StreamFP: Fingerprint-guided Data Selection for Efficient Stream Learning

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Abstract

Modern web applications—ranging from personalized recommendation to real-time fraud detection—rely on AI models to deliver timely and personalized services, yet the underlying user interaction data arrives as massive and evolving streams. *Stream Learning* (SL) offers a natural paradigm for building adaptive models, but it struggles with challenges such as redundant training data and catastrophic forgetting, which can undermine long-term predictive performance. To address these issues, recent studies have explored data selection strategies like coreset selection and buffer update, typically implemented through rule-based or model-based methods. However, fixed selection rules hinder the adaptability of rule-based approaches to changing data distributions, while model-based methods often depend on costly per-sample gradients, leading to throttled updates and reduced coverage of informative samples. In this paper, we propose *StreamFP*, a lightweight SL framework that introduces *fingerprints*—a set of compact, learnable parameter vectors that summarize the model state. Fingerprints compute similarity scores to jointly guide coreset selection and buffer update, prioritizing informative incoming samples while retaining representative historical ones. A lightweight fingerprint attunement plugin further calibrates fingerprints using pre-trained ViT attention with negligible overhead, thereby improving accuracy while mitigating forgetting. Extensive experiments demonstrate that *StreamFP* consistently achieves superior accuracy and efficiency compared with state-of-the-art methods across diverse real-world datasets and varying data arrival rates.

CCS Concepts

• **Computing methodologies** → **Online learning settings**.

Keywords

Stream Learning, Data Selection, Learnable Fingerprints

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1 Introduction

Real-time web video applications—such as user-generated content platforms and live streaming services—rely on AI models to analyze continuously arriving video streams. As illustrated in Figure 1, these streams are highly non-stationary and introduce two fundamental challenges for *Stream Learning* (SL). First, incoming batches often contain substantial redundancy (e.g., near-duplicate frames or static segments), which wastes computation, biases model updates toward frequent patterns, and under-represents rare but informative samples, ultimately reducing analysis accuracy. Second,

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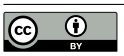

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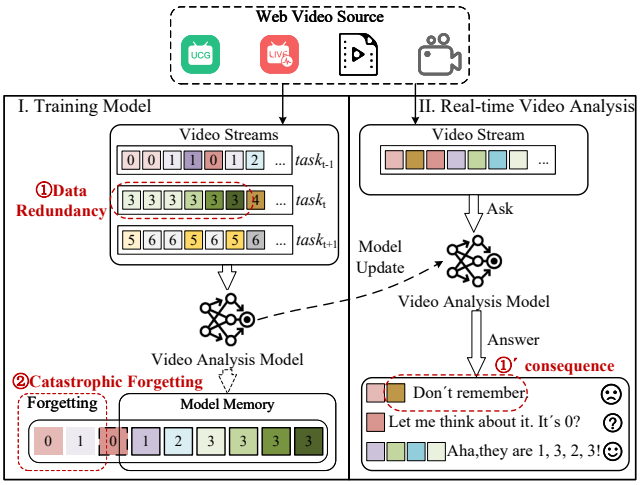

Figure 1: Illustration of a real-time web video analysis scenario for stream learning. Web video sources (e.g., UGC, live streams) produce non-stationary streams that are mini-batched for both model training (left) and online inference (right). On the training side, two challenges arise: (①) data redundancy, where consecutive batches contain many near-duplicate frames, and (②) catastrophic forgetting, where incremental updates overwrite earlier knowledge in memory. On the inference side, these issues manifest as (①') degraded predictions, where the model may fail to recall past knowledge or provide inconsistent answers.

frequent distribution shifts mean that incremental updates for new scenarios can overwrite earlier knowledge, eroding previously learned representations and leading to catastrophic forgetting [10]. Addressing data redundancy and knowledge preservation is therefore essential for effective SL in real-time video analysis.

A common strategy to mitigate these challenges in SL is **data selection**, which typically involves *coreset selection* and *buffer update*. Coreset selection identifies representative subsets from incoming batches, enabling efficient adaptation to evolving distributions while reducing redundant computation [16]. Buffer update maintains a small set of representative past samples, dynamically replacing them with new ones and replaying the buffer during training to alleviate forgetting [3]. To realize these two techniques, prior studies have adopted either *rule-based* or *model-based* approaches [2, 6, 11, 15, 16, 20, 25, 26, 34, 35].

As shown in Figure 2, existing coreset selection and buffer update methods fall short in real-time SL. For coreset selection, the test accuracy of representative rule-based approaches (*Camel* [16], *K-center* [25], *FreeSel* [34]) and model-based approaches (*GradMatch* [15], *Learn-Loss* [35], *Craig* [20]) remains below 40%, far behind our proposed *StreamFP*. For buffer update, *ER* [6] with predefined rules reaches 61.41%, but still trails *StreamFP*, while other baselines perform even worse. The reasons are twofold. (1) **Rule-based methods** [34] rely on fixed sampling and replacement rules, which fail to adapt to distribution shifts and sample informativeness, leading to redundant coresets and

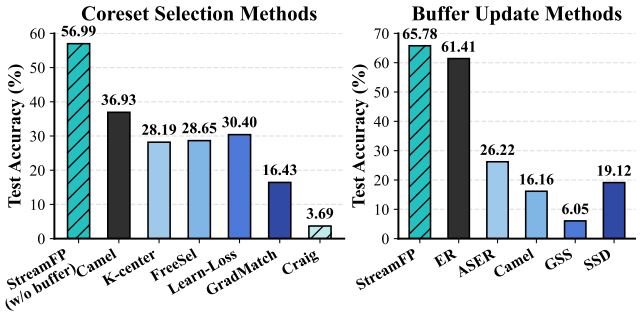

Figure 2: For the Stream-51 dataset with an arrival rate of 6,028 images per second, the test accuracy is evaluated across coreset selection and buffer update methods. Left: In coreset selection, *StreamFP* outperforms rule-based methods (*Camel* [16], *K-center* [25], *FreeSel* [34]) and model-based methods (*GradMatch* [15], *Learn-Loss* [35], *Craig* [20]). Right: In buffer update, *StreamFP* surpasses rule-based methods (*ER* [6], *ASER* [26], *Camel* [16]) and model-based methods (*GSS* [2], and *SSD* [11]).

low-quality buffers. (2) **Model-based methods** [11] require per-sample gradients to construct gradient-aware coresets and update buffers. This computation is costly, slowing down updates and reducing coverage of informative samples, which in turn lowers accuracy. Therefore, neither rule-based nor model-based methods can simultaneously achieve efficient data selection and robust adaptation to distribution shifts in SL.

