Ferret: An Efficient Online Continual Learning Framework under Varying Memory Constraints

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Abstract

In the realm of high-frequency data streams, achieving real-time learning within varying memory constraints is paramount. This paper presents Ferret, a comprehensive framework designed to enhance online accuracy *of Online Continual Learning (OCL) algorithms while dynamically adapting to varying memory budgets. Ferret employs a fine-grained pipeline parallelism strategy combined with an iterative gradient compensation algorithm, ensuring seamless handling of high-frequency data with minimal latency, and effectively counteracting the challenge of stale gradients in parallel training. To adapt to varying memory budgets, its automated model partitioning and pipeline planning optimizes performance regardless of memory limitations. Extensive experiments across 20 benchmarks and 5 integrated OCL algorithms show Ferret's remarkable efficiency, achieving up to 3.7× lower memory overhead to reach the same online accuracy compared to competing methods. Furthermore, Ferret consistently outperforms these methods across diverse memory budgets, underscoring its superior adaptability. These findings position Ferret as a premier solution for efficient and adaptive OCL framework in real-time environments.*

1. Introduction

Data is crucial for Machine Learning (ML), forming the basis for algorithms and models [30, 53, 75]. In real-world applications [23, 71], data arrives in high-frequency streams with varying distributions [52, 78]. This makes data time-sensitive and short-lived [11, 48, 76], rendering offline-trained models based on historical data ineffective for future data of unknown distribution [61]. Thus, the significance of *Online Continual Learning* (OCL) is growing [6, 40, 77], as it enables learning over data streams to adapt to dynamic data distributions in real-time.

In the literature, OCL tackles two main challenges: 1) mitigating catastrophic forgetting [51], where the model retains previously learned knowledge while acquiring new information (*e.g.*, regularization-based [2, 9, 10, 19], replay-based [12, 39, 68], sampling-based [3, 4, 83], others [25, 65], etc.), and 2) enhancing rapid adaptation [11, 48], which involves swiftly adjusting to new data or tasks (*e.g.*, latency-oriented [29, 70], buffering [54, 82], others [27, 69], etc.). In general, the increasing demand for resource-limited systems that can seamlessly integrate new information with minimal latency has driven the popularity of OCL [32] Therefore, this paper explores the challenge of rapid adaptation under varying memory constraints in OCL.

To effectively address the above OCL challenge, it is essential to explore solutions beyond mentioned algorithmic improvements by also optimizing the underlying framework. An efficient OCL framework must prioritize both processing speed and memory management under the limited memory capacity so that it can efficiently handle unlimited data streams with dynamic data distributions for increased *online accuracy* [11] (*i.e.*, a metric measuring real-time accuracy for continuous new data predictions). Specifically, the framework should quickly process incoming data to extract valuable insights and make informed decisions [56, 74] by minimizing both the latency from data receipt to its initial processing and the time taken for the learning process itself. Additionally, the framework is not only expected to operate within a predetermined memory allotment but also to demonstrate scalability across diverse memory capacities [18, 57]. This duality ensures that the framework remains efficient regardless of the memory resources available, thereby maintaining consistent performance in dynamic environments.

Numerous ML frameworks have been proposed that offer innovative approaches to scalable and flexible ML development [5, 17, 31, 36, 37, 42, 55, 84, 86]. For instance, Ray [55] facilitates distributed computing on any scale, while Pytorch [5] excels in dynamic computation graphs for model training. Despite their advancements, these frameworks often do not specifically address the unique requirements of learning over streaming data [29], which is a key focus of OCL. Recently, there are some frameworks dedicated to OCL by prioritizing real-time data processing [44, 46, 80]. Nevertheless, they either lack general applicability or fail to balance processing speed with consumed memory, leading to reduced online accuracy and low memory scalability, underscoring the need for innovative solutions in this domain.

In this work, we propose an OCL framework named Ferret, designed to achieve e**F**fici**E**nt pipeline lea**R**ning over f**R**equ**E**nt data s**T**reams for enhanced online accuracy across memory constraints. Ferret comprises a fine-grained pipeline parallelism component with an iterative gradient compensation algorithm and a model partitioning and pipeline planning component. Firstly, to facilitate rapid adaptation over frequent streaming data for higher online accuracy, Ferret employs a fine-grained pipeline parallel strategy, allowing precise control over each pipeline stage for seamless data management. Additionally, to mitigate the impact of stale gradients in parallel processing, Ferret integrates a novel iterative gradient compensation algorithm. Secondly, to guide the selection of optimal model partition schemes and pipeline configurations under given memory budgets, Ferret solves the involved multivariate optimization problem through a bi-level optimization algorithm.

Our contributions can be outlined as follows:

- We propose a framework named Ferret for boosting the online accuracy of OCL algorithms under memory constraints. To the best of our knowledge, this is the first work focusing on enhancing OCL by employing pipeline parallelism and scheduling.
- To process high-frequent data streams without delay, Ferret employs a fine-grained pipeline parallelism strategy, enabling interleaved processing of incoming streaming data. Furthermore, Ferret utilizes an iterative gradient compensation algorithm to efficiently mitigate the effects of stale gradients across different pipeline stages, preventing performance degradation.
- We derive the optimal parameters for automatic model partitioning and pipeline planning by mapping the involved multi-variable optimization problem into a bi-level optimization problem.
- Extensive experiments on 20 benchmarks demonstrate that our proposed framework consistently enables more efficient OCL within given memory budgets. The code is open-sourced for reproduction.

2. Related Work

The current OCL research focuses on two areas: mitigating catastrophic forgetting and enhancing rapid adaptation.

Mitigating catastrophic forgetting: Catastrophic forgetting, often quantified by the test accuracy [29, 46, 48], poses a significant barrier to the efficacy of OCL in dynamic environments, where the ability to preserve historical information is crucial. Multiple directions have emerged to reduce catastrophic forgetting, including: 1) regularization-based techniques [2, 9, 10, 19] impose constraints on weight updates to preserve important parameters that are crucial for past tasks. 2) replay-based techniques [12, 39, 68] help the model to rehearse old knowledge alongside new information by maintaining a memory of previous data. 3) sampling-based techniques [3, 4, 83] enhance the efficiency of replay mechanisms by selectively choosing the most relevant data samples for rehearsal. 4) other techniques [25, 65] focus on various novel approaches, such as modular networks and dynamically allocated resources, to protect previously learned information from being overwritten.

Enhancing rapid adaptation: Rapid adaptation is in scenarios where immediate processing of incoming data is required [11, 48], which is often quantified by the online accuracy [11] defined as $oacc_{\mathcal{A}}(t) = \sum_{i=1}^{t} acc(y^i, \hat{y}^i)/t$. Strategies developed to enhance rapid adaptation include: 1) latency-oriented techniques [29, 70] iteratively generate predictions and update model parameters immediately upon the arrival of streaming data by discarding data that cannot be processed in time. 2) buffering-oriented techniques [54, 82] buffers and samples incoming data streams and apply periodic batch-training [62]. 3) other techniques [27, 69] introduce novel methods like adapting model structures in response to new tasks and learning how to learn efficiently, to adapt to dynamic data distributions rapidly.

3. Motivation

To effectively navigate the challenges posed by OCL, it is crucial to expand our approach beyond merely refining mentioned OCL algorithms, by also enhancing the underlying ML framework to adaptively balance processing speed with efficient memory management under memory constraints. Particularly, boosting processing speed is essentially reducing data processing time, which can be represented as $t^l + F/R_h P_h$, where t^l denotes the latency from data arrival to processing, F denotes the required floating point operations (FLOPS) by the underlying OCL algorithm, R_h and P_h denote the hardware utilization rate and the theoretical floating point operations per second (FLOPs) of the hardware, respectively. Clearly, only t^l and R_h are optimizable by the framework.

Existing ML frameworks mainly focus on: 1) distributed and parallel computing [42, 55, 86], 2) Optimized model training and deployment [5, 36, 84], and 3) others including security [17, 37] and debugging [31]. These frameworks facilitate scalable and flexible ML, yet they rarely tackle the challenges of managing streaming data. Regrettably, the few ML frameworks designed for OCL [44, 46, 80] either lack general applicability or fail to concurrently optimize t^l and R_h within memory limitations. For instance, Kraken [80] is tailored for recommendation systems. Conversely, while Camel [46] and LifeLearner [44] boost R_h via buffering and sampling, they also raise t^l and memory usage, reducing online accuracy.

Pipeline parallelism can naturally process sequential streaming data while utilizing batch training. This motivates us to incorporate pipeline parallelism into OCL to simultaneously minimize t^l and maximize R_h under a given memory budget, thereby boosting online accuracy. We achieve this balance through refined scheduling strategies and better hardware integration, ensuring optimal resource utilization within the constraints of memory budgets.

