Overcoming Catastrophic Forgetting in Incremental Few-Shot Learning by Finding Flat Minima

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Abstract

This paper considers incremental few-shot learning, which requires a model to continually recognize new categories with only a few examples provided. Our study shows that existing methods severely suffer from catastrophic forgetting, a well-known problem in incremental learning, which is aggravated due to data scarcity and imbalance in the few-shot setting. Our analysis further suggests that to prevent catastrophic forgetting, actions need to be taken in the primitive stage – the training of base classes instead of later few-shot learning sessions. Therefore, we propose to search for flat local minima of the base training objective function and then fine-tune the model parameters within the flat region on new tasks. In this way, the model can efficiently learn new classes while preserving the old ones. Comprehensive experimental results demonstrate that our approach outperforms all prior state-of-the-art methods and is very close to the approximate upper bound.

1 Introduction

Why study incremental few-shot learning? Incremental learning enables a model to continually learn new concepts from novel data without forgetting previously learned knowledge. Rooted from real-world applications, this topic has attracted a significant amount of interest in recent years [5, 30, 31, 41, 26]. Incremental learning assumes sufficient training data is provided for new classes, which is impractical in many application scenarios, especially when the new classes are rare categories which are costly or difficult to collect. This motivates the study of incremental few-shot learning, a more difficult paradigm that aims to continually learn new tasks with only a few examples.

Challenges. The major challenge for incremental learning is *catastrophic forgetting* [14, 28, 36], which refers to the drastic performance drop on previous tasks after learning new tasks. This phenomenon is caused by the inaccessibility to previous data while learning on new data. Catastrophic forgetting presents a bigger challenge for incremental few-shot learning. Due to the small amount of training data in new tasks, the model tends to severely overfit on new classes while quickly forgetting old classes, resulting in catastrophic performance.

Current research. The study of incremental few-shot learning has just started [48, 42, 62, 9, 8, 34, 61]. Current works mainly borrow ideas from research in incremental learning to overcome the forgetting problem, by enforcing strong constraints on the model parameters to penalize the changes of parameters [35, 28, 58], or by saving a small amount of exemplars from old classes and adding constraints on the exemplars to avoid forgetting [41, 20, 4]. However, in our empirical study, we find that an intransigent model that only trains on base classes and does not tune on new tasks outperforms all state-of-the-art methods, including a joint-training method [49] that uses all encountered data for training and hence suffers from severe data imbalance. This observation motivates us to address this harsh problem from a different angle.

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Our solution. Unlike existing solutions that try to overcome catastrophic forgetting during the process of learning new tasks, we adopt a different approach by considering the catastrophic forgetting problem during the training of base classes. Specifically, we propose to search for flat local minima of the base training objective function by adding random noise to the model parameters. For any parameter vector in the flat minima region, the loss is small and the base classes are well separated. In the following incremental few-shot learning tasks, we fine-tune the model parameters within the flat region by clamping the parameters. In this way, the model can learn new classes while preserving the old ones. Our key contributions are summarized as follows:

- We conduct a comprehensive empirical study on existing incremental few-shot learning methods and discover that a simple baseline model that only trains on base classes outperforms prior state-of-the-art methods, demonstrating the severity of catastrophic forgetting.
- We propose a novel approach to overcome catastrophic forgetting in incremental few-shot learning by addressing the problem in the primitive stage. Through finding the flat minima region during training base classes and fine-tuning within the region on new tasks, our model can overcome catastrophic forgetting and avoid overfitting.
- Comprehensive experimental results on CIFAR-100, *mini*ImageNet and CUB-200-2011 show that our approach outperforms all state-of-the-art methods and achieves performance that is very close to the approximate upper bound.

2 Related Work

Few-shot learning aims to learn to generalize to new categories with a few labelled samples in each class. Current few-shot methods mainly consist of optimization-based methods [12, 23, 32, 40, 46, 47, 57] and metric-based methods [13, 19, 45, 51, 54, 60, 59, 55]. Optimization-based methods can achieve fast adaptation to novel tasks with limited samples by learning a specific optimization algorithm. Metric-based approaches exploit different distance metrics such as L2 distance [45], cosine similarity [51], and DeepEMD [60] in the learned representation space to measure the similarity between samples. Recently, Tian *et al.* [50] find that standard supervised training on meta-training sets can learn good metric representations even for unseen classes, which echoes with our observation on the proposed baseline model.