In this paper, we propose *StreamFP*, a lightweight SL framework designed to enable efficient data selection and knowledge retention under non-stationary streams. *StreamFP* introduces two fingerprint-guided data selection strategies augmented by a lightweight *fingerprint attunement* plugin. Inspired by fingerprint-based continual learning methods such as *CODA-Prompt* [27], we replace fixed rules and gradient-intensive selection with compact, dynamic, and learnable fingerprints that serve as model state summaries to track distribution shifts and guide data selection. This design improves predictive performance while mitigating catastrophic forgetting, with negligible computational overhead.

Concretely, *StreamFP* consists of three key modules. First, *fingerprint-based coreset selection* selects a compact and informative subset from each incoming batch, focusing computation on high-value samples while adapting to the current distribution. Second, *fingerprint-based buffer update* preserves representative past samples for replay, helping the model retain prior knowledge and reduce forgetting. Both modules are guided by a shared set of learnable fingerprints that co-evolve with the model and provide a unified signal for adaptive coreset construction and balanced buffer maintenance. Third, a lightweight *fingerprint attunement* plugin refines fingerprints online using pre-trained attention, further stabilizing their guidance with negligible overhead. In this work, *StreamFP* is instantiated with *ViT* [9] for incremental classification tasks, and can be readily extended to other Transformer architectures such as *CLIP* [21] and *LLaMA* [28].

In summary, our contributions are as follows:

- We propose *StreamFP*, a fingerprint-guided framework for incremental classification tasks over non-stationary data

streams, which unifies efficient data selection with robustness against forgetting.
- We introduce two modules: *fingerprint-based coreset selection*, which leverages fingerprint–batch similarity to select informative samples for rapid adaptation, and *fingerprint-based buffer update*, which uses fingerprint-guided retain/drop decisions to preserve representative history for replay.
- We design a lightweight *fingerprint attunement* plugin that calibrates fingerprints online via pre-trained ViT attention with negligible overhead, providing stable and transferable guidance across different Transformer backbones.
- Extensive experiments on Clear10, Clear100, CORe50, and Stream-51 demonstrate that *StreamFP* consistently improves predictive accuracy, accelerates training, and reduces catastrophic forgetting compared with state-of-the-art baselines.

The remainder of this paper is organized as follows. Section 2 reviews related work, and Section 3 formalizes the technical challenges. Section 4 introduces the architecture of *StreamFP*, including *fingerprint-based coreset selection* and *fingerprint-based buffer update*, while Section 5 details the *fingerprint attunement* module. Section 6 reports experimental results, and Section 7 concludes the paper.

2 Related Work

***Stream Learning* (SL).** SL faces challenges such as handling unbounded data streams and high computational resource consumption [37]. These challenges require maintaining processing efficiency while improving model accuracy and mitigating catastrophic forgetting. Recent work employs data selection strategies based on coreset selection and buffer updates to address these constraints [1, 6, 10, 12, 33]. However, current methods still have many limitations. Rule-based methods in SL struggle with distribution shifts [25], with notable contributions such as *Camel* [16], optimizing data selection by taking submodular maximization as its objective function. While model-based methods construct gradient-aware coresets and update buffers using per-sample gradient signals, the heavy per-sample computation and frequent recomputation reduce update frequency in streaming, thereby shrinking coreset coverage and stealing the buffer, ultimately degrading accuracy [15, 20, 35]. In SL scenarios, efficient data selection strategies to quickly filter representative data that constantly changes with the data distribution to construct coreset and update buffer remain key challenges [1, 2, 14].

***Fingerprint-based Continual Learning* (FCL).**[1] The transformer architecture has emerged as a cornerstone of modern machine learning, demonstrating remarkable success across domains [4, 8, 9]. Prompt tuning methods, which augment this frozen architecture with learnable parameters (fingerprints), have shown exceptional performance in both NLP [18] and CV tasks [13] by enabling efficient adaptation of pre-trained models to fine-tune on unseen data. In continual learning, these methods have evolved significantly, as evidenced by *L2P*'s learnable parameters [32], *DualPrompt*'s task-specific knowledge separation [31], *CODA-Prompt*'s attention mechanisms [27], and *HiDe-Prompt*'s hierarchical learning approach [29]. The primary focus of research on fingerprint-based methods has been to optimize learnable parameters for improving model performance. In contrast, *StreamFP* distinctively integrates these learnable parameters with data selection strategies, achieving a dual enhancement of model adaptability and computational efficiency within dynamic data streams.

[1]It is also termed as *Prompt for Continual Learning*.

3 Problem Statement

3.1 Preliminaries

Definition 1. (***Stream Learning Problem***) *Consider a stream-based classification problem where data arrives sequentially in batches at a high rate λ (samples/second). At each timestamp t, let $B^t = \{(x_i, y_i)\}_{i=1}^{b}$ denote a batch of instances, where $x_i \in \mathbb{R}^d$ represents the feature vector, $y_i \in \mathbb{R}^K$ denotes the corresponding label. Given B^t and a transformer model θ^{t-1} trained on previous batches, with the learning velocity $\mathcal{V}_\theta$ samples/second of the model, the stream learning problem aims to update θ^{t-1} to θ^t with B^t while maintaining a processing speed that matches the arrival rate λ, thereby minimizing the accumulation of unprocessed data. This problem is formulated as:*

$$\begin{aligned} &\min_{\theta^t \in \Theta} \frac{1}{|B^t|} \sum_{(x_i,y_i)\in\{B^t\}} \mathcal{L}(x_i, y_i; \theta^t), \\ &\text{s.t.} \begin{cases} \theta^t = f(\theta^{t-1}, B^t) \\ (\mathcal{V}_\theta - \lambda)^2 \to \min, \quad \mathcal{V}_\theta \gg \lambda \end{cases}, \\ &f(\theta^{t-1}, B^t) = \theta^{t-1} - \eta \frac{1}{|B^t|} \sum_{(x_i,y_i)\in B^t} \nabla_\theta \mathcal{L}(x_i, y_i; \theta^{t-1}). \end{aligned} \tag{1}$$

η is the learning rate, and ∇_θ denotes the gradient with respect to parameters θ.