4. Problem Formulation

In this section, we define the problem we aim to address. Note that the notations used throughout this paper are defined in Sec. 9 in the appendix.

Consider a general learning problem defined over a feature space $\mathcal{X}$ and a label space $\mathcal{Y}$ that aims to minimize a loss function $\mathcal{L}(D^t;\theta)$ where data $D^t = (\mathbf{x}^t, \mathbf{y}^t) \in \mathcal{X} \times \mathcal{Y}$ arrives at timestamp t. Our objective is to rapidly derive an updated model θ^t with D^t and θ^{t-1} under a given memory constraint M, so that the online accuracy of θ^t is high. Unlike updating a model offline with a pre-collected dataset, D^t will be discarded after updating θ^{t-1} in OCL.

Directly optimizing online accuracy in our objective during runtime is hard, as the online accuracy is only calculable after obtaining labels of incoming data. Instead, we measure the volume of data values learned by the model as a proxy to estimate and optimize online accuracy. Formally, assuming D^t has an initial data value of V_{D^t} and its data value declines as a time-dependent exponential decay function [76], we define the Adaptation Rate as follows.

Definition 4.1 (Adaptation Rate of A OCL framework)**.** Consider a OCL framework $\mathcal{A}$ receives a data $D^t = (\mathbf{x}^t, \mathbf{y}^t)$ at timestamp t that has an initial data value of V_{D^t}, and updates a model θ^{t-1} in the hypothesis space Θ at timestamp $t + r^t_{\mathcal{A}}$ ($r^t_{\mathcal{A}} = +\infty$ if D^t is discarded). Let the data value of D^t decline as a time-dependent exponential decay function, and new data D^t constantly arrives until $t = T$. The Adaptation Rate of $\mathcal{A}$ is defined as

$$R^T_{\mathcal{A}} = \frac{\sum_{t=0}^{T} e^{-cr^t_{\mathcal{A}}} V_{D^t}}{T}, \tag{1}$$

where the constant c describes the reduction rate of V_{D^t}.

With Def. 4.1, our objective can be formulated as

$$\max_{\mathcal{A}} \mathcal{R}^T_{\mathcal{A}} \text{ s.t. } \mathcal{M}_{\mathcal{A}} \le M, \tag{2}$$

where $\mathcal{M}_{\mathcal{A}}$ is the memory footprint of $\mathcal{A}$ during training.

5. Methodology

The workflow of Ferret is shown in Fig. 1, comprising a fine-grained pipeline parallelism component (A), followed by a model partitioning and pipeline planning component (B). In A, the model is trained using Ferret's fine-grained pipeline parallelism to manage high-frequent data streams with minimal latency. Given the high degree of parallelism within the system, gradient staleness can become significant and variable, potentially causing severe model degradation. To mitigate this issue, an iterative gradient compensation algorithm is applied prior to model updating. In B, the model is profiled to optimize Eq. 2, determining the optimal model partition scheme and pipeline configuration.

5.1. Fine-grained Pipeline Parallelism

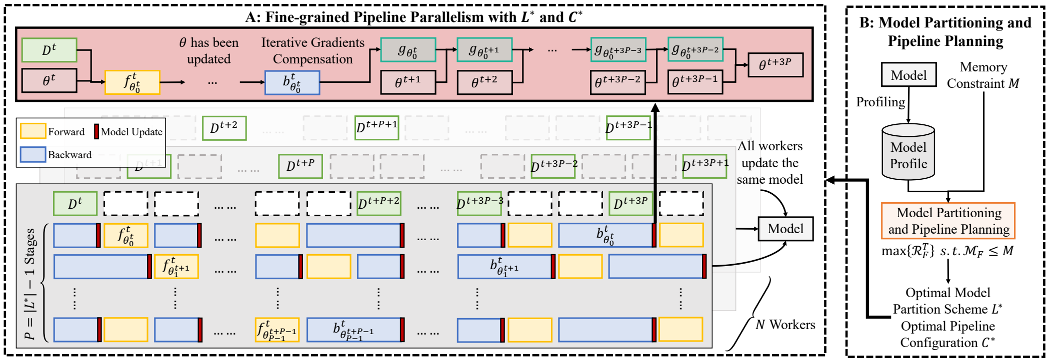
5.1.1 Architectural design

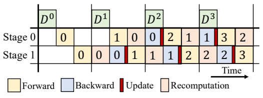
Ferret utilizes an asynchronous pipeline parallelism strategy with 1F1B scheduling to process streaming data immediately upon arrival. To efficiently handle high-frequency data streams without delay, it is imperative that $t^f + t^b$ is minimized. However, $t^f + t^b$ is inherently lower bounded by $(\max_i \hat{t}^f_i + \max_i \hat{t}^b_i)$, indicating that some of the data must be discarded if t^d is less than this lower bound. To prevent the loss of data, Ferret enhances system throughput by deploying $N \le \lceil (t^f + t^b)/t^d \rceil$ workers, each performing pipeline parallelism concurrently over interleaved data streams. Specifically, the i-th data is processed by the n-th worker if and only if $i \equiv c^d_n \mod \lceil (t^f + t^b)/t^d \rceil$. This strategy, while effective in reducing latency, significantly increases memory usage. Therefore, Ferret balances the trade-offs between $\mathcal{R}$ and $\mathcal{M}$ by collectively employing four **t**echniques: activation recomputation [13], gradient accumulation [59], back-propagation omission and worker removal, allowing precise control over each pipeline stage for seamless data management.

T1. Activation Recomputation: Activation recomputation exchanges additional computational overhead for reduced memory usage, as Fig. 1a illustrated. In Ferret, a binary indicator c^r_n within configuration C denotes whether activation recomputation is enabled for the n-th worker. When activation recomputation is enabled (*i.e.*, $c^r_n = 1$), an additional forward pass is executed prior to the backward pass, effectively managing memory consumption at the expense of increased computational load.

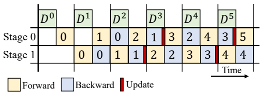
T2. Gradient Accumulation: Gradient Accumulation allows multiple forward and backward passes to accumulate gradients before model updating, thereby decreasing the frequency of parameter updates, as Fig. 1b depicted. In Ferret, the parameter $c^a_{n,j}$ in configuration C defaults to 1, indicating the number of gradient accumulation steps before model updating for the j-th stage in the n-th worker. By utilizing gradient accumulation, the j-th stage in the n-th worker only stores $(1 + \lceil (P - j - 1)/c^a_{n,j} \rceil)$, instead of $(P - j)$, models, thereby optimizing memory usage.

T3. Back-propagation Omission: To further reduce memory usage, back-propagation omission skips all back-

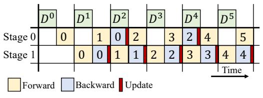




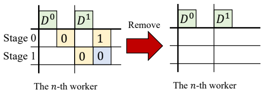
(a) Activation Recomputation (T1)



(b) Gradient Accumulation (T2)



(c) Backpropagation Omission (T3)



(d) Worker Removal (T4)

Figure 1. The overall workflow of Ferret. In A, based on the optimal model partition scheme L^* and pipeline configuration C^*, N workers are spawned to initiate fine-grained pipeline parallelism that consumes streaming data interleavedly, and update the same model asynchronously by iteratively compensating stale gradients. In B, L^* and C^* are obtained by optimizing Eq. 2.

ward passes that depend on previous model parameters, as Fig. 1c illustrated. In Ferret, the parameter $c_{n,j}^o$ in configuration C defaults to 0, indicating the number of backpropagation omission steps for the j-th stage in the n-the worker. This approach reduces memory overhead by eliminating the need to store multiple versions of models.

T4. Worker Removal: Spawning N workers increases the system throughput but also linearly increases the memory footprint. When resources are highly constrained, the n-th worker can be shut down and removed to reduce the memory overhead by setting $c_n^d = -1$ in configuration C.

