathcal{P}_m^r$ to investigate client similarity.[3] We denote $g(\cdot)$ as the normalized gradient for simplicity of exposition.

To accommodate partial input to the clustering algorithm, Auxo represents the problem as a mini-batch clustering problem and clusters clients adaptively. However, traditional mini-batch clustering algorithms (Sculley, 2010) usually maintain a running center for each cluster, which is used to assign the incoming batch of points. However, this strategy cannot directly be applied to our problem because we only know the gradients $\{g_m^r(x_{\mathcal{P}_m^r})\}$ instead of the raw data $x_{\mathcal{P}}$. Moreover, since the gradient $g_m^r(\cdot)$ depends on the initial model of round r and client data, which is unknown and different across rounds and cohorts, it is hard to maintain absolute running centers over rounds. Hence, Auxo approximates the cluster centers based on the gradients from the current round – that is, it averages the gradients with known cluster membership from the cluster (Algorithm 1 Lines 16–18). Then, Auxo uses the approximated cluster centers to update the cluster membership for new clients.

Hence, Auxo starts with one cohort with the entire FL population and adaptively identify cohorts. After using K-means to initialize the cluster prototype (Line 14), during every round, Auxo first estimates cluster centers by averaging corresponding cluster members' gradient from the current round (Lines 16–18), and then assigns new clients to their closest cluster (Line 19). With repeated cluster updating and clients assignment, Auxo can identify the cohorts at scale.

Hierarchical Partitioning While online clustering enables us to identify the clusters, we need to partition the cohort sometime accordingly in order to start training specialized models separately. Partitioning in Auxo specifically means splitting a cohort into K cohorts to start training over their own members with smaller statistical heterogeneity. After partitioning, each new cohort starts with the parent cohort model weights with the same architecture, performs conventional FL steps separately, and converges to different model weights. The function `PartitionCriteria()` (Line 20) provides the decision to partition the cohort, which is determined by two trade-offs related to model performance in Section 4.4.

Since new clusters may be found after exploring more clients from the large-scale population, Auxo will keep identifying and partitioning newly-discovered cohorts through conducting the same algorithm as in function `Auxo-Clustering` (Line 12) independently.

4.3 Cohort Selection

Because FL often involves a large training population, more clients participate in model training for the first time than not. The cohort membership of a new client is unknown a priori. This is because Auxo neither has access to client data nor has absolute cohort centers that can inform a new client to choose the closest cohort. To address this, Auxo adopts an

[3] Cosine similarity measures the similarity between two vectors of an inner product space (Xue et al., 2021).

exploration-exploitation strategy to efficiently identify the cohort membership for new participants (Line 11). Given a new client, Auxo first randomly assigns it to a cohort. After getting the feedback on how well the client fits in that cohort, Auxo attempts to identify a more suitable cohort for it the next time it participates again.

Auxo uses reward-based decaying ϵ-greedy selection (Sutton & Barto, 2018) to help the client find the best-fit cohort (Line 11). With an aim to maximize the expected reward for each client, there is a $1-\epsilon$ probability of selecting a cohort with a maximum reward and a ϵ probability of selecting cohorts randomly, where $\epsilon \in [0, 1]$ is the exploration factor that decays over time. Intuitively, smaller gradient divergence compared to the members within the explored cohort means a better fit and gives a higher reward. Hence, Auxo calculates the relative divergence between the clients and the explored cohort center, which is estimated by averaging the client gradients belonging to the cohort $\mathcal{P}^r_{m,Known}$, to be $D = ||g^r_m(x_{\mathcal{P}^r_m}) - avg(g^r_m(x_{\mathcal{P}^r_{m,Known}}))||_2$. We then compare each client's relative gradient divergence with $avg(D) + b \cdot std(D)$ to show its relationship to the chosen cohort. Specifically, we quantify the instant reward to be $\Delta R = 1 - \frac{1}{avg(D)+b \cdot std(D)} D$, where the client with a negative ΔR would be considered as an outlier of the cohort. The choice of b depends on input gradient distribution and expected ratio of outliers, where Auxo empirically set $b = 1$. Then, Auxo updates the reward between each client and its explored cohort with a discounting factor γ as $R_{\mathcal{P}^r_m,m} = \gamma * \Delta R + (1-\gamma) * R_{\mathcal{P}^r_m,m}$.

Efficient cohort exploration. During exploration, there may exist multiple cohorts for a client to try out with. To improve the searching efficiency and save device training resources, during both training and deployment, Auxo enables a new client to perform a binary search to find the most appropriate cohort by predicting the rewards for other unexplored cohorts m' through function `ExploreReward()` (Line 26): $R_{\mathcal{P}^r_m,m'} \mathrel{+}= \frac{R_{\mathcal{P}^r_m}}{d(m,m')+1}, \forall m \neq m'$.