Definition 2. (***Fingerprint-based Continual Learning*(*FCL*)**) *Consider $P \in \mathbb{R}^{N\times L_p\times D}$ denote a set of learnable parameters, i.e., **fingerprints**, where N represents the number of fingerprints, L_p denotes the fingerprint length, and D is the embedding dimension. FCL [27, 30, 32] aims to insert fingerprints to the specified layers of the transformer model and only optimize them from P^{t-1} to P^t while maintaining the frozen state of the original model parameters [27], while preserving the pre-trained knowledge in the frozen model parameters.*

Specifically, we integrate the fingerprint into the *Multi-head Self-Attention* (MSA) mechanism in the pre-trained ViT transformer by splitting the fingerprints P into $\{p_K, p_V\} \in \mathbb{R}^{N\times\frac{L_p}{2}\times D}$ and concatenating them with the key and value states as task-specific prefixes to guide feature extraction.

$$\begin{aligned} h_K^{'} = p_K \cup h_K, \quad h_V^{'} = p_V \cup h_V, \\ \text{MSA}\left(h_Q, h_K^{'}, h_V^{'}\right) = (h_1 \cup \ldots \cup h_{att\_n})W^O, \\ where\ h_i = \text{Attention}\left(h_Q W_i^Q, h_K^{'} W_i^K, h_V^{'} W_i^V\right). \end{aligned} \tag{2}$$

where $\{h_K, h_V\}$ is the original key and value states in each attention layer, W^O, W^Q, W^K, and W^V are projection matrices, and att_n is

the number of attention heads. Only P are learnable, allowing the fingerprints to adapt as new data is processed.

3.2 Problem Definitions

Definition 3. (***Coreset Selection for Stream Learning***) *Consider the stream learning problem in Definition 1, where data arrives sequentially in batches. Given batch $B^t = \{(x_i, y_i)\}_{i=1}^{b}$ at time step t with rate λ, we aim to select a coreset $C^t = \{(x_i, y_i)\}_{i=1}^{c}$ ($C^t \subseteq B^t$) that minimizes the approximation loss $\mathbf{L}(\cdot,\cdot;\theta)$ of model θ^{t-1} between training on the coreset versus the full batch, where the model learning velocity $\mathcal{V}_\theta$ should match the data arrival rate λ:*

$$\min_{\theta^{t-1}\in\Theta} \mathbf{L}(B^t, C^t; \theta^{t-1}) = |\frac{1}{b}\mathcal{L}(B^t;\theta^{t-1}) - \frac{1}{c}\mathcal{L}(C^t;\theta^{t-1})|. \quad (3)$$

To reduce the entire training time to match λ, *StreamFP* leverages a set of N fingerprints P to efficiently select the proper coreset that evolves with the data stream.

Definition 4. (***Buffer update for Stream Learning***) *Consider the stream learning problem in Definition 1, where catastrophic forgetting needs to be addressed through a rehearsal buffer. Given a memory buffer M^{t-1} ($|M| = m$) that stores m past samples for rehearsal, we aim to obtain a new buffer M^t by selecting samples from M^{t-1} and B^t under the size constraint m.*

To resolve the catastrophic forgetting problem, *StreamFP* uses fingerprints P to select appropriate new stream data from C^t and delete old buffer samples in M^{t-1} to update the buffer M^t.

4 Method

Figure 3 provides an overview of *StreamFP* architecture, highlighting its key components and their interactions. *StreamFP* centers on two core data-selection components: **fingerprint-based coreset selection** and **fingerprint-based buffer update**.

Before the first batch of streaming data enters *fingerprint-based coreset selection*, the fingerprints P are initialized as a uniformly distributed tensor and orthogonalized to encourage parameter independence. As streaming data batches gradually arrive, the batch data is filtered into the coreset based on P in *fingerprint-based coreset selection*. Then, a lightweight *fingerprint attunement* refines P online, and a detailed description is provided in Section 5. The coreset is merged with the previous buffer to form training data, and *fingerprint-based stream learning* updates the model and P jointly. Finally, in *fingerprint-based buffer update*, P guides the buffer refresh. This cycle repeats as new batches arrive, forming a closed loop of selection, learning, and buffer maintenance.

4.1 Fingerprint-based Coreset Selection (FCS)

To improve computational efficiency in stream learning, *StreamFP* adopts FCS that filters redundant samples and preserves diversity. FCS focuses training on the most informative data and enhances both efficiency and adaptability. For an incoming batch B^t, FCS applies PatchEmbedding to split each image into fixed-size, non-overlapping patches, projects each patch to a D-dimensional token, and forms a length-L sequence with positional embeddings, yielding $\text{emb}_{B^t} \in \mathbb{R}^{b\times L\times D}$ where b is the batch size. We then compute a fingerprint similarity vector $S \in \mathbb{R}^b$ between emb_{B^t} and fingerprints $P \in \mathbb{R}^{N\times L_p\times D}$ (N : number of fingerprints, L_p : length); for efficiency, P is compressed to $\mathbb{R}^{N\times D}$ before similarity calculation.

$$\begin{aligned} S' &= \text{sim}(emb_{B^t}, P) = \frac{P \cdot emb_{B^t}}{\|P\|\|emb_{B^t}\|}, \\ S &= \text{mean}(S'). \end{aligned} \quad (4)$$

The coreset selection strategy of FCS is to reorder the batch data based on fingerprint similarity S, and then select data points in the middle area from the sorted data index to construct the coreset. This strategy ensures that the selected coreset can introduce novel information to adapt to changes in the data stream while retaining relevance to existing knowledge, thereby maintaining the consistency and adaptability of the model in stream learning. The formula of the FCS coreset selection strategy is as follows:

$$\begin{aligned} c &= \sigma \times b, \\ I_{\text{sorted}} &= \text{argsort}(S), \\ C^t &= B^t[I_{\text{sorted}}[(\lfloor\frac{b}{2}\rfloor - \lfloor\frac{c}{2}\rfloor) : (\lfloor\frac{b}{2}\rfloor + \lfloor\frac{c}{2}\rfloor)]]. \end{aligned} \quad (5)$$

where c is the size of coreset C^t with the corresponding coreset ratio σ among B^t. Determining the standpoint as $\frac{b}{2}$, we select data from the vicinity of the midpoint in the newly ranked batch data index, based on similarity S. This selection identifies data points that balance novelty and familiarity, allowing the model to incorporate new knowledge while maintaining consistency with established learning.

4.2 Fingerprint-based Buffer Update (FBU)

The buffer update strategy FBU of the *StreamFP* framework effectively alleviates the catastrophic forgetting problem in stream learning by dynamically balancing the learning of new information and the retention of existing knowledge. As illustrated in Figure 3, FBU uses a *Retain-Drop* manner to perform buffer updates.

Firstly, we determine the number of buffer update samples γ^t:

$$\begin{aligned} n_{\text{remain}} &= \max(0, b - \max(0, m - n_{\text{seen}})), \\ \gamma^t &= \min(\lfloor\frac{b}{2}\rfloor, \max(1, |\text{Sample}(n_{\text{remain}}, \mathcal{U}(0, n_{\text{seen}})) < m|)). \end{aligned} \quad (6)$$

In these formulations, n_{seen} denotes the cumulative number of samples processed by the buffer, while n_{remain} represents the number of batch samples required for the update strategy. In order to ensure that the buffer can store enough historical data and thus better balance the retention and updating of new and old knowledge in stream learning, *StreamFP* requires the batch size b to be smaller than the buffer size m.

