A Device-Cloud Collaborative Data Enrichment Framework for Continual Learning on Devices

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***Abstract*—In modern mobile and edge applications, users and devices frequently encounter dynamic contexts, necessitating on-device continual learning (CL) to ensure consistent performance of machine learning models. While existing research predominantly focused on developing lightweight CL frameworks, we identify that data scarcity is a more severe bottleneck for on-device CL. In this work, we explore the potential of leveraging abundant cloud-side data to enrich scarce on-device data, and propose Delta, a private, efficient and effective data enrichment framework. Specifically, Delta introduces a directory dataset to decompose the data enrichment problem into device-side and cloud-side sub-problems without sharing raw sensitive data, mitigating privacy concerns and reducing communication overhead. Next, Delta designs a soft data matching strategy to effectively solve device-side sub-problem with sparse user data and an optimal data sampling scheme for cloud server to efficiently retrieve the most suitable dataset for enrichment. Further, Delta refines the data sampling scheme by jointly considering the impact of enriched data on both new and past contexts, mitigating the catastrophic forgetting issue from a new aspect. Finally, we enhance Delta's applicability to more private and rare user contexts by integrating differential privacy and domain adaptation techniques. Comprehensive experiments across four typical edge computing tasks with varied data modalities demonstrate that Delta significantly enhances overall model accuracy by an average of 15.1%, 12.4%, 1.1% and 5.6% for visual, IMU, audio and textual tasks compared with few-shot CL. Additionally, Delta reduces communication costs by over 90% compared to federated CL, making it suitable for resource-constrained edge networks.**

***Index Terms*—On-Device Continual Learning, On-Device Model Training, Device-Cloud Collaborative Data Enrichment**

I. Introduction

Machine learning (ML) models have become the indispensable components in modern mobile computing applications and services, such as image tagging in Google Smart Lens [1], speech recognition in Siri [2], text summarization and rewriting in Apple Intelligence [3] and etc. In a wide range of mobile apps, users encounter dynamic contexts in their daily lives and exhibit varying behaviors, leading to a non-stationary data distribution observed and collected by mobile devices. Consequently, on-device ML models are expected to evolve incrementally as new contextual data becomes available. This evolution, known as *continual learning (CL)* [4], [5], enables on-device ML models to gradually learn individual user preferences in different contexts and behaviors, and thus becoming more personalized and intelligent over time.

Unlike conventional ML built on the premise of learning static data distributions, CL learns from dynamic data distributions. A significant challenge in CL is balancing the model's learning plasticity (*i.e.* ability to assimilate new knowledge from new context) and memory stability (*i.e.* ability to preserve past knowledge from past contexts). For cloud servers with abundant hardware and data resources, many CL approaches have been proposed to address this challenge, such as regularizing parameter updates [6], [7], replaying historical data [8], [9], [10] and designing adaptive model architectures [11], [12], [13]. For resource-constrained devices, previous research has primarily focused on deploying cloud-side CL solutions on devices in a system-efficient manner [14], [15]. Existing methods include device-side hardware optimization (e.g., storage cost [16], [17], I/O speed [18], [19], computation [20], [21]) and cloud-assisted CL workload offloading (e.g., entire offloading [22], [23] and selective offloading [24], [25], [26], [27]), which are further elaborated in §VII.

Data Bottleneck. However, we identify that the scarce data resource on mobile devices is a more severe bottleneck for on-device CL. *First, data scarcity is a pervasive issue across various mobile applications.* For example, for image analysis applications, an average person takes around 4.9-20.2 photos daily [28]. For virtual assistants, only 16% of iPhone users reports using Siri several times a day [29]. *Second, the utilization of data resources fundamentally determines the performance ceiling for on-device CL*, whereas the optimization of hardware resources only influences the efficiency with which this ceiling can be reached. Limited data resources for a single context often results in the well-known issue of model overfitting [30], [31]. Further, inadequate data resources for both past and new contexts exacerbate the mutual interference between their learning processes, which deteriorates the model performance on past contexts, a phenomenon commonly referred to as catastrophic forgetting [32], [33], [6].

Limitation of Existing Work. Few-shot CL directly addresses the data scarcity challenge by leveraging a better model initialization, while federated CL helps mitigate it from the aspect of aggregating parameter updates from multiple devices.

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(1) Few-shot CL [34], [35], [36] involves pre-training ML models on common contexts with extensive data to capture general knowledge, which can be transferred to new contexts through model initialization and transfer learning techniques. However, this approach is ineffective for on-device settings due to the unpredictability and diversity of upcoming user contexts. *(2) Federated CL* [37], [38] suggests leveraging a cloud server to periodically aggregate the local models trained on distributed devices, which mitigates the overfitting problem on a single device and enables knowledge transfer across multiple devices. However, the model performance and convergence rate of federated CL are sensitive to device participation rate and data heterogeneity across devices [39], [40], [41], leading to high communication overhead and unstable model training process for real-world applications. Further, these solutions either complicate the parameter update formula or slow down the convergence rate, imposing extra hardware burden to the cumbersome on-device continual learning process.

Our Motivation. The data bottleneck of devices coupled with the limitations of existing methods motivate us to consider leveraging the abundant cloud-side data to enrich the scarce device-side data. This approach not only fundamentally addresses the data scarcity problem, but also adds no extra burden to the peak memory footprint or CPU/GPU utilization of on-device CL process. As we will elaborate in §II-B, simply increasing the training data size from 10 to 50 can yield a 10% improvement in model accuracy compared to the best few-shot CL approach, while incurring less than 5% communication costs compared with federated CL. The feasibility of such a cloud-assisted data enrichment framework is supported by two key observations: *(1) Abundant cloud-side data resource.* Cloud servers typically possess extensive datasets sourced from various channels, such as public datasets released by organizations *(e.g.* ImageNet [42]), open-source data crawled from the Internet webs (*e.g.* Common Crawl [43]), crowdsourced data contributed by authorized mobile users (*e.g.* DonateClient service of Huawei [44] and learn from this app in Apple [45]). *(2) Similarities among user contexts and behaviors.* Previous investigations have demonstrated that the preferences and behaviors of different mobile users in various contexts share similar patterns rather than being entirely unique [46], [47], [48]. This indicates the existence of a cloud-side data-subset that exhibits a similar distribution with the device-side data, offering an opportunity to enhance on-device CL performance.

Challenges. A feasible data enrichment framework for practical on-device CL needs to be *private*, *effective* and *efficient*, which are challenging to be achieved simultaneously.

• *Privacy vs. Efficiency.* In contemporary mobile applications, user data stored on devices is subject to stringent privacy regulations like GDPR [49]. However, to enrich device-side data with an optimal data-subset from cloud, one must either upload raw user data to the cloud for precise similarity comparison [50], or download numerous data-subsets from cloud and conduct trial-and-error processes to identify the appropriate data-subset [51]. Therefore, achieving efficient data enrichment without violating user privacy is challenging.

• *Effectiveness vs. Efficiency for New Context.* Given the diverse sources of cloud-side data, a randomly selected data-subset is likely to deviate significantly from the device-side data distribution, thereby degrading the CL performance over personal contexts. However, to identify the data-subset with the highest data enrichment performance for on-device CL, the cloud server needs to evaluate an exponential number of candidate data-subsets from the vast cloud-side dataset, which introduces prohibitively high time complexity and computational burden. Consequently, simultaneously reaching high effectiveness and efficiency poses another challenge.

• *Effectiveness for both Past and New Contexts.* As the data distributions of new contexts encountered by mobile users are dynamic, independently conducting data enrichment for each emerging context would compromise the on-device model's memory stability over past contexts, as the mutual interference among different contexts' learning processes can be escalated. Additionally, there is a lack of theoretical analysis or insight into the correlation between the enriched data of new context and model performance over past contexts, which further complicates the data enrichment problem for CL. Therefore, designing a data enrichment strategy that is effective for both new and past contexts is challenging.

Our Design. We propose Delta, a device-cloud collaborative data enrichment framework designed for on-device CL with high privacy protection, efficiency and effectiveness. First, we provide a generic formalization of the data enrichment problem for on-device CL, and analyze its practical challenges concerning user privacy and computation efficiency. Second, to mitigate privacy concerns, we propose the construction of a compact "directory" dataset for cloud-side data. This approach helps to decompose the original data enrichment problem into two sub-problems, which can be independently solved by mobile device and cloud server without necessitating the disclosure of sensitive raw data. Third, to achieve both efficient and effective data enrichment for each new context, we develop a soft data matching strategy to accurately solve the device-side sub-problem with sparse on-device data, and a theoretically optimal data sampling scheme for cloud-side data selection, which can be computed with low time complexity. Fourth, to maintain high effectiveness across both new and past contexts, we theoretically analyze the impact of new context's enriched data on model performance over all contexts, and re-optimize cloud-side data sampling strategy from a holistic perspective. Finally, to handle extremely rare device-side contexts or irrelevant cloud-side data, we integrate Delta with domain adaptation method by appending a lightweight model layer to the feature extractor. This module learns a transformation function to align the feature distributions of cloud enriched data with on-device data, guaranteeing Delta's effectiveness even when they are not perfectly matched.

Contributions of this work are summarized as follows:

• We identify the data bottleneck in on-device CL for dynamic user contexts, and explore the potential of utilizing cloud-side abundant data to enrich device-side data and then the performance of CL.

• We formalize the data enrichment problem for on-device CL and propose the first practical device-cloud collaborative data enrichment framework that simultaneously achieves privacy protection, effectiveness and efficiency.

- We evaluate Delta on real device Jetson Nano across four representative mobile computing tasks with various data modalities and models, demonstrating its broad applicability and superior performance over baselines in overall accuracy and communication efficiency.

II. Background and Motivation

A. On-Device Continual Learning

In mobile computing applications, users often encounter dynamic contexts and exhibit varying behaviors, leading to a non-stationary distribution of data collected by devices. For example, mobile users can encounter unseen objects, weather conditions and digital corruptions in image analytics applications [52], [53], experience new activities, physical conditions and device placements in human activity recognition (HAR) applications [54], or come across articles on various topics and in different languages in text analysis applications [55]. These applications necessitate timely and accurate responses from on-device ML models to ensure high service quality, driving the need for on-device CL. Figure 1 depicts the four stages a new context undergoes in on-device CL.

- *Context Detection:* When a new context is experienced by the user, it can be detected by mobile device through existing human-involved or automatic approaches [56], [52], [53]. For example, in HAR application, the former approach would suggest users to confirm a new activity, whereas the latter would detect a shift in sensor data distribution [56].
- *Data Collection:* For each new context, data samples following a new distribution are collected by mobile device as training data for the subsequent on-device CL process. In mobile applications, the data collected from an individual user's daily life is sparse, personalized and private, such as photos taken by user or interactions with a virtual assistant.
- *Enhancement:* Prior to conducting on-device CL for a new context, various enhancement techniques need to be applied to mitigate the severe impact of data scarcity, such as few-shot CL based on model initialization and federated CL approaches based on training algorithms. *Our work focuses on the design of this stage from the data perspective.*
- *Continual Learning*: The training data of both new and past contexts are mixed to update the on-device model, which has been recognized as one of the most effective methods to assimilate knowledge from new contexts without forgetting the knowledge of past contexts[1] [19], [57], [10], [58], [18].

It is important to note that we do not strictly limit what a context means or its granularity. This makes our framework inherently capable of handling highly dynamic data distributions by treating each individual data sample as a new context. While our primary experiments focus on more common scenarios where a context persists for a period of time and multiple samples are collected, our extended experiments in Section VI-D demonstrates our framework's scalability and robustness in such dynamic environments.

[1]It is noteworthy that our data enrichment framework can also benefit the classic CL approaches, such as parameter regularization [6], [7] and context-adaptive model architectures [12], [11], as illustrated in §VII.

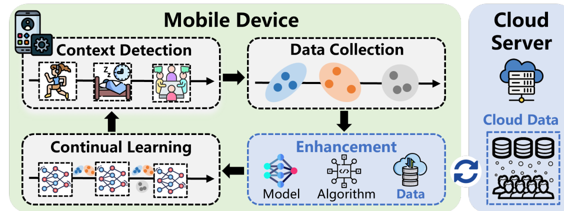
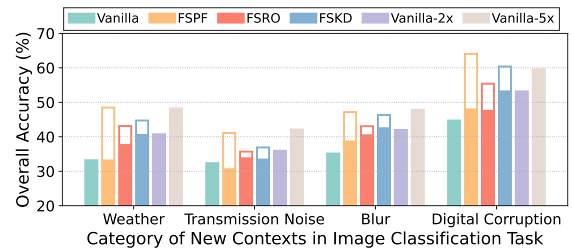
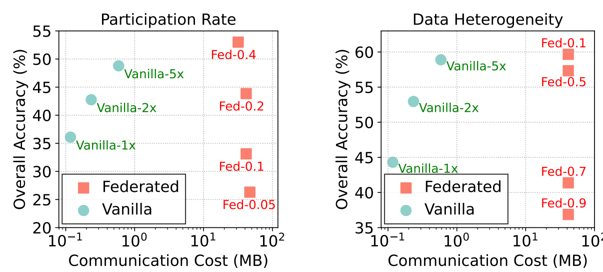


Fig. 1: On-device continual learning pipeline.