The intuition behind `RewardUpdate()` is that the client may perform similar to or receive similar rewards from the cohorts that are closer/similar to the previously explored ones, and vice versa. Thus, we first define the distance (d) between two cohorts to be the distance to their lowest common ancestral cohorts based on the hierarchical cluster relationship among cohorts. Given an explored cohort m and the reward ΔR_m for a participant, Auxo calculates the distance d and updates the rewards for unexplored cohorts to be inversely proportional to their distance. For example, if a client receives a negative reward for the chosen cohort, then he is more likely to explore another furthest cohort with higher reward given by `ExploreReward()` next time.

4.4 Cohort-Based Training

Training separate models for each cohort leads to a new trade-off between resource efficiency and model convergence. To understand the effect of client-level heterogeneity and training resources on model convergence, we analyze the rate of convergence for FedAvg (McMahan et al., 2016), which is the most widely used aggregation algorithm. As prior works have shown (e.g., Theorem 1 in SCAFFOLD (Karimireddy et al., 2020)), this convergence rate is largely dominated by heterogeneity, which suggests the promise of cohort-based training. However, as shown in Figure 3, generating more cohorts has diminishing returns: when the total training resource is constant, creating more cohorts leads to fewer resources for each individual cohort. In contrast, spawning too few can not reduce the intra-cohort client heterogeneity well. Therefore, Auxo must decide the right number of cohorts to find the sweet spot of better resource efficiency and model convergence.

We start by analyzing the relationship between heterogeneity and training resources in theory. Inspired by the convergence analysis of FedAvg in SCAFFOLD, we establish the following Lemma:

Lemma 1. *If the population and training resources are partitioned into up to K cohorts, to theoretically achieve better model convergence, intra-cohort heterogeneity should be reduced by $\sqrt{K}$ times when the training resource $|\mathcal{P}|$ is larger than $\alpha\sqrt{\frac{|\mathcal{P}_0|}{J_0^2}}$. α is a constant setting specified in SCAFFOLD that elaborates the relationship between model convergence and training resources.*

We elaborate more on the assumptions and proof of Lemma 1 in Appendix A. To this end, Auxo actively monitors the gradient divergence within each potential cohort to decide *the time of partitioning* and *the total number of cohorts to generate*. Based on Lemma 1, Auxo automatically decides to partition the population into up to K cohorts and equally allocates training resources to each cohort when it detects that the intra-cohort heterogeneity would reduce by $\sqrt{K}$ times. As a result, theoretically, model convergence can be benefited from cohort-based training in Auxo. As for some FL datasets with larger heterogeneity, FL developers can further improve model convergence by dynamically raising the resource budget to allow generating more cohorts.

Finally, as cohort partitioning may reduce the unique training data for each cohort model, the trade-off between model bias and variance can be affected by the time of partition. On the one hand, hard partitioning of the entire population at the beginning could reduce heterogeneity, but it could also reduce the amount of unique training data for each cohort model, leading to poor model generalizability. On the other hand, late partitioning exposes the model to diverse training data but leads to worse model variance due

Dataset	#Clients	#Samples
Google Speech (Warden, 2018)	2,618	105K
FEMNIST (Cohen et al., 2017)	3,400	640K
OpenImage-Easy	10,133	1M
OpenImage (OpenImg, 2018)	13,771	1.3M
Amazon Review (Keung et al., 2020)	42,031	2M
Reddit (Reddit, 2021)	63,058	5M

Table 2. Statistics of the six datasets in evaluation.

to high heterogeneity. These also guide the *reuse* of identified cohorts to facilitate other FL tasks. Auxo can naturally partition in appropriate times during training following the aforementioned technique to balance this trade-off. We report more results about the effect of partition time on model convergence in Section 6.4.

5 IMPLEMENTATION

We have implemented Auxo as an independent Python library ($1,664$ lines) to serve existing FL frameworks (e.g., TFF (tff, 2018) and PySyft (pys, 2019)), and integrated it with FedScale (Lai et al., 2022) for evaluations. Auxo abstracts away the cohort identification and partition so that FL developers can easily try out their FL algorithms or datasets on top of Auxo without any modifications.

Auxo's implementation consists of the three components described in Section 3: The cohort coordinator manages and spawns cohort processes, which initiate FL training tasks. Clients continuously submit their training requests based on their availability and affinity records. Then, the cohort coordinator takes client training requests as input and forwards the requests to corresponding cohorts. Each cohort process conducts conventional FL training with the assigned available clients independently. At the end of each individual round, the Auxo clustering algorithm runs within every cohort and reports clustering results to each participant over the network. All training metadata and model weights are checkpointed periodically for fault tolerance. Meanwhile, the cohort coordinator continuously monitors the progress of cohorts for resource management and failure recovery.

6 EVALUATION

We evaluate Auxo's effectiveness for six different ML tasks as well as different choices of FL algorithms. Our evaluation shows the following key highlights:

- Auxo speeds up model convergence on different FL datasets up to 2.2×, while improving final test accuracy by 3.4%-8.2%.
- Auxo cooperates with existing FL efforts (e.g., personalization) and boosts final test accuracy by 2.1%–6.7%.
- Auxo can mitigate model bias across devices by 19% on average and improve resource efficiency.
- Auxo outperforms existing clustered FL algorithms up to 4.8× in terms of time and 5.2× in terms of resources.
- Auxo performs well across a broad range of its parameter settings.

