ODE: A Data Sampling Method for Practical Federated Learning with Streaming Data and Limited Buffer

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Machine learning models have been deployed in mobile networks to deal with the data from different layers to enable automated network management and intelligence on devices. To overcome high communication cost and severe privacy concerns of centralized machine learning, Federated Learning (FL) has been proposed to achieve distributed machine learning among networked devices. While the computation and communication limitation has been widely studied in FL, the impact of on-device storage on the performance of FL is still not explored. Without an efficient and effective data selection policy to filter the abundant streaming data on devices, classical FL can suffer from much longer model training time (more than $4 \times$) and significant inference accuracy reduction (more than 7%), observed in our experiments. In this work, we take the first step to consider the online data selection for FL with limited on-device storage. We first define a new data valuation metric for data selection in FL: the projection of local gradient over an on-device data sample onto the global gradient over the data from all devices. We further design ODE, a framework of Online Data sElection for FL, to coordinate networked devices to store valuable data samples collaboratively, with theoretical guarantees for speeding up model convergence and enhancing final model accuracy, simultaneously. Experimental results on one industrial task (mobile network traffic classification) and three public tasks (synthetic task, image classification, human activity recognition) show the remarkable advantages of ODE over the state-of-the-art approaches. Particularly, on the industrial dataset, ODE achieves as high as $2.5 \times$ speedup of training time and 6% increase in final inference accuracy, and is robust to various factors in the practical environment.

1 INTRODUCTION

The next-generation mobile computing systems require effective and efficient management of mobile networks and networked devices in various aspects, including resource provisioning [10, 30], capacity planning [54], security and intrusion detection [4, 11], quality of service guarantee [16, 21], and performance monitoring [44]. Analyzing and controlling such an increasingly complex mobile network with traditional human-in-the-loop approaches [60] will not be possible any more, due to the low-latency requirement [69], massive real-time data and complicated correlation among the data [3]. For example, in network traffic measurement and analysis, a fundamental task in mobile networks, devices such as routers and Optical Network Terminals (ONTs) can receive/send as many as 5000 traffic packets ($\approx 5MB$) per second, which are expected to be associated with various real-time tasks, such as application identification [75], anomaly detection [11] and congestion control [28]. It is impractical to manually analyze such a huge quantity of high-dimensional data within the time scale of milliseconds. Thus, machine learning (ML) models have been widely applied to discover pattern behind high-dimensional networked data, enable data-driven network control, and fully automate the mobile network operation [7, 8, 62, 84].

Despite that ML model overcomes the limitations of human-in-the-loop approaches, its good performance highly relies on the huge amount of high quality data for model training [9, 22], which is hard to obtain in mobile networks as the data is resided on heterogeneous networked devices in a distributed manner. On the one hand, an on-device machine learning model trained locally with limited data and computational resource is unlikely to obtain desirable inference accuracy and generalization ability [86]. On the other hand, directly transmitting data from distributed networked devices to a cloud server for centralized model training will bring prohibitively high...
communication cost and severe privacy concerns [47, 51]. Recently, federated learning (FL) [55] emerges as a distributed privacy-preserving machine learning learning paradigm to resolve the above concerns, which allows networked devices to upload local model updates instead of raw data and a central server to aggregate these local models into a global model, solving the on-device data limitation, communication bottlenecks and potential privacy leakage, simultaneously.

**New Problem.** For applying FL to mobile networks, we identify two unique and important properties of networked devices: limited on-device storage and streaming networked data, which have not been fully considered in the FL literature. (1) Limited on-device storage: due to the hardware constraints, mobile devices have restricted storage volume for each mobile application and service, and can reserve only a small space to store data samples for ML model training without compromising the quality of other services. For example, most smart home routers have only 9-32MB storage to support various kinds of services [1], such as buffering packets awaiting transmission and storing configuration information for routing protocols, and thus only tens of training data samples can be stored. (2) Streaming networked data: data samples are generated/received by mobile devices in a streaming manner, and we need to make online decisions on whether to store each received data. Within this circumstance, the training data stored locally can be dynamic with time.

**Motivation and Formulation.** Without a carefully designed data selection policy to maintain the data samples in storage, the empirical distribution of the stored data could deviate from the true underlying data distribution and contain low-quality or noisy data, which further complicates the notorious problem of not independent and identically distributed (Non-IID) data distribution in FL [40, 51, 88]. Specifically, the naive random data selection policy significantly degrades the performance of classical FL algorithms in both model training and inference processes, with more than 4× longer training time and 7% accuracy reduction, observed in our experiments with an industrial network traffic classification dataset shown in Figure 1. This is intolerable in modern mobile computing systems: because the longer training time reduces the timeliness as well as effectiveness of the ML models in dynamical network environments, and inference accuracy reduction results in failure to guarantee the quality of service [81], incurs extra operational expenses [5] as well as security breaches [6, 70] and etc. Therefore, a fundamental problem when applying FL to mobile network is how to filter valuable samples from the streaming data on device to simultaneously accelerate model training convergence and enhance inference accuracy of the final global FL model?

**Design Challenges.** The design of such an online data selection framework for FL with limited on-device storage involves three key challenges:

1. **There is still no theoretical understanding about the impact of local on-device data on the training speedup and accuracy enhancement of global model in FL.** Due to the lack of information about raw data and local model updates of the other devices, it is challenging for a specific device to derive
the impact of one individual local data sample on the performance of the global model, which is an aggregation of all the devices’ local models in FL. Furthermore, the sample-level correlation between convergence rate and model accuracy is undiscovered and complicated in FL. Due to the data heterogeneity across devices, the impacts of local data samples on convergence rate and model accuracy could be quite different, and thus it is hard to simultaneously guarantee these two aspects through optimizing a unified data valuation metric.

(2) The lack of multiple dimensional information significantly complicates the online data selection in FL. For streaming networked data, we could not access the data samples coming from the future or discarded in the past, which we call as temporal information. With the lack of temporal information, one device is not able to leverage the complete statistical information (e.g. unbiased local data distribution) for accurate data quality evaluation\(^1\), such as outliers detection and noise removal \([48, 67]\). Additionally, due to the distributed paradigm of FL, one specific device has only local view, and cannot conduct efficient and effective online data selection without the knowledge of the other devices’ stored data and local models, which we call as spatial information. This is because the valuable data samples selected locally by different devices could be overlapped with each other and then the local valuable data may not be the global valuable one, which distorts the distribution of training data collected by all the devices.

(3) The on-device data selection needs to be low computation-and-memory-cost due to the conflict of limited hardware resources and requirement on QoE (Quality of user Experience) guarantee. As the additional computation and memory costs introduced by online data selection process influence the performance of mobile systems as well as user experience, the real-time data samples must be evaluated in a computation and memory efficient way. However, the streaming data and complex ML model structure raise several difficulties to achieve this goal. The streaming format of on-device data reduces the parallelism of GPU and CPU and increases per-sample evaluation delay. The complex ML model structure with large-scale parameters leads to high computational complexity and memory footprint for storing intermediate model outputs during the data selection process.

Limitations of Related Works. The prior works on data evaluation and selection in ML failed to solve the above challenges.

(1) The data selection in centralized ML, such as leave-one-out test \([20]\), Data Shapley \([29]\) and Importance Sampling \([53, 63, 68, 71]\), is not appropriate for online data selection in FL due to the first challenge: they could only measure the valuation of each data sample corresponding to the model trained locally, instead of the aggregated global model in FL.

(2) The prior works on data selection in FL did not consider the two new properties of FL devices identified in this work. Mercury \([86]\), FedBalancer \([67]\) and the work from Li et al. \([48]\) adopt importance sampling framework \([87]\) to select the data samples with high loss or gradient norm for reducing the training time per epoch but they failed to solve the second challenge of lacking temporal and spatial information. These methods need to inspect all the data in each training round for normalized sampling weight computation\(^2\) as well as noise and outliers removal \([35, 48]\).

Our Solutions. The challenges for FL in networked scenario and the limitations of existing methods motivate us to investigate the online data selection for FL with limited on-device storage. To this end, we design ODE, an online data valuation framework that coordinates networked devices to select and store valuable data samples locally and collaboratively for model training in FL, with the theoretical guarantee for speeding up model convergence and enhancing final model accuracy, simultaneously.

\(^1\)In this work, we use data quality and data value interchangeably, as both of them reflect the sample-level contribution to the global model training process in FL.

\(^2\)Although Weighted Random Sampling \([24]\) can select random samples with different weights from streaming data, it cannot work for network FL setting as the sample weight is dynamic with the variation of global model.
In ODE, we first provide theoretical analysis for the impact of an individual local data sample on convergence rate and final accuracy of the global model in FL. We discover a common term in these two analytical expressions, \( \langle \nabla_w l(w, x, y), \nabla_w F(w) \rangle \) (please refer to Section 3.1 for detailed notation definition), which implies that the projection of the local gradient of on-device data to the global gradient is a reasonable metric for data selection in FL. As this metric is a deterministic value, we can simply maintain a priority queue for each device to store the valuable data samples. Considering the lack of both temporal and spatial information, we also propose an efficient method for clients to approximate this data valuation metric by maintaining a local gradient estimator on each device and a global gradient estimator on the server. To overcome the potential distorted and overlapped stored data caused by data selection in a distributed manner, we further propose a coordination strategy for the server to achieve the collaborative cross-device data selection by coordinating each device to store high-quality data from different regions of global data distribution, which ensures the union of stored data from all the devices approximates the true global data distribution and the stored samples are valuable with respective to the performance of the global model. To address the challenge of computation and memory efficiency, we propose a simplified version of ODE, which substitutes the gradients of full model with the gradients of last few network layers to concurrently reduce the computational complexity of model backpropagation and save the memory footprint for storing extra intermediate outputs of the complex ML model.