(a) Performance of few-shot CL approaches without (■) and with (□) prior information on user contexts, and performance of vanilla CL with different training data size (Vanilla-$n\times$). The "without prior information" setting uses a general cloud dataset for model pre-training, while the "with prior information" setting simulates an oracle scenario by manually selecting a data subset with high similarity with a user's future contexts for pretraining.



(b) Communication cost and accuracy of federated CL with varying device participation rates and data heterogeneity degree. For the left sub-figure, Fed-p indicates that a p portion of devices participate in each round, while for the right figure, Fed-p denotes that a p portion of devices hold data from different contexts.

Fig. 2: Preliminary experiments on image classification task to illustrate the limitations of existing solutions.

B. Limitation of Existing Approaches

In this section, we elaborate the limitations of existing few-shot CL and federated CL approaches in mitigating device-side data scarcity problem through preliminary experiments[2].

Few-shot CL [35], [36], [59] proposes pretraining ML models on base contexts with massive public data to capture general knowledge, which is then transferred to new contexts through transfer learning techniques. Representative methods include: 1) knowledge distillation [59] (FS-KD), which distills past contexts' knowledge to the new context's model by keeping the model outputs of historical data samples unchanged, 2) robust optimization [36] (FS-RO), which constrains model parameters within the common flat minima of all contexts' training objective functions, and 3) parameter freezing [35]

[2]The detailed experimental settings are introduced in §VI-A.

(FS-PF), which freezes the important parameters with high value of the previously trained model.

However, most of these few-shot CL approaches depend on a powerful model pre-training process, which pretrain either a large model on data from diverse contexts to fully capture the general knowledge, or a tiny model on a customized dataset to learn personalized knowledge. Unfortunately, both of them are impractical for on-device scenarios due to limited hardware resources and unpredictable contexts. On one hand, the limited memory and computational capabilities of mobile devices restrict the size and capacity of deployed models, impeding effective model pretraining over diverse data. On the other hand, the uncertainty of future user contexts prevents the pre-selection of a tailored data-subset for pretraining before model deployment. Our preliminary experiments shown in Figure 2(a) reveal that the performance of few-shot CL declines significantly without prior information on user contexts, with model accuracy reduction ranging from $8.6-15.3\%$ for FS-PF, $1.9-7.9\%$ for FS-RO and $3.9-7.2\%$ for FS-KD. In contrast, simply increasing the training data size from 10 to 50 can outperform all few-shot CL approaches, underscoring the potential of data enrichment.

Federated CL [37], [38] utilizes a cloud server to periodically aggregate the parameters of models trained on distributed devices, thereby mitigating the overfitting issue on individual devices and facilitating knowledge transfer across multiple devices. However, the substantial communication overheads and unstable model training process render federated CL impractical for mobile devices. First, the frequent exchange of model parameters between mobile devices and the cloud server incurs significant communication costs and prolongs the wall-clock training time for on-device models. Second, the model performance of federated CL is relatively sensitive to the device participation rate (or amount) and the data heterogeneity across devices [39], [40]. Experimental results shown in Figure 2(b) indicate that: 1) Federated CL achieves superior performance only when $\geq 20\%$ devices participate in each round of model aggregation or when more than $\geq 30\%$ mobile users experience similar contexts, which can be unrealistic in real-world settings; 2) In comparison to federated CL, transmitting data with a suitable distribution from cloud to each device could reach the same target accuracy with communication costs reduced to less than 1%.

III. Problem Definition

In this section, we present a generic formalization of the cloud-assisted data enrichment problem for on-device CL. We consider a scenario where a mobile user or edge device sequentially encounters T new contexts. Each context $t=1,\dots,T$ has an underlying data distribution $\mathcal{D}_{de}^t$ and the device collects an empirical dataset $\widehat{\mathcal{D}}_{de}^t$ for training on-device model. Due to the scarcity of user data, a similar data-subset $\mathcal{S}^t$ is expected to be retrieved from the cloud-side dataset $\mathcal{D}_{cl}$ to enrich the on-device empirical dataset $\widehat{\mathcal{D}}_{de}^t$ and thereby enhance the CL performance.

To assess the effectiveness of data enrichment, we first define a metric to evaluate the similarity between two datasets in terms of their impacts on the model training process. In on-device CL, model parameters are typically fine-tuned by on-device data via gradient descent methods. Therefore, the similarity between two datasets $\mathcal{D}_1$ and $\mathcal{D}_2$ with respect to the training process of model θ can be quantified by the maximal difference between the average gradients of $\mathcal{D}_1$ and $\mathcal{D}_2$ within a nearby parameter space $\{\theta' | \|\theta' - \theta\| \leq \epsilon\}$:

$$Sim(\mathcal{D}_1, \mathcal{D}_2 | \theta) \triangleq - \max_{\|\theta'-\theta\|\leq\epsilon} \big|\big|\nabla L(\mathcal{D}_1, \theta') - \nabla L(\mathcal{D}_2, \theta')\big|\big|, \quad (1)$$

where $L(\mathcal{D}, \theta) = \mathbb{E}_{(x,y)\in\mathcal{D}}\big[l(x, y, \theta)\big]$ denotes the expected loss of model θ over dataset $\mathcal{D}$. A high similarity between two datasets $\mathcal{D}_1$ and $\mathcal{D}_2$ implies their comparable performance in updating model parameters for multiple steps, resulting in similar impacts on on-device model training.

Problem Formulation. For each new context t, the cloud server aims to select the most similar data-subset $\mathcal{S}^{t,*} \subseteq \mathcal{D}_{cl}$ to update the current on-device model θ^{t-1} in a similar way with the device-side underlying data distribution $\mathcal{D}_{de}^t$, which means that $\mathcal{S}^{t,*}$ and $\mathcal{D}_{de}^t$ should exhibit high similarity as measured by the metric in Equation (1). Consequently, the data enrichment problem can be formally expressed as:

$$\begin{aligned} \mathcal{S}^{t,*} &= \operatorname*{arg\,max}_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}, |\mathcal{S}^t| \leq B} Sim(\mathcal{S}^t, \mathcal{D}_{de}^t \mid \theta^{t-1}) \\ &\approx \operatorname*{arg\,max}_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}, |\mathcal{S}^t| \leq B} Sim(\mathcal{S}^t, \widehat{\mathcal{D}}_{de}^t \mid \theta^{t-1}), \end{aligned} \quad (2)$$

where B represents the maximum allowable size of the selected data-subset and is constrained by the communication cost budget of each device. This formulation enables the device to enhance model training performance by expanding the training data from the collected dataset $\widehat{\mathcal{D}}_{de}^t$ to the enriched larger-scale dataset $\mathcal{S}^t$, while ensuring that the enriched data follows a similar distribution.

Practical Challenges. Directly solving the data enrichment problem in Equation (2) brings severe privacy concerns for mobile users and high computational burden for cloud server. First, the mobile device needs to upload both the current model θ^{t-1} and raw user data $\widehat{\mathcal{D}}_{de}^t$ to the cloud server, which poses a severe breach of user privacy. Second, the cloud server has to compute the similarity score $Sim(\mathcal{S}^t, \widehat{\mathcal{D}}_{de}^t | \theta^{t-1})$ for every possible data-subset $\mathcal{S}^t \subseteq \mathcal{D}_{cl}$, $|\mathcal{S}^t| \leq B$, resulting in exponential computation complexity.

IV. Framework Design

Delta incorporates three key components to render data enrichment systematically practical: the construction of a directory dataset to address privacy concerns (§IV-A), device-side soft data matching strategy coupled with a cloud-side data sampling scheme to efficiently and effectively enrich data for new contexts (§IV-B), and a re-optimization of the cloud-side data sampling to further enhance its effectiveness across both past and new contexts (§IV-C). *Each component is inspired and supported by theoretical analysis presented in §V and the overall design rationale is illustrated in Figure 3.*

A. Directory Dataset Construction

To mitigate privacy concerns, Delta introduces the concept of "directory" dataset, which facilitates decomposing the data

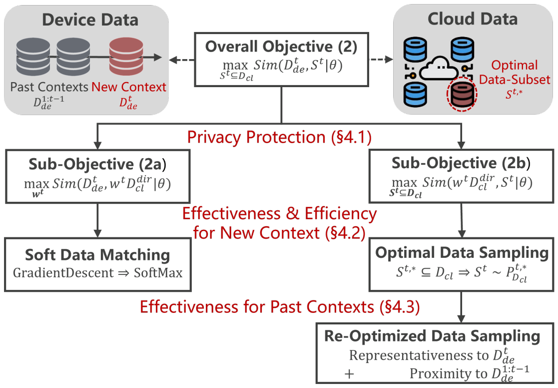


Fig. 3: Design Rationale of Delta.

enrichment problem (2) into two sub-problems, and allows the device and cloud to collaboratively solve the sub-problems without the need to share raw user data.

Design Rationale. Inspired by the directory structures in storage systems [60], Delta constructs a compact directory dataset consisting of a few data samples to represent the extensive cloud-side dataset, denoted as $\mathcal{D}_{cl}^{dir} = \{(\bar{x}_c, \bar{y}_c)\}_{c=1}^{|\mathcal{D}_{cl}^{dir}|}$. This directory dataset can be pre-downloaded by mobile devices along with the model deployment. As illustrated in Figure 3 and supported in Theorem 1, the objective function (2) of the data enrichment problem can be decomposed into the sum of two sub-objective functions:

• *Sub-objective (2a)*: similarity between the device-side dataset $\mathcal{D}_{de}^t$ and the weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$, where each data sample $(\bar{x}_c, \bar{y}_c) \in \mathcal{D}_{cl}^{dir}$ is assigned a weight w_c^t. The weight vector w^t is a variable to be optimized.

• *Sub-objective (2b)*: similarity between the weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$ and the cloud-side data-subset $\mathcal{S}^t$, where $\mathcal{S}^t$ is the variable to be optimized.

These two sub-objective functions can be optimized sequentially and independently by the mobile device and cloud server through the exchange of non-sensitive information:

• *Mobile device* optimizes sub-objective (2a) by computing the optimal weight $w^{t,*}$ for the directory dataset $\mathcal{D}_{cl}^{dir}$ to represent the device-side data distribution $\mathcal{D}_{de}^t$.

• *Cloud server* optimizes sub-objective (2b) by searching for the optimal cloud-side data-subset $\mathcal{S}^{t,*} \subseteq \mathcal{D}_{cl}$ to align with the weighted directory dataset $w^{t,*}\mathcal{D}_{cl}^{dir}$, with $w^{t,*}$ being uploaded by the mobile device after device-side optimization.

• *Device-cloud communication* involves the cloud-side directory dataset $\mathcal{D}_{cl}^{dir}$ and the device-side optimized weight $w^{t,*}$, which do not involve any raw user data and thus protect user privacy akin to classic federated learning [61]. Detailed discussion and comparison are presented in §VIII.

Practical Implementation. The practical effectiveness of the above decomposition process relies on an appropriate directory dataset that accurately represents the cloud-side public dataset. While classical data clustering methods can be used to select cluster centroids as the directory dataset elements, we observe that directly clustering raw data samples may not fully capture the influence of data on model training, due to the diverse sources, wide-ranging distributions and varying dimensions of cloud-side data. To address this issue, we take advantage of the typical paradigm of on-device model training [62], [63], [?], where the feature extractor ϕ is pre-trained on extensive cloud-side data for generalization ability and the classifier ψ is trained on device-side data for personalization performance. We propose clustering data samples $(x, y) \in \mathcal{D}_{cl}$ based on the feature extractor outputs $\phi(x)$ rather than raw input x, and selecting the cluster centroids as elements of the directory dataset, which offers two advantages: 1) features as model's intermediate outputs have a consistent dimension and are more relevant to model training than raw inputs, 2) the features of most cloud-side data samples are already available from the pre-training process of feature extractor, incurring minimal additional costs.

Privacy Consideration. In Delta framework, the information uploaded from devices to cloud include directory weights, which mitigates the privacy concerns from disclosing fine-grained raw user data to coarse-grained context likelihood distribution, inherently protecting privacy similar to federated learning (FL) [61]. For instance, in image analysis, the weights reveal the likelihood of weather conditions rather than specific pixel values, and in human activity recognition, the weights reflect the probability of device placement rather than IMU signals. Such design discloses only rough context information, making the recovery or identification of raw data significantly more challenging. To further mitigate privacy concerns, differential privacy [64] can be seamlessly integrated into Delta's communication and computation processes. Specifically, we inject Gaussian noise into the directory weights shared between devices and cloud, which obscures the identification of specific user context and controls the privacy protection degree through the noise distribution variance. In §VI-E, we analyze how Delta performance is impacted by inserting different degrees of noise into weight vectors. This provides insights into the privacy-performance trade-offs and helps identify the optimal configurations for different application scenarios. We acknowledge that our current design does not fully address privacy concerns. Achieving complete privacy requires dedicated integration with more advanced secure techniques, such as secure multi-party computation [65] or homomorphic encryption [66], which we plan to explore in future work.

