F-OAL: Forward-only Online Analytic Learning with Fast Training and Low Memory Footprint in Class Incremental Learning

**Abstract**

Online Class Incremental Learning (OCIL) aims to train models incrementally, where data arrive in mini-batches, and previous data are not accessible. A major challenge in OCIL is Catastrophic Forgetting, i.e., the loss of previously learned knowledge. Among existing baselines, replay-based methods show competitive results but requires extra memory for storing exemplars, while exemplar-free (i.e., data need not be stored for replay in production) methods are resourcefriendly but often lack accuracy. In this paper, we propose an exemplar-free approach—Forward-only Online Analytic Learning (F-OAL). Unlike traditional methods, F-OAL does not rely on back-propagation and is forward-only, significantly reducing memory usage and computational time. Cooperating with a pre-trained frozen encoder with Feature Fusion, F-OAL only needs to update a linear classifier by recursive least square. This approach simultaneously achieves high accuracy and low resource consumption. Extensive experiments on benchmark datasets demonstrate F-OAL’s robust performance in OCIL scenarios. Code is available at: https://github.com/liuyuchen-cz/F-OAL

**1 Introduction**

Class Incremental Learning (CIL) updates the model incrementally in a task-by-task manner with new classes in the new task. Traditional CIL most plans for static offline datasets which historical data are accessible. However, with the rapid increase of social media and mobile devices, massive amount of image data have been produced online in a streaming fashion, and render training models on static data less applicable. To address this, Online Class Incremental Learning (OCIL) is developed taking an online constraint in addition to the existing CIL setting. OCIL is a more challenging CIL setting in which data come in mini-batches, and the model is trained only in one epoch (i.e., learning from one pass data stream) [14]. The model is required to achieve high accuracy, fast training time, and low resource consumption [25].

However, CIL techniques (including OCIL) suffer from Catastrophic Forgetting (CF) [27], also known as the erosion of previous knowledge when new data are introduced. The problem becomes more severe in online scenarios since the model can only see data once. Two major factors contribute to CF: (1) Using the loss function to update the whole network leads to uncompleted feature capturing and diminished global representation [11]. (2) Using back-propagation to adjust linear classifier results in *recency bias*, which is a significantly imbalanced weight distribution, showing preference only on current learning data [15].

To address CF in an online setting, replay-based methods [9, 21] are the mainstream solution by preserving old exemplars and revisiting them in new tasks. This strategy has strong performance but is resource consuming, while exemplar-free methods [17, 20] have lower resource consumption but show less competitive results.

Recently, Analytic Continual Learning (ACL) [49] methods emerged as an exemplar-free branch, delivering encouraging outcomes. ACL methods pinpoint the iterative back-propagation as the main factor behind catastrophic forgetting and seek to address it through linear recursive strategies. Remarkably, for the first time, these methods achieve outcomes comparable to those utilizing replaybased techniques.

There are two limitations in existing ACL methods: (1) Multiple iterations of base training are needed when the model is applied. Subsequently, the acquired knowledge is encoded into a *regularized feature autocorrelation matrix* by analytic re-alignment. The incremental learning phase then unfolds, utilizing the recursive least squares method for updates. This pattern is repeated when the dataset is switched, significantly elevating the temporal cost in an online scenario. (2) Classic ACL methods demand data aggregation from a single task, facilitating analytic learning in one fell swoop. This process increases GPU memory footprint and is unsuitable for online contexts where data for each task is presented as mini-batches.

To address those limitations, we propose Forward-only Online Analytic Learning (F-OAL) that learns online batch-wise data streams. The F-OAL consists of a frozen pre-trained encoder and an Analytic Classifier (AC). The frozen encoder is capable of countering the uncompleted feature representation caused by using the loss function to update and replace the time-consuming base training. With Feature Fusion and Smooth Projection, the encoder provide informative representation for analytic learning. The AC is updated by recursive least square rather than back-propagation to solve recency bias and decrease calculation. Therefore, F-OAL is an exemplar-free countermeasure to CF and reduces resource consumption since the encoder is frozen and only the AC is updated.