**System Implementation and Experimental Results.** We have implemented ODE and evaluated it on three public tasks: synthetic task [12], Image Classification [80] and Human Activity Recognition [61], as well as one industrial mobile traffic classification dataset collected from our 30-days deployment on 30 ONT devices in practice. The industrial dataset consists of more than 560,000 packets from 250 mobile applications. We compare ODE against four categories of status quo data selection baselines: random sampling (such as First-In-First-Out and Reservoir Sampling [72]), importance-based sampling (such as loss based and gradient-norm based methods [48, 67, 86]), the existing data selection methods (such as FedBalancer [67] and Li et al.’s work [48]), and the ideal case with unlimited on-device storage. The experimental results show that ODE outperforms all these baselines with the same on-device storage capacity, achieving as high as 2.5× speedup of model training and 6% increase in final model accuracy on mobile traffic classification task, 9.52× and 7.56% on synthetic task, 1.35× and 1.4% on image classification, and 2.22× and 6.38% on human activity recognition, with low memory costs and evaluation delay. Moreover, ODE is robust to different environmental factors including local epoch number, client participation rate, on-device storage, mini-batch size and data heterogeneity across devices. We also conduct ablation experiments to demonstrate the importance of each component in ODE.

**Summary of Contributions.**

1. To the best of our knowledge, we are the first to identify two significant properties of networked devices in FL, i.e., limited on-device storage and streaming networked data, and demonstrate its enormity on the effectiveness and efficiency of FL model training process.

2. We provide analytical formulas on the impact of an individual local data sample on the convergence rate and the final inference accuracy of global model, based on which we propose a data valuation metric for data selection in FL. With this new data valuation metric, we propose ODE, an online data selection framework for FL including the on-device data evaluation and cross-device collaborative data storage, which provides theoretical guarantees for simultaneously accelerating convergence and enhancing model accuracy.

3. We conduct experiments on three public datasets and one industrial traffic classification dataset, and show that ODE outperforms state-of-the-art data sampling baselines in both training time and final inference accuracy and is robust to various environmental factors.
Remark
Loss over underlying global data distribution.
Set of all clients, set of participants in round $t$, one client.
$F(w)$ Loss over underlying global data distribution.
$F_c(w), \hat{F}_c(w)$ Loss over underlying and locally stored data distributions of client $c$.
$l(w, x, y)$ Loss of model $w$ over data sample $(x, y)$.
$B_c, |B_c|$ Data samples stored by client $c$ and storage capacity.
$w_c^{i,l}$ Local model of participant $c$ in round $t$ after $i$ local updates.
$w_{\text{fed}}^{t}, w_{\text{cen}}^{t}$ Models in round $t$ trained through FL and CL.
$\nu_c$ Data generation velocity of client $c$.
$\zeta_c$ Weight of client $c \in C$ in global objective function.
$\hat{\zeta}_c^t$ Weight of client $c \in C_t$ in the model aggregation of round $t$.
$\hat{g}_c, \hat{g}_t^t$ Local gradient estimator of client $c$, global gradient estimator in round $t$.

Table 1. Frequently Used Notations.

2 PRELIMINARIES
In this section, we present the learning model in FL and review the corresponding model training process. We consider the well-studied synchronous FL framework \[40, 52, 55\], where a server coordinates a set of mobile devices/clients\(^3\) $C$ to conduct distributed training process over multiple communication rounds from 1 to $T$. The client $c \in C$ generates/receives data samples in a streaming manner with a velocity $\nu_c$. We use $P_c$ to denote the client $c \in C$’s underlying local distribution of her streaming data, and $\hat{P}_c$ to represent the empirical distribution of the data samples $B_c$ stored in the local storage with a size of $|B_c|$. Due to different storage capacities and data selection strategies across clients, the data stored locally could be biased, i.e., $\hat{P}_c \neq P_c$. We have $\bar{P} = \bigcup_{c \in C} P_c$ to denote the true global distribution of the data generated by all devices, and $\hat{P} = \bigcup_{c \in C} \hat{P}_c$ to represent the empirical global distribution of all the locally stored data. The goal of FL is to train a global model $w$ from the locally stored data $\hat{P}$ with good performance with respect to the underlying unbiased data distribution $P$:

$$
\min_{w \in \mathbb{R}^n} \left\{ F(w) = \sum_{c \in C} \zeta_c \cdot F_c(w) \right\},
$$

(1)

where $\zeta_c = \frac{\nu_c}{\sum_{c' \in C} \nu_{c'}}$ denotes the normalized weight of each client, $n$ is the dimension of model parameters, $\hat{F}_c(w) = \mathbb{E}_{(x, y) \sim P_c}[l(w, x, y)]$ is the expected loss of the model $w$ over the underlying data distribution of client $c \in C$. We also use $\tilde{F}_c(w) = \frac{1}{|B_c|} \sum_{x, y \in B_c} l(w, x, y)$ to denote the empirical loss of the model $w$ over the data samples stored by client $c$.

In this work, we investigate the impacts of each client’s limited storage on the model training process of FL, and consider the widely adopted algorithm Fed-Avg \[55\] for easy illustration\(^4\). Under the synchronous FL framework, the global model is trained by repeating the following two steps for communication round $t$ from 1 to $T$:

**1 Local training:** In round $t$, the server selects a subset of clients $C_t \subseteq C$ to participate in the training process. Each participant $c \in C_t$ downloads the current global model $w_{\text{fed}}^{t-1}$ (the ending global model in the last round), and performs model updates with the locally stored data for $m$ epochs:

$$
   w_{c}^{t, l} \leftarrow w_{c}^{t, l-1} - \eta \nabla_w \tilde{F}_c(w_{c}^{t, l-1}), \quad i = 1, \ldots, m
$$

(2)

where the starting local model $w_{c}^{t, 0}$ is initialized as $w_{\text{fed}}^{t-1}$, and $\eta$ denotes the learning rate.

\(^3\)We will use mobile devices and clients interchangeably in this work.

\(^4\)Our results under the setting of limited on-device storage can be extended to other FL algorithms, such as FedBoost\[32\], FedNova\[73\], FedProx\[52\].
(2) Model aggregation: Each participant client $c \in C_t$ uploads the updated local model $w_{c}^{t,m}$ at the end of the $m^{th}$ epoch, and the server aggregates them to generate a new global model $w_{fed}^{t}$ by taking a weighted average:

$$w_{fed}^{t} \leftarrow \sum_{c \in C_t} \zeta_{c}^{t} \cdot w_{c}^{t,m},$$

where $\zeta_{c}^{t} = \frac{v_{c}}{\sum_{c' \in C_t} v_{c'}}$ is the normalized weight of client $c$ at round $t$.

In the scenario of FL with limited on-device storage and streaming data, we have an additional step of data selection for all the clients:

(3) Data selection: In round $t$, once receiving a new data sample $(x, y) \sim P_c$, the client $c \in C$ has to make an online decision on whether to store the new sample (in place of an old one if the storage area fills up) or discard it. The goal of this process is to select and store the representative/valuable data samples from streaming data for model training in the coming rounds, speeding up model training convergence and enhancing global model inference accuracy simultaneously.

We list the frequently used notations in Table 1.

3 DESIGN OF ODE

In this section, we first quantify the impact of a local data sample on the performance of global FL model in terms of convergence rate in model training process and final model inference accuracy. Based on the common term in the analytical expressions, we propose a new data valuation metric for data selection in FL. We further develop a practical method to estimate this metric with low extra computation and communication overhead, facilitating the efficient data evaluation and selection on device. We further design a strategy for the server to coordinate the data selection process across clients, ensuring the combination of all the stored data from clients approximates the unbiased global data distribution, which is critical to the performance of FL model and high utilization of limited on-device storage.

3.1 Data Valuation Metric

We evaluate the impact of a local data sample on the global FL model from the perspectives of convergence rate and final inference accuracy, which are two critical aspects for the success of FL. The convergence rate quantifies the reduction of global loss in each training round, and the number of training rounds determines the communication costs of FL. The inference accuracy reflects the performance and effectiveness of a FL model on guaranteeing the quality of service (QoS) and user experience. For theoretical analysis, we follow one typical assumption on the FL models, which is widely adopted in the literature [15, 52, 58, 88].

Assumption 1. (Lipschitz Gradient) For each client $c \in C$, the loss function $F_c(w)$ is $L_c$-Lipschitz gradient, i.e., $\| \nabla_w F_c(w_1) - \nabla_w F_c(w_2) \| \leq L_c \| w_1 - w_2 \|$, which implies that the global loss function $F(w)$ is $L$-Lipschitz gradient with $L = \sum_{c \in C} \zeta_{c} L_c$.

Due to the limitation of space, we provide all the proofs of theorems and lemmas in Appendices A.1.

Convergence Rate. We provide a lower bound on the reduction of the loss function of the global model after model aggregation in each communication round.
**Theorem 1.** (Global Loss Reduction) With Assumption 1, for an arbitrary set of clients $C_t \subseteq C$ selected by the server in round $t$, the reduction of global loss $F(w)$ is bounded by:

$$F(w_{fed}^{t-1}) - F(w_{fed}^t) \geq \sum_{c \in C_t} \sum_{i=0}^{m-1} \sum_{(x,y) \in B_c} \left[ - \alpha_c \| \nabla_w l(w_{c,i}^{t,i}, x, y) \|^2 + \beta_c \langle \nabla_w l(w_{c,i}^{t,i}, x, y), \nabla_w F(w_{fed}^{t-1}) \rangle \right],$$

where $\alpha_c = \frac{1}{2\tau_c} \cdot \left( \frac{n}{|B_c|} \right)^2$ and $\beta_c = \zeta_c^t \cdot \left( \frac{n}{|B_c|} \right)$.