Finally, assume the initial data value of any data is V_D, and the retained value of the data when updating a subset of model parameters is proportional to the size of the subset model parameters, given L and C, $\mathcal{R}$ and $\mathcal{M}$ of the fine-grained pipeline parallelism strategy can be respectively formulated as

$$\mathcal{R}_F^T = \sum_{\substack{n=1\\ c_n^d \geq 0}}^{N-1} \sum_{i=0}^{P-1} \frac{|w_i|}{\sum_{j=0}^{P-1}(|w_j|)} \frac{1}{c_{n,i}^a} \sum_{j=0}^{c_{n,i}^a-1} A_{i,j}, \text{where } A_{i,j} = \frac{e^{-c((P+j)t^f+(P-i+j)t^b+c_n^r(P-i+j)t^f)}V_D}{LCM(\{c_{n,k}^o+1|k\in[i,P-1]\})(t^f+t^b+c_n^r t^f)}, \quad (3)$$

$$\mathcal{M}_F = \sum_{\substack{n=1\\ c_n^d \geq 0}}^{N-1} \sum_{i=0}^{P-1} (1+\lceil \frac{P-i-1}{c_{n,i}^a} \rceil - c_{n,i}^o)(|w_i| + |a_i| - c_n^r \sum_{l=L_i+1}^{L_{i+1}-1} |\hat{a}_l|), \quad (4)$$

where $LCM(\cdot)$ denotes the Least Common Multiple.

5.1.2 Iterative Gradient Compensation

Since fine-grained pipeline parallelism is asynchronous, the model will be inevitably updated by stale gradients, leading to performance degradation. Moreover, different pipeline stages of the model are updated by gradients with varying staleness. To surmount the above challenges, Ferret firstly proposes to efficiently approximate $\nabla\mathcal{L}(D^{t-1};\theta^t)$ using $\nabla\mathcal{L}(D^{t-1};\theta^{t-1})$ by a cost-effective approximator $A_{\mathcal{I}}(\cdot)$ based on Taylor series expansion and the Fisher information matrix. Then, we extend this approximator to approximate $\nabla\mathcal{L}(D^{t-1};\theta^{t+\tau-1})$ using $\nabla\mathcal{L}(D^{t-1};\theta^{t-1})$ by iteratively applying $A_{\mathcal{I}}(\cdot)$.

Gradients Compensation via Taylor Series Expansion: In prior work, $\nabla\mathcal{L}(D^{t-1};\theta^t)$ was naively set to $\nabla\mathcal{L}(D^{t-1};\theta^{t-1})$ [58, 59] and can be regarded as a zero-order Taylor series expansion, leading to a high approximation error $||\nabla\mathcal{L}(D^{t-1};\theta^t) - \nabla\mathcal{L}(D^{t-1};\theta^{t-1})||^2$. To reduce the approximation error, we expand $\nabla\mathcal{L}(D^{t-1};\theta^t)$ at θ^{t-1} by a first-order Taylor series expansion as follows:

$$\nabla\mathcal{L}(D^{t-1};\theta^t) \approx \nabla\mathcal{L}(D^{t-1};\theta^{t-1}) + \mathbb{H}(\mathcal{L}(D^{t-1};\theta^{t-1})) \odot (\theta^t - \theta^{t-1}), \quad (5)$$

where $\mathbb{H}(\cdot)$ denotes the Hessian matrix of $\cdot$. Previous works have revealed that the Fisher information matrix (FIM) serves as an approximation of the Hessian matrix if $\mathcal{L}(\cdot)$ is a negative log-likelihood loss [28, 63]. Assuming θ^t gradually converges to its optimal value θ^* during training, we can achieve an unbiased estimation of $\mathbb{H}(\cdot)$ by:

$$\epsilon_t \triangleq \mathbb{E}_{D,\theta^*} ||\mathcal{I}(\theta^t) - \mathbb{H}(\mathcal{L}(\cdot;\theta^t))|| \to 0, t \to +\infty, \quad (6)$$

where $\mathcal{I}(\theta)$ is the FIM. To further mitigate space complexity, $\mathcal{I}(\theta)$ is approximated by its diagonal elements with a hyper-parameter λ to control variance, *i.e.*,

$$\mathbb{H}(\mathcal{L}(\cdot;\theta^t)) \approx \lambda \nabla\mathcal{L}(\cdot;\theta^{t-1}) \odot \nabla\mathcal{L}(\cdot;\theta^{t-1})^\top. \quad (7)$$

Incorporating Eq.7 into Eq.5, we obtain:

$$\nabla\mathcal{L}(D^{t-1};\theta^t) \approx A_{\mathcal{I}}(\nabla\mathcal{L}(D^{t-1};\theta^{t-1}), \theta^t, \theta^{t-1}) = \quad (8)$$
$$\nabla\mathcal{L}(D^{t-1};\theta^{t-1}) + \lambda \nabla\mathcal{L}(D^{t-1};\theta^{t-1}) \odot \nabla\mathcal{L}(D^{t-1};\theta^{t-1})^\top \odot \Delta\theta,$$

where $A_{\mathcal{I}}(\cdot)$ serves as the approximator to compensate $\cdot$.

Iterative Compensation: More generally, to approx-

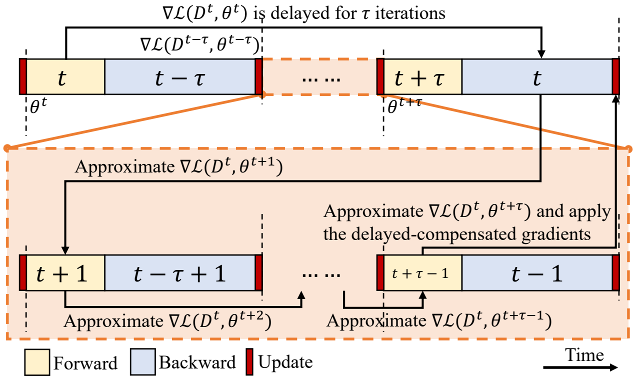


Figure 2. To adapt to different levels of staleness in fine-grained pipeline parallelism, $\nabla\mathcal{L}(D^t,\theta^{t+\tau})$ is iteratively approximated by $\nabla\mathcal{L}(D^t,\theta^t)$.

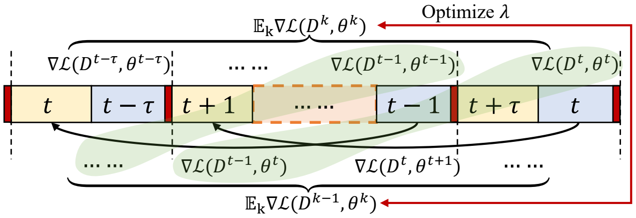


Figure 3. To further reduce approximation errors, we optimize λ automatically by comparing historical approximations ($\nabla\mathcal{L}(D^t,\theta^t)$, etc.) and observations ($\nabla\mathcal{L}(D^{t-1},\theta^t)$, etc.)

imate $\nabla\mathcal{L}(D^{t-1};\theta^{t+\tau-1})$ using $\nabla\mathcal{L}(D^{t-1};\theta^{t-1})$, Ferret proposes an iterative application of $A_{\mathcal{I}}(\cdot)$, as depicted in Fig. 2. This iterative process is defined as follows:

$$\begin{aligned}&\nabla\mathcal{L}(D^{t-1};\theta^{t+\tau-1}) \approx A_{\mathcal{I}}(\nabla\mathcal{L}(D^{t-1};\theta^{t+\tau-2}),\theta^{t+\tau-1},\theta^{t+\tau-2})\\ &\approx A_{\mathcal{I}}(\dots A_{\mathcal{I}}(\nabla\mathcal{L}(D^{t-1};\theta^{t-1}),\theta^t,\theta^{t-1})\dots,\theta^{t+\tau-1},\theta^{t+\tau-2}).\end{aligned} \tag{9}$$

However, this iterative process introduces a cascade of errors, wherein the approximation error $||g^t - A_{\mathcal{I}}(g^{t-1},\theta^t,\theta^{t-1})||^2$ is propagated and amplified with each successive approximation. This arises because each approximation depends on the output of the preceding one.