Incremental learning focuses on the challenging problem of continually learning to recognize novel classes in new coming data without forgetting the old classes [6, 7, 10, 53]. Existing works mainly include two groups, multi-class incremental learning [4, 39, 22, 33, 56, 53] and multi-task incremental learning [21, 31, 43]. To overcome catastrophic forgetting, some attempts impose strong constraints on model parameters by penalizing the changes of parameters [28, 1]. Other attempts enforce constraints on the exemplars of old classes such as restricting the output logits [41] and penalizing the changes of embedding angles [20]. Our empirical experiments reveal that imposing strong constraints on the arriving novel classes may not be a promising way to tackle incremental few-shot learning due to data scarcity.

Incremental few-shot learning [48, 42, 62, 9, 8] aims to incrementally learn from very few samples. TOPCI [48] adopts a neural gas (NG) network to learn and preserve the topology of the feature manifold formed by different classes. FSLL [34] selects very few parameters from the model for incremental learning and ensure that the parameters are close to the optimal parameters. To overcome catastrophic forgetting, IDLVQC [8] imposes constraints on the exemplars by restricting the embedding drift, and Zhang *et al.* [61] propose to fix the embedding networks for incremental learning. Similar to Zhang *et al.*, we discover that a simple baseline model with embedding fixed for inference can outperform prior state-of-the-art methods.

Robust Optimization. It has been found that flat local minima leads to better generalization capabilities than sharp minima in the sense that a flat minimizer is more robust when the test loss is shifted due to random perturbations [18, 17, 24]. A substantial body of methods [2, 38, 11, 15] have been proposed to optimize neural networks towards flat local minima. In this paper, we show that for incremental few-shot learning, finding flat minima in the base session and tuning the model within the flat region on new tasks can significantly mitigate catastrophic forgetting.

3 Severity of Catastrophic Forgetting in Incremental Few-Shot Learning

3.1 Problem Statement

Incremental few-shot learning (IFL) aims to continually learn to recognize new classes with only a few examples. Similar to incremental learning (IL), an IFL model is trained by a sequence of training sessions $\{\mathcal{D}^1, \cdots, \mathcal{D}^t\}$, where $\mathcal{D}^t = \{z_i = (x_i^t, y_i^t)\}_i$ is the training data of session t and x_i^t is an example of class $y_i^t \in \mathcal{C}^t$ (the class set of session t). In IFL, the base session $\mathcal{D}^1$ usually contains a large number of classes with sufficient training data for each class, while the following sessions ($t \geq 2$) only have a small number of classes with a few training samples per class, e.g., $\mathcal{D}^t$ is often presented as an N-way K-shot task with small N and K. The key difference between IL and IFL is, for IL, sufficient training data is provided in each session. Similar to IL, in each training session t of IFL, the model has only access to the training data $\mathcal{D}^t$ and possibly a small amount of saved exemplars from previous sessions. After training in session t, the model is evaluated on test samples from all the encountered classes $\mathcal{C} = \bigcup_{i=1}^{t} \mathcal{C}^i$, where it is assumed that there is no overlap between the classes of different sessions, i.e., $\forall i, j$ and $i \neq j$, $\mathcal{C}^i \bigcap \mathcal{C}^j = \emptyset$.

Catastrophic forgetting. IFL is undoubtedly a more challenging problem than IL due to the data scarcity setting. IL suffers from catastrophic forgetting, a well-known phenomenon and long-standing issue, which refers to the drastic drop in test performance on previous (old) classes, caused by the inaccessibility of old data in the current training session. Unfortunately, catastrophic forgetting is an even bigger issue for IFL, because data scarcity makes it difficult to adapt well to new tasks and learn new concepts, whereas the adaptation process could easily lead to catastrophic forgetting of the base classes. In the following, we illustrate this point by evaluating a simple baseline model for IFL.