We compute the batch and buffer fingerprint similarities, S_{batch} and S_{buffer}, using Equation 4. Given a set of similarity scores $S = \{s_i\}$, we convert them to relative rank probabilities: let r_i be the rank of s_i after sorting S in descending order (smaller r_i means larger similarity). The relative rank probability π_i is then defined as:

$$\begin{aligned} r_i &= \text{rank}(s_i), \\ \pi_i &= 1 - \frac{1/r_i}{\sum_{j=1}^{n} 1/r_j}. \end{aligned} \quad (7)$$

Aggregating the rank probabilities $\{\pi_i\}$ yields two categorical distributions, π_{batch} and π_{buffer}. We then sample according to these distributions to update the buffer by assigning higher

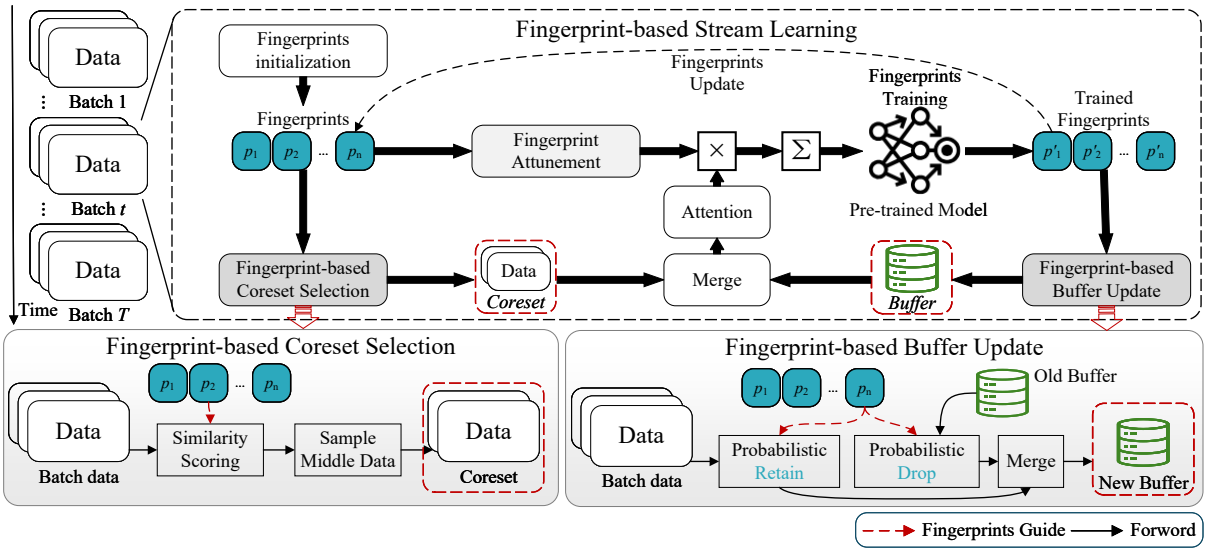

Figure 3: Our *StreamFP* centers on two data-management components: *Fingerprint-based Coreset Selection* (FCS) and *Fingerprint-based Buffer Update* (FBU). The workflow operates as follows: (1) Before training, FCS selects coreset data and integrates it with buffer samples for the training process; (2) Post-training, the system leverages these refined fingerprints to perform FBU. Building on these components, *StreamFP* adds a lightweight *Fingerprint Attunement* (FA) to further stabilize representations and improve streaming performance.

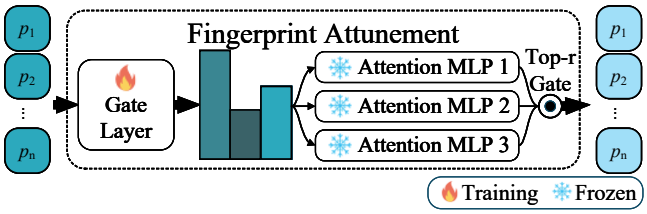

Figure 4: The structure of the fingerprint attunement plugin

probability to items with lower similarity, which prioritizes diverse samples and strengthens coverage of novel information. The formal representation of this process is:

$$I_{\text{batch}} = \mathbb{S}(B^t, \pi_{\text{batch}}, \gamma^t),$$
$$I_{\text{buffer}} = \mathbb{S}(M^{t-1}, \pi_{\text{buffer}}, \gamma^t). \tag{8}$$

Let $\mathbb{S}(B^t, \pi, \gamma^t)$ denote probabilistic sampling that selects γ^t items from batch B^t according to the distribution π. The buffer update writes the retained batch indices into the positions of the discarded buffer indices, i.e., $\mathcal{M}[I_{\text{buffer}}] \leftarrow B^t[I_{\text{batch}}]$. This operation maintains a dynamic, diversity-aware buffer that remains relevant throughout SL.

5 Fingerprint Attunement (FA): A Lightweight Plugin Refinement

FA is a lightweight plug-in that leverages pre-trained ViT attention to perform online calibration of the learnable fingerprints, improving data selection efficiency and model adaptation in streaming settings, as illustrated in Figure 4.

The core of FA is the lightweight dual-module design. (1) *Gating layer* assigns weights to each expert based on its contribution to fingerprint generation, and selects the top-r experts with the highest weights to guide subsequent optimization. (2) *R attention-MLP experts*, initialized from the layers of ViT, refine the fingerprints by leveraging their attention mechanism to extract meaningful features. Only the gating module is trained online, while the experts are kept frozen to preserve general knowledge and constrain computational cost.

In fact, FA can effectively stabilize fingerprint signals even when the data distribution changes, resulting in higher-quality feature set selection and more balanced buffer management, while its lightweight design incurs almost no additional resource consumption.

6 Experiments

In this section, we present the results of our experimental evaluation. The experiments are conducted on a server equipped with an i7-13700K CPU, a GeForce RTX A6000 GPU, and 64 GB of memory.

6.1 Methodologies

Datasets. We evaluate data management performance in streaming environments using four datasets: Clear10, Clear100 [17], CORe50 [19], and Stream-51 [23].

Evaluation Metrics. We evaluate SL with average ***Accuracy*** (Acc) and average ***Forgetting*** (Fgt) [26]. Let tasks be $1, \ldots, T$ and $a_{i,j}$ the accuracy on task j after learning tasks 1 through i.

$$\text{Acc} = \frac{1}{T}\sum_{j=1}^{T} a_{T,j},$$
$$\text{Fgt} = \frac{1}{T-1}\sum_{j=1}^{T-1} f_{T,j}, \textit{where } f_{i,j} = \max_{k<i}\left(a_{k,j} - a_{i,j}\right). \tag{9}$$

Table 1: Comparison of state-of-the-art coreset selection and buffer update methods on four datasets, where $\lambda = 6028$. For coreset selection without buffer, we compare *StreamFP* method with rule-based methods (*Camel, K-center, FreeSel*) and model-based methods (*GradMatch, Learn-Loss, Craig*). Parallelly, based on the coreset selection of *StreamFP*, we compare five state-of-the-art strategies (*ER, ASER, Camel, GSS, SSD*) for buffer update. Note that "Runtime" measures the overall running time of each method without considering the skipping constraints imposed by data arrival rates, and "-" indicates method failure due to excessive overall training time.