To mitigate this problem, we propose to optimize λ under the mild assumption that the distributions of $\mathbb{E}_k D^k$ and $\mathbb{E}_k D^{k+1}$ are similar, as illustrated in Fig. 3. Thus, the objective of minimizing the approximation error of iterative gradients compensation can be formulated as follows:

$$\begin{aligned}&\min_{\lambda}\mathbb{E}_k||\nabla\mathcal{L}(D^k;\theta^k) - A_{\mathcal{I}}(\nabla\mathcal{L}(D^{k-1},\theta^k,\theta^{k-1}))||^2 + \nu||\lambda||^2\\ &= \min_{\lambda}||D-E-\lambda F||^2 + \nu||\lambda||^2,\end{aligned} \tag{10}$$

where $D = \mathbb{E}_k\nabla\mathcal{L}(D^k;\theta^k)$, $E = \mathbb{E}_k\nabla\mathcal{L}(D^{k-1};\theta^{k-1})$,
$F = \mathbb{E}_k\nabla\mathcal{L}(D^{k-1};\theta^{k-1}) \odot \nabla\mathcal{L}(D^{k-1};\theta^{k-1})^\top \odot (\theta^k - \theta^{k-1})$,

where $\nu||\lambda||^2$ is an ℓ_2 regularization term to constrain the solution of λ for better stability. To reduce memory overhead, D and E can be approximated by Exponential Moving Average (EMA), *i.e.*,

$$\mathbb{E}_k\nabla\mathcal{L}(D^k;\theta^k) = \alpha\mathbb{E}_k\nabla\mathcal{L}(D^{k-1};\theta^{k-1}) + (1-\alpha)\nabla\mathcal{L}(D^{k-1};\theta^{k-1}), \tag{11}$$

where α is the EMA coefficient. Hence, we have

$$D - E = (1-\alpha)(\nabla\mathcal{L}(D^{k-1};\theta^{k-1}) - \mathbb{E}_k\nabla\mathcal{L}(D^{k-1};\theta^{k-1})). \tag{12}$$

Convergence: Similar to the analyses in [85], our iterative gradient compensation algorithm yields convergence rates of $\mathcal{O}(V_1^2\tau/T)$ and $\mathcal{O}(V_2/\sqrt{T})$ for convex and non-convex case, respectively. Here, V_1 and V_2 represent the upper-bound of the $||\cdot||^2$ norm and the variance of the delay-compensated gradient $A_{\mathcal{I}}(\cdot)$, accordingly. Compared to the work in [85], Ferret fixes τ to 1, and minimizes V_1 and V_2 by Eq. 10, boosting algorithm's robustness and accelerating the convergence of the model.

Algorithm Design: The algorithm of Ferret's iterative gradient compensation is illustrated in Alg. 1 in the appendix. Since the maximum possible τ equals $(P-1)$, the time complexity of the algorithm is $\mathcal{O}(P-1)$, which is considered negligible during model training. Moreover, since two additional variables, v_r and v_a, are stored in memory for optimizing λ, the space complexity of this algorithm is $\mathcal{O}(2\sum_{j=0}^{P-1}|w_i|)$. However, by setting $\eta_\lambda = 0$, the optimization of λ is effectively terminated, and λ remains fixed at λ^0. This adjustment allows for manual tuning of λ and eliminates the need for v_r and v_a, thereby increasing flexibility and avoiding additional memory overhead.

5.2. Model Partitioning and Pipeline Planning

The objective of model partitioning and pipeline planning is to find an optimal model partition scheme L^* and its corresponding pipeline configuration C^* that maximize $\mathcal{R}$ within a given memory constraint M, namely,

$$L^*, C^* = \arg\max_{L,C}\mathcal{R}_F^T \ \text{ s.t. } \ \mathcal{M}_F \leq M. \tag{13}$$

This problem can be reformulated as a bi-level optimization problem, decomposing it into two interrelated subproblems: (1) determining the optimal C given a L, and (2) identifying the optimal L based on the solution from (1):

$$\begin{aligned}&L^* = \arg\max_{L}\{\mathcal{R}_F^T|C_L^*\}\\ &s.t.\ \ C_L^* = \arg\max_{C}\{\mathcal{R}_F^T|L\}, \mathcal{M}_F \leq M.\end{aligned} \tag{14}$$

5.2.1 Iterative Configuration Search (Sub-problem 1)

Given a model partition scheme, the objective of subproblem (1) is to solve

$$C^* = \arg\max_{C}\{\mathcal{R}_F^T|L\} \ \text{ s.t. } \ \mathcal{M}_F \leq M. \tag{15}$$

With more than $2^{N(P+1)}$ potential combinations for C, a brute-force enumeration of C is impractical. Observing that $\mathrm{d}\mathcal{M}_F/\mathrm{d}\max_C\{\mathcal{R}_F^T|L\} \geq 0$, we employ an iterative algorithm to determine the optimal C that maximize $\mathcal{R}_F^T$ while ensuring $\mathcal{M}_F$ remains within the memory budget. Specifically, to prevent memory over-consumption, we progressively deploy **T1-T4** as follows to balance $\mathcal{R}_F^T$ and $\mathcal{M}_F$.

S1. Deploy T1 for all workers: By setting $c_n^r = 1$ for all workers, the data processing time increases. Specifically, for the n-th worker, setting $c_n^r = 1$ will respectively reduce $\mathcal{R}_F^T$ and $\mathcal{M}_F$ by Eq. 19 in the appendix.

S2. Deploy T2 for the j-th stage in the n-th worker: If $c_{n,j}^o = 0$, increasing $c_{n,j}^a$ by $\Delta c_{n,j}^a = \lceil \frac{P-j-1}{\lceil (P-j-1)/c_{n,j}^a \rceil - 1} \rceil - c_{n,j}^a$ will lead to a reduced frequency of model parameter updates. Here, the value of $\Delta c_{n,j}^a$ is determined to prevent $\Delta_{c_{n,j}^a \rightarrow c_{n,j}^a+1} \mathcal{M}_F = 0$ due to the ceiling function. Consequently, $\mathcal{R}_F^T$ and $\mathcal{M}_F$ will be respectively decreased by Eq. 20 in the appendix.

S3. Deploy T3 For the j-th stage in the n-th worker: If $\Delta c_{n,j}^a = +\infty$, setting $c_{n,j}^a = 1$ and $c_{n,j}^o = P - 1 - j$ will completely eliminate the need for the j-th stage in the n-th worker to store additional model parameters by bypassing any backward pass that requires previous model parameters. Consequently, $\mathcal{R}_F^T$ and $\mathcal{M}_F$ will be respectively reduced by Eq. 21 in the appendix.

S4. Deploy T4 for the n-th worker: If $c_{n,j}^o \neq 0$ for all $j \in [0, p-1)$, removing the n-th worker will lead to a decrease in $\mathcal{R}_F^T$ and $\mathcal{M}_F$ by Eq. 22 in the appendix.

Algorithm Design: The algorithm of the proposed searching is illustrated in Alg. 2 in the appendix. Overall, the time complexity of this algorithm is $\mathcal{O}(NP^2)$, and it will be executed only once before fine-grained pipeline parallelism begins.

5.2.2 Brute-force Planning (Sub-problem 2)

In Ferret, L is determined by first establishing an upper bound on the time consumed for each stage (t^c), and then solving the following optimization problem:

$$L = \arg\min_{L}\{P\} \;\; s.t. \;\; t^f + t^b \leq t^c. \tag{16}$$

Namely, minimizing the number of pipeline stages while ensuring the time consumed for each stage is bounded. Since the layers in a stage must be consecutive, this problem can be solved in linear time by iteratively grouping consecutive layers into a stage until no additional adjacent layer can be grouped. Therefore, the solution space for L is not extensive, being limited to $(\hat{L}^2 - \hat{L})/2$ at worst. Thus, to solve sub-problem (2), we can simply enumerate all possible model partition schemes, feeding them into Alg. 2 in the appendix to obtain the global optimum L^*.

Algorithm Design: The algorithm of the proposed planning is illustrated in Alg. 3 in the appendix. The time complexity of this algorithm is $\mathcal{O}(\hat{L}^3)$. Nevertheless, the algorithm will be executed only once before fine-grained pipeline parallelism begins.

6. Experiments

In this section, we seek answers to the following questions. (1) How does Ferret boost online accuracy? (Sec. 6.2) (2) How does Ferret mitigate catastrophic forgetting. (Sec. 6.2) (3) How does our fine-grained pipeline parallelism perform? (Sec. 6.3) (4) What are influences of different pipeline configurations? (Sec. 6.3) (5) How does our iterative gradient compensation algorithm perform?(Sec. 6.4)

6.1. Evaluation Setup

Datasets and models: Following the conventions of the community [46], 18 image classification datasets, including MNIST [22], FMNIST [79], CIFAR10 [43], CIFAR100 [43], SVHN [60], Tiny-ImageNet [45], CORe50 [50], CORe50-iid, Split-MNIST, Split-FMNIST, Split-CIFAR10, Split-CIFAR100, Split-SVHN, Split-Tiny-ImageNet, Covertype [8], CLEAR10 [48], CLEAR100 [48], are used in our experiments. More details about the datasets can be found in the appendix. To cover both simple and complicated learning problems, five models including Multi-Layer Perceptron (MLP), MNISTNet, ConvNet, ResNet-18 [34] and MobileNet [35] are used in the experiments. Note that ResNet-18 and MobileNet are pretrained on the ImageNet-1K dataset [21].