B. Data Enrichment for New Context

While the directory dataset safeguards user privacy by decomposing the data enrichment problem into device-side and cloud-side sub-problems, it is non-trivial to solve them in an effective and efficient manner due to the scarcity of on-device data and diversity of cloud-side data.

• *Device-side ineffectiveness*: Solving sub-problem (2a) requires determining the optimal weight $w^{t,*}$ to align the weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$ with the device-side data distribution $\mathcal{D}_{de}^t$. However, the underlying data distribution is typically approximated by the sparse empirical dataset $\widehat{\mathcal{D}}_{de}^t$ stored by mobile device, which can cause conventional gradient descent algorithms to converge to local optima. Consequently, the derived weight becomes overfitted to the limited empirical dataset and ineffective in representing the device-side data distribution.

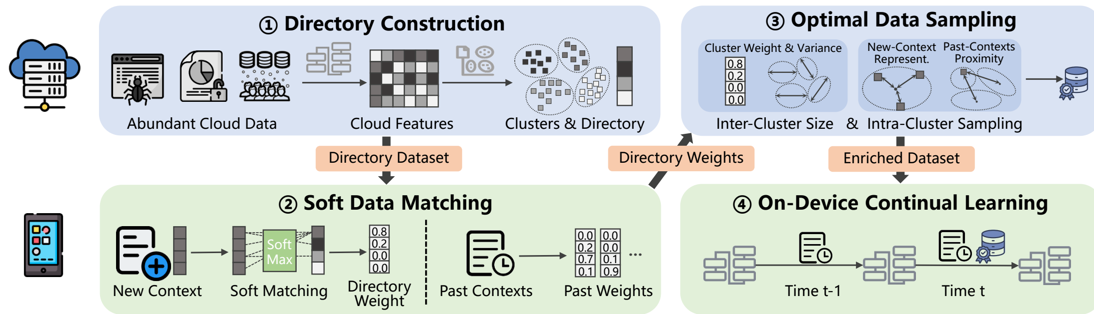


Fig. 4: Overall Workflow of Delta Framework. Delta serves as a plug-in for on-device continual learning.

• *Cloud-side inefficiency*: Exactly solving sub-problem (2b) involves evaluating the similarity score for each potential cloud-side data subset, which requires exploring a vast feasible region of candidate data-subsets $\mathcal{S}^t \subseteq \mathcal{D}_{cl}, |\mathcal{S}| \leq B$ and results in exponential computation and time complexity for cloud server, leading to low efficiency.

To achieve an efficient and effective data enrichment process for each coming context, we propose a soft data matching strategy for mobile device to derive a representative directory weight by fully leveraging the limited on-device data, and a data sampling scheme for cloud server to sample an optimal data-subset with constant time complexity.

Device-Side: Soft Data Matching. To prevent the directory weight w^t from overfitting to scarce on-device data, we propose to assign physical meanings to w^t by interpreting each element w^t_c as the fraction of on-device data that exhibits high similarity with the cloud-side cluster centroid $(\bar{x}_c, \bar{y}_c) \in \mathcal{D}^{dir}_{cl}$. Thus, for each data sample $(x,y) \in \widehat{\mathcal{D}}^t_{de}$ collected by mobile device, its similarities with all the cluster centroids are computed, and the weight of the most similar one is incremented by one step:

$$c^* = \arg\max_c Sim\big((x,y), (\bar{x}_c, \bar{y}_c) \mid \theta^{t-1}\big),$$
$$w^t_{c^*} \leftarrow w^t_{c^*} + 1. \qquad \text{(Hard Matching)}$$

However, in our experiments, we observe that each on-device data sample can exhibit high similarity with more than one cloud-side cluster centroids, which is influenced by the granularity of cloud-side data clustering (*i.e.* the number of data clusters) during the directory construction process. However, the "hard" matching function $argmax$ is incapable of capturing the correlation between one device-side sample and multiple cloud-side clusters. Thus, we propose to employ a "soft" matching function $softmax$, allowing each data sample to contribute to the weights of more than one clusters:

$$\forall c, w^t_c \leftarrow w^t_c + Softmax\left(\frac{Sim\big((x,y), (\bar{x}_c, \bar{y}_c) \mid \theta^{t-1}\big)}{\tau}\right), \quad (3)$$

where τ is a temperature hyperparameter to control the weight increments of clusters with different degrees of similarity. As $\tau \to 0$, $softmax$ gradually degrades to $argmax$.

Cloud-Side: Optimal Data Sampling. To enhance efficiency and reduce the computational overhead on the cloud server, we propose transforming the "hard" data selection process into a "soft" data sampling process. The key difference is that the former seeks to find an exact data-subset $\mathcal{S}^{t,*}$ to optimize sub-problem (2b), whereas the latter aims to compute a data sampling policy $P^{t,*}_{\mathcal{D}_{cl}}$ such that the sampled data-subset is optimal for sub-problem (2b) in expectation:

$$\max_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} Sim(\mathcal{S}^t, w^t \mathcal{D}^{dir}_{cl} | \theta^{t-1}) \qquad \text{(Hard Selection)}$$
$$\Rightarrow \max_{P^t_{\mathcal{D}_{cl}}} \mathbb{E}_{\mathcal{S}^t \sim P^t_{\mathcal{D}_{cl}}} \big[Sim(\mathcal{S}^t, w^t \mathcal{D}^{dir}_{cl} | \theta^{t-1})\big]. \qquad \text{(Soft Sampling)}$$

This transformation allows the cloud server to directly identify an appropriate data-subset through data sampling policy, which can be computed with low time complexity.

We outline the specific operations of cloud-side data sampling scheme, with theoretical foundation provided in §V-B. The scheme involves *inter-cluster size allocation* and *intra-cluster data sampling*, which determine *how many* and *which* data samples to select from each cloud-side data cluster:

• *Inter-cluster size allocation.* Given that the size of the selected data-subset is limited by the communication cost budget, the cloud server needs to allocate distinct sampling sizes to different data clusters to maximize the overall similarity between the sampled data-subset and the weighted directory dataset, *i.e.* sub-objective (2b). As demonstrated in Lemma 1, the optimal sampling size $|\mathcal{S}^{t,*}_c|$ for each cluster $\mathcal{D}_{cl,c}$ depends on its directory weight w^t_c and the dispersion degree of intra-cluster feature distribution $\mathbb{E}_x||\phi(x)-\phi(\bar{x})||$:

$$|\mathcal{S}^{t,*}_c| \propto w^t_c \cdot \mathbb{E}_{(x,y)\in\mathcal{D}_{cl,c}} \big|\big|\phi(x) - \phi(\bar{x}_c)\big|\big|. \quad (4)$$

For each cluster, a higher weight suggests a higher similarity with the device-side data for on-device CL, and a wider feature distribution indicates the need for more data samples to comprehensively represent the cluster .

• *Intra-Cluster Data Sampling.* Within each cloud-side data cluster $\mathcal{D}_{cl,c}$, the optimal sampling probability for each data sample (x, y) is proportional to the feature distance between such data sample and the cluster centroid $(\bar{x}_c, \bar{y}_c)$:

$$P^{t,*}_{\mathcal{D}_{cl,c}}(x,y) = \frac{\big|\big|\phi(x) - \phi(\bar{x}_c)\big|\big|}{\sum_{(x',y')\in\mathcal{D}_{cl,c}} \big|\big|\phi(x') - \phi(\bar{x}_c)\big|\big|}. \quad (5)$$

Theoretically, our analysis in Lemma 1 demonstrates that this sampling probability could maximize the expected similarity between each data cluster $\mathcal{D}_{cl,c}$ and the corresponding selected data-subset $\mathcal{S}^t_c$, thereby optimizing sub-objective (2b) in expectation given fixed directory weights w^t. Intuitively, this sampling strategy favors data samples that are farther from the cluster centroid, which enhances the diversity and informativeness of the selected data-subset while ensuring unbiasedness and representativeness through data re-weighting technique like importance sampling [67].

Our framework can also handle dynamically updated cloud-side dataset. When the cloud-side data is updated, the pre-downloaded directory dataset becomes less representative and covers only part of the cloud-side data distribution. However, this does not break the theoretical guarantee of Theorem 1 and only impacts the similarity of the selected cloud-side data subset. Such problem can be further addressed by a simple extension: periodically updating the directory dataset and sending it to device. This process does not compromise privacy, as the information shared by device remains consistent, i.e., the lightweight directory weight.

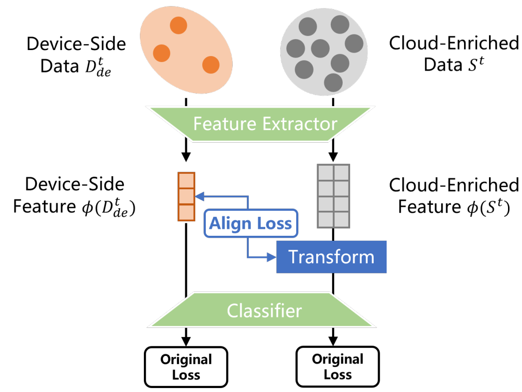


Fig. 5: Extend data enrichment to unique user contexts by aligning the feature distributions of device and cloud data.

C. Data Enrichment for all Contexts

Although the previous components ensure a private, efficient and effective data enrichment process for each new context, the notorious issue of catastrophic forgetting (*i.e.* inferior memory stability) is also exacerbated. First, as model parameters θ continually adapt to the enriched data $\{\mathcal{S}^i\}_{i=1}^t$, the similarity between each past context i's enriched data $\mathcal{S}^i$ and the underlying distribution $\mathcal{D}_{de}^i$ gradually diminishes, hindering the use of $\{\mathcal{S}^i\}_{i=1}^t$ for retaining past knowledge. Second, independently enriching data solely for the new context will exacerbate the mutual interference between the model training processes of new and past contexts.

To address these issues, we take the first step to theoretically analyze the correlation between new context's enriched data and the model performance on both new and past contexts. Further, we re-optimize the data sampling scheme for cloud server to identify a data-subset that could contribute to the learning processes of both new and past contexts.

Theoretical Analysis. Theorem 3 reveals that the overall CL performance, quantified by the average loss of model over all contexts, is primarily determined by three terms:
1) New-context representativeness, which is quantified by the feature distance between the enriched dataset $\mathcal{S}^t$ and the underlying data distribution of new context $\mathcal{D}_{de}^t$.
2) Past-contexts proximity, which is measured by the feature distance between the enriched dataset $\mathcal{S}^t$ and the underlying data distributions of all the past contexts $\{\mathcal{D}_{de}^i\}_{i=1}^{t-1}$.
3) Cross-Context Heterogeneity, which is a fixed term and determined by the heterogeneity between the new context and the past contexts encountered by the mobile user.
Consequently, the original intra-cluster data sampling strategy in Equation (5) can be seen as focusing only on the first term (*i.e.* effectiveness for new context), while overlooking the second term (*i.e.* effectiveness for past contexts.)

Practical Implementation. Guided by the theoretical results, we further derive the analytical expression for the re-optimized cloud-side data sampling policy, with the detailed mathematical derivation provided in §V-C. Specifically, for intra-cluster data sampling, the optimal sampling probability for each data sample is proportional to the weighted sum of new-context representativeness and past-contexts proximity:

$$P_{\mathcal{D}_{cl,c}}^{t,*}(x,y) \propto \left|\left|\phi(x)-\phi(\bar{x}_c)\right|\right| + \alpha \left|\left|\phi(x) - \frac{\sum_{i=1}^{t-1}\phi(w^{i,*}\mathcal{D}_{cloud}^{dir})}{t-1}\right|\right|,$$

where α is a hyperparameter determined by the device to balance the model performance over the new context and past contexts when conducing data enrichment.

D. Rare User Context Extension

The proposed design enables the cloud server to efficient and effectively select a data subset that exhibits the highest similarity with the device-side data distribution. However, in real-world networking scenarios, the majority of edge devices and mobile users operate in common scenarios, while a small subset may encounter rare of unique contexts. This can lead to a significant divergence between the cloud-side selected data subset and the actual device-side data distribution, thereby diminishing the effectiveness of data enrichment.

To address this challenge, we propose integrating domain adaptation techniques [68] into the design of Delta. By treating the massive cloud-enriched data $\mathcal{S}^t$ as the source domain and the scarce device-side data $\mathcal{D}_{de}^t$ as the target domain, we can "transform" the enriched dataset to better align with the device-side data distribution. Since the feature extractor of ML models on devices is typically pre-trained and fixed, we focus on transforming the feature representations of the source domain to match those of the target domain. This approach minimizes the feature distribution discrepancy between these two domains, and ensures that the training data from both domains contributes to the continual learning performance over the true device-side data distributions (i.e. rare context).