3.2 A Simple Baseline Model for IFL

We consider an intransigent model that simply does not adapt to new tasks. Particularly, the model only needs to be trained in the base session $\mathcal{D}^1$ and is directly used for inference in all sessions.

Training ($t = 1$). We train a feature extractor f parameterized by ϕ with a fully-connected layer as classifier by minimizing the standard cross-entropy loss using the training examples of $\mathcal{D}^1$. The feature extractor f is *fixed* for the following sessions ($t \geq 2$) without any fine-tuning on new classes.

Inference (test). In each session, the inference is conducted by a simple nearest class mean (NCM) classification algorithm [37]. Specifically, all the training and test samples are mapped to the embedding space of the feature extractor f, and Euclidean distance $d(\cdot, \cdot)$ is used to measure the similarity between them. The classifier is given by

$$c_k^* = \underset{c \in \mathcal{C}}{\operatorname{argmin}}\, d(f(x; \phi), p_c), \text{ where } p_c = \frac{1}{N_c} \sum_k \mathbb{1}(y_i = c) f(x_i; \phi), \tag{1}$$

where $\mathcal{C}$ denotes all the encountered classes, p_c refers to the prototype of class c (the mean vector of all the training samples of class c in the embedding space), and N_c denotes the number of the training images of class c. Note that we *save* the prototypes of all classes in $\mathcal{C}^t$ for later evaluation.

The baseline model outperforms state-of-the-art IFL and IL methods. We compare the baseline model against state-of-the-art IFL methods including FSLL [35], IDLVQC [8] and TOPIC [49], IL methods including Rebalance [20] and iCarl [41], and a joint-training method that uses all previously seen data including the base and the following few-shot tasks for training. The performance for IFL is evaluated on miniImageNet, CIFAR-100, and CUB-200. All the compared methods are tuned to their best performance (higher than the results reported in the original papers). More experimental details are provided in Sec. 5. As shown in Fig. 1, the baseline model consistently outperforms all the compared methods including the joint-training method (suffers from severe data imbalance) on every dataset[1]. The fact that an intransigent model performs best suggests that

- For IFL, preserving the old (base classes) may be more critical than adapting to the new. Due to data scarcity, the performance gain on new classes is limited and cannot make up for the significant performance drop on base classes.

[1] We notice that a similar observation is made in a newly released paper [61].

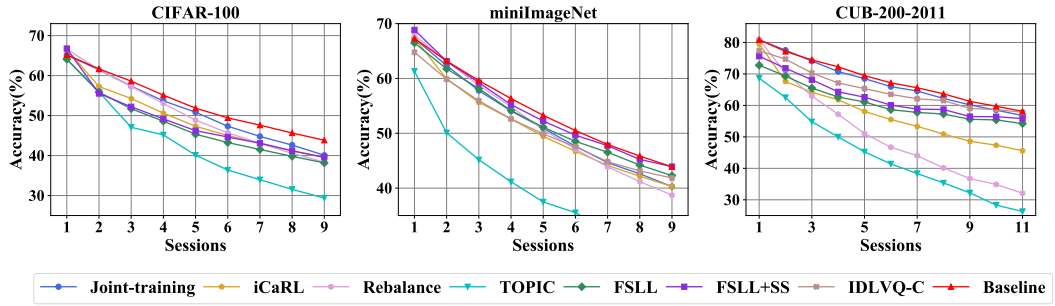

Figure 1: Comparison of the proposed baseline model with state-of-the-art IFL and IL methods and the joint-training method.The Baseline model outperforms all the other methods.

- Prior works [49, 8, 35, 20, 41] that enforce strong constraints on model parameters or exemplars during fine-tuning on new classes cannot effectively prevent catastrophic forgetting in IFL, indicating that actions may need to be taken in the base training stage.