Compared methods: For question (1): **Oracle**, **1-Skip** [29], **Random-N B-Skip**, **Last-N B-Skip** and Camel [46]. Here, Oracle is an ideal method that sequentially processes every streaming data without any delay. B-Skip and Camel selects a subset from the latest B unprocessed data using Random-N, Last-N and Coreset sampler, respectively. For question (2): **Vanilla**, **ER** [12], **MIR** [3], **LwF** [47], **MAS** [2]. For question (3) and (4): **DAPPLE** [24], **Pipedream** [58], **Pipedream$_{2BW}$** [59], **Zero-Bubble** [66] and **Hanayo** [49]. For question (5): **None**, **Step-Aware** [33, 41], **Gap-Aware** [7], **Fisher** [14], and **Iter-Fisher** (*i.e.*, iterative gradient compensation).

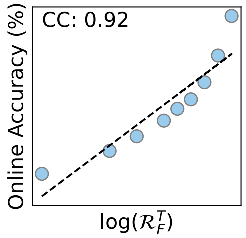


Figure 7. Relation between $oacc$ and $\log(\mathcal{R}_F^T)$

Evaluation metrics: To measure catastrophic forgetting while accounting for memory footprint, Test Accuracy [29, 46] Gain per unit of Memory[1] (the higher the better) is defined as

$$tagm_{\mathcal{B}}(\mathcal{A}, t) = \log(\frac{\exp(tacc_{\mathcal{A}}(t) - tacc_{\mathcal{B}}(t))}{\mathcal{M}_{\mathcal{A}}/\mathcal{M}_{\mathcal{B}}}), \tag{17}$$

where $tacc$ computes the test accuracy and $\mathcal{B}$ is the baseline

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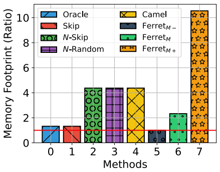
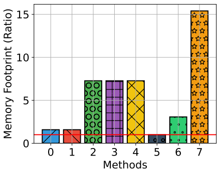
[1] Results in the appendix show standard test accuracy and online accuracy but ignore memory consumption during training.

Table 1. Online Accuracy Gain per unit of Memory ($agm_{\mathcal{B}}(\mathcal{A}, T)$) of different algorithms, where $\mathcal{B}$ is the 1-Skip. "M-", "M", "M+" refer to the ferret method with minimal, medium and maximal memory footprint, respectively.

Setting	Oracle	1-Skip	Random-N	Last-N	Camel	Ferret$_{\mathrm{M}-}$	Ferret$_{\mathrm{M}}$	Ferret$_{\mathrm{M}+}$
MNIST/MNISTNet	$27.32_{\pm0.71}$	$0_{\pm0}$	$-0.43_{\pm0.6}$	$-0.26_{\pm0.14}$	$-0.71_{\pm0.32}$	$5.31_{\pm0.7}$	$\underline{16.26}_{\pm0.37}$	$\mathbf{26.34}_{\pm0.7}$
FMNIST/MNISTNet	$19.35_{\pm0.99}$	$0_{\pm0}$	$-0.31_{\pm0.47}$	$-0.25_{\pm0.5}$	$-0.6_{\pm0.4}$	$5.93_{\pm0.81}$	$\underline{12.69}_{\pm0.81}$	$\mathbf{18.37}_{\pm1.01}$
EMNIST/MNISTNet	$13_{\pm0.48}$	$0_{\pm0}$	$1.94_{\pm0.04}$	$2.02_{\pm0.03}$	$1.55_{\pm0.1}$	$4.19_{\pm0.17}$	$\underline{8.8}_{\pm0.4}$	$\mathbf{12.09}_{\pm0.47}$
CIFAR10/ConvNet	$10.57_{\pm0.09}$	$0_{\pm0}$	$4.71_{\pm0.05}$	$4.78_{\pm0.03}$	$4.7_{\pm0.05}$	$3.21_{\pm0.16}$	$\underline{6.21}_{\pm0.15}$	$\mathbf{9.44}_{\pm0.12}$
CIFAR100/ConvNet	$5.24_{\pm0.01}$	$0_{\pm0}$	$0.78_{\pm0.07}$	$0.83_{\pm0.06}$	$0.75_{\pm0.08}$	$1.58_{\pm0.04}$	$\underline{2.6}_{\pm0.03}$	$\mathbf{4.39}_{\pm0.05}$
SVHN/ConvNet	$15.41_{\pm0.23}$	$0_{\pm0}$	$7.04_{\pm0.08}$	$7.24_{\pm0.11}$	$7.39_{\pm0.09}$	$5_{\pm0.1}$	$\underline{11.52}_{\pm0.23}$	$\mathbf{14.34}_{\pm0.31}$
TinyImagenet/ConvNet	$2.13_{\pm0.07}$	$0_{\pm0}$	$-0.22_{\pm0.04}$	$-0.2_{\pm0.03}$	$-0.21_{\pm0.05}$	$0.48_{\pm0.03}$	$\underline{0.54}_{\pm0.03}$	$\mathbf{1.19}_{\pm0.07}$
CORe50/ConvNet	$26.01_{\pm0.42}$	$0_{\pm0}$	$12.13_{\pm0.42}$	$12.27_{\pm0.44}$	$11.07_{\pm0.48}$	$9.08_{\pm0.45}$	$\underline{17.95}_{\pm0.45}$	$\mathbf{24.49}_{\pm0.43}$
CORe50-iid/ConvNet	$19.24_{\pm2.9}$	$0_{\pm0}$	$2.87_{\pm5.71}$	$5.74_{\pm2.8}$	$5.21_{\pm2.49}$	$3.55_{\pm2.77}$	$\underline{10.74}_{\pm2.76}$	$\mathbf{17.96}_{\pm2.88}$
SplitMNIST/MNISTNet	$18.21_{\pm0.76}$	$0_{\pm0}$	$2.34_{\pm0.43}$	$2.37_{\pm0.63}$	$3.3_{\pm0.48}$	$6.11_{\pm0.84}$	$\underline{14.55}_{\pm0.55}$	$\mathbf{17.05}_{\pm0.72}$
SplitFMNIST/MNISTNet	$11.32_{\pm1.47}$	$0_{\pm0}$	$1.53_{\pm0.47}$	$1.49_{\pm0.42}$	$1.96_{\pm0.39}$	$5.43_{\pm0.56}$	$\underline{9.37}_{\pm1.35}$	$\mathbf{10.29}_{\pm1.47}$
SplitCIFAR10/ConvNet	$7.49_{\pm0.12}$	$0_{\pm0}$	$3.05_{\pm0.11}$	$3.11_{\pm0.11}$	$3.12_{\pm0.09}$	$2.91_{\pm0.19}$	$\underline{4.84}_{\pm0.2}$	$\mathbf{6.19}_{\pm0.07}$
SplitCIFAR100/ConvNet	$10.51_{\pm0.15}$	$0_{\pm0}$	$2.81_{\pm0.07}$	$2.86_{\pm0.05}$	$2.74_{\pm0.13}$	$3.54_{\pm0.03}$	$\underline{6.13}_{\pm0.13}$	$\mathbf{9.61}_{\pm0.04}$
SplitSVHN/ConvNet	$6.49_{\pm0.33}$	$0_{\pm0}$	$2.9_{\pm0.19}$	$2.91_{\pm0.21}$	$2.89_{\pm0.21}$	$2.76_{\pm0.16}$	$\underline{5}_{\pm0.28}$	$\mathbf{5.38}_{\pm0.35}$
SplitTinyImagenet/ConvNet	$2.14_{\pm0.1}$	$0_{\pm0}$	$-0.24_{\pm0.03}$	$-0.21_{\pm0.02}$	$-0.26_{\pm0.01}$	$0.47_{\pm0.01}$	$\underline{0.62}_{\pm0.01}$	$\mathbf{1.19}_{\pm0.06}$
CLEAR10/ResNet	$10.37_{\pm0.06}$	$0_{\pm0}$	$7.84_{\pm0.07}$	$\underline{7.93}_{\pm0.06}$	$-2.9_{\pm10.55}$	$2.44_{\pm0.06}$	$7.71_{\pm0.06}$	$\mathbf{9.26}_{\pm0.08}$
CLEAR10/MobileNet	$20.36_{\pm0.2}$	$0_{\pm0}$	$11.8_{\pm0.22}$	$12_{\pm0.14}$	$11.85_{\pm0.07}$	$-1.77_{\pm0.15}$	$\underline{14.68}_{\pm0.5}$	$\mathbf{18.51}_{\pm0.35}$
CLEAR100/ResNet	$21.71_{\pm0.43}$	$0_{\pm0}$	$15.19_{\pm0.49}$	$15.36_{\pm0.46}$	$14.39_{\pm0.46}$	$7.51_{\pm0.44}$	$\underline{15.53}_{\pm0.35}$	$\mathbf{20.84}_{\pm0.57}$
CLEAR100/MobileNet	$23.51_{\pm1.03}$	$0_{\pm0}$	$9.16_{\pm0.28}$	$9.39_{\pm0.15}$	$8.72_{\pm0.06}$	$1.05_{\pm0.13}$	$\underline{15.8}_{\pm0.39}$	$\mathbf{22.11}_{\pm0.59}$
Covertype/MLP	$7.66_{\pm0.27}$	$0_{\pm0}$	$-1.33_{\pm0.3}$	$-1.3_{\pm0.31}$	$-1.34_{\pm0.29}$	$0.74_{\pm0.21}$	$\underline{1.61}_{\pm0.29}$	$\mathbf{3.38}_{\pm0.42}$

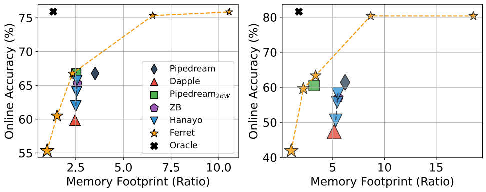


(a) EMNIST/MNISTNet



(b) CIFAR100/ConvNet

Figure 4. Consumed memory of different stream learning algorithms. Ferret achieves rapid adaptation across varying memory constraints.