6.1 Experiment Setup

Evaluation environment We use 24 NVIDIA Tesla P100 GPUs on CloudLab (Duplyakin et al., 2019) to emulate the large-scale client training in our evaluations. The client data distribution follows the real-world partition, where client data can vary in quantities, data, and label distribution. We use an open-source benchmark (Lai et al., 2021; 2022) with standardized setup and report the simulated wall clock time by relying on realistic FL system and data traces, including the FedScale device availability and device speed trace in simulating FL client behaviors.

Datasets and models We run three categories of applications with six FL datasets (Lai et al., 2022) of different scales using real-world partitions, whose statistics are reported in Table 2. Each of the dataset has realistic data partition among clients. *a*) *Speech Recognition*: We train Resnet-34 (He et al., 2016) on a small-scale Google Speech dataset with 35 types of commands. *b*) *Image Classification*: We train Resnet-18 on small-scale FEMNIST with 62 handwritten digits to classify. Also, we train ShuffleNet (Zhang et al., 2018) and MobileNet (Sandler et al., 2018) on middle-scale OpenImage with 596 classes to classify, whereas OpenImage-Easy only has 60 classes. *c*) *Language Modeling*: We train logistic regression on middle-scale Amazon Review to predict review ratings, and Albert model (Lan et al., 2020) on large Reddit for word prediction.

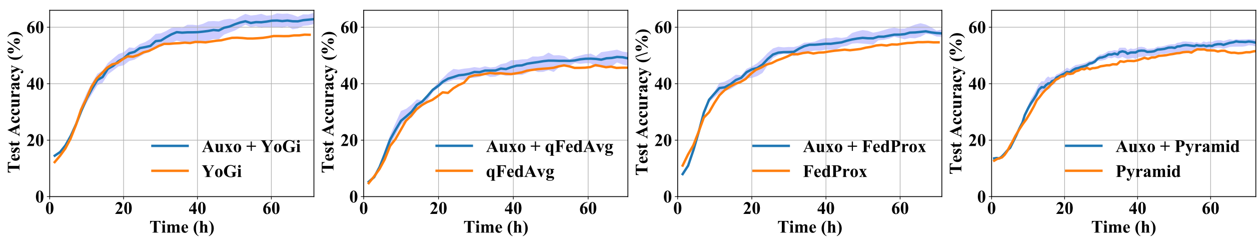
These applications are widely used in real end-device applications (Xu et al., 2018), and these models are lightweight.

Parameters We follow the standardized experiment and parameter settings in FedScale. We adopt an overcommitment strategy to mitigate stragglers which allow 25% failures or stragglers every round as in real FL deployments (Bonawitz et al., 2019). We set the number of participants per round to be 200, the local minibatch size to be 6, and the initial learning rate to be 4e-5 for the Albert model, and 0.05 for other models. And we use the linear scaling rule (Goyal et al., 2017) to scale the learning rate after partition.

Metrics The *time-to-accuracy* performance, *final test accuracy*, and *model bias* are our key metrics. We use the cohort member's test data, which follows the realistic data partition, to evaluate each cohort model. The test data would be the global test data if we end up with one global model. For each experiment, we report the average top-1 accuracy based on the results over 3 runs.

Task	Dataset	Model	Target Acc.	Auxo Speedup	Auxo Acc. Impr.
Image Ccalassification	FEMNIST	ResNet-18	82.2%	1.2×	7.3%
	OpenImg	MobileNet	56.5%	1.3×	4.8%
		ShuffleNet	58.2%	2.2×	5.0%
	OpenImg-Easy	MobileNet	65.4%	1.4×	3.4%
		ShuffleNet	64.8%	1.2×	4.4%
Language Modeling	Amazon Review	Logistic Regression	65.3%	1.2×	8.2%
	Reddit	Albert	7 perplexity	1×	0 perplexity
Speech Recognition	Google Speech	ResNet-34	78.5%	1.5×	5.7%

Table 3. Summary of improvements on time to accuracy. We tease apart the overall improvement with statistical and system ones, and take the highest accuracy that YoGi can achieve as the target, which is moderate due to the high task complexity and lightweight models.



(a) Yogi (b) q-Fedavg (c) FedProx (d) PyramidFL + YoGi

Figure 7. Auxo with different FL algorithms.

6.2 End-to-End Performance

Auxo's performance on different datasets. We first evaluate Auxo's performance on different real-world FL datasets. In the following experiments, we adopt YoGi as the FL algorithm because it outperforms other FL algorithms most of the time. Table 3 summarizes the key time-to-accuracy performance of all datasets. We quantify the time-to-accuracy as speedup by Auxo, which measures how many times Auxo can speed up to achieve the target accuracy compared to the baseline time cost. In Appendix C.1, Figure 12 reports the timeline of training to achieve different accuracy, as different cohorts perform FL asynchronously.

We notice that Auxo speeds up the wall-clock time to reach target accuracy up to 2.2× faster. Moreover, the final accuracy for different datasets is improved by 3.4%–8.2%. The benefit of Auxo varies over datasets. For most of the datasets, Auxo can achieve significant final accuracy improvement. Nevertheless, Auxo does not improve Reddit task because the clients' texting behavior is similar to each other that makes it hard to identify significant groups as shown in Figure 3. In order to maximize the benefit of clustering in FL training, Auxo decides not to partition into multiple cohorts as a result.