4 Overcoming Catastrophic Forgetting in IFL by Finding Flat Minima

The goal of IFL is to preserve the old while adapting to the new efficiently. The results and analysis in Sec. 3 suggest that it might be "a bit late" to try to prevent catastrophic forgetting in the few-shot learning sessions ($t \geq 2$), which motivates us to consider this problem in the base training session.

Overview of our approach. To overcome catastrophic forgetting in IFL, we propose to find a b-flat ($b > 0$) local minima $\theta^\star$ of the base training objective function and then fine-tune the model within the flat region in later few-shot learning sessions. Specifically, for any parameter vector θ in the flat region, i.e., $\theta^\star - b \preceq \theta \preceq \theta^\star + b$, the risk (loss) of the base classes is minimized such that the classes are well separated in the embedding space of f_θ. In the later incremental few-shot learning sessions ($t \geq 2$), we fine-tune the model parameters within this region to learn new classes, i.e., to find

$$\theta' = \arg\min_{\theta} \sum_{z \in \mathcal{D}^t} \mathcal{L}(z;\theta), \quad \text{s.t.} \quad \theta^\star - b \preceq \theta \preceq \theta^\star + b.$$

As such, the fine-tuned model θ' can adapt to new classes while preserving the old ones. Also, due to the nature of few-shot learning, to avoid excessive training and overfitting, it suffices to tune the model in a relatively small region. A graphical illustration of our approach and prior arts, as well as the notions of sharp minima and flat minima, are presented in Fig. 2.

4.1 Searching for Flat Local Minima in the Base Training Stage

A formal definition of b-flat local minima is given as follows.

Definition 1 (**b-Flat Local Minima**) *Given a real-valued objective function $\mathcal{L}(z;\theta)$, for any $b > 0$, $\theta^\star$ is a b-flat local minima of $\mathcal{L}(z;\theta)$, if the following conditions are satisfied.*

- *Condition 1: $\mathcal{L}(z;\theta^\star) = \mathcal{L}(z;\theta^\star + \epsilon)$, where $-\mathbf{b} \preceq \epsilon \preceq \mathbf{b}$ and $\mathbf{b}_i = b$.*
- *Condition 2: there exist $\mathbf{c}_1 \prec \theta^\star - b$ and $\mathbf{c}_2 \succ \theta^\star + b$, s.t. $\mathcal{L}(z;\theta) > \mathcal{L}(z;\theta^\star)$, where $\mathbf{c}_1 \prec \theta \prec \theta^\star - b$ and $\mathcal{L}(z;\theta^\star) < \mathcal{L}(z;\theta)$, where $\theta^\star + b \prec \theta \prec \mathbf{c}_2$.*

In practice, it is hard to find the flat local minima that strictly satisfies the above definition, which may not even exist. Hence, our goal is to find an approximately flat local minima of the base training objective function. To this end, we propose to add some small random noise to the model parameters. The noise can be added for multiple times to obtain similar but different loss functions, which will be optimized together to locate the flat minima region. The intuition is clear – the parameter vectors around the flat local minima also have small function values.

To formally state the idea, we assume that the model is parameterized by $\theta = \{\phi, \psi\}$, where ϕ denotes the parameters of the embedding network and ψ denotes the parameters of the classifier.