Our main contributions can be concluded as follows:

*•* We present the F-OAL, an exemplar-free technique that achieves high accuracy and low resource

consumption together for the OCIL.

*•* F-OAL redefines the OCIL problem into a recursive least square manner and is updated in a

mini-batch manner.

*•* F-OAL introduces a framework of frozen pre-trained encoder with Feature Fusion to generate

representative features and Smooth Projection for recursively updating AC to counter CF.

*•* We conduct massive experiments on benchmark datasets with other OCIL baselines. The results

demonstrate that F-OAL achieves competitive results with fasting training speed and low GPU

footprint.

\*\*F-OAL：仅前向在线解析学习——类增量学习中快速训练与低内存占用的方法\*\*

\*\*摘要\*\*

在线类增量学习（Online Class Incremental Learning, OCIL）旨在通过小批量数据流逐步训练模型，且无法访问历史数据。OCIL的核心挑战是灾难性遗忘（Catastrophic Forgetting），即旧知识丢失。现有方法中，基于回放（replay-based）的方法需额外内存存储样本，而无需样本保留（exemplar-free）的方法虽资源友好但精度不足。本文提出一种无需样本保留的方法——仅前向在线解析学习（Forward-only Online Analytic Learning, F-OAL）。与传统方法不同，F-OAL无需反向传播，仅通过前向计算显著降低内存与计算开销。结合预训练冻结编码器与特征融合技术，F-OAL仅需通过递归最小二乘法更新线性分类器，同时实现高精度与低资源消耗。基准数据集实验验证了F-OAL在OCIL场景下的鲁棒性能。代码已开源：https://github.com/liuyuchen-cz/F-OAL

\*\*1 引言\*\*

类增量学习（Class Incremental Learning, CIL）以任务为单位逐步扩展模型至新类别，传统CIL多针对可访问历史数据的静态离线场景。然而，随着社交媒体与移动设备的爆发式增长，在线流式数据训练需求激增，静态数据训练模型适用性受限。在线类增量学习（OCIL）由此提出，其数据以小批量形式到达且仅单次遍历（单轮训练），要求模型兼顾高精度、快速训练与低资源消耗[14, 25]。

然而，CIL（含OCIL）面临灾难性遗忘（CF）问题[27]，即引入新数据时旧知识被侵蚀。在线场景下CF更为严重，因模型仅单次接触数据。CF主因有二：(1) 损失函数更新全网络导致特征捕获不完整与全局表征退化[11]；(2) 反向传播调整分类器引发近因偏差，即权重分布严重失衡，仅偏好当前数据[15]。

现有方法中，基于回放的方法[9,21]通过存储旧样本缓解CF，性能优越但资源消耗高；无需样本保留的方法[17,20]资源友好但精度不足。近期兴起的解析持续学习（Analytic Continual Learning, ACL）[49]无需样本保留，通过线性递归策略替代反向传播，首次取得与回放方法相当的成果。

现有ACL方法存在两大局限：(1) 需多轮基础训练迭代，通过解析重对齐编码特征自相关矩阵，再以递归最小二乘法增量更新，任务切换时重复此流程，显著增加在线时间成本；(2) 传统ACL需单任务数据聚合以一次性解析学习，增加GPU内存占用，无法适应任务数据以小批量到达的在线场景。

为此，本文提出仅前向在线解析学习（F-OAL），其由冻结预训练编码器与解析分类器（Analytic Classifier, AC）构成。冻结编码器通过特征融合（Feature Fusion）与平滑投影（Smooth Projection）生成强表征，替代耗时的基础训练；AC通过递归最小二乘法更新，避免反向传播的近因偏差，减少计算量。F-OAL无需样本保留，且因仅更新AC而显著降低资源消耗。

\*\*主要贡献\*\*如下：

- 提出F-OAL，一种兼顾高精度与低资源消耗的OCIL无样本保留方法；

- 将OCIL问题重构为递归最小二乘形式，支持小批量增量更新；

- 设计冻结编码器框架，结合特征融合与平滑投影，生成高质量表征并更新AC以对抗CF；

- 基准实验表明，F-OAL在训练速度与GPU内存占用上均优于现有OCIL基线。