Theorem 1 shows that the loss reduction of the global FL model $F(w_{fed}^t)$ in each round is closely related to two terms of each participating client $c$’s local data sample: term 1: local gradient magnitude of a data sample $(x, y)$, i.e., $\| \nabla_w l(w_{c,i}^{t,i}, x, y) \|^2$, and term 2: the projection of the local gradient of a data sample $(x, y)$ onto the direction of global gradient over global data distribution, i.e., $\langle \nabla_w l(w_{c,i}^{t,i}, x, y), \nabla_w F(w_{fed}^{t-1}) \rangle$. As term 1 scaled by $\alpha_c \propto \frac{n}{|B_c|}$ is relatively small compared with the term 2 scaled by $\beta_c \propto \frac{n}{|B_c|}$, we can thus focus on the term 2 to evaluate a local data sample’s impact on the convergence rate.

We next briefly describe how to evaluate data samples based on the term 2. The local model parameter $w_{c,i}^{t,i}$ in term 2 is computed from (2), where the gradient $\nabla_w \hat{F}_c(w_{c,i}^{t-1})$ depends on all the locally stored data samples. In other words, the value of term 2 depends on the “cooperation” of all the stored samples. With this interpretation, we can formulate the process to calculate term 2 as a cooperative game, where each data sample $(x, y)$ represents a player and the utility of each data sample set is the value of term 2. Within this cooperative game, we can regard the individual contribution of one data sample on the value of term 2 as its data value, and calculate it through leave-one-out [20, 43] or Shapley Value [29, 65]. As both of them require multiple times of model retraining to compute the marginal contribution of an individual data sample, we propose a one-step look-ahead strategy to roughly evaluate the individual data sample’s value by only focusing on the first local epoch, which will be illustrated later.

**Inference Accuracy.** We can assume that the optimal global model can be obtained through gathering all the clients’ generated data samples (not only the stored data samples) and conducting centralized learning. Moreover, as the accurate test dataset is hard to obtain in FL, we cannot directly evaluate the inference accuracy of model on the test data. Thus, we use the weight divergence between the models trained through FL and CL, i.e., $\| w_{fed}^t - w_{cen}^{mt} \|$, to quantify the accuracy of the global model of FL in round $t$. With $t \to \infty$, we can obtain the final accuracy of the global FL model at the end of model training. Compared with existing works on bounding this divergence [88], which only considered cross-entropy as loss function and full clients participation, our results can handle any loss functions with Lipschitz continuous property under Assumption 1 and arbitrary partial participation $C_t$. Additionally, we use AM–GM inequality trick to further reveal the individual impact of each local data sample on the inference accuracy.

**Theorem 2.** (Model Weight Divergence) With each client’s loss function satisfying Assumption 1, for arbitrary set of participating clients $C_t$ selected by the server, we have the following inequality for the weight divergence after the $t^{th}$ training round between the models trained through FL and CL.

$$\| w_{fed}^t - w_{cen}^{mt} \| \leq (1 + \eta L)^m \| w_{fed}^{t-1} - w_{cen}^{mt(t-1)} \| + \sum_{c \in C_t} \zeta_c^t \left[ \eta \sum_{i=0}^{m-1} (1 + \eta L)^{m-1-i} G_c(w_{c,i}^{t,i}) \right],$$

where $G_c(w) = \| \nabla_w \hat{F}_c(w) - \nabla_w F(w) \|$ represents the divergence of gradients of locally stored data distribution and that of the unbiased global data distribution.
The left figure compares the normalized values of term 1 and term 2 in (1) for different data samples. The middle figure compares the values of each data sample computed in round 0 and round 30. The right figure compares the values of each data sample computed using gradients of full model layers and the last layer.

The following lemma further shows the impact of a local data sample on \( \| w_t^{fed} - w_{mt}^{cen} \| \) through \( G_c(w_t) \):

**Lemma 1.** (Gradient Divergence) For an arbitrary client \( c \in C \), the divergence of loss gradients over locally stored data distribution and unbiased global data distribution is bounded by:

\[
G_c(w) \leq \sqrt{n} \sqrt{\frac{\delta}{\sum_{(x,y) \in B_c} \left( \| \nabla_w l(w, x, y) \| \right)^2} - 2 \langle \nabla_w l(w, x, y), \nabla_w F(w) \rangle},
\]

where \( \delta = \| \nabla_w F(w) \|^2 \) is a constant term for different data samples.

Intuitively, due to different coefficients, the twofold projection (term 2) has a larger variance among different data samples than the gradient magnitude (term 1), which is also demonstrated by experimental results shown in Figure 2(a). Thus, we can quantify the impact of a local data sample on \( G_c(w) \) and the inference accuracy mainly through term 2 in (6), which happens to be the same as the term 2 in the bound of global loss reduction in (4).

**Data Valuation.** Based on the above analysis on the impact of a local data sample on the convergence rate during model training process and the inference accuracy of the final model, especially the term 2 in both (4) and (6), we first define a new data valuation metric in FL, and provide the theoretical understanding as well as intuitive interpretation.

**Definition 1.** (Data Valuation Metric) In the \( t^{th} \) round, for a client \( c \in C \), the value of a data sample \( (x, y) \) is defined as the projection of its local gradient onto the global gradient direction of the current global model calculated with the unbiased global data distribution:

\[
v(x, y) \overset{def}{=} \langle \nabla_w l(w_t^{fed}, x, y), \nabla_w F(w_t^{fed}) \rangle.
\]

Based on this new data valuation metric, once a client receives a new data sample, she can make an online decision on whether to store this sample by comparing the data value of the new sample and those of old samples in the local storage, which can be easily implemented as a priority queue.

**Theoretical Understanding.** On the one hand, maximizing the above data valuation of the selected data samples is a one-step greedy strategy for minimizing the loss of global model in each training round, because it optimizes the dominant term (term 2) in the lower bound of global loss reduction in (4). The one-step-look-ahead strategy means that we only consider the first epoch of the local model training in (4), i.e., \( \langle \nabla_w l(w_t^{fed}, x, y), \nabla_w F(w_t^{fed}) \rangle \), where the index \( i \) is set as 0 and \( w_t^{0} = w_t^{fed} \).

On the other hand, this data valuation metric also improves the inference accuracy of the final global model by narrowing the gap between the models trained through FL and CL, as it reduces the high-weight term of the dominant part, i.e., \( (1 + \eta L)^{m-1} G_c(w_t^{0}) \), in the model weight divergence.
bound shown in (5). The above two perspectives have also been demonstrated by our empirical results in Section 4.4.

Intuitive Interpretation. Under the proposed new data valuation metric, large data value of one data sample also indicates that its impact on the global FL model is similar to the unbiased global data distribution, guiding the clients to continuously choose and store the data samples which not only follow their own local data distribution, but also have similar effect with the global data distribution. In this way, the data heterogeneity across clients is largely reduced, which have been demonstrated to improve FL performance in the literature [13, 73, 85].

3.2 On-Client Data Selection
In practical FL scenario, it is non-trivial for one client to directly calculate the above data valuation metric for online data selection. This comes from the following two problems in obtaining the global model and gradient for the client: (1) lack of the latest global model: due to the partial participation of clients in FL [37], the client \( c \in C \) does not receive the global FL model \( w_{fed}^{t-1} \) in the rounds that she does not participate in, and only has the outdated global FL model from the previous participating round, i.e., \( w_{fed}^{t_{\text{last}}-1} \); (2) lack of unbiased global gradient: the accurate global gradient over the unbiased global data distribution can only be obtained by aggregating all the clients’ local gradients over their unbiased local data distributions, i.e., \( \nabla_w F(w) = \sum_{c \in C} [\xi_c \nabla_w F_c(w)] \). This is hard to achieve because the locally stored data distribution could become biased during the online data selection process and not all clients participate in each communication round.

We can consider that problem (1) does not affect the online data selection process too much as the value of each data sample remains stable across a few training rounds, and thus clients just use slightly outdated global model for data valuation, which is demonstrated in Figure 2(b). For problem (2) caused by biased local data distribution and partial client participation, we propose a global gradient estimator.

First, to solve the issue of skew local gradient caused by the biased stored data, we require each client \( c \in C \) to maintain a local gradient estimator \( \hat{g}_c \approx \nabla_w F_c(w) \), which will be updated whenever the client receives the \( n^{th} \) new data sample \((x, y)\) from the last participating round:

\[
\hat{g}_c \leftarrow \frac{n-1}{n} \hat{g}_c + \frac{1}{n} \nabla_w l(w_{fed}^{t_{\text{last}}-1}, x, y),
\]

where \( w_{fed}^{t_{\text{last}}-1} \) is the global model received in client \( c \)'s last participating training round. When the client \( c \) is selected to participate in FL at a certain round \( t \), the client uploads the current local gradient estimator \( \hat{g}_c \) to the server, and resets the local gradient estimator, i.e., \( \hat{g}_c \leftarrow 0, n \leftarrow 0 \). This is because a new global FL model \( w_{fed}^{t-1} \) is received.

Second, to solve the problem of skew global gradient \( \nabla_w F(w) \) due to the partial client participation, the server also maintains a global gradient estimator \( \hat{g}' \), which is an aggregation of the local gradient estimators, \( \hat{g}' = \sum_{c \in C} \xi_c \hat{g}_c \). As it would incur high communication cost to collect \( \hat{g}_c \) from all the clients, the server only uses \( \hat{g}_c \) of participating clients to update global gradient estimator \( \hat{g}' \) in each round \( t \):

\[
\hat{g}' \leftarrow \hat{g}'^{t-1} + \sum_{c \in C_t} \xi_c (\hat{g}_c - \hat{g}'^{t-1}_c),
\]

Thus, in each training round \( t \), the server needs to distribute both the current global FL model \( w_{fed}^{t-1} \) and the latest global gradient estimator \( \hat{g}'^{t-1} \) to each selected client \( c \in C_t \), who will conduct local model training and upload both locally updated model \( w_c^{t,m} \) and local gradient estimator \( \hat{g}_c \) back to the server.