(a) EMNIST/MNISTNet (b) CORe50/ConvNet

Figure 6. Relationships between online accuracy and memory consumption of different pipeline parallelism strategies, the marker size represents the standard errors of means.

Table 2. Online Accuracy Gain per unit of Memory ($agm_{\mathcal{B}}(\mathcal{A}, T)$) and Test Accuracy Gain per unit of Memory ($tagm_{\mathcal{B}}(\mathcal{A})$) of different integrated OCL algorithms on CORe50/ConvNet, where $\mathcal{B}$ is the 1-Skip. Camel has its dedicated component to mitigate catastrophic forgetting and cannot be integrated with various OCL algorithm.

	Metric	Oracle	1-Skip	Random-N	Last-N	Camel	Ferret$_{\mathrm{M}-}$	Ferret$_{\mathrm{M}}$	Ferret$_{\mathrm{M}+}$
Vanilla	agm	$26.01_{\pm0.42}$	$0_{\pm0}$	$12.13_{\pm0.42}$	$12.27_{\pm0.44}$	$11.07_{\pm0.48}$	$9.08_{\pm0.45}$	$\underline{17.21}_{\pm0.45}$	$\mathbf{24.82}_{\pm0.43}$
	$tagm$	$2.36_{\pm0.64}$	$0_{\pm0}$	$1.08_{\pm0.62}$	$0.97_{\pm0.39}$	$\underline{1.48}_{\pm0.42}$	$1.01_{\pm0.45}$	$1.07_{\pm0.49}$	$\mathbf{1.73}_{\pm0.53}$
ER [12]	agm	$24.03_{\pm0.26}$	$0_{\pm0}$	$7.84_{\pm0.17}$	$8.11_{\pm0.29}$	-	$7.12_{\pm0.09}$	$\underline{16.09}_{\pm0.16}$	$\mathbf{23.5}_{\pm0.25}$
	$tagm$	$4.18_{\pm0.43}$	$0_{\pm0}$	$1.94_{\pm0.26}$	$2.34_{\pm0.29}$	-	$0.82_{\pm0.29}$	$\underline{3.1}_{\pm0.25}$	$\mathbf{4.06}_{\pm0.36}$
MIR [3]	agm	$24.03_{\pm0.26}$	$0_{\pm0}$	$7.82_{\pm0.21}$	$8.06_{\pm0.22}$	-	$7.12_{\pm0.09}$	$\underline{16.09}_{\pm0.15}$	$\mathbf{23.5}_{\pm0.25}$
	$tagm$	$4.18_{\pm0.43}$	$0_{\pm0}$	$2.1_{\pm0.15}$	$2.2_{\pm0.14}$	-	$0.82_{\pm0.29}$	$\underline{3.1}_{\pm0.25}$	$\mathbf{4.06}_{\pm0.36}$
LwF [47]	agm	$26.02_{\pm0.42}$	$0_{\pm0}$	$12.25_{\pm0.42}$	$12.4_{\pm0.45}$	-	$9.02_{\pm0.4}$	$\underline{17.96}_{\pm0.46}$	$\mathbf{24.67}_{\pm0.4}$
	$tagm$	$2.36_{\pm0.64}$	$0_{\pm0}$	$1.2_{\pm0.62}$	$1.09_{\pm0.39}$	-	$0.91_{\pm0.44}$	$\underline{1.88}_{\pm0.49}$	$\mathbf{1.54}_{\pm0.53}$
MAS [2]	agm	$25.86_{\pm0.25}$	$0_{\pm0}$	$12.04_{\pm0.23}$	$12.23_{\pm0.22}$	-	$8.7_{\pm0.17}$	$\underline{17.79}_{\pm0.22}$	$\mathbf{24.46}_{\pm0.23}$
	$tagm$	$2.7_{\pm0.23}$	$0_{\pm0}$	$0.81_{\pm0.41}$	$0.91_{\pm0.24}$	-	$0.59_{\pm0.23}$	$\underline{1.66}_{\pm0.18}$	$\mathbf{1.69}_{\pm0.21}$

method for comparison. Similarly, as Fig. 7 shows online accuracy can be used to estimate $\mathcal{R}_F^T$ [11], Online Accuracy Gain per unit of Memory[1] (the higher the better) is defined as

$$agm_{\mathcal{B}}(\mathcal{A}, t) = \log(\frac{\exp(oacc_{\mathcal{A}}(t) - oacc_{\mathcal{B}}(t))}{\mathcal{M}_{\mathcal{A}}/\mathcal{M}_{\mathcal{B}}}). \tag{18}$$

We evaluate three versions of Ferret under different memory constraints: Ferret$_{\mathrm{M}-}$ (minimal), Ferret$_{\mathrm{M}}$ (the same memory constraint as Pipedream$_{2BW}$), and Ferret$_{\mathrm{M}+}$ (no constraint). Without clarification, each experiment is independently repeated three times to obtain the final results. In all tables, the best and second-best performance are highlighted by **bold** and $\underline{\text{underline}}$, respectively. More details about the evaluation setup can be found in Sec. 12.

6.2. Overall Comparisons

Table 1 shows $agm_{\mathcal{B}}(\mathcal{A}, T)$ across 20 different settings to evaluate both performance and consumed memory of different frameworks. Here, $\mathcal{B}$ is chosen to be the 1-Skip due to its low memory footprint. From the table, it is evident that Ferret$_{\mathrm{M}}$ and Ferret$_{\mathrm{M}+}$ constantly outperform other competing algorithms. Notably, Ferret$_{\mathrm{M}+}$ even achieves comparable performance compared to Oracle, indicating that Ferret effectively enables rapid adaptation. On the other hand, while Ferret$_{\mathrm{M}-}$ shows slightly inferior performance compared to its counterparts, it demands less memory for OCL, as depicted in Fig. 4. This implies that in scenarios where memory is severely constrained, Ferret is the only method capable of learning.

Furthermore, various OCL algorithms are integrated on CORe50/ConvNet in Table 2. It can be observed that Ferret not only mitigates catastrophic forgetting (*i.e.*, increased $tagm$) but also markedly enhances online performance (*i.e.*, increased agm), validating its orthogonality and superiority compared to other OCL frameworks for rapid adaptation.