Auxo's performance on different FL algorithms. We then evaluate Auxo's performance on ShuffleNet-OpenImage with different FL Algorithms, which are complementary to Auxo. We refer to YoGi running atop Auxo as YoGi+Auxo, and similarly for FedProx, q-FedAvg and PyramidFL+YoGi.

As shown in Figure 7, Auxo speeds up the time to reach the target accuracy of baseline algorithms, from 1.2× to 2.2× faster and improve the final test accuracy by 3%–6.8%.

As for the personalization algorithm FTFA, we adopt the cohort models generated by Auxo to conduct local training using FTFA on corresponding cohort members. In addition to faster convergence of the initial model, Auxo also improves the average test accuracy of FTFA from 63.18% to 67.40% with local fine-tuning.

Auxo's benefit on model bias. We show that Auxo can also mitigate the model bias due to smaller intra-cohort statistical heterogeneity. We report the variance of the final accuracy distributions, the worst and best 10% test accuracy in Appendix C.2 Table 5. Our experiment show that the variance of test accuracy is decreased across all devices for all the datasets by 19% on average.

Auxo's benefit on resource efficiency. We finally show that Auxo can optimize resource efficiency on OpenImg dataset by saving 55% training resources. We also account for the affinity maintaining overhead into the client resource usage, which is around 0.02% of the total resource consumption. As shown in Figure 8, Auxo achieves higher resource efficiency about 2.2× over baseline.

6.3 Clustered FL Comparison

We compare Auxo with four existing clustered FL algorithms CFL, FL+HC, FlexCFL, and IFCA in terms of three metrics: time-to-accuracy, resource-to-accuracy, and final accuracy. Since these algorithms do not meet some real-world FL constraints (Table 1), we simplify the settings

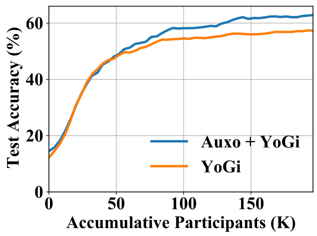
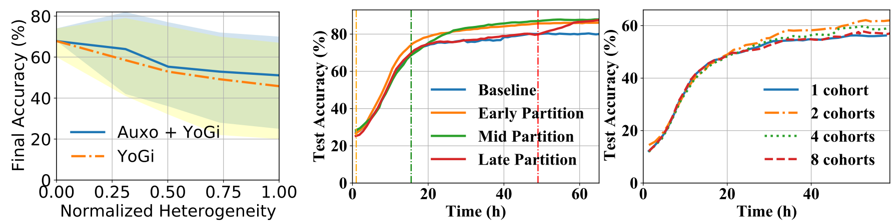


Figure 8. Resource Efficiency.



(a) Different degrees of heterogeneity. (b) Different partition time (FEMNIST). (c) Different number of cohorts (OpenImg).

Figure 9. Sensitivity analysis.

		FL+HC	FlexCFL	IFCA	Auxo
FEMNIST	Speedup	1.7×	1.3×	0.5×	2.4×
	Efficiency	1.6×	1.8×	0.5×	2.4×
	Final acc.	5.8%	7.1%	1.3%	9.1%
Amazon Review	Speedup	0.4×	0.4×	0.5×	2.3×
	Efficiency	0.4×	0.5×	0.5×	2.1×
	Final acc.	-2.9%	-2.7%	0.6%	5.4%

Table 4. Summary of improvements over baseline (i.e., no cohorts) in terms of time, resource and accuracy.

accordingly.

We compare with CFL in small-scale settings ($\sim$ 100 clients) from the FEMNIST dataset to meet their full participation assumption. We observe little difference between CFL, Auxo, and baseline (i.e., no cohorts) in terms of time and resources used due to the absence of significant clusters within small populations. However, this highlights the need for large-scale FL settings, where CFL cannot even be applied as it does not support partial participation.

To compare with FL+HC, FlexCFL and IFCA, we conduct experiments with the full FEMNIST and Amazon Review datasets *without* the client availability traces to align with their constraints. As shown in Table 4 and Appendix C.3, Auxo achieve better time efficiency $1.4\times - 4.8\times$ and better resource efficiency $1.3\times - 4.8\times$ compared to the related works especially for the large-scale Amazon dataset, due to our efficient and scalable algorithm design. Also, our result for IFCA are consistent with Motley (Wu et al., 2022).

6.4 Sensitivity Analysis

Impact of different degrees of heterogeneity. We generate different statistical heterogeneity by applying affine shift (Reisizadeh et al., 2020) on OpenImage, then we evaluate Auxo with YoGi across different degrees of statistical heterogeneity. Figure 9a reports the final test accuracy as well as top 10% and worst 10% client test accuracy on different degrees of heterogeneity. We observe that Auxo can improve model accuracy and mitigate model bias under different degrees of heterogeneity. Moreover, similar to the previous experiment, Auxo achieves faster time-to-accuracy performance from $1.2\times$ to $1.8\times$.