Simplification. In both of the local gradient estimation in (8) and data valuation in (7) for a new data sample, we need to backpropagate the entire model parameters for computing the gradient...
\n\n\n\n\n∇_\text{w}\left(\text{w}_\text{fed}^{t_{\text{last}}}, x, y\right), which will introduce high computational cost and large extra memory footprint for storing intermediate outputs for model back propagation. To reduce such additional costs, we turn to only use the gradients of the last few network layers instead of the whole deep learning model, as part of the model gradient is able to reflect the tendency of the full model gradients, which can also be verified in the experimental results shown in Figure 2(c). We also demonstrate the advantage of this simplified method in Section 4.4.

**Privacy Concern.** The transmission of local gradient estimators may disclose the local gradient of each client, which can be avoided by applying Gaussian noise to each local gradient estimator before uploading, as in differential privacy [23, 77].

### 3.3 Cross-Client Data Storage

Since the local data distributions of clients may overlap with each other to some extent, independently optimizing the data selection process for each individual client may lead to the selected data samples from different clients concentrated in the overlapped distributed region. One potential solution is to divide the global data distribution into several regions, and coordinate each client to store valuable data samples from some specific distribution regions, while the union of all clients’ stored data can still approximate the global unbiased data distribution. In this work, we consider the label of data samples as the dividing criterion for the global data distribution. Thus, before the training process of FL, the server needs to instruct each client the labels and the corresponding quantity of data samples to save in the local storage. Considering the partial client participation and heterogeneous data distribution among clients, the cross-client coordination strategy need to satisfy the following four desirable properties:

1. **Efficient Data Selection:** To improve the efficiency of data selection, the label \( y \in Y \) should be assigned to the clients who receive/generate more data samples with this label. This principle follows the intuition that there is a higher probability to select the more valuable data samples from a larger pool of candidate data samples.

2. **Redundant Label Assignment:** To ensure that all the labels are likely to be covered in each round even with partial client participation, we require each label \( y \in Y \) to be assigned to more than \( n_t^{\text{label}} \) clients, which is a hyperparameter decided by the server.

3. **Limited Storage:** Due to limited on-device storage, each client \( c \) should be assigned to less than \( n_c^{\text{client}} \) labels to ensure a sufficient number of valuable data samples for each label, and \( n_c^{\text{client}} \) is a hyperparameter decided by the server.

4. **Unbiased Global Distribution:** The weighted average of all clients’ local data distribution is expected to be equal to the global unbiased data distribution, i.e., \( \tilde{P}(y) = P(y) \).

We formulate the cross-client data storage with the above four properties by representing the coordination strategy as a matrix \( D \in \mathbb{N}^{C \times |Y|} \), where \( D_{c,y} \) denotes the number of data samples with label \( y \) that client \( c \) should collect and store. We use matrix \( V \in \mathbb{R}^{C \times |Y|} \) to denote the statistical information of each client’s generated/received data, where \( V_{c,y} = v_c P_c(y) \) denote the number of data samples with label \( y \) generated by client \( c \) in the previous period of time. The cross-client coordination strategy can be obtained by solving the following optimization problem, where the condition (1) is formulated as the optimization objective and conditions (2)(3)(4) are described by

---

\(5\)There are many criteria and methods to divide the global data distribution, such as K-means [45] and Hierarchical Clustering [56], and our results are independent on different data distribution division methods.
the constraints (10b)(10c)(10d), respectively:

\[
\begin{align*}
\max_D & \sum_{c \in C} \sum_{y \in Y} D_{c,y} \cdot V_{c,y} = \|DV\|_1 \\
n_s. t. & \|D^T y\|_0 \geq n_y^\text{label}, \quad \forall y \in Y, \quad (10b) \\
& \|D_c\|_0 \leq n_c^\text{client}, \quad \forall c \in C, \quad (10c) \\
& \|D_c\|_1 = |B_c|, \quad \forall c \in C, \quad (10d) \\
& \sum_{c \in C} D_{c,y} = \sum_{c \in C} V_{c,y}, \quad \forall y \in Y. \quad (10d)
\end{align*}
\]

**Complexity Analysis.** It is easy to verify that the above optimization problem with $l_0$-norm is a general convex-cardinality problem, which is NP-hard [27, 57] and can only be solved globally by dividing it into two subproblems: (1) decide which elements of matrix $D$ are non-zero, i.e., $S = \{(c, y)|D_{c,y} \neq 0\}$, to assign labels to clients under the constraints of (10b) and (10c), and (2) determine the specific values of the non-zero elements of matrix $D$ by solving the following simplified convex optimization problem:

\[
\begin{align*}
\max_D & \sum_{c \in C, y \in Y, (c,y) \in S} D_{c,y} \cdot V_{c,y} \\
n_s. t. & \sum_{y \in Y, (c,y) \in S} D_{c,y} = |B_c|, \quad \forall c \in C, \quad (11) \\
& \sum_{c \in C, (c,y) \in S} D_{c,y} = \sum_{c \in C} V_{c,y}, \quad \forall y \in Y.
\end{align*}
\]

As the number of possible $S$ can be exponential to $|C|$ and $|Y|$, it is prohibitively expensive for the server to derive the globally optimal solution of the distribution matrix $D$ with large $|C|$ (massive clients in FL). The classic tractable approach is to replace the non-convex discontinuous $l_0$-norm constraints with the convex continuous $l_1$-norm regularization terms in the objective function [27], which fails to work in our situation because simultaneously minimizing as many as $|C| + |Y|$ non-differentiable $l_1$-norm in the objective function will lead to excessive amounts of computation and memory costs as well as unstable solutions [64, 66]. Thus, we propose a greedy strategy for the server to determine the label-client assignment and the corresponding quantity of data samples for each label assigned to the client.

**Greedy Cross-Client Coordination Strategy.** The selection of $S$ needs to satisfy the four conditions discussed before, which can be achieved simultaneously through the proposed greedy strategy with the following five steps:

1. **Local Information Collection:** Each client $c \in C$ sends the rough information about local data to the server, including the storage capacity $|B_c|$ and data velocity $V_{c,y}$ of each label $y$, which can be obtained from the statistics of the previous time period and brings little privacy concern.

2. **Redundant Label Assignment:** After collecting the data information from all the clients, the server can construct the vector of storage size $B \in \mathbb{N}^{|C|}$ and the matrix of data velocity $V \in \mathbb{R}^{[C \times |Y|]}$. The server sorts the class labels according to a non-decreasing order of the total number of clients having this label. We prioritize the labels with top rank in label-client assignment, because these labels are more difficult to find the enough clients to meet the Redundant Label Assignment property in constraint (10b). For each considered label $y \in Y$ in the order, there could be multiple clients to be assigned, and the server allocates the label $y$ to the clients $c \in C$ who receives/generates data
Fig. 3. A simple example to illustrate the greedy coordination. ① Sort classes according to owners and obtain class order {2, 1, 3}; ② Sort and allocate clients for each class under the constraint of \(n_y^{\text{class}}\); ③ Obtain coordination matrix \(D\) and compute class weight \(\gamma\) according to (12).

Fig. 4. The overview of ODE framework.

samples with label \(y\) in a higher data velocity. By doing this, we attempt to satisfy the property of Efficient Data Selection.

3) Limited Data Storage: Once the number of labels assigned to a client is larger than \(n_c^{\text{client}}\), the client will be removed from the sorting list.

4) Unbiased Global Distribution: With the above three steps, we have decided the non-zero elements of the client-label matrix \(D\), i.e., the set \(S\). To further reduce the computational complexity and avoid the imbalanced on-device data storage for each label, we do not directly solve the optimization problem in (11). Instead, we require each client to divide the local storage area evenly, i.e., \(\frac{|B_c|}{\|D_c\|_1}\), to the assigned labels, and compute a weight \(\gamma_y\), \(y \in Y\) for each label to guarantee that the weighted distribution of the stored data approximates the unbiased global data distribution, i.e., satisfying \(\gamma_y \hat{P}(y) = P(y)\). Accordingly, we can derive the weight \(\gamma_y\) for each label \(y\) by setting

\[
\gamma_y = \frac{P(y)}{\hat{P}(y)} = \frac{\left\| V^T \right\|_1 / \left\| V \right\|_1}{\left\| D^T \right\|_1 / \left\| D \right\|_1}. \tag{12}
\]

Thus, each client \(c\) only needs to maintain one priority queue with a size \(\frac{|B_c|}{\|D_c\|_1}\) for each assigned label. In the local model training, each participating client \(c \in C_t\) updates the local model using the weighted stored data samples:

\[
w^{t,i}_c \leftarrow w^{t,i-1}_c - \frac{\eta}{\zeta_c} \sum_{(x,y) \in B_c} \gamma_y \nabla_w l(w^{t,i-1}_c, x, y) \tag{13}
\]

where \(\zeta_c = \sum_{(x,y) \in B_c} \gamma_y\) denotes the new weight of each client, and the normalized weight of client \(c \in C_t\) for model aggregation in round \(t\) becomes \(\zeta^t_c = \frac{\zeta_c}{\sum_{c \in C_t} \zeta_c}\).

We illustrate a simple example in Figure 3 for better understanding of the above procedure.