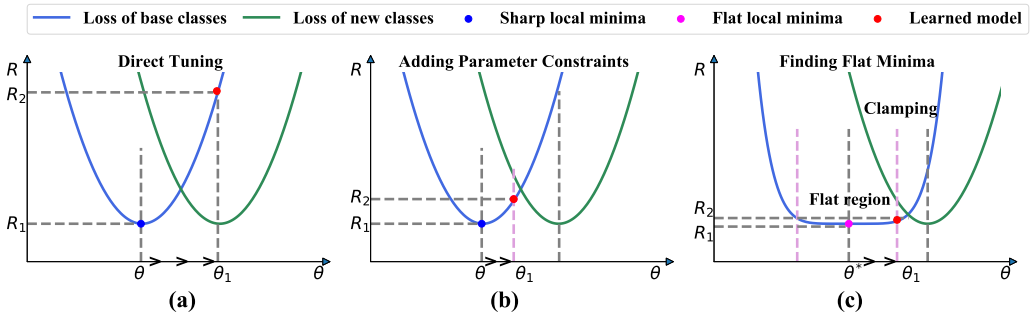

Figure 2: Illustration of our approach and existing solutions. $\rightarrow$ indicates the incremental learning steps on new classes. R_1 and R_2 respectively denote the loss of base classes before and after minimizing the loss of new classes. (a) SGD finds sharp minima in the base training. Directly tuning the model on novel classes will result in a severe performance drop on base classes. (b) Enforcing strong constraints on parameters by penalizing parameter changes [1, 28, 35] may still lead to a significant performance drop on base classes. (c) Finding flat local minima of base classes and clamping the parameters after trained on new classes to make them fall within the flat region can effectively mitigate catastrophic forgetting.

z denotes a labelled training sample. Denote the loss function by $\mathcal{L}$: $\mathbb{R}^{d_z} \rightarrow \mathbb{R}$. Our target is to minimize the expected loss function R: $\mathbb{R}^d \rightarrow \mathbb{R}$ w.r.t. the joint distribution of data z and noise ϵ, i.e.,

$$R(\theta) = \int_{\mathbb{R}^{d_\epsilon}} \int_{\mathbb{R}^{d_z}} \mathcal{L}(z; \phi + \epsilon, \psi)\, dP(z) dP(\epsilon) = \mathbb{E}[\mathcal{L}(z; \phi + \epsilon, \psi)], \tag{2}$$

where $P(z)$ is the data distribution and $P(\epsilon)$ is the noise distribution, and z and ϵ are independent. Since it is impossible to minimize the expected loss, we minimize its estimation, the empirical loss, which is given by

$$\mathcal{L}(\theta) = \frac{1}{M} \sum_{j=1}^{M} \mathcal{L}_{\text{base}}(z; \phi + \epsilon_j, \psi), \text{ where} \tag{3}$$

$$\mathcal{L}_{\text{base}}(z; \phi + \epsilon_j, \psi) = \frac{1}{|\mathcal{D}^1|} \sum_{z \in \mathcal{D}^1} \mathcal{L}_{ce}(z; \phi + \epsilon_j, \psi) + \lambda \frac{1}{|\mathcal{C}^1|} \sum_{c \in \mathcal{C}^1} \|p_c - p_c^*\|_2^2, \tag{4}$$

where ϵ_j is a noise vector sampled from $P(\epsilon)$, M is the sampling times, $\mathcal{L}_{ce}(z; \phi + \epsilon_j, \psi)$ refers to the cross-entropy loss of a training sample z, and p_c and p_c^* are the class prototypes before and after injecting noise respectively. The first term of $\mathcal{L}_{base}$ is designed to find the flat region where model parameters can well separate the base classes. The second term of $\mathcal{L}_{base}$ enforces class prototypes fixed within such region, which is designed to solve the prototype drift problem [56, 8] (the class prototypes changes after updating the model) in later incremental learning sessions. As such, the saved prototypes of the base classes can be directly used for evaluation in later sessions.

4.2 Incremental Few-shot Learning within the Flat Region

In the incremental few-shot learning sessions ($t \geq 2$), we fine-tune the model parameters *within the flat region* to learn new classes. It is worth noting that though the flat region is relatively small, the model capacity is enough for incremental few-shot learning. More importantly, since only a few training samples are given for each new class, to avoid overfitting, only a small number of update iterations needs to be applied when learning few-shot tasks.

We employ a metric-based classification algorithm with Euclidean distance to fine-tune the model. The loss function is defined as

$$\mathcal{L}_m(z; \phi) = -\sum_{c \in \mathcal{C}} \mathbb{1}_{(y=c)} \log\left(\frac{e^{-d(p_c, f(x;\phi))}}{\sum_{c_k \in \mathcal{C}} e^{-d(p_{c_k}, f(x;\phi))}}\right), \tag{5}$$

where $d(\cdot, \cdot)$ denotes Euclidean distance, p_c is the prototypes of class c, and $\mathcal{C} = \bigcup_{i=1}^{t} \mathcal{C}^i$ refers to all the encountered classes. Note that the prototypes of new classes are computed by Eq. 1, and those of

Algorithm 1: F2M

Input: the flat region bound b, randomly initialized $\theta = \{\phi, \psi\}$, the step sizes α and β.