Impact of time to partition. We investigate the impact of different cohort partition time on the model convergence. As mentioned in Section 4.4, the partition time relates to the trade-off between model generalizability and intra-cohort heterogeneity. As shown in Figure 9b, we choose different partition times with the same cohort composition and report the test accuracy to time performance on FEMNIST. We observe that cohort-based training all outperform the baseline experiment with one cohort. However, early partition as FlexCFL and IFCA is worse than intermediate partition, because it sacrifices the model generalizability. Similarly, late partition after convergence as CFL does not outperform intermediate partition, because it slows down the model convergence to a smaller heterogeneous population.

Impact of the number of cohorts. We investigate the impact of the number of cohorts generated by Auxo, which relates to the trade-off between training resources and intra-cohort heterogeneity (§4.4). As shown in Figure 9c, we observe that the model convergence is negatively affected once the number of cohorts exceeds 4 under the same resource budget. By further comparing the reduce of heterogeneity with different number of cohorts indicated in Figure 3, this result verifies that better model convergence can be achieved as long as the heterogeneity can proportionally compensate the reduced training resources

7 CONCLUSION

In this paper, with the observation of the natural groups among real-world FL clients, Auxo identifies cohorts with reduced intra-cohort heterogeneity at scale, which addresses the root cause of FL challenges. Auxo proposes an efficient algorithm and practical system that can be applied under real-world FL constraints to maximally benefit the FL training in terms of model convergence, final accuracy, and model bias.

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A Proof of Lemma 1

We first make precise some definitions that are related to the proof from SCAFFOLD and then see the proof of Lemma 1.

A.1 Additional definitions

Assumption 1. $g_i(w)$ is unbiased stochastic gradient of f_i with bounded variance, where f_i represents the loss function on client i.

$$\mathbb{E}_{x_i}[||g_i(w) - \nabla f_i(w)||^2] \leq \sigma^2, \forall i, x.$$

where w is the aggregated server model. Note that σ only bounds the variance within clients not across clients.

Assumption 2. $\{f_i\}$ are β-smooth and satisfy:

$$||\nabla f_i(w) - \nabla f_i(v)|| \leq \beta ||w - v||, \forall i, w, v.$$

Assumption 3. f_i is μ-convex for $\mu \geq 0$ and satisfies:

$$\langle \nabla f_i(w), v - w\rangle \leq -(\nabla f_i(w) - \nabla f_i(v) + \frac{\mu}{2}||w-v||^2), \forall i, w, v.$$

Assumption 4. (G, B)-BGD or Bounded Gradient Similarity: there exist constants $G \geq 0$ and $B \geq 1$ such that

$$\frac{1}{N}\sum_{i=1}^{N} ||\nabla f_i(w)||^2 \leq G^2 + B^2 \nabla f(w)), \forall w.$$

A.2 Theoretical Results

Lemma 1. If the population and training resources are partitioned into up to K cohorts, to theoretically achieve better model convergence, intra-cohort heterogeneity should be reduced by $\sqrt{K}$ times when the training resource $|\mathcal{P}|$ is larger than $\alpha\sqrt{\frac{|\mathcal{P}_0|}{J_0^2}}$. α is a constant setting specified in SCAFFOLD that elaborates the relationship between model convergence and training resources.

Proof. We first borrow the proof of convergence analysis on FedAvg (Theorem 1) from SCAFFOLD following the same assumptions mentioned above:

$$\mathbb{E}[f(w^R)] - f(w^*) \leq 3||w^0 - w^*||^2 \mu e^{-\frac{\widetilde{\eta}}{2}R}$$
$$+\widetilde{\eta}(\frac{2\sigma^2}{kP}(1 + \frac{P}{\eta_g^2}) + \frac{8G^2}{P}(1 - \frac{P}{N})) + \widetilde{\eta}^2(36\beta G^2),$$
$$\forall \frac{1}{\mu R} \leq \widetilde{\eta} \leq \frac{1}{8(1+B^2)\beta}$$

where P denotes the training resources, k is the number local steps, η_l is the local step-size, η_g is the global step-size and $\widetilde{\eta} = k\eta_l\eta_g$ is the effective step-size

Since we only care about the effect of training resources P and heterogeneity G on the convergence analysis, we further simplify the right hand side equation to be

$$h(P, G) = \frac{\theta}{P} + \gamma\frac{G^2}{P} + \rho G^2 + \xi$$

where θ, γ, ρ and ξ are constant settings. Since we proportionally partition the population and training resources, we can assume $(1 - \frac{S}{N})$ to be constant before and after partition.