6.3. Comparisons on Pipeline Parallelism

Table 3 compares $agm_{\mathcal{B}}(\mathcal{A}, T)$ of different pipeline parallelism strategies across 20 different settings to evaluate the performance of Ferret's fine-grained pipeline parallelism

Table 3. Online Accuracy Gain per unit of Memory ($agm_{\mathcal{B}}(\mathcal{A}, T)$) of different pipeline parallelism strategies, where $\mathcal{B}$ is the DAPPLE. Note that "1W", "2W" and "3W" refer to 1, 2 and 3 wave(s) for the Hanayo algorithm, and no gradients compensation is applied to all asynchronous pipeline parallelism strategies for fair comparisons

Setting	Synchronous PP					Asynchronous PP		
	DAPPLE	ZB	Hanayo$_{1W}$	Hanayo$_{2W}$	Hanayo$_{3W}$	Pipedream	Pipedream$_{2BW}$	Ferret$_M$
MNIST/MnNet	$0_{\pm0}$	$6.79_{\pm0.4}$	$2.44_{\pm0.3}$	$5_{\pm0.16}$	$7.12_{\pm0.38}$	$8.16_{\pm0.35}$	$\underline{8.23}_{\pm0.39}$	$\mathbf{8.35}_{\pm0.35}$
FMNIST/MnNet	$0_{\pm0}$	$4.06_{\pm0.36}$	$1.52_{\pm0.45}$	$2.8_{\pm0.65}$	$4.26_{\pm0.64}$	$5.29_{\pm0.53}$	$\underline{5.36}_{\pm0.54}$	$\mathbf{5.48}_{\pm0.53}$
EMNIST/MnNet	$0_{\pm0}$	$2.33_{\pm0.08}$	$0.9_{\pm0.02}$	$1.81_{\pm0.05}$	$2.55_{\pm0.04}$	$2.84_{\pm0.09}$	$\underline{2.99}_{\pm0.07}$	$\mathbf{3.02}_{\pm0.09}$
C10/CNet	$0_{\pm0}$	$1.76_{\pm0.08}$	$0.96_{\pm0.14}$	$1.51_{\pm0.04}$	$1.93_{\pm0.12}$	$2.53_{\pm0.04}$	$\underline{2.78}_{\pm0.06}$	$\mathbf{3.05}_{\pm0.15}$
C100/CNet	$0_{\pm0}$	$0.71_{\pm0.04}$	$0.05_{\pm0.05}$	$0.56_{\pm0.06}$	$0.74_{\pm0.06}$	$0.87_{\pm0.09}$	$\underline{1.11}_{\pm0.06}$	$\mathbf{1.72}_{\pm0.01}$
SVHN/CNet	$0_{\pm0}$	$2.13_{\pm0.32}$	$0.36_{\pm0.15}$	$1.52_{\pm0.23}$	$2.21_{\pm0.26}$	$3.3_{\pm0.24}$	$\underline{3.32}_{\pm0.19}$	$\mathbf{3.61}_{\pm0.16}$
TinyI/CNet	$0_{\pm0}$	$0.18_{\pm0.02}$	$0.03_{\pm0.01}$	$0.19_{\pm0.02}$	$0.19_{\pm0.04}$	$0.26_{\pm0.01}$	$\mathbf{0.52}_{\pm0.03}$	$\underline{0.5}_{\pm0.06}$
CORe50/CNet	$0_{\pm0}$	$4.18_{\pm0.23}$	$1.38_{\pm0.12}$	$3.6_{\pm0.16}$	$4.69_{\pm0.11}$	$\underline{6.03}_{\pm0.17}$	$5.91_{\pm0.22}$	$\mathbf{7.13}_{\pm0.18}$
CORe50-iid/CNet	$0_{\pm0}$	$3.58_{\pm0.02}$	$1.19_{\pm0.18}$	$2.94_{\pm0.02}$	$3.74_{\pm0.07}$	$5.07_{\pm0.13}$	$\underline{5.24}_{\pm0.07}$	$\mathbf{6.18}_{\pm0.05}$
S-MNIST/MnNet	$0_{\pm0}$	$2.94_{\pm0.29}$	$1.33_{\pm0.26}$	$2.97_{\pm0.21}$	$3.69_{\pm0.23}$	$\underline{4.3}_{\pm0.29}$	$4.11_{\pm0.33}$	$\mathbf{4.47}_{\pm0.29}$
S-FMNIST/MnNet	$0_{\pm0}$	$1.56_{\pm0.29}$	$0.91_{\pm0.16}$	$1.48_{\pm0.2}$	$1.89_{\pm0.31}$	$2.06_{\pm0.28}$	$\underline{2.09}_{\pm0.27}$	$\mathbf{2.24}_{\pm0.28}$
S-C10/CNet	$0_{\pm0}$	$0.96_{\pm0.14}$	$0.44_{\pm0.13}$	$1.19_{\pm0.03}$	$1.42_{\pm0.14}$	$\underline{2.21}_{\pm0.08}$	$2.16_{\pm0.05}$	$\mathbf{2.58}_{\pm0.1}$
S-C100/CNet	$0_{\pm0}$	$1.57_{\pm0.05}$	$0.54_{\pm0.14}$	$1.25_{\pm0.12}$	$1.67_{\pm0.12}$	$2.48_{\pm0.12}$	$\underline{2.49}_{\pm0.1}$	$\mathbf{3.49}_{\pm0.06}$
S-SVHN/CNet	$0_{\pm0}$	$0.86_{\pm0.05}$	$0.49_{\pm0.08}$	$0.88_{\pm0.06}$	$1.13_{\pm0.03}$	$1.39_{\pm0.04}$	$\underline{1.58}_{\pm0.06}$	$\mathbf{1.75}_{\pm0.03}$
S-TinyI/CNet	$0_{\pm0}$	$0.27_{\pm0.05}$	$0.08_{\pm0.03}$	$0.14_{\pm0.02}$	$0.22_{\pm0.03}$	$0.29_{\pm0.03}$	$\underline{0.47}_{\pm0.01}$	$\mathbf{0.66}_{\pm0.04}$
CLEAR10/RNet	$0_{\pm0}$	$0.38_{\pm0.13}$	$0.46_{\pm0.08}$	$1.04_{\pm0.06}$	$1.4_{\pm0.04}$	$1.8_{\pm0.06}$	$\underline{1.92}_{\pm0.05}$	$\mathbf{2.12}_{\pm0.05}$
CLEAR10/MoNet	$0_{\pm0}$	$1.03_{\pm0.64}$	$0.65_{\pm0.23}$	$2.31_{\pm0.15}$	$2.65_{\pm0.49}$	$\underline{4.25}_{\pm0.09}$	$3.82_{\pm0.26}$	$\mathbf{5.34}_{\pm0.11}$
CLEAR100/RNet	$0_{\pm0}$	$2.76_{\pm0.1}$	$1.36_{\pm0.22}$	$2.52_{\pm0.21}$	$3.3_{\pm0.23}$	$3.85_{\pm0.2}$	$\underline{3.98}_{\pm0.19}$	$\mathbf{4.24}_{\pm0.22}$
CLEAR100/MoNet	$0_{\pm0}$	$3.11_{\pm0.53}$	$1.26_{\pm0.12}$	$3.03_{\pm0.52}$	$4.24_{\pm0.12}$	$5.66_{\pm0.19}$	$\underline{5.88}_{\pm0.58}$	$\mathbf{7.42}_{\pm0.69}$
Covertype/MLP	$0_{\pm0}$	$0.62_{\pm0.14}$	$0.24_{\pm0.12}$	$0.6_{\pm0.16}$	$0.83_{\pm0.16}$	$\mathbf{0.92}_{\pm0.16}$	$0.82_{\pm0.13}$	$\underline{0.89}_{\pm0.08}$

Table 4.
Online Accuracy differences between Ferret with and without gradients compensation algorithms .