Privacy Concern. The potential privacy leakage of uploading rough local information is tolerable in practice, and can be further avoided through Homomorphic Encryption [2], which enables to sort \(n\) encrypted data samples with complexity \(O(n \log n^2)\) [33].

3.4 Overall Procedure of ODE

Generally, ODE incorporates cross-client data storage and on-client data evaluation to coordinate mobile devices to store valuable samples collaboratively, simultaneously speeding up model training and improving inference accuracy of the final model. The overall procedure is shown in Figure 4.
Cross-Client Data Storage. Before the FL process, the central server coordinates clients to store valuable data samples from different data distribution regions, by collecting rough distribution information from each client (①) and solving the optimization problem in (9), which can be efficiently calculated through our greedy solution (②).

On-Client Data Evaluation. During the FL process, clients conduct the on-device data evaluation and selection by leveraging our proposed data valuation metric in (7) and the global gradient estimator $\hat{g}$ in (8). Specifically, in the $t^{th}$ training round, non-selected clients, selected clients and server perform different operations:

- **Non-selected clients**: (③) Data Evaluation: Each non-selected client $c \in C \setminus C_t$ continuously evaluates the real-time data samples according to the data valuation metric in (7), replacing the unbiased global gradient $\nabla w F(w)$ with the estimated one $\hat{g}_{t-1}^{last}$ received in last participation round, i.e., the used data valuation metric $\langle \nabla w^l (w_{fed}^{last-1}, x, y), \hat{g}_{t-1}^{last-1} \rangle$. (④) Local Gradient Estimator Update: The client also continuously updates the local gradient estimator $\hat{g}_c$ in (8) using the local gradient of the received data samples.

- **Selected Clients**: (⑤) Local Model Updates: After receiving the new global model $w_{fed}^{t-1}$ and new global gradient estimator $\hat{g}_{t-1}^{l}$ from the server, each selected client $c \in C_t$ performs local model updates using the data samples stored locally by (13). (⑥) Local Model and Estimator Transmission: Then, each selected client sends server the updated model $w_{c,m}^{t}$ as well as the local gradient estimator. And the estimator $\hat{g}_c$ will be reset to 0 for approximating local gradient of the latest received global model, i.e. $\nabla w F_c (w_{fed}^{t-1})$.

- **Server**: (⑦) Global Model and Estimator Transmission: At the beginning of each training round, the server distributes the global model $w_{fed}^{t-1}$ and the global gradient estimator $\hat{g}_{t-1}^{l}$ to the selected clients. (⑧) Local Model and Estimator Aggregation: At the end of each training round, the server collects the updated local models $w_{c,m}^{t}$ as well as local gradient estimator $\hat{g}_c$ from participants $c \in C_t$, which will be aggregated to obtain a new global model by (3) and a new global gradient estimator by (9).

4 EVALUATION

In this section, we first introduce experiment setting, baselines and evaluation metrics. Second, we provide the complete experimental evidences for our motivation by showing that limited on-device storage can deteriorate the FL model training process significantly. Third, we present the overall performance of ODE on model training speedup and inference accuracy improvement, as well as the extra memory footprint and evaluation delay of different data selection methods. Next, we show the robustness of ODE against various factors in industrial environment, such as the number of local training epochs $m$, participation rate $|C_t|/|C|$, storage capacity $B_c$, mini-batch size and data heterogeneity across clients. We also analyze the individual effects of different components of ODE.

4.1 Experiment Setting

Tasks, Datasets and ML Models. To demonstrate the ODE’s good performance across various learning tasks, datasets and ML models, we evaluate ODE on one synthetic dataset, two real-world datasets and one industrial dataset, all of which vary in data quantities, distributions and outputs, and cover the tasks of Synthetic Task (ST), Image Classification (IC), Human Activity Recognition (HAR) and Traffic Classification (TC). The statistics of the tasks and the default configurations are summarized in Figure 5 and Table 2, and the establishment process is shown in Appendix A.2.

(1) Synthetic Task. The synthetic dataset we used is proposed in LEAF benchmark [12] and is also described in details in [52]. It contains 200 clients and 1 million data samples, and a Logistic Regression model is trained for this 10-class task.
(2) **Image Classification.** Fashion-MNIST [80] contains 60,000 training images and 10,000 testing images, which are divided into 50 clients according to labels [55]. We train LeNet [46] for the 10-class image classification.

(3) **Human Activity Recognition.** HARBOX [61] is the 9-axis OMU dataset collected from 121 users’ smartphones in a crowdsourcing manner, including 34,115 data samples with 900 dimension. Considering the simplicity of the dataset and task, a lightweight customized DNN with two dense layers followed by a SoftMax layer is deployed for this 5-class human activity recognition task [49].

(4) **Traffic Classification.** The industrial dataset about the task of mobile application classification is collected by our deployment of 30 ONT devices in a simulated network environment from May 2019 to June 2019. Generally, the dataset is contains more than 560,000 data samples and has more than 250 applications as labels, which cover the application categories of videos (such as YouTube and TikTok), games (such as LOL and WOW), files downloading (such as AppStore and Thunder) and communication (such as WhatsApp and WeChat). We manually label the application of each data sample. The model we applied is a CNN consisting of 4 convolutional layers with kernel size $1 \times 3$ to extract features and 2 fully-connected layers for classification, which is able to achieve 95% accuracy through CL and satisfy the on-device resource requirement due to the small number of model parameters. To reduce the training time caused by the large scale of dataset, we randomly select 20 out of 250 applications as labels with various numbers of data samples, whose distribution is shown in Figure 6.

**Parameters Configurations.** For all the experiments, we use SGD as the optimizer and decay the learning rate per 100 rounds by $\eta_{new} = 0.95 \times \eta_{old}$. To simulate the setting of streaming data, we set the on-device data velocity to be $v_c = \frac{\text{#training samples}}{500}$, which means that each device $c \in C$ will receive $v_c$ data samples one by one in each communication round, and the training data samples would be shuffled per 500 rounds. Other default configurations for the FL model training including total number of devices $|C|$, participation rate $\frac{|C_t|}{|C|}$, initial learning rate $\eta$, number of local epochs $m$, storage capacity $|B_c|$ are shown in Table 2, and the normalized data volume/speed distribution among devices of different tasks are shown in Figure 5. Note that for each experiment, we repeat 5 times for each experiment and show the average results.

**Baselines.** In our experiments, we compare two versions of ODE, ODE-Exact (using exact and accurate global gradient) and ODE-Est (using estimated global gradient), with four categories of data selection methods:

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We choose these experimental parameters for easy illustration. We have also evaluated different parameters, whose results are consistent with those shown in this section.
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#Label per Average #Local Convergence Rate Inference Accuracy Client Variance Epoch \( T_{RS}/T_{FullData} \) RS FullData

| Settings | #Label per Client | Average Variance | #Local Epoch | \( T_{RS}/T_{FullData} \) | RS | FullData |
|----------|-------------------|------------------|--------------|--------------------------|-----|---------|
| Setting 1 | 5 | 0.227 | 2 | 2.18 | 0.867 | 0.912 |
|          | 5 |            | 1.70 | 2.50 | 0.855 | 0.890 |
| Setting 2 | 10 | 0.234 | 2 | 2.50 | 0.894 | 0.932 |
|          | 5 |            | 2.84 | 3.46 | 0.874 | 0.926 |
| Setting 3 | 15 | 0.235 | 2 | 3.46 | 0.906 | 0.960 |
|          | 5 |            | 3.92 | 5 | 0.890 | 0.957 |

Table 3. Impact of limited on-device storage in the settings with different Non-IID data distribution.

1. **Random sampling methods** including RS (Reservoir Sampling) and FIFO (First-In-First-Out: storing the latest \(|B_c|\) data samples).

2. **Importance sampling-based methods** including HighLoss, using the loss of each data sample as data value to reflect the informativeness of data [53, 63, 68], and GradientNorm, quantifying the impact of each data sample on model update through its gradient norm [38, 87].

3. **Previous data selection methods** for canonical FL including FedBalancer [67] and SLD (Sample-Level Data selection) [48] which are revised slightly to adapt to streaming data setting: (1) We store the loss/gradient norm of the latest 50 samples for noise removal; (2) For FedBalancer, we ignore the data samples with loss larger than top 10% loss value, and for SLD, we remove the samples with gradient norm larger than the median norm value.

4. **Ideal case** with unlimited on-device storage, denoted as FullData, using the entire dataset of each client for training to simulate the unlimited storage scenario.

**Metrics for Training Performance.** We use two metrics to evaluate the performance of ODE and the other baselines:

1. **Time-to-Accuracy Ratio:** we measure the speedup of each method in the model training by the ratio of training time of RS\(^7\) and the considered method to reach the same target accuracy, which is set to be the final inference accuracy of RS, i.e., \( \frac{T_{RS}}{T_{method}} \). As the time of one communication round is usually fixed in FL scenario, we can quantify training time with the number of training rounds.

2. **Final Inference Accuracy:** we evaluate the inference accuracy of the final global model on each device’s testing data and report the average accuracy over all the devices for evaluation.

### 4.2 Impact of Limited On-device Storage

To discover how the characteristics of data, such as distribution range and variance, impact the FL with limited on-device storage, we conduct experiments over three settings with different numbers of labels owned by each client, which is constructed from the industrial traffic classification task.

The experimental results shown in Table 3 demonstrate that: (1) With local data variance increasing, the reduction of convergence rate and model accuracy is becoming larger. This is because the stored data samples are more likely to be biased; (2) When the number of local epoch \( m \) increases, the negative impact of limited on-device storage is becoming more serious due to larger steps towards the biased update direction, slowing down the convergence time by 4× and decreasing the final model accuracy by as high as 7%.