In order to have no worse model convergence bound after partitioning, we need $h(P, G)$ to be non-increasing with the reduce of training resources P. As proposed in Lemma 1, Auxo partitions K cohorts when the intra-cohort heterogeneity can be reduced by $\sqrt{K}$ times, which approximately give $\frac{G^2}{P}$ be constant as the one before partition $\frac{G_0^2}{P_0}$. By substituting this relationship into $h(P, G)$, we can derive the lower bound for the range of training resources required to achieve better convergence bound:

$$P \geq \sqrt{\frac{\theta P_0}{G_0^2 \rho}} = \sqrt{\frac{\sigma^2}{18k\widetilde{\eta}^2\beta}\frac{P_0}{G_0^2}} = \alpha$$

B Auxo System Design

In this section, we discuss how to design a scalable and robust system on top of the clustering algorithm under real-world challenges.

B.1 Distributed Implementation of Cohort Clustering

As the scale of training grows, the server faces more server challenges for tremendous storage, fault tolerance, and response time in order to maintain the cohort information. Thus, Auxo designs a solution to use a soft-state server that offloads cohort-related information to individual clients to mitigate the challenges. In this subsection, we describe how to implement the proposed clustering algorithm in a distributed fashion, while achieving the same objective.

Firstly, we introduce *affinity message*, which is a lightweight message containing all necessary state information needed to identify cohorts in a distributed fashion. Affinity message consists of two pieces of information between a client and a cohort to enable efficient state transmission: (*Reward* $R \in \mathbb{R}$, *Cluster index* $L \in [0, K)$). The *reward* implies how well the client fits for this cohort. The *cluster index* expresses the client's cluster membership within this cohort and is used to indicate its future cohort index.

Through exchanging affinity messages between different components, Auxo encourages similar clients to collaborate more in a distributed fashion. As shown in Figure 10, we next describe (a) how a cohort informs its relationship with its participants, (b) how clients request for their preferred

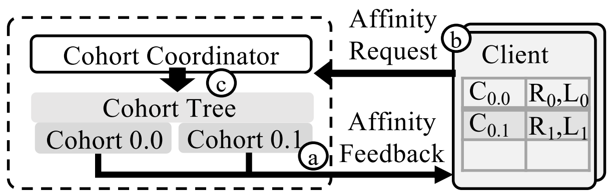


Figure 10. Scalable Design Overview **a.** Cohort affinity feedback. **b.** Client affinity request. **c.** Cohort coordinator request match.

cohort based on the affinity feedback and ⓒ how the cohort coordinator matches different requests.

Affinity Feedback At the end of each round, every cohort computes the affinity feedback to inform participants about their relationship with the cohort. These affinity feedback correspond to the clustering results returned by Algorithm 1 Line 8 (reward R) and Line 19 (cluster index L). These clustering results would be sent back to the participants respectively in the format of affinity messages, which informs the participant about whether the cohort is a good fit and which sub-cohort to select after partitioning.

Client Reaction After receiving the affinity feedback from the cohort, the client would update its affinity records itself based on the equation in Algorithm 1 Line 25- 26 and copy the cluster index directly. Following the same decaying $\epsilon-$greedy selection method (§4.3), clients select the cohort to train by themselves. Then, clients ready to participate would submit the corresponding affinity request to the cohort coordinator.

Request Match After receiving the affinity request, the cohort coordinator matches each client to the cohort it requests. Note that only the leaf cohort in the cohort tree would be returned as it conducts actual FL training inside. However, sometimes the requested cohort may not be the leaf cohort because some clients may not be aware of the cohort partitioning, which is not yet transparent to all clients. Thus, the cohort coordinator should assist clients to select their best-fit cohort through finding the closest leaf cohort indicated by the requested cohort and cluster index in the affinity message.

After finding a proper cohort, cohort coordinator would forward this affinity request to the corresponding cohort to initiate traditional FL rounds. Moreover, these forwarded affinity requests provide each cohort with all necessary input to conduct the clustering algorithms. Thus, after receiving the gradients from its participants, each cohort is able to run the Algorithm 1 independently to compute the aforementioned affinity feedback.

B.2 Fault Tolerance

Auxo enables fast recovery to minimize the impact on the model training. Upon a cohort process failure in the server, the cohort coordinator spawns a new cohort process. The new cohort loads the model from the latest checkpoint and restarts the incomplete round.

If the cohort coordinator fails, cohort processes would continue their current independent FL training and wait until a new cohort coordinator to be re-spawned. Clients checking in within that recovery period would be ignored.

Finally, Auxo is resilient to client failures just like traditional FL by design. Most client failure handlers, which are orthogonal to Auxo, can be applied directly. In addition, a failed client, who may lose its own affinity records, would restart exploring again. We empirically show that Auxo can tolerate a certain amount of such client failures while continuing to benefit the FL training (§B.4).