Methods		Clear10			Clear100			CORe50			Stream-51		
		Acc (%)	Fgt (%)	Runtime (s)	Acc (%)	Fgt (%)	Runtime (s)	Acc (%)	Fgt (%)	Runtime (s)	Acc (%)	Fgt (%)	Runtime (s)
Coreset Selection	None	29.35	23.44	387.75	9.20	6.46	1291.33	9.33	4.72	1407.65	33.17	13.11	1770.73
	Camel	31.22	25.11	326.70	11.96	8.25	1088.01	12.58	14.25	1186.02	36.93	13.35	1491.93
	K-center	22.26	21.44	415.80	8.39	6.19	1384.74	7.63	9.50	1509.48	28.19	12.71	1898.82
	FreeSel	27.16	23.93	407.55	8.35	6.22	1357.27	9.93	4.38	1479.53	28.65	13.11	1861.15
	Learn-Loss	22.48	22.36	412.50	8.48	6.37	1373.75	7.50	10.24	1497.50	30.40	12.82	1883.75
	GradMatch	19.27	**17.61**	592.35	6.70	4.86	1972.71	6.74	7.57	2150.41	16.43	12.85	2705.07
	Craig	17.29	17.82	1465.20	1.76	**3.02**	4879.56	4.03	**4.03**	5319.12	3.69	**9.97**	6691.08
	StreamFP **(w/o buffer)**	**40.11**	23.17	**229.35**	**19.85**	8.30	**763.81**	**17.70**	10.99	**832.61**	**56.99**	12.00	**1047.37**
Buffer Update	ER	54.00	0.95	**427.35**	35.97	4.42	**1423.21**	24.07	9.23	**1551.41**	61.41	6.11	**1951.57**
	ASER	19.92	4.32	1320.00	11.69	**0.16**	4396.00	6.98	3.22	4792.00	26.22	1.86	6028.00
	Camel	19.90	4.34	1994.85	5.96	0.49	6643.46	5.09	**0.83**	7241.91	16.16	1.28	9109.82
	GSS	-	-	4600.20	-	-	15320.06	6.35	1.23	16700.12	6.05	**0.93**	21007.58
	SSD	16.37	6.73	1577.40	6.04	0.36	5253.22	6.90	4.43	5726.44	19.12	2.12	7203.46
	StreamFP	**54.94**	**0.82**	448.80	**36.57**	3.02	1494.64	**25.24**	7.68	1629.28	**65.78**	1.53	2049.52

Data Arrival Rate. The data arrival rate is λ, which represents the amount of data arriving per second in SL. Real-world stream data does not always arrive at a rate that matches the model's learning speed [10]. Following prior work, we simulate diverse arrival rates by skipping batches. Specifically, given an arrival rate λ and the dataset batch size N_{Batch}, the *total duration* is $T_{\text{total}} = \frac{N_{\text{Batch}}}{\lambda}$. For each method, we run 500 batches to measure the training time t_{train} per batch, and the *expected overall training time* is $T_{\text{expected}} = t_{\text{train}} \times N_{\text{Batch}}$. We obtain the *stream-model relative complexity* $C_S = \frac{T_{\text{expected}}}{T_{\text{total}}}$. When $C_S > 1$, data batches have to be skipped as training time exceeds the total duration. We then perform uniform sampling across all batch data, retaining only a fraction $\frac{1}{C_S}$ of the overall batches, effectively skipping batches.

Comparing methods. We evaluate *StreamFP* against frameworks that perform coreset selection and buffer update, using Acc and Fgt. The baseline *None* is *CODA-Prompt* [27], which uses neither coreset selection nor buffer updates. For coreset selection, we include rule-based methods *Camel* [16], *K-center* [25], *FreeSel* [34] and model-based methods *GradMatch* [15], *Learn-Loss* [35], *Craig* [20]. For buffer update, we compare *ER* [6], *ASER* [26], *Camel* [16], *GSS* [2], and *SSD* [11].

Model Architecture. We adopt the ViT-B/16 backbone [9]; comparisons across pre-trained models appear in Appendix B. Building on *CODA-Prompt* [27], we set fingerprint length $L_p = 8$ and count $N = 100$. Unless noted, the coreset ratio is $\sigma = 0.4$ and the rehearsal buffer size for buffer methods is $m = 102$. Optimization uses Adam with learning rate 10^{-3}, one gradient step per timestamp ($K = 1$), and batch size 20. All methods share the same pre-trained ViT-B/16 backbone to extract features, losses, or gradients. In *Learn-Loss*, the input dimension is $D = 768$ with a hidden size of 128.

6.2 Experiment Results

E1: Comparison of Coreset Selection and Buffer Update Methods. Table 1 shows that *StreamFP* surpasses conventional coreset selection and buffer update across datasets. By using fingerprints as model states, *StreamFP* selects more informative samples for both components and remains effective in dynamic environments.

In coreset selection (upper part of Table 1), *StreamFP* consistently surpasses all baselines, delivering accuracy gains of 8.89%, 7.89%, 5.12%, and 20.06% over the respective second-best methods on Clear10, Clear100, CORe50, and Stream-51. Although rule-based approaches (*Camel*, *K-center*, *FreeSel*) are competitive, with *Camel* benefiting from submodular maximization, they still lag behind *StreamFP* because they cannot exploit evolving model knowledge. Model-based methods (*GradMatch*, *Learn-Loss*, *Craig*) perform worse due to high per-sample gradient costs and limited adaptability to distribution shift. *StreamFP* achieves these improvements with the lowest runtimes (229.35s, 763.81s, 832.61s, and 1047.37s), which highlights its efficiency in constructing representative coresets via fingerprint-based selection.

In contrast, *StreamFP* improves accuracy over *ER* by 0.94%, 0.60%, 1.17%, and 4.37% with comparable computational efficiency, demonstrating that the fingerprint-based data management strategy can effectively balance training efficiency and performance to achieve robust knowledge preservation.