\(^6\)The experimental results of the two random sampling methods are similar, and thus we choose RS for random sampling only.

\(^7\)We do not choose Importance Sampling and previous data selection methods here because they have poor performance on the datasets with noisy data, such as HARBOX and Industrial Traffic Classification Dataset.
Fig. 7. Test accuracy of ODE and baselines on four datasets.

| Tasks | Model Training Speedup | Inference Accuracy |
|-------|------------------------|--------------------|
|       | RS       | HL | GN | FB | SLD | ODE-Exact | ODE-Est | FD |
| ST    | 1.0× | – | 4.87× | – | 4.08× | 9.52× | 5.88× | 2.67× |
| IC    | 1.0× | – | – | – | – | 1.35× | 1.20× | 1.01× |
| HAR   | 1.0× | – | – | – | – | 2.22× | 1.55× | 4.76× |
| TC    | 1.0× | – | – | – | – | 2.51× | 2.50× | 3.92× |

Table 4. ODE’s improvements on model training speedup and inference accuracy (RS: Random Sampling, FD: FullData, HL: HighLoss, GN: GradientNorm, FB: FedBalancer, SLD: Sample-level Data selection). The symbol ‘−’ means that the model fails to reach the target accuracy.

4.3 Overall Performance

We next compare the overall performance of ODE (ODE-Exact and ODE-Est) with random sampling method (RS), importance sampling methods (HighLoss, GradientNorm), previous data selection methods (FedBalancer and SLD), and the ideal case with all data (FullData) on the four datasets, and show the results in Figure 7 and Table 4.

ODE speeds up the model training process. We observed that both of ODE-Exact and ODE-Est improve time-to-accuracy performance over the baselines on all the four datasets. Compared with random sampling method (RS), ODE achieves the final target accuracy 5.88×∼9.52× faster on synthetic task; 1.20×∼1.35× faster on Fashion-MNIST; 1.55×∼2.22× faster on HARBOX; 2.5× faster on industrial traffic classification dataset, which outperforms all the baselines. Also, we observe that the largest speedup is achieved on synthetic dataset, because the high non-i.i.d degree across clients and large data divergence within clients leave a great potential for ODE to reduce data heterogeneity and then improve training process through data selection.

ODE improves the final inference accuracy. Table 4 shows that in comparison with baselines, ODE enhances final accuracy on all the datasets, achieving 3.24%∼7.56% higher on synthetic dataset, 3.13%∼6.38% increase on HARBOX dataset, and 6% rise on traffic classification dataset. We also notice that ODE has a marginal accuracy improvement (≈1.4%) on FashionMNIST, because this dataset has less data variance within each label, and a randomly selected mini-dataset is sufficient to represent the entire data distribution for model training.

Importance-based data selection methods perform poorly. Table 4 shows that these methods are even not able to reach the target final accuracy of in the datasets of IC, HAR and TC. The reason is that these datasets are collected from real world and thus contain noise data, making such importance-based methods fail to work [48, 67]. Despite that GradientNorm seems to outperform
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(a) Inference Accuracy  
(b) Training Speedup  
(c) Memory Footprint  
(d) Evaluation Latency

Fig. 8. Performance and cost of simplified ODE using different number of network layers.

| Tasks | Memory Footprint (MB) | Evaluation Time (ms) |
|-------|-----------------------|----------------------|
|       | RS        | HL        | GN       | ODE-Est   | ODE-S   | RS        | HL        | GN       | ODE-Est   | ODE-S   |
| IC    | 1.70      | 11.91     | 16.89    | 18.27     | 16.92    | 0.05      | 11.1      | 21.1     | 22.8      | 11.4     |
| HAR   | 1.92      | 7.27      | 12.23    | 13.46     | 12.38    | 0.05      | 0.36      | 1.04     | 1.93      | 0.53     |
| TC    | 0.75      | 10.58     | 19.65    | 25.15     | 14.47    | 0.05      | 1.03      | 9.06     | 9.69      | 1.23     |

Table 5. The memory footprint and evaluation delay per sample of baselines (RS: Random Sampling, HL: High Loss, GN: Gradient Norm) and our framework (ODE and simplified version ODE-S) on three real-world tasks.

ODE-Est on synthetic dataset, we demonstrate in Appendix A.3 that the model trained by GradientNorm performs really bad with only a little noisy data in the synthetic dataset, similar to the results of real-world datasets.

Previous data selection methods outperform importance sampling methods but worse than ODE on all the datasets. As is shown in Figure 7, FedBalancer and SLD perform better than traditional importance sampling methods, but worse than RS in a large degree, which is different from the phenomenon in traditional settings [41, 48, 67]. These are because (1) their noise reduction steps, such as removing samples with large loss or gradient norm, highly rely on the complete statistical information of full dataset, and (2) their on-client data valuation metrics fail to work for FL, as discussed in Section 1.

Simplified ODE saves computation and memory costs significantly, with little performance reduction. To evaluate the performance of the simplified ODE, we conduct another two experiments which consider only the last 1 and 2 layers (5 layers in total) for gradient estimation and data valuation on the industrial traffic classification dataset. Empirical results shown in Figure 8 demonstrate that, compared with the original ODE, the simplified version achieves only slightly weaker performance, but can save much computational resource and memory footprint, saving as high as 44% memory and 83% delay for traffic classification task.

ODE introduces small extra memory footprint and data processing delay during the data valuation process, and utilizes the idled resource of mobile devices for data selection. The memory footprint and computational time per data sample of three baselines, ODE-Est and ODE-S (simplified version only using the last network layer for gradient computation and data evaluation) are shown in Table 5. The table demonstrates that (1) Compared with RS, importance sampling methods have more memory footprint and evaluation latency caused by forward and backward propagation [41]; (2) The ODE-S brings only tiny evaluation latency and memory burden to mobile devices, and thus can be applied to practical scenario within the delay scale of millisecond.

4.4 Robustness of ODE

In this subsection, we mainly compare the performance of ODE with the baselines on traffic classification dataset\(^8\) to demonstrate these methods’ robustness to various factors in the industrial settings.
environment, such as the number of local epoch $m$, participation rate $\frac{|C_1|}{|C|}$, storage capacity $|B_c|$, mini-batch size and data heterogeneity across clients.

**Number of Local Epoch.** Empirical results shown in Figure 9 demonstrate that: (1) ODE can work with various local training epochs. With the increasing number of local epoch, ODE achieves less training speedup will be achieved by ODE, but obtains higher inference accuracy final model compared with the all other baselines and thus higher improvement on user experience, which satisfies the target of network ML models; (2) ODE-Est has the similar effect with ODE-Exact on improving the model performance. The first phenomenon coincides with the previous analysis in Section 3.1: (1) For convergence rate, the one-step-look-ahead strategy of ODE only optimizes the loss reduction of the first local epoch in (4), and thus the influence on model convergence will be weakened when the number of local epoch becomes larger; (2) For inference accuracy, ODE narrows the gap between the models trained through FL and CL by optimizing the dominant term with the maximum weight, i.e., $(1 + \eta L)^m - 1 G_c(w^0_c)$, of the gap bound in (6), leading to better final inference accuracy with a larger $m$.

**Participation Rate.** The results in Figure 10 demonstrate that ODE is able to improve the FL process significantly even with small participation rates, speeding up the model training process 2.57 times and increasing the final inference accuracy by 6.6%. This augments the practicality of ODE in the industrial environment, where only a small proportion of devices could be ready to participate in the FL training round.

**Storage Capacity.** We also conduct experiments to discover how on-device storage impacts ODE. For each of the four data selection methods (RS, ODE-Exact, ODE-Est, FullData$^9$), we conduct experiments on various on-device storage capacities ranging from 5 to 20, and plot the training time as well as corresponding final accuracy. The training time is normalized by the time-to-accuracy of FullData to exhibit the variation of training time more clearly. Empirical results shown in Figure 11 indicate that (1) the performance of RS (both of inference accuracy and convergence rate) degrade rapidly with the decrease of storage capacity; (2) ODE has stable and good performances

---

$^9$We choose to compare with RS because it outperforms importance sampling and previous distributed data selection methods in general cases, and here we mainly want to discover the robustness of ODE.
| Batch Size | Speedup ODE-Est | Final Accuracy ODE-Est | #Label | Speedup ODE-Est | Final Accuracy ODE-Est |
|------------|----------------|------------------------|--------|----------------|------------------------|
| 1          | 2.42×           | 92.0%                  | 1      | 1.56×           | 81.8%                  |
| 2          | 2.07×           | 92.4%                  | 5      | 2.19×           | 85.5%                  |
| 5          | 1.97×           | 92.9%                  | 15     | 2.07×           | 89.0%                  |

Table 6. Different mini-batch sizes.

Table 7. Different data heterogeneity among clients.

independent on storage capacity and thus are robust to potential diverse storage capacity of heterogeneous devices in practice; (3) Compared with ODE, baseline needs more than twice storage space to achieve the same model performance.

**Mini-batch Size.** As mini-batch is widely used in model training of FL to reduce training time, we conduct the experiments with different mini-batch sizes, and adjust the learning rate from 0.005 to 0.001 and local epoch number from 5 to 2 to reduce the instability caused by the multiple local model updates. We show the performance of ODE-Est and RS in Table 6, which demonstrates that (1) ODE can improve the training process with various mini-batch sizes, increasing the model accuracy from 92% to 95% and speeding up the model convergence by as high as 2.42×; (2) The smaller batch size is, the more training speedup can be obtained by ODE, which coincides the results of different numbers of local updates.