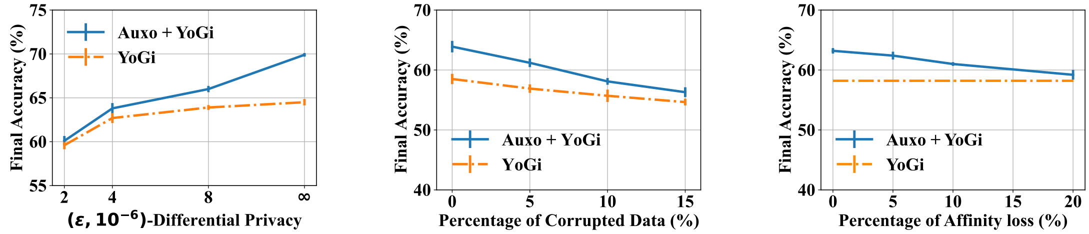
B.3 Robustness

Based on Auxo's threat model, Auxo can naturally cooperate with some existing privacy-preserving approaches (Erlingsson et al., 2014; McMahan et al., 2018; Minto et al., 2021) to address potential threats from both the server and clients. To handle the honest-but-curious server, Auxo can be used with local differential privacy (LDP), which is used to provide user-level privacy guarantees. Since differential privacy is immune to post-processing (Dwork & Roth, 2014) and Auxo's clustering is post-processing, Auxo incurs no additional privacy loss.

To handle a small fraction of unreliable clients (Bagdasaryan et al., 2020; Biggio et al., 2012), Auxo can be used with existing adversary-resilient solutions (Chen et al., 2019; So et al., 2020). For Auxo-specialized adversaries, such as fake affinity requests, Auxo detects anomalies by comparing its position in the cluster with its claimed affinity (Algorithm 1 Line 8). For example, if a client claims high reward but is actually far away from the cohort center, Auxo will detect and blacklist it. In Appendix B.4, we empirically evaluate Auxo's robustness under these scenarios.

B.4 System Assessment

Impact of differential privacy. Auxo is robust to local differential privacy (LDP). LDP is used to protect user-level privacy by adding Gaussian noise to the client update before sending it to the server, but it hurts model accuracy. We evaluate Auxo's performance under LDP for a learning task on the Amazon Review dataset. To achieve (ϵ, δ)-differential privacy, where $\delta = 10^{-6}$ based on the training scale and $\epsilon = 2, 4, 8$, we set the noise scale $\sigma = 1.0, 0.77, 0.6$. As shown in Figure 11a, Auxo can still benefit FL training



(a) Local DP. (b) Corrupted client. (c) Client affinity loss.

Figure 11. Robustness of Auxo under different scenarios.

across different differential privacy guarantees.

Impact of malicious attacks. We investigate the robustness of Auxo by manually involving corrupted clients. Following a popular adversarial ML setting that introduces local model poisoning (Fang et al., 2020), we randomly flip the ground-truth data labels for these corrupted clients. As shown in Figure 11b, we introduce different percentages of corrupted clients to the OpenImg task. We set the percentage of corruption below 15%, which is a practical percentage under the real-world setting (Fang et al., 2019). We observe that Auxo still improves performance across different degrees of corruption through identifying malicious clients and eliminating their interference.

Impact of unstable client. Finally, we show Auxo is robust with unstable clients who fail to maintain their affinity records, which may result in less accurate clustering results. We consider loss rates from 0% to 20% and report the corresponding final test accuracy in Figure 11c. We notice Auxo outperforms the baseline across different affinity loss rates.

C Additional Experiment Results

C.1 Auxo End-to-End Performance Plot

Figure 12 reports the timeline of training to achieve different accuracy, as different cohorts perform FL asynchronously. The shaded portion covers the test accuracy among all cohorts generated by Auxo.

C.2 Auxo Benefit on Model Bias

We show that Auxo can also mitigate the model bias, as the model bias is partially raised by the statistical heterogeneity, which is mitigated within cohorts.

Dataset	Setting	Worst 10% (%)	Best 10% (%)	Variance
OpenImg	Auxo	38	83	267
	Baseline	34	79	296
OpenImg -Easy	Auxo	38	88	234
	Baseline	33	84	273
Review	Auxo	50	100	460
	Baseline	32	100	995
FEMNIST	Auxo	63	97	171
	Baseline	60	93	185
Speech	Auxo	57	100	479
	Baseline	52	100	503

Table 5. Summary of improvements on model bias.