In buffer update comparisons (lower part of Table 1), *StreamFP* achieves the best results on all datasets, reducing forgetting by 0.13%, 1.40%, 1.55%, and 4.58% over the strongest baselines. These gains arise from fingerprint-guided sampling that tracks the model's knowledge evolution. Rule-based methods generally surpass model-based ones due to higher throughput; *ER*, while strong via reservoir sampling (54.00% to 61.41%), is limited by randomness and its inability to exploit model states, and model-based *GSS* and *SSD* incur heavy computation (4600.20s to 21007.58s) with occasional failures. *StreamFP* further improves accuracy over *ER* by 0.94%, 0.60%, 1.17%, and 4.37% with comparable runtime, demonstrating that fingerprint-based data management effectively balances efficiency and performance for robust knowledge preservation.

Table 2: Comprehensive comparison of SL methods on three settings. Note that: the * notation indicates that *StreamFP* serves as either coreset selection for buffer update methods (*ASER*, *GSS*, and *SSD*) or as buffer update for coreset selection methods (*K-center*, *FreeSel*, *Learn-Loss*, *GradMatch*, and *Craig*), since these methods involve only a single component. *ER employs random sampling for coreset selection.**

(a) Comparing on four datasets with λ=6028

Method	Clear10			Clear100			CORe50			Stream-51		
	Acc (%)	Fgt (%)	Runtime (s)	Acc (%)	Fgt (%)	Runtime (s)	Acc (%)	Fgt (%)	Runtime (s)	Acc (%)	Fgt (%)	Runtime (s)
None	25.21	13.68	**384.45**	7.95	7.11	**1280.34**	8.10	13.02	**1395.67**	38.04	12.12	**1755.66**
Camel	22.71	1.39	2090.55	5.96	0.48	6962.17	5.15	**0.93**	7589.33	13.20	0.85	9546.85
K-center*	50.45	0.50	638.55	23.27	1.23	2126.57	19.81	7.61	2318.13	44.90	1.23	2916.05
FreeSel*	46.37	0.23	618.75	23.27	1.70	2060.63	20.41	7.46	2246.25	46.21	2.10	2825.63
Learn-Loss*	49.73	0.62	628.65	22.28	0.53	2093.60	17.67	7.72	2282.19	40.72	3.86	2870.84
GradMatch*	48.31	**0.32**	815.10	16.88	0.60	2714.53	12.48	6.00	2959.06	42.74	1.35	3722.29
Craig*	22.99	1.38	1686.30	12.06	0.39	5615.89	8.89	4.26	6121.78	22.87	**0.00**	7700.77
ER*	51.90	1.09	412.50	36.24	4.04	1373.75	23.95	9.71	1497.50	59.99	3.70	1883.75
ASER*	19.92	4.32	1320.00	11.69	**0.16**	4396.00	6.98	3.22	4792.00	27.82	0.74	6028.00
GSS*	-	-	4600.20	-	-	15320.06	6.35	1.23	16700.12	5.99	0.27	21007.58
SSD*	16.37	6.73	1577.40	6.04	0.36	5253.22	6.90	4.43	5726.44	22.80	1.15	7203.46
StreamFP	**54.94**	0.82	448.80	**36.57**	3.02	1494.64	**25.24**	7.68	1629.28	**64.44**	2.25	2049.52

(b) Comparison on Stream-51 with diverse λ

Method	λ=30140		λ=15070		λ=6028	
	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)
None	4.70	5.43	11.59	11.07	38.04	12.12
Camel	-	-	3.76	2.86	13.20	0.85
K-center*	9.57	0.47	18.40	2.10	44.90	1.23
FreeSel*	9.32	0.69	18.18	0.82	46.21	2.10
Learn-Loss*	9.97	0.46	18.67	1.34	40.72	3.86
GradMatch*	6.79	0.32	13.13	**0.34**	42.74	1.35
Craig*	6.07	**0.23**	4.96	2.23	22.87	0.00
ER*	14.18	0.77	30.89	1.03	59.99	3.70
ASER*	5.99	0.27	8.52	1.63	27.82	0.74
GSS*	-	-	-	-	5.99	**0.27**
SSD*	5.37	0.40	5.88	2.84	22.80	1.15
StreamFP	**15.99**	0.36	**33.41**	0.68	**64.44**	2.25

(c) Comparison under different class orders on Stream-51 with λ=6028

Method	Class order 1		Class order 2		Class order 3		Class order 4		Class order 5		Overall	
	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)
None	38.04	12.12	34.72	10.16	34.70	10.93	27.88	10.20	32.87	11.99	33.64±4.62	11.08±1.17
Camel	13.20	0.85	15.51	1.43	11.31	1.66	17.25	2.13	14.73	2.01	14.40±2.81	1.62±0.63
K-center*	44.90	1.23	53.64	2.53	49.33	2.15	46.57	6.46	48.26	2.30	48.54±4.11	2.93±2.52
FreeSel*	46.21	2.10	51.30	2.11	49.91	3.67	48.77	6.26	50.99	0.41	49.44±2.56	2.91±2.73
Learn-Loss*	40.72	3.86	54.48	2.23	50.09	3.35	45.96	7.11	51.85	1.36	48.62±6.70	3.58±2.73
GradMatch*	42.74	1.35	41.85	2.13	40.96	2.20	40.79	3.53	40.29	1.32	41.33±1.21	2.11±1.12
Craig*	22.87	**0.00**	17.80	1.55	19.08	2.26	18.95	**0.93**	19.19	**0.41**	19.58±2.39	**1.03±1.12**
ER*	59.99	3.70	60.60	2.27	57.57	6.49	54.89	9.19	58.11	6.76	58.23±2.80	5.68±3.38
ASER*	27.82	0.74	24.07	**0.91**	25.68	**0.59**	29.01	3.26	23.81	1.04	26.08±2.84	1.31±1.37
GSS*	5.99	0.27	7.11	1.69	4.69	1.63	5.92	1.77	6.72	1.39	6.09±1.15	1.35±0.77
SSD*	22.80	1.15	20.35	2.35	22.10	1.38	16.22	1.95	24.11	0.85	21.12±3.79	1.54±0.75
StreamFP	**64.44**	2.25	**62.31**	2.56	**62.20**	3.74	**62.81**	6.61	**60.44**	1.85	**62.44±1.78**	3.40±2.39

E2: Comparison of SL Methods on Four Datasets. Table 2a demonstrates *StreamFP*'s superior performance against state-of-the-art SL methods across four datasets at λ=6028. Our method achieves higher accuracy on all benchmarks (54.94%, 36.57%, 25.24%, and 64.44% on Clear10, Clear100, CORe50, and Stream-51), consistently outperforming the strongest baseline *ER** with margins of 3.04%, 0.33%, 1.29%, and 4.45%. Notably, *StreamFP* exhibits significantly reduced forgetting rates (0.82% on Clear10 versus 1.09% for *ER**; 2.25% on Stream-51 versus 3.70% for *ER**), while competing approaches suffer substantial performance degradation, particularly model-based methods like *GradMatch** and *Craig** (achieving only 12.48% and 8.89% on CORe50).