**Data Heterogeneity.** The data heterogeneity (Non-IID data) among clients has always been an obstacle for accelerating convergence and improving accuracy in FL. Experimental results in Table 7 show that ODE can achieve at least 3.6% increase in inference accuracy and 1.56 speedup in training time in the most extremely heterogeneous case. As the client has more labels of data and thus a larger variance in a less heterogeneous setting, the limitation of on-device storage capacity will become more serious and the advantage of ODE can become more obvious on speeding up the convergence and increasing the final inference accuracy.

### 4.5 Component-wise Analysis

In this subsection, we evaluate the effectiveness of each of the three components in ODE: on-device data selection, global gradient estimator and cross-client coordination strategy. The results altogether show that each component is critical for the good performance guarantee of ODE.

**On-Client Data Selection.** To show the effect of on-client data selection, we compare ODE with another baseline, named Valuation-, which replaces the on-device data selection strategy with random sampling, but still allows the central server to coordinate the clients. The results in Figure 12 demonstrate that without data valuation module, Valuation- performs slightly better than RS but much worse than ODE-Est, which demonstrates the positive role of our data valuation metric used for on-device data selection.

**Global Gradient Estimator.** To show the effectiveness of the global gradient estimator, we compare ODE-Est with a naive estimation method, named Estimator-, where server only utilizes
the local gradient estimators of participating clients instead of all clients and each participant only leverages the samples stored locally to calculate the local gradient instead of utilizing all the generated data samples. Figure 12 shows that the naive estimation method has poor performance, due to the partial clients and biased local data used for estimating global gradient.

**Cross-Client Coordination.** We conduct another experiment where clients select and store data samples only based on their local information without the coordination of the server, named Coor-. Figure 12 shows that in this situation, the advantage of ODE on speeding up convergence and improving accuracy is largely weakened, as all the clients may tend to store the same valuable data samples and the other data will be under-represented.

5 **RELATED WORKS**

**Federated Learning** is a distributed learning framework that aims to collaboratively learn a global statistical model over the networked devices’ data under the constraint that the data is stored and processed locally [51, 55]. Existing works mostly focus on how to overcome the data heterogeneity problem [13, 18, 78, 85], reduce the communication cost [34, 42, 42, 82], select important clients [19, 47, 50, 59] or train a personalized model for each client [25, 36]. Despite that there exist a few works considering the problem of online FL or continuous FL [17, 31, 83], they did not consider the device properties of limited on-device storage and streaming networked data, and thus cannot be applied to the practical FL scenarios.

**Data Selection.** In FL, selecting data from streaming data can be seen as sampling batches of data from its data distribution, which is similar to mini-batch SGD. To accelerate the training process of SGD, the majority of existing methods quantify the importance of each data sample (such as loss [53, 63, 68], gradient norm [38, 87], uncertainty [14, 79]) and leverage importance sampling to select training samples for each round. Another closer area to our work is data evaluation, which tries to measure the contribution/importance of each data sample to the training process, such as leave-one-out test [20] and data shapley [29]. These methods fail to work for the network scenario as they require arbitrary access to the full dataset for model retraining.

**Traffic Classification** is a significant task in mobile network, which associates traffic packets with specific applications for the downstream network management task, like user experience, capacity planning and resource provisioning. The techniques for traffic classification can be classified into three categories. Port-based approaches [39] utilize the association of ports in the TCP or UDP header with well-known port numbers assigned by the IANA. Payload-based approach [76] identifies applications by inspecting the packet headers or payload, which has very high computational consumption and cannot handle encrypted traffic classification [26]. Statistics-based approach leverages payload-independent parameters such as packet length, inter-arrival time and flow direction to circumvent the problem of payload encrypted and user’s privacy [74].

6 **CONCLUSION**

In this work, we point out two key properties of networked FL: limited on-device storage and streaming networked data, which have not been fully explored in the literature. Then, we present the design, implementation and evaluation of ODE, which is an online data selection framework for FL with limited on-device storage. Our theoretical results show that ODE improves both convergence rate and inference accuracy of the global model, simultaneously. ODE contains on-device data selection and cross-device collaborative data storage, where the server coordinates devices to store valuable data samples from different regions of data distribution, and each device leverages the proposed new data valuation metric to conduct on-device data selection. We evaluate ODE on three public datasets and one industrial traffic classification dataset. Our results demonstrate that ODE significantly outperforms the state-of-the-art methods in convergence time and final accuracy.
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A APPENDIX

A.1 Proofs

Proof of Theorem 1.

\[ F(w^t_{\text{fed}}) \]

\[ \leq F(w^{t-1}_{\text{fed}}) + \langle \nabla_w F(w^{t-1}_{\text{fed}}), w^t_{\text{fed}} - w^{t-1}_{\text{fed}} \rangle + \frac{L}{2} \| w^t_{\text{fed}} - w^{t-1}_{\text{fed}} \|^2 \]

\[ \leq F(w^{t-1}_{\text{fed}}) + \langle \nabla_w F(w^{t-1}_{\text{fed}}), \sum_{c \in C_T} \zeta_c^t w^t_{c,m} - w^{t-1}_{\text{fed}} \rangle + \frac{L}{2} \| \sum_{c \in C_T} \zeta_c^t w^t_{c,m} - w^{t-1}_{\text{fed}} \|^2 \]

\[ \leq F(w^{t-1}_{\text{fed}}) + \sum_{c \in C_T} \zeta_c^t \langle \nabla_w F(w^{t-1}_{\text{fed}}), w^t_{c,m} - w^{t-1}_{\text{fed}} \rangle + \frac{L}{2} \| w^t_{c,m} - w^{t-1}_{\text{fed}} \|^2 \]

\[ \leq F(w^{t-1}_{\text{fed}}) + \sum_{c \in C_T} \zeta_c^t \left[ \frac{L}{2} \| w^t_{c,m} - w^{t-1}_{\text{fed}} \|^2 - \frac{\eta}{|B_c|} \sum_{i=0}^{m-1} \sum_{(x,y) \in B_c} \langle \nabla_w F(w^{t-1}_{\text{fed}}), \nabla_w l(w^t_{c,l}, x, y) \rangle \right] \]

\[ \leq F(w^{t-1}_{\text{fed}}) + \sum_{c \in C_T} \left[ \zeta_c^t \sum_{i=0}^{m-1} \left( \frac{L \eta^2}{2} \| \sum_{x,y \in B_c} \frac{1}{|B_c|} \nabla_w l(w^t_{c,l}, x, y) \|^2 \right) \right. \]

\[ - \frac{\eta}{|B_c|} \sum_{(x,y) \in B_c} \langle \nabla_w F(w^{t-1}_{\text{fed}}), \nabla_w l(w^t_{c,l}, x, y) \rangle \]

\[ \leq F(w^{t-1}_{\text{fed}}) + \sum_{c \in C_T} \left[ \zeta_c^t \sum_{i=0}^{m-1} \sum_{x,y \in B_c} \left( \frac{L \eta^2}{2|B_c|^2} \| \nabla_w l(w^t_{c,l}, x, y) \|^2 \right) \right. \]

\[ - \frac{\eta}{|B_c|} \langle \nabla_w F(w^{t-1}_{\text{fed}}), \nabla_w l(w^t_{c,l}, x, y) \rangle \]

Inequality 1 is from the L-Lipschitz continuity of global loss function \( F(w) \). Equality 2 is derived from the aggregation formula of Fed-Avg[55]. Equality 3 is according to the local update formula of each participant \( c \in C_T \) with data stored in \( B_c \).
Proof of Theorem 2

\[
\| w_{fed}^t - w_{cen}^m \| = \| \sum_{c \in C_t} \zeta_c^t [w_c^{t,m-1} - \nabla w \tilde{F}_c(w_c^{t,m-1})] - w_{cen}^m + \eta \nabla F(w_{cen}^m) \| \\
\leq \| \sum_{c \in C_t} \zeta_c^t [w_c^{t,m-1} - w_{cen}^m] + \eta \| \sum_{c \in C_t} \zeta_c^t \nabla w \tilde{F}_c(w_c^{t,m-1}) - \nabla F(w_{cen}^m) \| \\
\leq \sum_{c \in C_t} \zeta_c^t \| w_c^{t,m-1} - w_{cen}^m \| + \eta \| \sum_{c \in C_t} \zeta_c^t \nabla w \tilde{F}_c(w_c^{t,m-1}) - \nabla F(w_c^{t,m-1}) \| \\
+ \eta \| \nabla w F(w_c^{t,m-1}) - \nabla F(w_{cen}^m) \| \\
\leq 4 \sum_{c \in C_t} \zeta_c^t (1 + \eta L) \| w_c^{t,m-1} - w_{cen}^m \| \\
+ \eta \| \sum_{c \in C_t} \zeta_c^t \nabla w \tilde{F}_c(w_c^{t,m-1}) - \nabla F(w_c^{t,m-1}) \| \\
\leq \sum_{c \in C_t} \zeta_c^t [(1 + \eta L) \| w_c^{t,m-1} - w_{cen}^m \| + \eta G_c(w_c^{t,m-1})],
\]

where \( G_c(w) = \| \nabla w \tilde{F}_c(w) - \nabla w F(w) \| \). Inequality 4 holds because of assumption 1. In terms of \( \| w_c^{t,m-1} - w_{cen}^m \| \) for client \( c \in C \), we have:

\[
\| w_c^{t,m-1} - w_{cen}^m \| \\
= \| w_c^{t,m-2} - \nabla w \tilde{F}_c(w_c^{t,m-2}) - w_{cen}^{m-2} + \eta \nabla w F(w_{cen}^{m-2}) \| \\
\leq \| w_c^{t,m-2} - w_{cen}^{m-2} \| + \eta \| \nabla w \tilde{F}_c(w_c^{t,m-2}) - \nabla w F(w_{cen}^{m-2}) \| \\
\leq \| w_c^{t,m-2} - w_{cen}^{m-2} \| + \eta \| \nabla w F(w_c^{t,m-2}) - \nabla F(w_{cen}^{m-2}) \| \\
+ \eta \| \nabla w \tilde{F}_c(w_c^{t,m-2}) - \nabla w F(w_c^{t,m-2}) \| \\
\leq (1 + \eta L) \| w_c^{t,m-2} - w_{cen}^{m-2} \| + \eta G_c(w_c^{t,m-2}) \\
\leq (1 + \eta L)^{m-1} \| w_c^0 - w_{cen}^{(t-1)} \| + \eta \sum_{i=0}^{m-2} (1 + \eta L)^{m-2-i} G_c(w_c^{t-i})
\]