Practical Implementation. A widely adopted method for feature-level alignment is to learn a non-linear transformation function that maps source features to the target feature space. This method can be seamlessly integrated into Delta by introducing a new loss function term to learn the transformation function, as shown in Figure 5. For practical implementation, we introduce a lightweight, fully connected layer with minimal parameters between the feature extractor and classifier of the on-device model. This layer is designed to learn the mapping between cloud-enriched data and device-side data, and it is continuously updated during the model training process for each new context. During the inference phase on edge devices, this small module can be omitted without compromising the model's performance for rare context, ensuring computational efficiency and scalability. When learning new contexts, the transformation modules associated with past contexts are dynamically loaded to facilitate model re-training on historical data. Despite this, the relatively small size of the transformation module ensures that the additional computation and memory overheads imposed on edge devices remain marginal.

E. Overall Framework

We illustrate the overall workflow of Delta framework in Figure 4, which comprises four stages.

❶ **Directory Construction:** Initially, the cloud server utilizes the pre-trained feature extractor to extract features from diverse datasets and performs data clustering to construct the directory dataset. The directory dataset is then distributed to mobile devices along with the model deployment.

❷ **Soft Data Matching:** For each coming new context t, the mobile device solves sub-problem (2a) through the soft data matching strategy outlined in Equation (3), and uploads the optimal directory weights for both the new and past contexts to the cloud server.

❸ **Optimal Data Sampling:** Upon receiving the directory weights, the cloud server computes the analytical expressions for the optimal data sampling scheme, which includes inter-cluster size allocation in Equation (4) and intra-cluster data sampling in Equation (5). The optimal data-subset is then sampled according to the scheme and transmitted back to the mobile device.

❹ **On-Device Continual Learning:** The mobile device conducts CL process using the enriched datasets of both new and past contexts. *Generally, Delta serves as a plug-in module to enhance on-device CL performance with privacy protection, effectiveness and efficiency.*

V. Theoretical Analysis

In this section, we provide theoretical foundations for the three key components of Delta framework.

A. Theoretical Results for Directory Construction

To facilitate data enrichment as outlined in Equation (2) without disclosing raw user data, we introduce the directory dataset $\mathcal{D}_{cl}^{dir}$ to decompose the original objective function into the sum of two sub-objective functions. The performance of this decomposition is theoretically guaranteed by Theorem 1, which establishes the correlation between the original objective function and two sub-objective functions.

Theorem 1. *Given the directory dataset $\mathcal{D}_{cl}^{dir}$, the maximal similarity between the device-side dataset $\mathcal{D}_{de}^{t}$ and the cloud-side data-subset $\mathcal{S}^t \subseteq \mathcal{D}_{cl}$ for model θ^{t-1} can be bounded:*

$$\underbrace{\max_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} Sim(\mathcal{D}_{de}^t, \mathcal{S}^t|\theta^{t-1})}_{\text{original objective}} \geq \underbrace{\max_{w^t} Sim(\mathcal{D}_{de}^t, w^t\mathcal{D}_{cl}^{dir}|\theta^{t-1})}_{\text{sub-objective (2a) for optimal weight}} + \underbrace{\max_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} Sim(\mathcal{S}^t, w^{t,*}\mathcal{D}_{cl}^{dir}|\theta^{t-1})}_{\text{sub-objective (2b) for optimal subset}},$$

where $w^t\mathcal{D}_{cl}^{dir}$ represents the weighted directory dataset.

Proof. According to the definition of similarity function $Sim()$, we can decompose the original objective function by introducing an intermediary term involving a weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$:

$$\begin{aligned}
&\max_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} Sim(\mathcal{D}_{de}^t, \mathcal{S}^t|\theta^{t-1}) \\
&= -\min_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} \max_{\|\theta' - \theta^{t-1}\| \leq \epsilon} \big|\big|\nabla L(\mathcal{D}_{cl}, \theta') - \nabla L(\mathcal{S}^t, \theta')\big|\big| \\
&\overset{(a)}{\geq} -\min_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} \max_{\|\theta' - \theta^{t-1}\| \leq \epsilon} \Big\{\big|\big|\nabla L(\mathcal{D}_{cl}, \theta') - \nabla L(w^t\mathcal{D}_{cl}^{dir}, \theta')\big|\big| \\
&\quad + \big|\big|\nabla L(w^t\mathcal{D}_{cl}^{dir}) - \nabla L(\mathcal{S}^t, \theta')\big|\big|\Big\}, \quad \forall w^t\mathcal{D}_{cl}^{dir},
\end{aligned} \tag{6}$$

where inequality (a) follows from the Triangle inequality of the norm function [69]. Next, we apply the max-sum inequality, which states that $\max_x \{f(x)+g(x)\} \leq \max_x f(x) + \max_x g(x)$, to further simplify the expression:

$$\begin{aligned}
(6) &\geq -\min_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} \Big\{\max_{\|\theta' - \theta^{t-1}\| \leq \epsilon} \big|\big|\nabla L(\mathcal{D}_{cl}, \theta') - \nabla L(w^t\mathcal{D}_{cl}^{dir}, \theta')\big|\big| \\
&\quad + \max_{\|\theta' - \theta^{t-1}\| \leq \epsilon} \big|\big|\nabla L(w^t\mathcal{D}_{cl}^{dir}) - \nabla L(\mathcal{S}^t, \theta')\big|\big|\Big\} \\
&= -\max_{\|\theta' - \theta^{t-1}\| \leq \epsilon} \big|\big|\nabla L(\mathcal{D}_{cl}, \theta') - \nabla L(w^t\mathcal{D}_{cl}^{dir}, \theta')\big|\big| \\
&\quad - \min_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} \max_{\|\theta' - \theta^{t-1}\| \leq \epsilon} \big|\big|\nabla L(w^t\mathcal{D}_{cl}^{dir}) - \nabla L(\mathcal{S}^t, \theta')\big|\big| \\
&= Sim(\mathcal{D}_{cl}, w^t\mathcal{D}_{cl}^{dir}|\theta^{t-1}) + \max_{\mathcal{S}^t \subseteq \mathcal{D}_{cl}} Sim(w^t\mathcal{D}_{cl}^{dir}, \mathcal{S}^t).
\end{aligned}$$

Since the above deduction holds for any weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$ as an intermediary term, we can minimize the divergence between the final objective function and original objective function by optimizing the weight w^t. This leads to the conclusion presented in Theorem 1. □

Theorem 1 establishes that the optimal value of the original objective function (2) is bounded from below by the sum of the optimal values of the two sub-objective functions (2a) and (2b). Consequently, Delta essentially optimizes the worst-case performance of data enrichment across diverse contexts, ensuring robustness even in dynamic and unpredictable user contexts. The practical gap between the original and decomposed objective functions is primarily determined by the representativeness of the cloud-side directory dataset. When the directory dataset is constructed through a fine-grained data clustering process and thoroughly represents the cloud-side dataset, sub-objective (2a) gradually converges to the original objective function (2). In §VI-C, we empirically demonstrate that a directory dataset compromising approximately 10^2 elements is sufficient to represent a cloud-side dataset consisting of 10^6 data samples across 10^2 contexts.

B. Theoretical Results for New Context's Enrichment

To establish the theoretical guarantees for the optimality of the cloud-side data sampling scheme described in Eq (4) and (5), we introduce Theorem 2 to partition the on-device model θ into a feature extractor ϕ and a classifier ψ with a Lipstchiz continuity constant L_ψ. The feature extractor is typically pre-trained by cloud server and remains fixed during on-device model training process.

Theorem 2. *The expected similarity between the weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$ and the data-subset $\mathcal{S}^t$ selected according to the sampling scheme $P_{\mathcal{D}_{cl}}^t$ is bounded by:*

$$\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\left[Sim(\mathcal{S}^t, w^t\mathcal{D}_{cl}^{dir} \mid \theta^{t-1})\right]$$
$$\geq -\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t} L_\psi \Big|\Big|\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\Big|\Big|.$$

where ϕ represents the feature extractor and ψ denotes the classifier with L_ψ-Lipschitz continuous gradient.

Proof. According to the definition of similarity, we have:

$$\begin{aligned}
&\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\left[Sim(\mathcal{S}^t, w^t\mathcal{D}_{cl}^{dir}|\theta^{t-1})\right]\\
=&\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big[-\max_{\|\theta'-\theta^{t-1}\|\leq\epsilon}\big|\big|\nabla L(\mathcal{S}^t,\theta') - \sum_c w_c^t\nabla l(\bar{x}_c,\bar{y}_c,\theta')\big|\big|\Big]\\
\geq&\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big[-\big|\big|\nabla L(\mathcal{S}^t,\theta^{t-1}) - \sum_c w_c^t\nabla l(\bar{x}_c,\bar{y}_c,\theta^{t-1})\big|\big| - 2L_\psi\epsilon\Big]\\
\geq&-\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\big|\big|\nabla L(\mathcal{S}^t,\theta^{t-1}) - \sum_c w_c^t\nabla l(\bar{x}_c,\bar{y}_c,\theta^{t-1})\big|\big|\\
\geq&-\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t} L_\psi\big|\big|\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\big|\big|,
\end{aligned}$$

where $(\bar{x}_c,\bar{y}_c)$ denotes elements of directory dataset and the inequality is due to L_ψ-Lipschitz continuous gradient. □

In Lemma 1, we further show that the expected value of sub-objective function (2b) (i.e., lower bound of the above inequality) is determined by two factors: inter-cluster sampling size $|\mathcal{S}_c^t|$ and intra-cluster sampling probability $P_{\mathcal{D}_{cl,c}}^t(x,y)$ for each cloud-side data cluster c.

Lemma 1. *The expected similarity between the sampled data-subset $\mathcal{S}^t$ and the weighted directory dataset $w^t\mathcal{D}_{cl}^{dir}$ is determined by each cluster c's sampling size $|\mathcal{S}_c^t|$ and intra-cluster data sampling probability $P_{\mathcal{D}_{cl,c}}^t(x,y)$:*

$$\begin{aligned}
&\min_{P_{\mathcal{D}_{cl}}^t}\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big|\Big|\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\Big|\Big|\\
=&\min_{|\mathcal{S}_c^t|,P_{\mathcal{D}_{cl,c}}^t}\sum_c\left[\frac{(w_c^t)^2}{|\mathcal{S}_c^t|}\cdot\sum_{(x,y)\in\mathcal{D}_{cl,c}}\frac{\big|\big|\phi(x)-\phi(\bar{x})\big|\big|^2}{|\mathcal{D}_{cl,c}|^2\cdot P_{\mathcal{D}_{cl,c}}^t(x,y)}\right]
\end{aligned}$$

Proof. According to the definition of data variance $\mathbb{V}[x] = \mathbb{E}\,\|x\|^2 - \|\,\mathbb{E}[x]\,\|^2$, we have:

$$\begin{aligned}
&\arg\min_{P_{\mathcal{D}_{cl}}^t}\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big|\Big|\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\Big|\Big|\\
=&\arg\min_{P_{\mathcal{D}_{cl}}^t}\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big|\Big|\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\Big|\Big|^2\\
=&\arg\min_{P_{\mathcal{D}_{cl}}^t}\mathbb{V}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big[\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\Big]\\
&+\Big|\Big|\underbrace{\mathbb{E}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\big[\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\big]}_{\text{0 due to unbiased importance sampling}}\Big|\Big|^2\\
=&\arg\min_{P_{\mathcal{D}_{cl}}^t}\mathbb{V}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big[\mathbb{E}_{(x,y)\in\mathcal{S}^t}\left[\phi(x)\right] - \sum_c w_c^t\phi(\bar{x}_c)\Big],
\end{aligned}\tag{7}$$

where the unbiasedness property of importance sampling has been proved in previous research on importance sampling strategies [67], [70].