Regarding computational efficiency, *StreamFP* maintains stable runtimes (448.80s, 1494.64s, 1629.28s, and 2049.52s) across all datasets, comparable to simple baselines like *None* and *ER**. In contrast, some methods face severe computational challenges: *GSS** fails to complete on Clear10 and Clear100 due to excessive runtime (reaching 21007.58s on Stream-51), and *SSD** suffers from high computational overhead (1577.40s-7203.46s). These comprehensive results validate that our synergistic approach, integrating adaptive coreset selection and dynamic buffer update, achieves superior performance in streaming scenarios.

E3: Comparison of SL Methods on Data Arrival Rates. Table 2b evaluates *StreamFP* against state-of-the-art SL methods on Stream-51 under varying data arrival rates (λ), demonstrating our method's robustness and superiority. In terms of accuracy, *StreamFP* consistently outperforms existing methods across all arrival rates. At high arrival rate (λ=30140), *StreamFP* achieves 15.99% accuracy while maintaining a low forgetting rate of 0.36%, surpassing *ER** (14.18% accuracy, 0.77% forgetting). Notably, several methods, including *Camel*, *GSS**, and *ASER** fail to handle such rapid data streams. At medium arrival rate (λ=15070), *StreamFP* reaches 33.41% accuracy with 0.68% forgetting, significantly outperforming the accuracy of *ER** (30.89%) and *Learn-Loss** (18.67%). The advantage becomes more pronounced at lower arrival rate (λ=6028), where *StreamFP* attains 64.44% accuracy, substantially exceeding *ER** (59.99%) and *FreeSel** (46.21%).

The performance trend across arrival rates reveals an interesting pattern: while all methods benefit from lower arrival rates (more processing time per batch), *StreamFP* maintains the largest performance margins (improvements of 1.81%, 2.52%, and 4.45% over *ER**) and the stable forgetting values (0.36%, 0.68%, and 2.25%). This robust scaling can be attributed to our synergistic design, which combines adaptive coreset selection for balanced

Table 3: Comparison of the settings with and without skipping batches under five class orders on Stream-51 with λ=300

Setting	Class order 1		Class order 2		Class order 3		Class order 4		Class order 5		Overall	
	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)	Acc (%)	Fgt (%)
batch skipping	64.11	31.03	64.91	36.51	63.76	37.61	59.50	44.86	71.25	29.00	64.71±5.24	35.80±7.73
low-ratio processing	**73.04**	**30.28**	**74.45**	**27.89**	**77.11**	**27.10**	**68.54**	**37.19**	**77.16**	**25.03**	**74.06**±4.42	**29.50**±5.83

knowledge acquisition and dynamic buffer updates for optimized memory utilization, enabling effective continual learning even under challenging streaming conditions.

E4: Comparison of Class Orders. In streaming scenarios, the order in which classes appear is critical in determining model performance. Variations in performance across different class orders arise from differences in knowledge similarity between consecutive tasks. When consecutive tasks share a higher degree of similarity, knowledge transfer is typically more effective, as the model can leverage shared features or patterns learned from earlier tasks to better adapt to new ones. In contrast, tasks with lower similarity may lack such shared characteristics, hindering the transfer of useful knowledge and resulting in degraded performance.

Experimental results in Table 2c validate the effectiveness of *StreamFP* across diverse class orders. *StreamFP* consistently outperforms baseline methods, achieving 62.44% mean accuracy compared to 58.43% (*ER**) and 49.44% (*FreeSel**). More importantly, *StreamFP* exhibits superior stability with only 4% accuracy variation (60.44%-64.44%) across different orders, while *ER** shows larger fluctuations (54.89%-60.60%). In terms of catastrophic forgetting, *StreamFP* achieves a mean forgetting rate of 3.40%, substantially outperforming *ER** (5.68%).

E5: Comparison of Different Skipping Settings. To handle stream–model mismatch under a fixed time budget, following prior work [10], we evaluate two skipping strategies in streaming scenarios. (1) Batch skipping refers to dropping a fraction of entire batches when real-time processing is infeasible, while maintaining a predefined in-batch coreset ratio for the processed batches. (2) Low-ratio processing refers to processing every batch while using a uniformly small per-batch selection ratio to satisfy the real-time constraint.

As shown in Table 3, batch skipping consistently yields better results: average accuracy improves from 64.71% to 74.06% (+9.35%), and forgetting decreases from 35.80% to 29.50% (-6.30%). The gains hold across all class orders, with the largest improvements on Class order 3 (63.76%→77.11%, +13.35%) and Class order 4 (59.50%→68.54%, +9.04%). These results suggest that, although batch skipping is not ideal, it allows the model to prioritize more relevant data, thereby enhancing training efficiency and performance. While skipping shows better results, a fixed selection ratio may not be optimal due to a lack of adaptivity.

6.3 Effectiveness of Key Components

E6: Ablation Studies. Table 4 reports an ablation of *StreamFP* on Stream-51 at $\lambda = 6028$ with selection ratio $\sigma = 0.4$ and buffer size $m = 102$. The model without any component attains 33.29% accuracy and 15.41% forgetting. Adding FA alone raises performance to 35.69% accuracy and 13.82% forgetting with only 37.68s overhead. Incorporating FCS further improves to 56.74% accuracy and 11.35% forgetting, validating its ability to surface informative samples and accelerate training. The full system (FA+FCS+FBU) achieves the best results—65.78% accuracy and 1.53% forgetting—indicating that FBU effectively balances acquisition and retention. Overall, relative to the baseline, the full configuration improves accuracy by 32.49 points and reduces forgetting by 13.88 points with only 346.61s additional time, and the combination of all components yields the optimal outcome. Besides, we also investigate the impact of hyperparameters on model performance. Due to space limitations, the detailed sensitivity analysis is provided in Appendix C.

Table 4: Ablation study on Stream-51 with λ=6028

FA	FCS	FBU	Acc(%)	Fgt(%)	Runtime(s)
✗	✗	✗	33.29	15.41	1702.91
✓	✗	✗	35.69	13.82	1740.59
✓	✓	✗	56.74	11.35	1047.37
✓	✓	✓	64.44	2.25	2049.52

7 Conclusion

In this paper, we present *StreamFP*, a fingerprint-guided stream learning framework that uses compact, dynamically learned fingerprints to drive end-to-end optimization of coreset selection and buffer maintenance, thereby achieving efficient data selection and knowledge retention. *StreamFP* consists of three key innovations. (1) Fingerprint-based coreset selection prioritizes representative samples in each incoming batch. (2) Fingerprint-based buffer update balances retention of prior knowledge with the assimilation of new information during replay. (3) Fingerprint attunement calibrates the fingerprints online via a lightweight gating module over pre-trained ViT attention. Through coreset selection and buffer update, *StreamFP* effectively balances learning new information while preserving existing knowledge, addressing the core challenges of SL. Fingerprint attunement mechanism efficiently leverages pre-trained knowledge with minimal computational overhead, further enhancing overall performance. Extensive experiments on various datasets and in different scenarios demonstrate that our method significantly outperforms existing SL methods in terms of accuracy, adaptability, and training efficiency.