// Training over base classes $t = 1$

for epoch k = 1,2,... **do**

  for j = 1,2,..., M **do**

    Sample a noise vector $\epsilon_j \sim P(\epsilon)$, s.t. $-\mathbf{b} \preceq \epsilon_j \preceq \mathbf{b}$

    Add noise to the parameters, i.e. $\theta = \{\phi + \epsilon_j, \psi\}$

    Compute the base loss $\mathcal{L}_{base}$ with Eq. 4

    Reset the parameters, i.e. $\theta = \{\phi, \psi\}$

  end

  Update $\theta = \theta - \alpha \nabla \mathcal{L}(\theta)$ (Eq. 3)

end

Save the prototype of each class

// Incremental learning $t \geq 2$

Combine the exemplar sets of previous few-shot tasks $2 \leq t_e < t$ and the training data $\mathcal{D}^t$

for epoch k = 1,2,... **do**

  Compute the metric-based classification loss $\mathcal{L}_m$ by Eq. 5

  Update $\phi = \phi - \beta \nabla \mathcal{L}_m(z; \phi)$

  Clamp the parameters to ensure they fall in the flat minima region

end

Randomly select and save the exemplars from the training data

Normalize the prototypes and save the prototypes

Output: Model parameters $\theta = \{\phi, \psi\}$

base classes are saved in the base session. After updating the model parameters, we clamp them to ensure that they fall within the flat region, i.e. $\phi^\star - b \preceq \phi \preceq \phi^\star + b$, where $\phi^\star$ denotes the optimal parameter vector learned in the base session. After fine-tuning, we evaluate the model using the nearest class mean classifier as in Eq. 1, with previously saved prototypes and newly computed ones.

4.3 Convergence Analysis

Our aim is to find a flat region within which all parameter vectors work well. We then minimize the expected loss w.r.t. the joint distribution of noise ϵ and data z. To approximate this expected loss, we sample from $P(\epsilon)$ for multiple times in each iteration and optimize the objective function using stochastic gradient descent (SGD). In this section, we provide theoretical guarantees for our method. Given the non-convex loss function in Eq. 3, we prove the convergence of our method. Our proof idea is inspired by the convergence analysis of SGD [3, 27].

Formally, in each batch k, let z_k denote the batch data, $\{\epsilon_j\}_{j=1}^M$ be the sampled noises, and α_k be the step size. In the base training session, we update the model parameters as follows:

$$\theta_{k+1} = \theta_k - \frac{\alpha_k}{M} \sum_{j=1}^{M} \nabla \mathcal{L}_{\text{base}}(z_k; \phi_k + \epsilon_j, \psi_k) = \theta_k - \frac{\alpha_k}{M} \sum_{j=1}^{M} g(z_k; \phi_k + \epsilon_j, \psi_k), \tag{6}$$

where $g(z_k; \phi_k + \epsilon_j, \psi_k) = \nabla \mathcal{L}_{\text{base}}(z_k; \phi_k + \epsilon_j, \psi_k)$ is the gradient. To formally analyze the convergence of our algorithm, we define the following assumptions.

Assumption 4.1 (L-smooth risk function) *The expected loss function $R : \mathbb{R}^d \to \mathbb{R}$ (Eq. 2) is continuously differentiable and L-smooth with constant $L > 0$ such that*

$$\|\nabla R(\theta) - \nabla R(\theta')\|_2 \leq L\|\theta - \theta'|. \tag{7}$$

This assumption is significant for the convergence analysis of gradient-based optimization algorithms, since it limits how fast the gradient of the loss function can change w.r.t. the parameter vector.