Building on this foundation, we decompose the overall sampling variance into the sum of weighted variances of different clusters. In this process, the variables transition from the overall sampling function $P_{\mathcal{D}_{cl}}^t$ to the intra-cluster sampling function $P_{\mathcal{D}_{cl,c}}^t$ for each cluster c.

$$\begin{aligned}
(7)=&\arg\min_{P_{\mathcal{D}_{cl}^t}}\mathbb{V}_{\mathcal{S}^t\sim P_{\mathcal{D}_{cl}}^t}\Big[\sum_c w_c^t\Big(\mathbb{E}_{(x,y)\in\mathcal{S}_c^t}\left[\phi(x)\right]-\phi(\bar{x}_c)\Big)\Big]\\
\overset{(b)}{=}&\arg\min_{\mathcal{S}_c^t,P_{\mathcal{D}_{cl,c}}^t}\sum_c(w_c^t)^2\cdot\mathbb{V}_{\mathcal{S}_c^t\sim P_{\mathcal{D}_{cl,c}}^t}\Big[\mathbb{E}_{(x,y)\in\mathcal{S}_c^t}\left[\phi(x)\right]-\phi(\bar{x}_c)\Big]\\
=&\arg\min_{\mathcal{S}_c^t,P_{\mathcal{D}_{cl,c}}^t}\sum_c\frac{(w_c^t)^2}{|\mathcal{S}_c^t|}\cdot\mathbb{V}_{(x,y)\sim P_{\mathcal{D}_{cl,c}}^t}\left[\phi(x)-\phi(\bar{x}_c)\right]\\
\overset{(c)}{=}&\arg\min_{\mathcal{S}_c^t,P_{\mathcal{D}_{cl,c}}^t}\sum_c\frac{(w_c^t)^2}{|\mathcal{S}_c^t|}\cdot\mathbb{E}_{(x,y)\sim P_{\mathcal{D}_{cl,c}}^t}\big|\big|\phi(x)-\phi(\bar{x}_c)\big|\big|^2\\
=&\arg\min_{\mathcal{S}_c^t,P_{\mathcal{D}_{cl,c}}^t}\sum_c\frac{(w_c^t)^2}{|\mathcal{S}_c^t|}\sum_{(x,y)\in\mathcal{D}_{cl,c}}\frac{\big|\big|\phi(x)-\phi(\bar{x}_c)\big|\big|^2}{|\mathcal{D}_{cl,c}|^2\cdot P_{\mathcal{D}_{cl,c}}^t(x,y)}.
\end{aligned}$$

Equality (b) holds because we decompose the overall variance of the sampled data into variances for different clusters, and equality (c) is also due to the unbiasedness property of importance sampling. □

Finally, by leveraging Cauchy-Schwarz inequality, we derive the analytical expressions for the optimal data sampling policy (i.e. $|\mathcal{S}_c^{t,*}|$ and $P_{\mathcal{D}_{cl}}^{t,*}$), which can be computed directly using the directory weights uploaded by mobile device:

$$\begin{cases}
|\mathcal{S}_c^{t,*}| & \propto\quad w_c^t\cdot\mathbb{E}_{(x,y)\in\mathcal{D}_{cl,c}}\big|\big|\phi(x)-\phi(\bar{x}_c)\big|\big|\\
\mathcal{P}_{\mathcal{D}_{cl,c}}^{t,*}(x,y) & \propto\quad \big|\big|\phi(x)-\phi(\bar{x}_c)\big|\big|,\quad\forall(x,y)\in\mathcal{D}_{cl,c}.
\end{cases}$$

C. Theoretical Results for All Contexts' Enrichment

In §IV-C, we propose to refine the cloud-side data sampling scheme to ensure that the enriched data for the new context contributes effectively to the learning processes of both new and past contexts. To achieve this, we first analyze the impact of the new context's enriched data on the model performance across all contexts in Theorem 3. This theorem identifies three key factors influencing the model's performance improvement: representativeness to the new context, proximity to past contexts and the data heterogeneity across different contexts.

Theorem 3. *In m-th training round for context t, when the model parameters are updated from $\theta^{t,m}$ to $\theta^{t,m+1}$ using the enriched data S^t sampled by policy $P^t_{\mathcal{D}_{cl}}$, the expected reduction in model loss (i.e., improvement in model performance) over all contexts' data distribution $\mathcal{D}^{1:t}_{de}$ can be bounded by:*

$$\begin{aligned}&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\underbrace{L(\mathcal{D}^{1:t}_{de},\theta^{t,m+1})-L(\mathcal{D}^{1:t}_{de},\theta^{t,m})}_{\text{loss reduction in } m\text{-th model update}}\Big]\\ \le&\frac{1}{2}(H\eta^2-\eta)L_\psi\underbrace{\mathbb{V}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\left[\phi(\mathcal{D}^t_{de})-\phi(\mathcal{S}^t)\right]}_{\text{representativeness to new context } t}+\\ &\frac{\eta L_\psi}{2}\underbrace{\mathbb{V}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\left[\phi(\mathcal{D}^{1:t-1}_{de})-\phi(\mathcal{S}^t)\right]}_{\text{proximity to past contexts } 1\sim t-1}+\frac{\eta L_\psi}{2}\underbrace{||\phi(\mathcal{D}^t_{de})-\phi(\mathcal{D}^{1:t-1}_{de})||^2}_{\text{heterogeneity across contexts}},\end{aligned}$$

where $\mathbb{V}_x[f(x)]$ denotes the variance of function $f(x)$ and we assume that the commonly used loss functions are $\frac{H}{2}$-smooth similar with previous works on model convergence analysis.

Proof. First, we decompose the overall performance improvement of on-device model in the m-th round into the improvements over past and new contexts by using the $\frac{H}{2}$-smooth property of the commonly seen loss functions:

$$\begin{aligned}&L(\mathcal{D}^{1:t}_{de},\theta^{t,m+1})-L(\mathcal{D}^{1:t}_{de},\theta^{t,m})\\ \le&\langle\nabla L(\mathcal{D}^{1:t}_{de},\theta^{t,m}),\theta^{t,m+1}-\theta^{t,m}\rangle+\frac{H}{2}||\theta^{t,m+1}-\theta^{t,m}||^2\\ =&\langle\nabla L(\mathcal{D}^{1:t}_{de},\theta^{t,m}),-\eta\nabla L(\mathcal{S}^t,\theta^{t,m})\rangle+\frac{H\eta^2}{2}||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ \overset{(d)}{=}&\langle\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})+\nabla L(\mathcal{D}^t_{de},\theta^{t,m}),-\eta\nabla L(\mathcal{S}^t,\theta^{t,m})\rangle\\ &+\frac{H\eta^2}{2}||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ =&-\eta\langle\nabla L(\mathcal{D}^t_{de},\theta^{t,m}),\nabla L(\mathcal{S}^t,\theta^{t,m})\rangle+\frac{H\eta^2}{2}||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &-\eta\langle\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m}),\nabla L(\mathcal{S}^t,\theta^{t,m})\rangle,\end{aligned}\tag{8}$$

where equality (d) is derived by decomposing the overall training loss function into the loss functions of past contexts $1\sim t$ and new context t.

To better analyze the impact of the data sampling policy on model training performance, we transform the relationship between the enriched training data $\mathcal{S}^t$ and the on-device empirical data $\mathcal{D}^t_{de}$ from a multiplicative form to a difference form. This transformation is achieved by leveraging the classic equality: $-ab=\frac{1}{2}[(a-b)^2-a^2-b^2]$:

$$\begin{aligned}(8)=&\frac{\eta}{2}\Big[||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2-||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &-||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})||^2\Big]+\frac{H\eta^2}{2}||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &+\frac{\eta}{2}\Big[||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &-||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2-||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})||^2\Big]\\ =&\frac{\eta}{2}||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2-\frac{\eta}{2}||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})||^2\\ &+(\frac{H\eta^2}{2}-\eta)||\nabla L(\mathcal{S}^t,\theta^{t,m})||^2-\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})||^2\\ &+\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2.\end{aligned}\tag{9}$$

Next, we aim to analyze the impact of new context's enriched data $\mathcal{S}^t$ on the overall model training performance across all contexts $\mathcal{D}^{1:t}_{de}$. Since the enriched data $\mathcal{S}^t$ is sampled from the cloud-side dataset $\mathcal{D}_{cl}$ with uncertainty, we focus on the expected training loss reduction, i.e. $\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}[(9)]$. By decomposing the term $||\nabla L(\mathcal{S}^t,\theta^{t,m})||$ using the equality $b^2=(a-b)^2-a^2+2ab$, we can obtain:

$$\begin{aligned}&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}[(9)]\\ =&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\frac{\eta}{2}||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &+(\frac{H\eta^2}{2}-\eta)\Big(||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &-||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})||^2+2\langle\nabla L(\mathcal{D}^t_{de},\theta^{t,m}),\nabla L(\mathcal{S}^t,\theta^{t,m})\rangle\Big)\\ &-\frac{\eta}{2}||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})||^2-\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})||^2\\ &+\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\Big].\end{aligned}$$

Due to the unibasedness property of cloud-side sampling policy, as established in importance sampling works [67], [70], we have the following approximation:

$$\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\left[\nabla L(\mathcal{S}^t,\theta^{t,m})\right]=\nabla L(w^t\mathcal{D}^{dir}_{cl},\theta^{t,m})\approx\nabla L(\mathcal{D}^t_{de},\theta^{t,m}),$$

which further simplifies the expectation of Eq. (9):

$$\begin{aligned}&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}[(9)]\\ =&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\frac{1}{2}(H\eta^2-\eta)||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &+(\frac{H\eta^2}{2}-\eta)||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})||^2\\ &+\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &-\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})||^2-\frac{\eta}{2}||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})||^2\Big]\\ \overset{(e)}{\le}&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\frac{1}{2}(H\eta^2-\eta)||\nabla L(\mathcal{D}^t_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\\ &+\frac{\eta}{2}||\nabla L(\mathcal{D}^{1:t-1}_{de},\theta^{t,m})-\nabla L(\mathcal{S}^t,\theta^{t,m})||^2\Big].\end{aligned}$$

The inequality (e) holds due to the typically small learning rate η and non-negative property of the norm function.

Finally, by leveraging the Lipschitz property of feature extractor ψ and the definition of variance , we have:

$$\begin{aligned}&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}[(9)]\\ \le&\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\frac{L_\psi}{2}(H\eta^2-\eta)||\phi(\mathcal{D}^t_{de})-\phi(\mathcal{S}^t)||^2\Big]\\ &+\mathbb{E}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\frac{\eta L_\psi}{2}||\phi(\mathcal{D}^{1:t-1}_{de})-\phi(\mathcal{S}^t)||^2\Big]\\ =&\frac{L_\psi}{2}(H\eta^2-\eta)\mathbb{V}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\phi(\mathcal{D}^t_{de})-\phi(\mathcal{S}^t)\Big]\\ &+\frac{\eta L_\psi}{2}\mathbb{V}_{\mathcal{S}^t\sim P^t_{\mathcal{D}_{cl}}}\Big[\phi(\mathcal{D}^{1:t-1}_{de})-\phi(\mathcal{S}^t)\Big]\\ &+\frac{\eta L_\psi}{2}||\phi(\mathcal{D}^{1:t-1}_{de})-\phi(\mathcal{D}^t_{de})||^2\end{aligned}$$

□

Building on this analysis, we observe that to improve the overall CL performance and reduce the model loss across all contexts, the cloud-side sampling scheme $P^t_{\mathcal{D}_{cl}}$ should take both the representativess to new context and the proximity to past contexts into consideration. From a theoretical perspective, we further derive the analytical expression of the re-optimized data sampling scheme $P^{t,*}_{\mathcal{D}_{cl}}$ in Lemma 2.

Lemma 2. *To optimize the model performance on the overall data distribution of all encountered contexts, the intra-cluster data sampling probability* $P^{t,*}_{\mathcal{D}_{cl}}$ *needs to be refined as:*

$$P^{t,*}_{\mathcal{D}_{cl}}(x,y) \propto \sqrt{\big|\big|\phi(x)-\phi(\bar{x}_c)\big|\big|^2 + \alpha\big|\big|\phi(x)-\phi(\mathcal{D}_{de}^{1:t-1})\big|\big|^2},$$

where $\alpha = \frac{1}{L_\psi \eta - 1}$ *can be regarded as a hyper-parameter to balance the model performance over new and past contexts.*

VI. Evaluation Results

A. Experimental Setup

Tasks, Datasets and Models. To demonstrate Delta's broad applicability, we evaluate Delta on four typical mobile computing tasks with diverse data modalities, model structures and categories of user contexts (summarized in Table I).

- *Image Classification (IC).* The Cifar10-C dataset [71] contains around $750,000$ images of 10 objects across four context categories: weather, noise, blur and digital corruptions. For each context category, the dataset is processed into 5 subsets with 2 new objects and 1 new context per subset. ResNet-18 [72] is trained for this 10-class image classification task.
- *Human Activity Recognition (HAR).* HHAR [73], UCI [74], MotionSense [75] and Shoaib [76] are four public datasets collected from 73 users performing 6 basic activities (still, walking, upstairs, downstairs, jogging, bike) with 5 device placements (pocket, belt, arm, wrist, waist). For each context category, the dataset is processed into 6 subsets with 1 new activity in a new context. A lightweight CNN-based model DCNN [77] is trained for this 6-class classification task.
- *Audio Recognition (AR).* Google Speech command [78] comprises 100,000 sound files of 20 commands from over 2,000 users with varied tones and environmental conditions. The dataset is processed into 5 subsets for each context category, each containing 4 new commands in 1 new context. A deep neural network VGG-11 [79] is deployed for this task.
- *Text Classification (TC).* The NC corpus in XGLUE benchmark [80] is a cross-lingual understanding dataset consisting of $50,000$ articles on 10 topics and in 5 languages (German, English, Spanish, French, Russian). For each context category, the dataset is processed into 5 subsets with 2 new topics and 1 new context. A transformer-based model BERT [81] is fine-tuned for this 10-class classification task.