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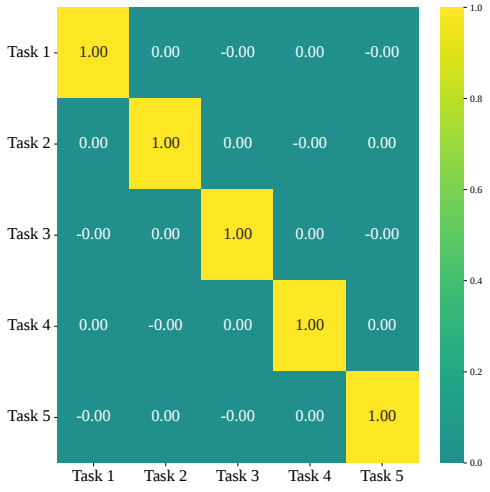
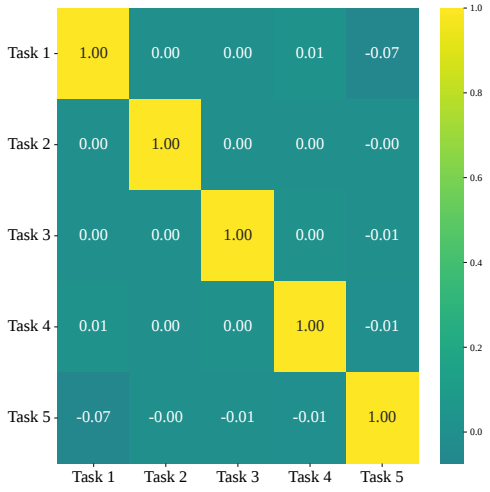


(a) Gradient Correlations of Fingerprints



(b) Gradient Correlations of the Last Layer

Figure 5: Heatmap of gradient correlations for diverse tasks on Stream-51.

A Gradient Correlations between different Tasks

As demonstrated in Figure 5, the gradients of both fingerprints and the last layer demonstrate strong orthogonality across distinct tasks, as evidenced by near-zero correlation coefficients in off-diagonal elements. This gradient orthogonality indicates that fingerprint parameters evolve along task-specific trajectories during stream learning. The gradient correlation analysis of the last layer further reveals that independently optimized fingerprints, leveraging model-specific knowledge, effectively minimize cross-task interference in the final layer outputs.

B Comparison of Different Pre-trained Models.

As *StreamFP* builds on the pre-trained ViT backbone, we further experiment with varying pre-trained models. Specifically, we consider supervised models (ImageNet-1K [24] and ImageNet-21K [22]), and self-supervised models (iBOT [36], DINO [5], and MoCo v3 [7]). Results are shown in Table 5. Across all pre-training settings, *StreamFP* consistently outperforms *ER** in both accuracy and forgetting. For example, with the pre-trained model ImageNet-1K, *StreamFP* attains 64.44% accuracy, compared to 59.99% for *ER**. With the pre-trained model ImageNet-21K, *StreamFP* achieves the lowest forgetting while maintaining competitive accuracy.

C Sensitivity Study.

Sensitivity analysis on Stream-51 at $\lambda = 6028$ (Figure 6) examines batch size b, selection ratio σ, buffer size m, and gradient steps per timestamp K.

(1) Batch size: performance declines as b grows from 20 to 500, with the best accuracy at $b = 20$, since smaller batches enable finer coreset selection (Figure 6a).

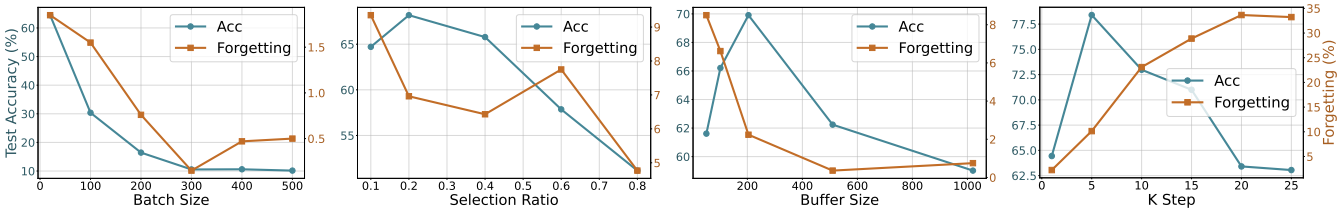
(2) Selection ratio: lower $\sigma \in \{0.2, 0.4\}$ yields high accuracy and lower forgetting; $\sigma = 0.8$ degrades accuracy and makes forgetting unstable, indicating that fewer updates per timestamp improve the accuracy–retention balance under fast streams (Figure 6b).

(3) Buffer size: moderate $m \in \{102, 204\}$ outperforms larger $m \in \{510, 1020\}$; $m = 204$ offers the best accuracy–forgetting trade-off, while larger buffers reduce forgetting with diminishing accuracy gains due to maintenance overhead (Figure 6c). Larger buffers reduce forgetting but offer diminishing accuracy gains, due to increased maintenance overhead. Finally, we fix the buffer size ($m = 102$).

(4) Gradient steps: both accuracy and forgetting deteriorate when $K \geq 10$; the optimum is $K = 5$ with 78.40% accuracy and 10.14% forgetting, as excessive repeated updates overwrite knowledge given a limited buffer (Figure 6d). Sanity checks with $m \in \{51, 204, 510\}$ show the optimal K increases to 5, 10, and 15, respectively, confirming that larger buffers support more update iterations while preserving learned information.

Table 5: Comparison of ER* and *StreamFP* based on different pre-trained models on Stream-51 with λ=6028

Method	ImageNet-1K		ImageNet-21K		DINO-1K		iBOT-1K		iBOT-21K		MoCo-1K	
	Acc	Fgt	Acc	Fgt	Acc	Fgt	Acc	Fgt	Acc	Fgt	Acc	Fgt
ER*	59.99	3.70	55.68	2.09	44.83	5.43	39.07	2.50	2.12	9.71	2.00	10.03
StreamFP	**64.44**	**2.25**	**60.45**	**0.00**	**47.44**	**4.91**	**41.79**	**1.35**	**3.12**	**8.00**	**2.52**	**7.01**



(a) Impact of batch sizes b **(b) Impact of selection ratio σ** **(c) Impact of buffer sizes m** **(d) Impact of gradient descent steps**

Figure 6: Sensitivity study on Stream-51 with λ=6028