Combining inequalities 15 and 16, we have:

\[
\| w_{fed}^t - w_{cen}^m \| \\
\leq \sum_{c \in C_t} \zeta_c^t [(1 + \eta L)^m \| w_c^0 - w_{cen}^{(t-1)} \| + \eta \sum_{i=0}^{m-1} (1 + \eta L)^{m-1-i} G_c(w_c^{t-i})] \\
\leq (1 + \eta L)^m \| w_c^0 - w_{cen}^{(t-1)} \| + \sum_{c \in C_t} \zeta_c^t [(1 + \eta L)^m \| w_c^0 - w_{cen}^{(t-1)} \| + \eta \sum_{i=0}^{m-1} (1 + \eta L)^{m-1-i} G_c(w_c^{t-i})] \\
= (1 + \eta L)^m \| w_{fed}^t - w_{cen}^{(t-1)} \| + \sum_{c \in C_t} \zeta_c^t [(1 + \eta L)^m \| w_c^0 - w_{cen}^{(t-1)} \| + \eta \sum_{i=0}^{m-1} (1 + \eta L)^{m-1-i} G_c(w_c^{t-i})],
\]

Equality 1 is due to that \( \sum_{c \in C_t} \zeta_c^t = 1 \).
Proof of Lemma 1

\[ G_c (w) = \| \nabla_w \tilde{F}_c (w) - \nabla_w F (w) \| \]

\[ \leq \sqrt{n} \left( \| \nabla_w F (w) \|^2 + \sum_{(x,y) \in B_c} \frac{\nabla_w l(w, x, y)}{|B_c|} \| 2 - 2 \langle \nabla_w F (w), \sum_{(x,y) \in B_c} \frac{\nabla_w l(w, x, y)}{|B_c|} \rangle \right) \]

\[ \leq \sqrt{n} \left( \| \nabla_w F (w) \|^2 + \sum_{(x,y) \in B_c} \frac{1}{|B_c|} \left( \| \nabla_w l(w, x, y) \|^2 - 2 \langle \nabla_w F (w), \nabla_w l(w, x, y) \rangle \right) \right) \]

where \( n \) is the dimension of model parameter. Inequality 1 is based on the inequality of arithmetic and geometric means:

\[ \| \bar{a} - \bar{b} \|_1 = |a_1 - b_1| + \ldots |a_n - b_n| = \sum_{i=1}^{n} |a_i - b_i| \]

\[ \leq \sqrt{n} \sum_{i=1}^{n} (a_i - b_i)^2 = \sqrt{n} \| \bar{a} - \bar{b} \|_2^2 \]

A.2 Experimental Methodology

Tasks, Datasets, and ML Models. To demonstrate ODE’s generality across tasks, datasets, and ML models, we evaluate ODE on four public datasets that are commonly used for benchmarking: synthetic task, image classification, human activity recognition, and traffic classification. These tasks, datasets and models are selected for the on-device training settings for edge devices.

• Synthetic Task. The dataset we use is proposed in LEAF benchmark [12] and is described in details in [51]. In particular, for each device \( c \), we generate samples \( (X + k, Y_k) \) according to the model \( y = \text{argmax}(\text{softmax}(Wx + b)) \), where \( x \in \mathbb{R}^{60}, W \in \mathbb{R}^{10 \times 60}, b \in \mathbb{R}^{10} \). We model \( W_k \sim \mathcal{N}(u_k, 1), b_k \sim \mathcal{N}(u_k, 1), u_k \sim \mathcal{N}(0, \alpha), x_k \sim \mathcal{N}(v_k, \Sigma) \), where the covariance matrix \( \Sigma \) is diagonal with \( \Sigma_{j,j} = 10^5 \). Each element in the mean vector \( v_k \) is drawn from \( \mathcal{N}(B_k, 1), B_k \sim \mathcal{N}(0, \beta) \).

• Image Classification (IC). Image classification is a popular computer vision application. With the advancement of the computation power, it has become attractive to deploy image classification applications on mobile devices. In this work, we use LeNet [46] as the base model for training, and fashion-MNIST [80] dataset for training and evaluation. For Fashion-MNIST, we have 50 devices, where each device holds 5-class data and this five classes can be varies across devices. In addition, the data volume of each class is unbalanced on a device, and the test data follows the same distribution as the training data.

• Human Activity Recognition (HAR). Human activity recognition has become an attractive feature for smart-phones using data collected from different types of on-board sensors, such as accelerometer, gyroscope, etc. This task aims to recognize activities performed by an individual based on the sensor data. To build this task scenario, we use the HARBOX [61] dataset which is a 9-axis IMU data collected from 121 users’ smartphones for human activity recognition in a crowdsourcing manner. Such a controlled collection makes it less non-i.i.d in all four evaluated datasets. We further apply the resampling with a sliding time window of 2s at 50Hz to deliver a 900-dimension feature for all 34,115 data samples[61], and distribute each individual’s data to one device. Considering the simplicity of the dataset and task, a
lightweight customized DNN with two dense layers followed by the SoftMax layer is deployed in the FL processing.

• **Traffic Classification (TC).** The raw traffic packets are collected from the daily life of 30 participating ONT devices from May 2019 to June 2019 in a simulated network environment, and the application of each traffic package is labeled manually. For each package, we find its two adjacent packets in the same flow, extract the first 256 bytes of their headers or payloads as feature with dimension $3 \times 256$. Generally, the dataset is consisting of more than 560,000 data samples and has more than 250 applications as labels, which covers the application categories of videos (such as YouTube and Tiktok), games (such as LOL and WOW), files downloading (such as AppStore and Thunder) and communication (such as WhatsApp and WeChat). Due to the large-scale data, we select 20 applications out of 250 randomly as labels for experiments. The selected 20 labels have different numbers of data samples, ranging from 700+ to 4000+ and thus are imbalanced, whose distribution is shown in Figure 6. In our default dataset, the number of clients (remote mobile devices) is set to 30 and for each client, we draw samples from 15 classes, split the data samples into train/test datasets randomly with ratio 4 : 1, set the velocity to be $v_c = \frac{\text{#training samples}}{500}$ which means that each device $c \in C$ will receive $v_c$ data samples one by one in each communication round, and the training data samples will be shuffled and appear again per 500 rounds.

### A.3 Robustness Analysis

We analyze ODE’s robustness and sensitivity to various experimental parameters including participation rate, number of local epochs, storage capacity, number of noisy clients. Note that $ODE-Exact$ indicates the performance upper bound of $ODE$ and $ODE-Est$ reflects the effect of applying $ODE$ in three public datasets.

**Impact of participation rate.** We evaluate the impact of the number of participating devices in each communication round. Figure 13 reveals the same tendency of all the FL tasks: with the increasing of participating devices in each round, the final inference accuracy of all the data selection methods are improved. Also, the random sampling method ($RS$) is more sensitive to participation rates and will be improved a lot with more participating devices, while $FullData$ and $ODE$ are more robust to this factor.

**Impact of local epoch number.** We also evaluate the impact of local training epoch number. Figure 14 shows that: with the increasing of local training epochs, the inference accuracy gap between $RS$ and $ODE-Exact$ is becoming larger, while the inference accuracy gap between $RS$ and $ODE-Est$ is becoming smaller. The reason is that $i)$ $ODE$ theoretically improves the inference accuracy by improving the dominant term with high weight, i.e., $(1 + \eta L)^{m-1} G_c(w_c^0)$, leading to better final performance with larger $m$, but $ii)$ larger $m$ means larger global gradient estimation error as the problem of lacking current global FL model is becoming more serious.

**Impact of storage capacity.** Figure 15 shows the impact of storage capacity on synthetic dataset. We observed that the final accuracy of $RS$ decreases rapidly with the reduction of on-device storage (buffer size), while $FullData$ and $ODE$ are more robust to various on-device storage, making it more practical to apply $ODE$ to real FL scenario as the on-device storage may be dynamic with time due to new installed apps.

**Number of noisy devices.** We also examine the impact of the number of noisy devices, where we randomly choose some devices as noisy ones and manually revise the original labels of 10% local data samples to randomly wrong ones. Figure 16 shows that with noisy data, importance-based

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10In Section 3.1, we change the number of local labels to construct settings of different local data variances in order to discover the impact of on-device storage on FL training process.
methods (*HighLoss* and *GradientNorm*) cannot reach the target accuracy, but our proposed *ODE* is able to improve the final accuracy and accelerate training. We observed that the noisy data influences *ODE-Est* a lot, while *ODE-Exact* can still largely improve the model training process. The reason is that our local and global gradient estimators have larger approximation error with more noisy clients, which limits the effect of Estimation method.
Fig. 14. The impact of local training epochs.

(a) Synthetic

(b) FashionMNIST

(c) HARBOX

Fig. 15. The impact of Storage Capacity on Synthetic dataset.
(a) #Noisy clients=25%
(b) #Noisy clients=50%
(c) #Noisy clients=75%

Fig. 16. The impact of noisy device number.