Note that we standardize the total number of on-device contexts to approximately 5 to ensure a consistent evaluation of Delta across various tasks, models and modalities, and thus the class number per context may vary for different datasets.

Configurations. For each task, we collect data from 50% users (or randomly select 50% samples for IC and TC tasks) to form the cloud-side public dataset, with the remaining data used to simulate the on-device empirical data across different contexts. For cloud server, data samples from different users and contexts are mixed to reflect the typical scenario where the specific context of each raw data sample is unknown. For mobile device, we use 5 samples per class in each context as empirical data for model fine-tuning, consistent with the statistics that an average European citizen takes over around 4.9 photos daily [28] and uses Siri several times a day [29]. The remaining data samples are used as testing data

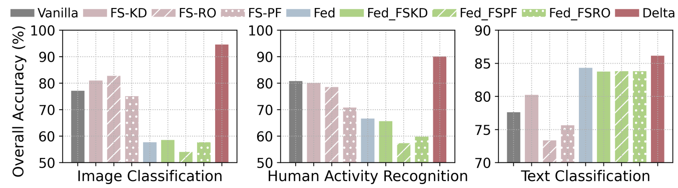


Fig. 6: Extended comparison with hybrid approaches that combine baselines of few-shot learning and federated learning.

for each context. For Delta, the temperature τ for device-side soft matching is set to 0.1 and the number of cloud-side data clusters is $20 \times num\_class$ (i.e. $200/120/400/200$ for IC/HAR/AR/TC). The hyperparameter α is set to 1.0 to balance the effects of cloud-side data sampling on new and past contexts. The default communication budget is set to 25 samples/class for each new context, and an in-depth analysis of the impacts of such budget and on-device data amount is presented in §VI-C.

Baselines. To our best knowledge, Delta is the first data enrichment framework for on-device CL, and we compare it against the model- and algorithm-based baselines (few-shot CL and federated CL) and a random data enrichment baseline. 1) *Few-shot CL* pre-trains model on cloud-side data in advance to capture the general knowledge, which is transferred to device-side new contexts through knowledge distillation [59] (FS-KD), robust optimization [36] (FS-RO) and parameter freezing [35] (FS-PR). 2) *Federated CL* leverages the cloud server to periodically aggregate the models trained on multiple devices per 10 local model updates. In our experiments, the default device number is 50, except for 35 for HAR task. We use Fed-p to denote different settings of device participation rate p. For IC and TC tasks, the data samples from each user are from the same context category to simulate the common data heterogeneity across users (e.g. W/N/B/D for IC and L for TC). The CL performance is evaluated on an independent test dataset, constructed according to the user contexts specified by the experimental setting. 3) *Random* method selects a random cloud-side data-subset to enrich device-side empirical data.

Metrics. We assess the on-device CL performance using four metrics. *Overall performance* measures the inference accuracy of the final model across all the encountered contexts. *Learning plasticity* is the average of each new context's highest accuracy during its learning process. *Memory stability* is the average ratio between each context's final accuracy to its maximal accuracy. *System overheads* include the computation latency, communication costs, memory footprint and energy consumption for both the device side and cloud side.

Deployments. We employ a cloud server equipped with one NVIDIA 3090Ti GPU and a mobile platform featuring an NVIDIA Jetson Nano [82]. This setup aligns with the hardware configurations commonly used in prior works on edge computing.

B. End-to-End Performance

We begin by comparing the end-to-end performance of Delta against the baselines across all four tasks.

TABLE I: Summary of tasks, modalities, contexts, datasets and models.

Modality	Category of Dynamic Context	Dataset	Model(#params)
Image	Object (O), Weather (W), Noise (N), Blur (B), Digital Corruption (D)	Cifar10-C	ResNet18(11.2M)
IMU	Activity (A), Physical Condition (P), Device Placement (D)	HHAR, UCI, Motion, Shoaib	DCNN(17.3K)
Audio	User Command (C), Tone (T), Environmental Noise (N)	Google Speech	VGG11(9.75M)
Text	Article Topic (T), Language (L)	XGLUE	BERT(0.178B)

TABLE II: Summary of overall CL performance (average accuracy of final model on all contexts). We also mark Delta's improvement on accuracy (over few-shot CL) and reduction in communication costs (over federated CL).

Tasks	Context Category	Vanilla CL	Few-Shot CL			Federated CL			Data Enrichment		ΔAcc.	ΔComm.
			FSKD	FSRO	FSPF	Fed0.1	Fed0.2	Fed0.4	Random	Delta		
IC	O+W	32.7±1.49	41.7±1.78	39.2±2.13	36.9±2.87	31.8±0.24	46.4±1.65	55.1±0.42	42.5±2.42	57.7±0.54	16.0%↑	93.7%↓
	O+N	31.3±1.74	36.2±2.34	35.5±1.65	32.3±1.25	31.1±0.04	40.4±0.51	45.0±0.12	35.8±1.00	50.9±1.66	14.8%↑	93.5%↓
	O+B	35.6±0.94	43.7±1.12	40.6±0.24	39.2±0.06	32.6±0.16	39.6±0.24	50.1±0.31	39.9±1.69	57.7±0.98	14.0%↑	91.1%↓
	O+D	45.0±2.57	55.1±1.17	51.5±2.66	52.2±3.10	36.9±0.04	49.0±0.51	61.7±0.34	53.7±2.24	72.3±2.27	17.1%↑	92.2%↓
	O+W+N+B+D	77.3±0.49	81.2±1.53	80.4±0.81	75.3±0.41	30.0±0.05	39.8±0.71	50.8±0.41	47.8±6.64	94.8±2.74	13.6%↑	95.3%↓
HAR	A	52.4±3.67	55.0±3.93	52.9±2.55	48.3±2.69	54.0±0.64	60.0±0.21	61.3±0.55	58.4±0.35	69.3±1.96	14.3%↑	99.6%↓
	A+P	51.2±4.53	53.3±3.20	50.1±3.52	49.4±2.95	60.5±1.28	61.1±1.89	63.1±0.85	58.5±0.75	66.6±1.78	13.3%↑	99.8%↓
	A+P+D	81.0±4.75	80.3±2.35	78.7±4.37	71.0±4.27	62.2±3.58	66.8±3.97	70.1±4.28	61.1±3.25	90.3±5.09	10.0%↑	99.7%↓
AR	C	93.6±0.16	93.5±0.07	92.9±0.65	94.2±0.28	88.1±1.65	88.3±0.83	88.5±1.78	90.4±0.19	94.3±0.17	0.2%↑	99.9%↓
	C+T	89.0±0.41	89.4±0.57	89.4±0.38	90.3±0.79	86.5±0.24	88.5±0.62	88.7±0.25	90.3±0.26	91.1±1.17	0.8%↑	99.9%↓
	C+T+N	84.7±0.64	84.8±1.52	86.2±0.79	86.9±0.40	87.5±0.54	87.7±0.31	88.0±0.61	88.5±1.45	89.2±1.60	2.3%↑	99.9%↓
TC	T	73.2±2.15	73.5±1.35	75.7±4.07	73.3±2.56	79.6±0.37	79.6±0.19	79.8±0.14	73.9±2.69	83.1±2.26	7.3%↑	99.8%↓
	T+L	77.7±3.19	82.2±0.29	80.1±3.02	80.0±1.89	84.3±0.14	84.4±0.18	84.7±0.09	79.7±2.21	86.2 2.16	4.0%↑	99.4%↓

Delta significantly improves the overall performance of on-device CL. Table II summarizes the average accuracy of the final model across all contexts. Compared with the best-performing few-shot CL method, Delta achieves a notable improvement, with accuracy increases of $13-16\%$ higher accuracy on IC, $10-14\%$ on HAR, $0.2-2.5\%$ on AR, and $4-7.3\%$ on TC. Note that Delta's improvement on AR task is minimal because its data heterogeneity across contexts is relatively low (i.e. different tones and background noises) and vanilla CL could perform well. When compared to federated CL, Delta consistently achieves the highest overall performance across all settings, and reduces total communication costs by $91-99\%$, demonstrating its superior effectiveness and efficiency in enhancing CL performance. Furthermore, we observe that for most tasks (IC, HAR and TC), all methods tend to perform better on contexts with mixed categories (last line of each task in Table II). The potential reason is that data samples with different context categories exhibit a greater distribution divergence, making it easier for the on-device model to learn the decision boundary. To provide a more comprehensive comparison, we perform an additional evaluation on hybrid approaches that combine few-shot learning and federated learning approaches. As shown in Figure 6, these hybrid baselines (e.g., Fed_FSKD, Fed_FSRO and Fed_FSPF) consistently show only marginal or even negative performance gains compared to non-hybrid approaches, and are mainly determined by the performance of the pure federated learning method. The primary reason is that while few-shot CL provides a better model initialization for local model updates, the negative impact of cross-device data heterogeneity on model aggregation is also amplified significantly. This instability makes these hybrid methods unreliable as strong baselines in our target scenario which deserve dedicated designs.

Delta enhances the learning plasticity of on-device CL with various new contexts. Figure 7 reports the average value of each new context's peak accuracy during the learning process, a metric widely adopted to assess the learning plasticity. A key observation is that Delta consistently outperforms the baselines across various tasks, data modalities and context categories, demonstrating high robustness and applicability to diverse new contexts. For example, Delta achieves around 90% and 100% accuracy for new context in IC and HAR tasks regardless of context categories and fluctuates less than 3% accuracy on the other two tasks. The high accuracy for new contexts can be attributed to the limited classes within each new context and the enriched data from cloud side. In contrast, the performance of baselines on new contexts is sensitive to the diversity of context categories, such as few-shot CL dropping from 95% to 90% on AR task and federated CL reducing from 93% to 87% on TC task. The rationale behind these is that few-shot CL depends on the high relevance between the on-device context and the base contexts during pre-training to facilitate effective knowledge transfer. Similarly, the performance of federated CL is largely influenced by the data heterogeneity across different users' ongoing contexts. Conversely, Delta can consistently identify an appropriate cloud-side data-subset that contributes to the device-side CL process, making it relatively robust.

Delta achieves high memory stability and low forgetting. Figure 8(a) plots the average ratio between each context's final accuracy and its peak accuracy, which indicates that Delta can maintain over 90% of its relative performance on past contexts. To further analyze this, Figure 8(b) shows how the average accuracy drop (i.e., forgetting performance) of past contexts evolves as new contexts are continuously learned. We observe that while all methods tend to forget more over time, Delta

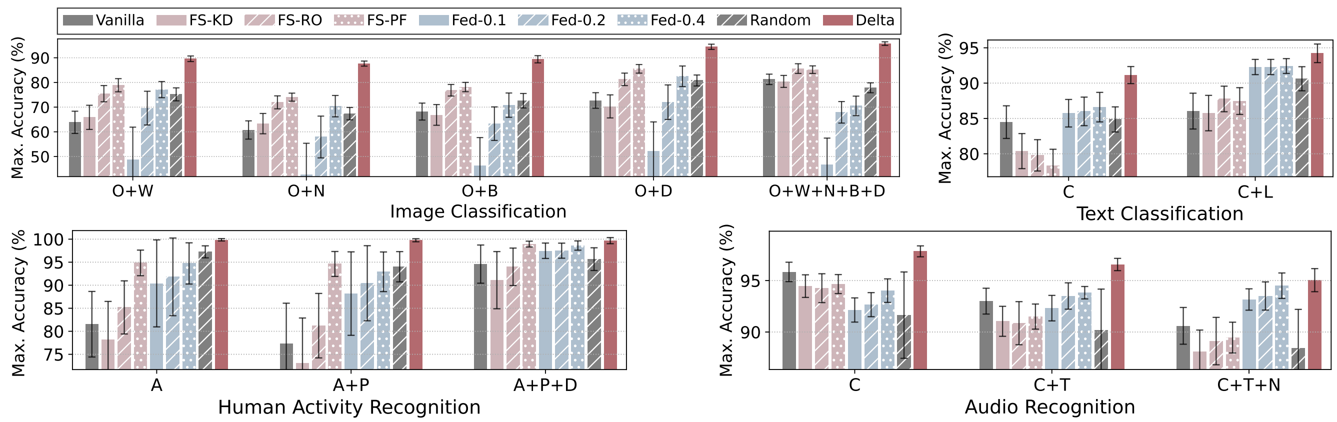


Fig. 7: Comparison of learning plasticity (maximum model accuracy for each new context during CL).

consistently achieves a low absolute drop, ranking 1st on the HAR task, 2nd on the IC and TC tasks, and 4th on the AR task. While some baselines may show a slightly lower drop, this is often because their initial peak accuracy on each new context is significantly lower than Delta's (e.g. a 10% accuracy gap in IC task shown in Figure 7). This highlights that Delta's strength lies in its ability to achieve high learning plasticity (high peak accuracy) while simultaneously maintaining high memory stability and low forgetting.