Ferret$_{M+}$				Ferret$_M$			
Step-Aware	Gap-Aware	Fisher	Iter-Fisher	Step-Aware	Gap-Aware	Fisher	Iter-Fisher
$-56.04_{\pm}2.78$	$-14.03_{\pm}1.24$	$\underline{-0.02}_{\pm}0.01$	$\mathbf{0.01}_{\pm}0$	$-43.53_{\pm}2.36$	$-12.11_{\pm}1.03$	$\underline{-0.01}_{\pm}0.01$	$\mathbf{0.02}_{\pm}0$
$-37.75_{\pm}2.17$	$-9.07_{\pm}0.63$	$\underline{-0.02}_{\pm}0.03$	$\mathbf{0.05}_{\pm}0.01$	$-37.74_{\pm}2.53$	$-7.07_{\pm}0.55$	$\underline{-0.01}_{\pm}0.01$	$\mathbf{0.02}_{\pm}0$
$-20.5_{\pm}0.05$	$-4.81_{\pm}0.15$	$\underline{0.01}_{\pm}0.02$	$\mathbf{0.04}_{\pm}0.02$	$-33.36_{\pm}0.13$	$-3.46_{\pm}0.33$	$\underline{0.01}_{\pm}0.01$	$\mathbf{0.04}_{\pm}0.02$
$-10.12_{\pm}0.19$	$-1.71_{\pm}0.43$	$\underline{-0.32}_{\pm}0.07$	$\mathbf{0.25}_{\pm}0.06$	$-9.6_{\pm}0.19$	$-1.22_{\pm}0.39$	$\underline{-0.14}_{\pm}0.3$	$\mathbf{0.42}_{\pm}0.21$
$-8.08_{\pm}0.17$	$-2.17_{\pm}0.05$	$\underline{-0.04}_{\pm}0.08$	$\mathbf{0.13}_{\pm}0.05$	$-5.4_{\pm}0.07$	$-1.04_{\pm}0.04$	$\underline{-0.01}_{\pm}0.07$	$\mathbf{0.1}_{\pm}0.02$
$-14.92_{\pm}0.42$	$-2.63_{\pm}0.04$	$\underline{0.02}_{\pm}0.04$	$\mathbf{0.31}_{\pm}0.2$	$-24.7_{\pm}1.18$	$-2.91_{\pm}0.11$	$\underline{0.22}_{\pm}0.07$	$\mathbf{0.3}_{\pm}0.07$
$-3.72_{\pm}0.16$	$-1.06_{\pm}0.09$	$\underline{-0.01}_{\pm}0.02$	$\mathbf{0.06}_{\pm}0.03$	$-1.32_{\pm}0.17$	$-0.11_{\pm}0.19$	$\underline{0.17}_{\pm}0.19$	$\mathbf{0.35}_{\pm}0.15$
$-23.93_{\pm}0.16$	$-3.27_{\pm}0.05$	$\underline{-0.22}_{\pm}0.11$	$\mathbf{0.1}_{\pm}0.08$	$-33.41_{\pm}0.24$	$-4.18_{\pm}0.34$	$\underline{0.02}_{\pm}0.12$	$\mathbf{0.34}_{\pm}0.07$
$-24.56_{\pm}0.22$	$-3.91_{\pm}0.2$	$\underline{0.22}_{\pm}0.08$	$\mathbf{0.32}_{\pm}0.06$	$-23.77_{\pm}0.3$	$-3.15_{\pm}0.53$	$\underline{0.23}_{\pm}0.12$	$\mathbf{0.39}_{\pm}0.1$
$-26.8_{\pm}3.2$	$-4.21_{\pm}0.21$	$\underline{-0.05}_{\pm}0.02$	$\mathbf{0.03}_{\pm}0.01$	$-46.24_{\pm}1.41$	$-4.82_{\pm}0.48$	$\underline{-0.03}_{\pm}0.01$	$\mathbf{0.02}_{\pm}0$
$-14.43_{\pm}2.83$	$-2.37_{\pm}0.14$	$\underline{0.01}_{\pm}0.02$	$\mathbf{0.03}_{\pm}0.02$	$-46.07_{\pm}4.03$	$-2.1_{\pm}0.33$	$\underline{-0.01}_{\pm}0.01$	$\mathbf{0}_{\pm}0$
$-6.93_{\pm}0.12$	$-1_{\pm}0.14$	$\underline{-0.19}_{\pm}0.09$	$\mathbf{0.1}_{\pm}0.03$	$-8.11_{\pm}0.75$	$-0.99_{\pm}0.24$	$\underline{-0.12}_{\pm}0.12$	$\mathbf{0.23}_{\pm}0.12$
$-14.14_{\pm}0.37$	$-3.05_{\pm}0.1$	$\underline{-0.23}_{\pm}0.18$	$\mathbf{0.38}_{\pm}0.23$	$-12.56_{\pm}0.23$	$-1.92_{\pm}0.09$	$\underline{-0.1}_{\pm}0.19$	$\mathbf{0.24}_{\pm}0.09$
$-5.69_{\pm}0.46$	$-1.18_{\pm}0.12$	$\underline{-0.03}_{\pm}0.03$	$\mathbf{0.05}_{\pm}0.03$	$-12.13_{\pm}0.87$	$-1.27_{\pm}0.09$	$\underline{-0.05}_{\pm}0.02$	$\mathbf{0.03}_{\pm}0.01$
$-3.61_{\pm}0.14$	$-1.01_{\pm}0.05$	$\underline{0.05}_{\pm}0.1$	$\mathbf{0.12}_{\pm}0.1$	$-1.7_{\pm}0.12$	$-0.37_{\pm}0.03$	$\underline{0.08}_{\pm}0.07$	$\mathbf{0.18}_{\pm}0.08$
$-6.26_{\pm}0.18$	$-0.72_{\pm}0.08$	$\underline{0.02}_{\pm}0.06$	$\mathbf{0.14}_{\pm}0.04$	$-11.25_{\pm}0.28$	$-0.52_{\pm}0.05$	$\underline{-0.02}_{\pm}0.04$	$\mathbf{0.08}_{\pm}0.04$
$-18.17_{\pm}0.26$	$-1.7_{\pm}0.05$	$\underline{-0.14}_{\pm}0.32$	$\mathbf{0.5}_{\pm}0.15$	$-20.69_{\pm}0.58$	$-1.88_{\pm}0.46$	$\underline{-0.28}_{\pm}0.37$	$\mathbf{0.36}_{\pm}0.18$
$-17.45_{\pm}0.02$	$-0.38_{\pm}0.54$	$\underline{-0.07}_{\pm}0.04$	$\mathbf{0.65}_{\pm}0.32$	$-24.62_{\pm}0.24$	$\underline{0.18}_{\pm}0.32$	$-0.2_{\pm}0.18$	$\mathbf{1.27}_{\pm}0.21$
$-30.65_{\pm}0.93$	$-0.3_{\pm}0.17$	$\underline{0.63}_{\pm}0.46$	$\mathbf{1.2}_{\pm}0.48$	$-26.85_{\pm}1.22$	$-0.3_{\pm}0.33$	$\underline{0.58}_{\pm}0.78$	$\mathbf{1.03}_{\pm}0.7$
$-9.2_{\pm}1.13$	$-2.8_{\pm}0.1$	$\underline{-0.09}_{\pm}0.05$	$\mathbf{0.05}_{\pm}0.02$	$-10.27_{\pm}0.39$	$-1.52_{\pm}0.14$	$\underline{-0.01}_{\pm}0$	$\mathbf{0.09}_{\pm}0.01$

under memory constraints. Specifically, $\mathcal{B}$ is selected as DAPPLE, and no gradients compensation is applied to any asynchronous pipeline parallelism strategies. Additionally, Hanayo$_{1W}$, Hanayo$_{2W}$ and Hanayo$_{3W}$ are three variants with 1, 2, and 3 waves, respectively.

In general, all asynchronous pipeline parallelism strategies significantly outperform synchronous pipeline parallelism strategies, even ZB, which claims to eliminate pipeline bubbles. This is because synchronous pipeline parallelism strategies, in an effort to achieve higher hardware utilization rates and avoid conflicting model versions, must design complex workflows that stage gradients and update model parameters synchronously, resulting in delays in data processing and wasted data value. Conversely, asynchronous pipeline parallelism strategies process data and update model parameters immediately, thereby minimizing processing latency. Among all asynchronous pipeline parallelism strategies, Ferret$_M$'s fine-grained pipeline parallelism strategy consistently surpasses the others due to its more efficient memory utilization.

To investigate the impact of different pipeline configurations for Ferret, we select five different memory constraints ranging from minimum to maximum to simulate learning under varying memory budgets Fig. 6 shows that Ferret successfully solves Eq. 2 for obtaining optimal pipeline configurations under dynamic environments, scaling effectively as we increase the memory constraint. Specifically, lack of precise control over each pipeline stage to balance between performance and memory footprint prevents competing strategies from scaling well.

6.4. Comparisons on Gradients Compensation

To evaluate the effectiveness of Iter-Fisher, we apply various gradients compensation algorithms to Ferret$_{M+}$ and Ferret$_M$, and compare the final online accuracy gain. The results are shown in Table 4. From the table, we can observe that applying Step-Aware and Gap-Aware algorithms for compensating stale gradients significantly reduces the online accuracy. This is because these algorithms mitigate the gradient staleness problem by simply penalizing the step size of stale gradients, leading to a slow convergence rate when the system is highly paralleled. Although Fisher leverages first-order information for better compensation, it does not consider varying levels of staleness at different stages of pipeline parallelism, resulting in a marginal decrease in accuracy compared to no compensation. On the other hand, Iter-Fisher consistently improves online accuracy across all settings, without requiring manual hyperparameters tuning. This indicates that Iter-Fisher effectively adapts to different levels of staleness in parallelism, and automatically optimizes λ for better compensation, demonstrating its robustness and effectiveness.

7. Conclusion

This paper introduces Ferret, a novel framework designed to boost online accuracy of OCL algorithms under varying memory constraints. Ferret employs a fine-grained pipeline parallelism strategy to adapt to varying distributions of incoming streaming data rapidly. To mitigate the gradient staleness problem in parallel processing, Ferret integrates an iterative gradient compensation algorithm to prevent performance degradation. Additionally, pipelines are automatically scheduled to improve performance under any memory scenario by optimizing a bi-level optimization problem. Extensive experiments conducted on 18 datasets and 5 models confirm Ferret's superior efficiency and robustness compared to existing methods, demonstrating its potential as a scalable solution for adaptive, memory-efficient OCL.

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