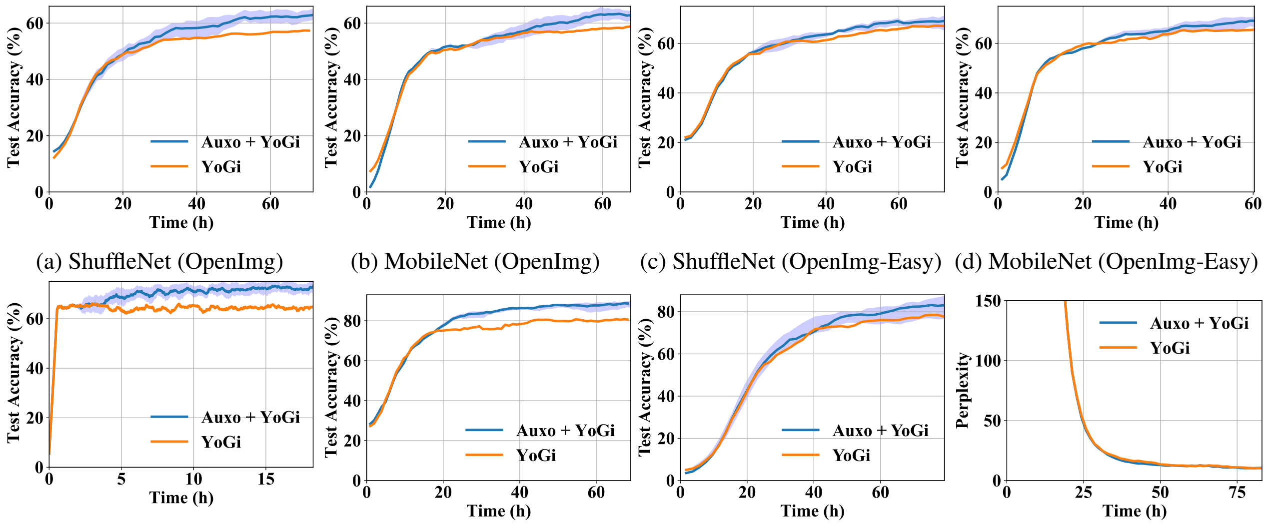
C.3 Clustered FL Comparison

We compare Auxo with related clustered FL works in terms of time-to-accuracy, resource-to-accuracy, and final accuracy performance using FEMNIST and Amazon dataset. As shown in Figure 13, Auxo achieve better time efficiency $1.4\times - 4.8\times$ and better resource efficiency $1.3\times - 4.8\times$ needed to reach the target accuracy.

D Related Work

Distributed Machine Learning Distributed ML in data centers has been well-studied (Mai et al., 2020; Narayanan et al., 2019; Yu et al., 2021), where homogeneous data and workers are assumed (Gu et al., 2019). With the same training goal, FL raises its unique challenges including the data heterogeneity and system heterogeneity. As a result, Auxo aims at speeding up the training process through directly reducing the intra-cohort heterogeneity at scale.

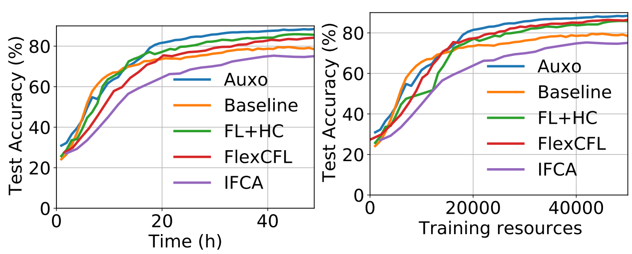
Federated Learning FL is a distributed machine learning paradigm (Bonawitz et al., 2019; Kourtellis et al., 2020) with two key challenges: statistical and system heterogeneity. State-of-the-art FL algorithms try to tackle these two challenges and optimize different targets including model convergence (Reddi et al., 2021; Li et al., 2020a; Lai et al., 2021; Zhao et al., 2022), fairness (Li et al., 2021; 2020b), privacy (Bonawitz et al., 2017; Roth et al., 2021; 2019; 2020), efficiency (McMahan et al., 2017; Guo et al., 2021; Alistarh et al., 2016), and robustness (Li et al., 2021). However, they underperform in FL because they do not tackle the root cause of FL challenges but mitigate the negative effect caused by heterogeneity.



(a) ShuffleNet (OpenImg) (b) MobileNet (OpenImg) (c) ShuffleNet (OpenImg-Easy) (d) MobileNet (OpenImg-Easy)

(e) Logistic Regression (Amazon) (f) ResNet (FEMNIST) (g) ResNet (Google Speech) (h) Albert (Reddit)

Figure 12. Time-to-Accuracy performance on different dataset. For the language modeling (LM) task, a lower perplexity is better. The solid line reflects the average test accuracy. The shaded portion covers the test accuracy performance among all cohorts generated by Auxo.



(a) Accuracy-Time (FEMNIST) (b) Accuracy-Resource (FEMNIST)

Figure 13. Comparison with clustered FL works.

Federated Analytics There has been significant work on geo-distributed data analytics (Hsieh et al., 2017; Lai et al., 2018; Viswanathan et al., 2016; Pu et al., 2015). They mainly optimize the execution latency (Lai et al., 2020) and resource efficiency (Wu et al., 2013; Hou et al., 2018). To further preserve privacy for distributed data, Orchard (Roth et al., 2020) and Honeycrisp (Roth et al., 2019) have been proposed to enable large-scale differentially private analytics. Helen (Zheng et al., 2019) and Cerebro (Zheng et al., 2021) allow multiple parties to securely train models without revealing their data.

Traditional Clustering Algorithms Clustering algorithms (Xu & Wunsch, 2005; Berkhin, 2006) are used in popular data mining techniques, which usually assume access to all data. However, under FL setting, it is non-trivial to design a clustering algorithm because of the unavailability of data. Auxo proposes a clustering algorithm that can be applicable to the FL settings.

FL Client Clustering In order to leverage the nature of clusters in real-world FL dataset, many algorithms have been proposed to identify the clusters among FL clients. However, existing clustered FL solutions (Sattler et al., 2021; Ghosh et al., 2020; Briggs et al., 2020; Duan et al., 2021) mainly suffer from scalability and practicality, which are hard to adapt to large-scale, low-participation, and resource-constraint FL training. Considering all real-world constraints, Auxo build a practical system to identify cohorts and benefit FL training.