Delta incurs marginal system overheads for both mobile device and cloud server, as depicted in Figure 9.

• *Device-Side.* The soft matching solution for sub-problem (2a) requires computing the feature of each local data sample and its distance to each element of directory dataset. This results in additional latency of 23.8/1.05/ 4.25/109ms and energy consumption of $0.49/0.30/0.42/2.47$J per sample for IC/HAR/AR/TC tasks, respectively. Moreover, Figure (9(c)) shows that soft matching process has a lower memory footprint than CL process for avoiding model backpropagation, indicating that Delta does not increase peak memory usage due to the sequential execution of Delta and on-device CL.

• *Cloud-Side.* The analytical solution for optimal cloud-side data sampling can be computed within $2.56-7.15$ ms using a single 10-core Intel CPU with a memory footprint of 0.12–7.8 MB. This high computational efficiency allows for parallel cloud-side operations for numerous devices simultaneously.

Device-cloud Communication. For each context, the communication overhead includes the uploading of device-side directory weight, which consists of only several vectors ($\leq$ 1KB), and the downloading of cloud-side enriched data, which requires a total of 30.4/2.89/23.5/6.43 KB for IC/HAR/ AR/TC tasks under default settings.

C. Component-wise Analysis

We delve into the functionality of each key component.

Device-Side Data Soft Matching. To illustrate the importance of soft matching strategy, we assess the performance of Delta using various strategies to address sub-objective (2a), including gradient descent (GD), hard matching ($argmax$) and soft matching ($softmax$) with varying temperatures τ. Figure 10 indicates that GD underperforms across most tasks, while $softmax$ consistently outperforms $argmax$. The reasons are twofold: 1) GD is susceptible to getting trapped in local optima and leads to the overfitted directory weight; 2) $argmax$ fails to exploit the similarities between one device-side sample and multiple cloud-side clusters, which is essential when the cloud-side data is finely clustered. We also note that the optimal τ differs by task due to varying feature distributions, and we set $\tau = 1.0$ for stable performance.

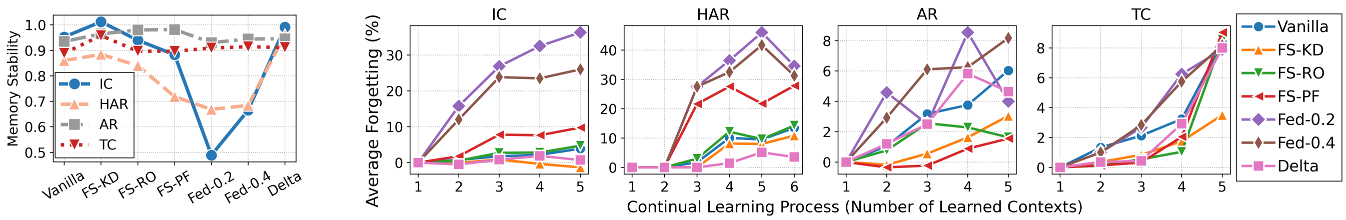
Cloud-Side Optimal Data Sampling. To evaluate the importance of cloud-side optimal data sampling, we assess Delta's performance with different sampling schemes, including random sampling, optimal sampling for solely new context ($\alpha = 0$) and optimal sampling considering both new and past contexts but with different weights ($\alpha > 0$). Figure 11 indicates that optimal data sampling for only new context ($\alpha = 0$) improves overall model accuracy of random sampling by $5.3/0.9/1.0/5.7\%$ for IC/HAR/AR/TC tasks. When we gradually consider the impact of enriched data on past contexts more as α increases from 0 to 1, the performance of Delta is further improved by $0.9/3.9/1.5/1.7\%$. However, performance degrades when α increases from 1 to 10, indicating that an excessive focus on past knowledge can hinder the model's ability to learn the new context.

D. Sensitivity Analysis

In this section, we analyze how Delta's performance is affected by different factors.

Device-Side Data Size. Figure 12 shows the impact of on-device data size on Delta and baseline performances, where we present testing loss instead of accuracy for clearer comparison. Delta demonstrates relatively high robustness, which is attributed to 1) the effective solution of the device-side sub-problem with scarce on-device data through our soft matching strategy, and 2) the substantial performance improvement brought by the abundant cloud-side enriched data compared to additional device-side user data. Also, we observe that baselines show greater sensitivity to on-device data quantity, highlighting the critical role of on-device data enrichment and further motivates our work.

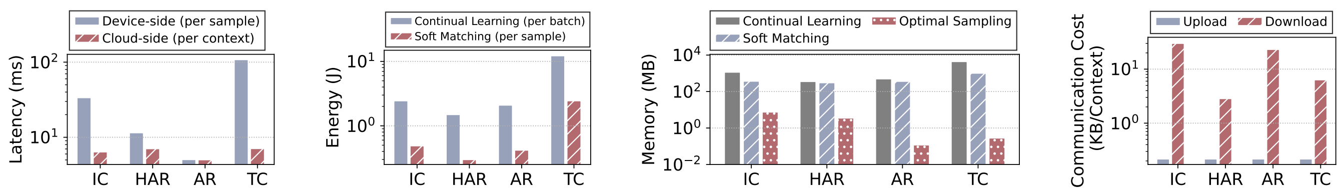
We further extend our evaluations to extreme data scarcity scenarios where the number of samples per label is less



(a) Memory stability

(b) Forgetting performance when learning each new context.

Fig. 8: Comparison of memory stability and forgetting performance of different methods.



(a) Latency

(b) Energy Consumption

(c) Memory Footprint

(d) Communication Cost

Fig. 9: System overheads of Delta.

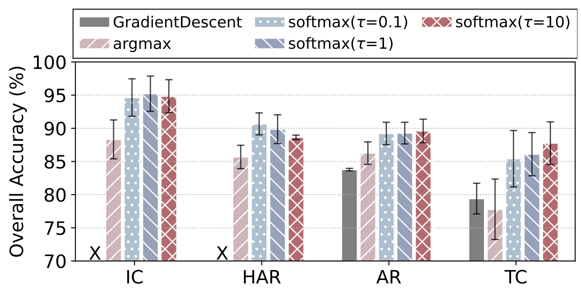


Fig. 10: Sensitivity to soft matching temperature.

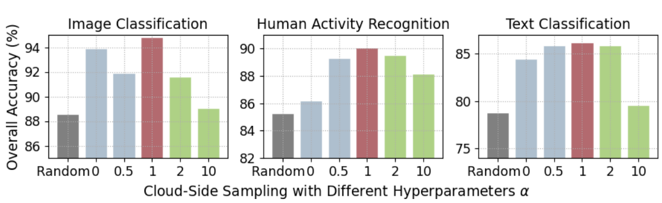


Fig. 11: Analysis of cloud-side optimal data sampling.

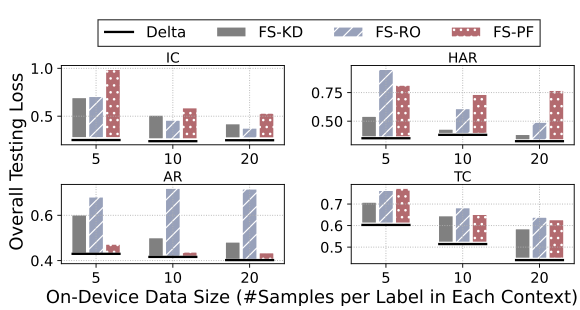


Fig. 12: Sensitivity to on-device dataset size.

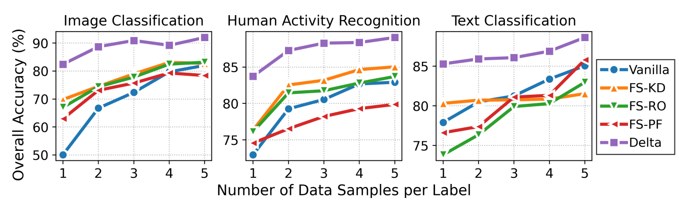


Fig. 13: Sensitivity to data scarcity degree.

than 5. Figure 13 reveals that, as expected, the performance of nearly all methods degrades as data scarcity becomes more severe. For three representative tasks IC, , HAR and TC, the overall accuracy of vanilla CL method drops by as high as 31.9%, 9.95% and 7.14%, and the accuracy of few-shot CL approaches drops by 12.9-16.1%, 5.31-8.68% and 1.21-9.18%. In contrast, our proposed Delta framework's performance degrades by a much smaller margin of 9.57%, 5.32% and 3.33% on the three tasks, implying more substantial performance gains compared to baselines. This demonstrates Delta's remarkable robustness and capability in handling such challenging scenarios, owing to its unique ability to fundamentally address the data scarcity problem via data enrichment.

Cloud-Side Directory Dataset. Figure 14 plots the performance of Delta with varying numbers of cloud-side data clusters for directory dataset construction, where we replace the cloud-side data sampling scheme with random sampling to isolate the effects of directory dataset. We observe that a slight increase in cluster number can improve Delta's performance by making directory dataset more representative and aligning the cloud-side sub-objective (2b) more closely with the overall objective (2). However, an excessively large cluster number can result in numerous similar clusters, leading to the selection of redundant data for enrichment. For stable performance, we set cluster number per label to 20.

Device-Cloud Communication Budget. We further eval-

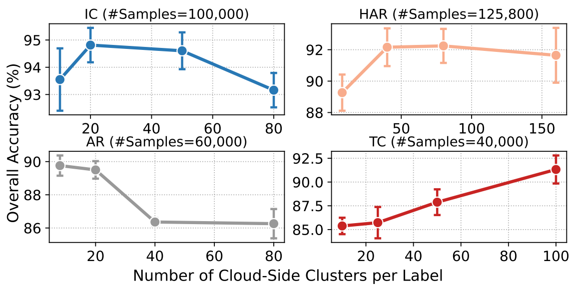


Fig. 14: Sensitivity to cluster number of directory dataset.

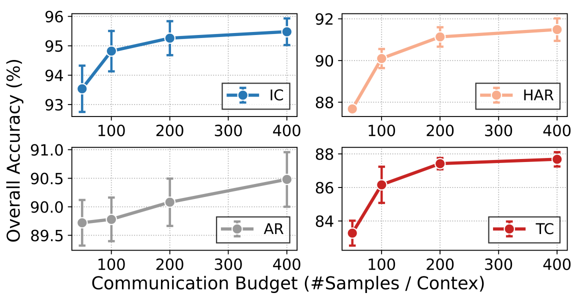


Fig. 15: Impact of Cloud-Device Communication Budget.

uate Delta's performance with varying sizes of cloud-side enriched data to simulate different communication budgets. We find that as the size of enriched dataset increases, the performance improvement provided by Delta consistently increases for all the tasks. This demonstrates that enriching with more data by Delta is always beneficial, and inspires us to utilize the full communication budget to maximize Delta's performance. We also notice that the marginal contribution of more enriched data stabilizes after a certain point. For instance, Delta's performance improves significantly as the enriched data size per context increases from 50 to 200, but the gains are more marginal thereafter. This robustness highlights Delta's applicability for real-world devices with diverse network conditions.

Size of Trainable Model Parameters. Figure 16 plots the CL performance of different methods as a function of the number of trainable parameters of the feature extractor. We observe that when more parameters of on-device models are trainable, the absolute overall accuracy of nearly all methods drops, as the limited on-device data lead to increased model overfitting. However, compared to baselines, the relative performance gains of Delta become larger, because the enriched on-device data helps to better exploit the larger model capacity for learning new contexts.

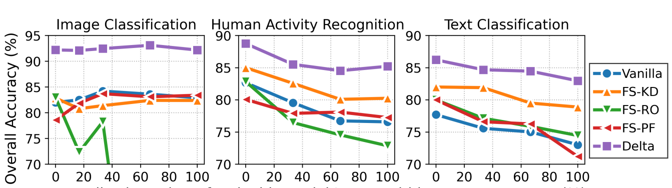


Fig. 16: Impact of trainable parameters of on-device models.

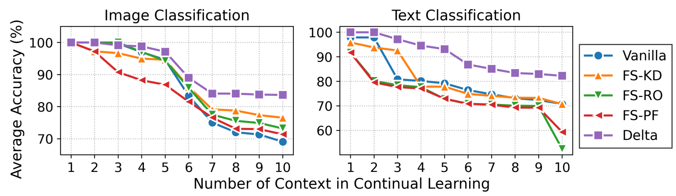
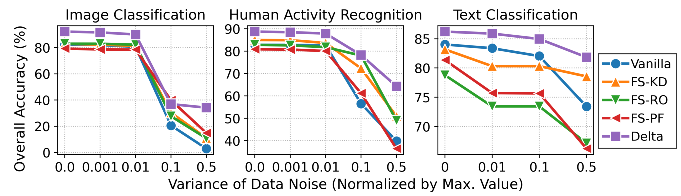
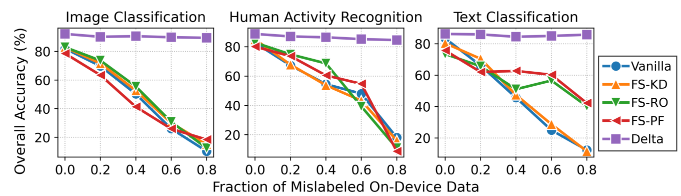


Fig. 17: Sensitivity to the number of contexts.