Assumption 4.2 *The expected loss function satisfies the following conditions:*

- *Condition 1: R is bounded below by a scalar R^*, given the sequence of parameters $\{\theta_k\}$.*
- *Condition 2: For all $k \in \mathbb{N}$ and $j \in [1, M]$,*

$$\mathbb{E}_{z_k,\epsilon_j}[g(z_k; \phi_k + \epsilon_j, \psi_k)] = \nabla R(\theta_k). \tag{8}$$

- *Condition 3: There exist scalars $m_1 \geq 0$ and $m_2 \geq 0$, for all $k \in \mathbb{N}$ and $j \in [1, M]$,*

$$\mathbb{V}_{z_k,\epsilon_j}[g(z_k; \phi_k + \epsilon_j, \psi_k)] \leq m_1 + m_2 \|\nabla R(\theta_k)\|_2^2. \tag{9}$$

$\mathbb{E}_{z_k,\epsilon_j}[\cdot]$ denotes the expectation w.r.t. the joint distribution of random variables z_k and ϵ_j, and $\mathbb{V}_{z_k,\epsilon_j}[\cdot]$ denotes the variance. Condition 1 ensures that the expected loss function has a lower bound during updates. Condition 2 assumes that the gradient $g(z_k; \phi_k + \epsilon_j, \psi_k)$ is an unbiased estimate of $\nabla R(\theta_k)$. Condition 3 restricts the variance of gradient $g(z_k; \phi_k + \epsilon_j, \psi_k)$ in a relatively small range. To facilitate later analysis, we restrict the step sizes similar to [44] as follows.

Assumption 4.3 *The learning rates satisfy:*

$$\sum_{k=1}^{\infty} \alpha_k = \infty, \ \sum_{k=1}^{\infty} \alpha_k^2 < \infty. \tag{10}$$

Based on the above assumptions, we can derive the following theorem.

Theorem 4.1 *Under assumptions 4.1, 4.2 and 4.3, we further assume that the risk function R is twice differentiable, and that $\|\nabla R(\theta)\|_2^2$ is L_2-smooth with constant $L_2 > 0$, then we have*

$$\lim_{k \to \infty} \mathbb{E}[\|\nabla R(\theta_k)\|_2^2] = 0. \tag{11}$$

This theorem establishes the convergence of our algorithm. The proof is provided in Appendix A.1.

5 Experiments

We evaluate our method (F2M) on CIFAR-100 [29], miniImageNet [51] and CUB-200-2011 [52]. We randomly split these datasets into multiple tasks. In each novel session, we randomly select 10 batches of images for all encountered classes for evaluation and report the average accuracy.

5.1 Experimental Setup

Datasets. For CIFAR-100 and *mini*ImageNet, we randomly select 60 classes as base classes and the remaining 40 classes for novel classes. In each incremental learning session, we construct 5-way 5-shot tasks, i.e., randomly select 5 classes with 5 samples per class. For CUB-200-2011 with 200 classes, we select 100 classes as base classes and 100 classes as novel ones. For this dataset, we test the 10-way 5-shot setting.

Baselines. We adopt ResNet18 [16] as the backbone [49, 35]. We compare our method with 9 methods: the proposed Baseline model, joint training using all encountered data, and a long-tailed classification method cRT [25] trained by all encountered classes, iCaRL [41], Rebalance [20], and TOPIC [49], FSLL [35], IDLVQ-C [8]. For fair comparison, we re-implement cRT [25], iCaRL [41], Rebalance [20], FSLL [35] and the joint-training method. Note that in IL, joint-training is naturally the upper bound of incremental learning algorithms, however, in IFL, joint-training is not a good approximation of the upper bound because the extremely imbalanced data makes the model perform significantly poorly on novel classes (tailed classes). To address the data imbalance problem, we re-implement a classical long-tailed classification method, Classifier Re-training (cRT), as the *approximate upper bound*. For a fair comparison, we keep the same number of exemplars for all of our re-implementation. See more implementation details in the Appendix A.2. To verify the correctness of our implementation, we conduct experiments on incremental learning and compare our results to those reported for CIFAR-100 in Appendix A.3.