(a) Impact of feature noise.



(b) Impact of label noise.

Fig. 18: Robustness to data noise.

Number of Contexts. We also evaluated the scalability of our framework by investigating the impact of a growing number of contexts over long-term deployment. As shown in Figure 17, while the performance of all CL methods degrades as more contexts are learned, Delta demonstrates superior long-term stability. For text classification task, most baselines show a significant performance drop after just 2 contexts, while Delta remains stable throughout the entire process. This stability allows Delta to maintain its performance much more effectively than other baselines. As a result, the performance gap between Delta and the best baseline widens significantly with each new context. For instance, after learning 3, 6, 10 contexts, the accuracy gap between Delta and the best method is 0%, 3.11%, 10% on image classification task and 4.61%, 11.4%, 12.1% on the text classification task. These results confirm Delta's remarkable robustness and scalability in practical, long-term on-device CL scenarios.

Noisy On-Device Data. We further evaluate the robustness of Delta framework to two common types of data noise in practical on-device scenarios: feature noise and label noise.

- Feature noise denotes the corruptions introduced to input features x of on-device data during data collection process, where we add Gaussian noise $n \sim \mathcal{N}(0, \sigma \cdot \max(values))$ to x and the noise degree is controlled by parameter σ. As shown in Figure 18(a), we observe that all CL approaches are sensitive to feature noise, and their performance drops dramatically when the noise degree is high ($\sigma \geq 0.1$). However, Delta still outperforms baselines across all noise levels and tasks.
- Label noise represents corruptions introduced to label y of on-device data during data labeling process, where we randomly select a fraction of data samples and change their

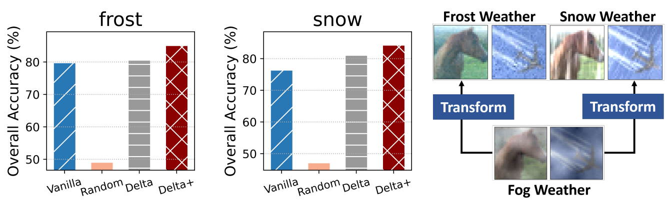


Fig. 19: Delta performance on rare and unique contexts.

labels to wrong ones. As shown in Figure 18(b), we notice that Delta demonstrates exceptional robustness to label noise, which significantly degrades the performance of all other baselines. This unique resilience stems from our directory-based data enrichment mechanism, which relies on input features x rather than labels y to compute directory weight w for data enrichment.

E. Extension to Rare and Private User Contexts

Rare User Contexts. In real-world networking scenarios, while the majority of edge devices and mobile users operate under common scenarios, a small subset may encounter rare of unique contexts. To simulate such scenarios, we pre-define several specific contexts as the unique contexts and manually remove all corresponding data samples from the cloud-side public dataset. For instance, in an image classification task, we designate snowy and frosty weather conditions as rare contexts, and remove all related images from the cloud-side data, and force the device to conduct CL exclusively on these rare contexts to mimic real cases.

Experimental results, as shown in Figure 19, compare the performance of four approaches: no data enrichment (Vanilla), random data enrichment (Random), the original Delta system and Delta with feature alignment module. We observe that random data enrichment consistently leads to significantly inferior CL performance, while the original Delta system provides only marginal improvements over vanilla case in such rare contexts. However, the introduction of the feature alignment module significantly enhances CL performance. The right image in Figure 19illustrates the module's functionality:while the original Delta can only retrieve data samples in similar contexts (e.g., foggy weather images) to enrich device-side data (e.g., frost and snow weather), the feature alignment module helps to transforms the feature distribution to align with the true device-side data. This ensures that the model updates over enriched dataset are consistent and effective model updates for device-side rare contexts.

Private User Context. Although the information transmitted from edge devices to the cloud server only reflects the similarity between device-side data and cloud-side directory dataset – providing coarse context information rather than specific user data samples – there are scenarios where even such context information necessitates protection. To address this, we propose leveraging differential privacy by injecting Gaussian noise into the directory weights shared between devices and the cloud, which increases the difficulty of identifying context likelihood, thereby enhancing user privacy. However, the introduction of noise into the weights can also degrade the enrichment performance of Delta, creating a trade-off between privacy and utility. To systematically analyze the impact of noise on Delta's performance, we simulate various user scenarios with differing security demands by injecting Gaussian noise with controlled variances, measured relative to the magnitude of weights. Specifically, each This implies that each directory weight w^t uploaded by a device is perturbed with noise ϵ drawn from a Gaussian distribution $\mathcal{N}(0, r \cdot ||w^t||)$, where r denotes the relative variance and controls the noise intensity. Empirical results on the mixed context category setting of each task are shown in Figure 20, which reveal three key findings: (i) injecting less than 5% noise into the weights has negligible impact on Delta performance, (ii) higher levels of noise injection lead to progressively inferior data enrichment performance, and (iii) even with 100% noise injected into weights, Delta still significantly outperforms a random data enrichment baseline.

VII. Related Work

Cloud-Side Continual Learning aims to train ML models over non-stationary data streams to acquire new contextual knowledge without forgetting past contexts. This approach is inspired by the capability of biological neural networks to modulate synaptic memory and plasticity in response to dynamic inputs [7], [83]. Existing solutions include: 1) stabilizing previously-learned synaptic changes by penalizing parameter changes of the past optimal model [6], [7]; 2) expanding and pruning synaptic connections to form new synaptic memory via creating additional parameter space for new contexts and re-normalizing them with past contexts [11], [12]; 3) consolidating synaptic memory by storing the important data of past contexts and replaying them during learning new contexts [9], [10], where the data importance can be measured by representativeness [84], [85], diversity [86] or uncertainty [87]. Previous studies [54], [18], [14] have found that data replay methods provides the best trade-off between model performance and system efficiency, and thus our experiments are mainly conducted in this case. *Delta framework serves as a plug-in component to enrich on-device data and enhance performance for all these methods.*

Device-Side Continual Learning focuses on optimizing the utilization of hardware resources to implement cloud-side CL algorithms on resource-constrained devices. This includes saving storage cost through data quantization techniques [16], [17], reducing memory overhead through context-aware parameter sparsity [88], [13], accelerating data loading via hierarchical memory management [18], [19], and accelerating computation with adaptive computing resource [20], [15], [89], [21]. However, most of these works overlook the data bottleneck on mobile device (scarce, personal and unpredictable user data), and thus *Delta is complementary to existing on-device CL works focusing on hardware bottleneck.*

Cloud-Device Collaborative Continual Learning fully exploits the cloud-side abundant hardware resources by balancing the CL workloads between devices and cloud. Initial works [22], [23] entirely offload CL workloads to cloud

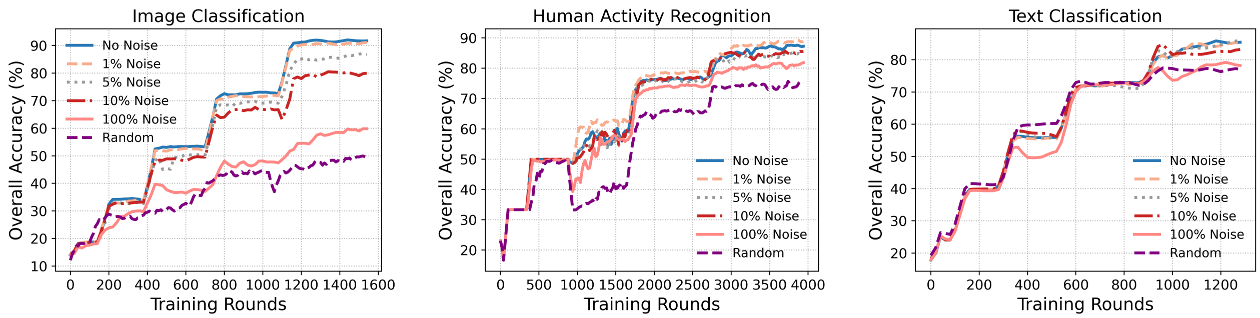


Fig. 20: Impact of varying degrees of Gaussian noise injected into transmitted weights on Delta's model training performance.

by allowing each device to upload local data for cloud-side CL and receive the updated model for inference. They maximize service throughput by carefully allocating network bandwidth and cloud-side computation resources to different devices. Later works like AdaEvo [24] and U-VPA [25] further reduce communication and computation costs by selectively transmitting only unlearned local data to cloud server for necessary CL, based on inference uncertainty or estimated accuracy drop. More recent systems like MOCHA [26] and ELITE [27] optimize the trade-off between accuracy and costs by offloading only a portion of cumbersome and important CL workloads to cloud server.

Federated Continual Learning aims to train global models across decentralized clients with evolving tasks, tackling the dual challenges of catastrophic forgetting and data heterogeneity [90]. Early parameter decomposition methods like FedWeIT [37] mitigated interference via sparse task-specific weights, but recent work prioritizes communication-efficient, exemplar-free strategies. These include knowledge distillation frameworks [91] that leverage synthetic data to preserve history, and gradient-correction mechanisms like FedINC [92] for data-scarce sensor networks. To further address heterogeneity, researchers have employed federated meta-learning for fast adaptation [93] and generative replay for class-incremental learning [38], [94]. Unlike these model-centric approaches that focus on refining aggregation logic or gradients, Delta adopts a distinct data-centric strategy, establishing a new efficient and privacy-preserving device-cloud loop to directly enrich sparse on-device data.

On-Device Data Augmentation is a powerful technique to improve model training performance by generating diverse data from existing user data, such as leveraging geometric and color space transformation and random erasing for visual images [95], using techniques grounded in physical principles for IMU signal [96], as well as employing language rule-based transformations and synonym replacement for textual data [97]. However, a significant limitation of data augmentation is that each data modality and task necessitates specifically designed augmentation techniques to accommodate unique data characteristics, making the data augmentation process cumbersome and inefficient. *Delta serves as a generally solution to complement these works by directly expanding the on-device available data.*

VIII. Discussion

Limitation of Delta. While Delta effectively addresses data scarcity in on-device continual learning, we acknowledge certain limitations that warrant further investigation in real-world deployments. First, regarding storage overhead, Delta currently necessitates the retention of both local and enriched data from new and past contexts. While this is manageable for typical task sequences, it presents a potential storage risk for scenarios involving super long contexts, where the cumulative storage requirement may eventually exceed the constraints of edge devices. Future iterations could explore exemplar-free continual learning techniques [98], [99], [100] to mitigate this growth. Second, the effectiveness of Delta relies on the assumption that the cloud-side directory dataset remains reasonably representative of the on-device data distributions. Over extended periods, as user behaviors and contexts evolve, a static cloud dataset may become obsolete. To maintain performance, the cloud-side dataset requires a mechanism for periodic updates to capture the latest data trends and align with new user contexts. Designing an efficient mechanism for such cloud-side evolution remains an open challenge that we plan to explore in future work.

Comparison with FL. The intuitions behind Delta framework and FL paradigm are distinct. FL aims to leverage device-side data to develop a global model that can generalize well across diverse user contexts, i.e. *global knowledge aggregation*. In contrast, Delta utilizes cloud-side data to enhance the personalization of local models for individual user contexts, i.e. *local knowledge augmentation*. As a result, the applicability of FL is primarily limited by device-side constraints, including the vast number of devices, high participation rates, cross-device data heterogeneity and tolerance for communication overheads. Delta, on the other hand, seeks to shift the limitations to the cloud, assuming that cloud server can collect abundant public data to match different users. This aligns with the recent success of training billion-scale models over sufficiently diverse datasets for various tasks. Additionally, when confronted with extremely rare user contexts, Delta could still identify the most helpful and relevant cloud-side data-subsets to provide data foundation for existing model or algorithm-based augmentation methods. In conclusion, FL and Delta are applicable for different scenarios and could potentially be complementary.

IX. Conclusion

In this work, we explore the potential of leveraging cloud-side abundant data resource to address the data bottleneck in on-device CL. We formalize the data enrichment problem and propose Delta, a device-cloud collaborative data enrichment framework for on-device CL with high privacy protection, efficiency and effectiveness. On extensive experiments, Delta shows superior model performance and system efficiency across various mobile computing tasks, data modalities and model structures.

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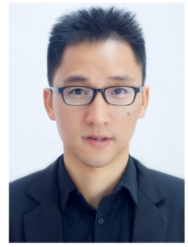

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