Table 1: Classification accuracy on CIFAR-100 for 5-way 5-shot incremental learning. * indicates our re-implementation.

Method	**sessions**									**The gap with cRT**
	1	2	3	4	5	6	7	8	9	
cRT [25]*	65.18	63.89	60.20	57.23	53.71	50.39	48.77	47.29	45.28	-
Joint-training*	65.18	61.45	57.36	53.68	50.84	47.33	44.79	42.62	40.08	-5.20
Baseline	65.18	61.67	58.61	55.11	51.86	49.43	47.60	45.64	43.83	-1.45
iCaRL [41]*	66.52	57.26	54.27	50.62	47.33	44.99	43.14	41.16	39.49	-5.79
Rebalance [20]*	**66.66**	61.42	57.29	53.02	48.85	45.68	43.06	40.56	38.35	-6.93
FSLL [35]*	65.18	56.24	54.55	51.61	49.11	47.27	45.35	43.95	42.22	-3.08
iCaRL [41]	64.10	53.28	41.69	34.13	27.93	25.06	20.41	15.48	13.73	-31.55
Rebalance [20]	64.10	53.05	43.96	36.97	31.61	26.73	21.23	16.78	13.54	-31.74
TOPIC [49]	64.10	55.88	47.07	45.16	40.11	36.38	33.96	31.55	29.37	-15.91
FSLL [35]	64.10	55.85	51.71	48.59	45.34	43.25	41.52	39.81	38.16	-7.12
FSLL+SS [35]	66.76	55.52	52.20	49.17	46.23	44.64	43.07	41.20	39.57	-5.71
F2M	64.71	**62.05**	**59.01**	**55.58**	**52.55**	**49.96**	**48.08**	**46.28**	**44.67**	**-0.61**

Table 2: Classification accuracy on *mini*ImageNet for 10-way 5-shot incremental learning. * indicates our re-implementation.

Method	**sessions**									**The gap with cRT**
	1	2	3	4	5	6	7	8	9	
cRT [25]*	67.30	64.15	60.59	57.32	54.22	51.43	48.92	46.78	44.85	-
Joint-training*	67.30	62.34	57.79	54.08	50.93	47.65	44.64	42.61	40.29	-4.56
Baseline	67.30	63.18	59.62	56.33	53.28	50.50	47.96	45.85	43.88	-0.97
iCaRL [41]*	67.35	59.91	55.64	52.60	49.43	46.73	44.13	42.17	40.29	-4.56
Rebalance [20]*	67.91	63.11	58.75	54.83	50.68	47.11	43.88	41.19	38.72	-6.13
FSLL [35]*	67.30	59.81	57.26	54.57	52.05	49.42	46.95	44.94	42.87	-1.11
iCaRL [41]	61.31	46.32	42.94	37.63	30.49	24.00	20.89	18.80	17.21	-27.64
Rebalance [20]	61.31	47.80	39.31	31.91	25.68	21.35	18.67	17.24	14.17	-30.68
TOPIC [49]	61.31	50.09	45.17	41.16	37.48	35.52	32.19	29.46	24.42	-20.43
FSLL [35]	66.48	61.75	58.16	54.16	51.10	48.53	46.54	44.20	42.28	-2.57
FSLL+SS [35]	**68.85**	63.14	59.24	55.23	52.24	49.65	47.74	45.23	43.92	-0.93
IDLVQ-C [8]	64.77	59.87	55.93	52.62	49.88	47.55	44.83	43.14	41.84	-3.01
F2M	67.28	**63.80**	**60.38**	**57.06**	**54.08**	**51.39**	**48.82**	**46.58**	**44.65**	**-0.20**

5.2 Comparison with the State-of-the-Art

F2M outperforms all state-of-the-art methods. The main results on CIFAR-100, miniImageNet and CUB-200-2011 are presented in Table 1, Table 2 and Table 3 respectively. Based on the experiment results, we have the following observations: **(1)** The Baseline model introduced in Sec. 3 outperforms the state-of-the-art approaches on all incremental sessions. **(2)** As expected, cRT consistently outperforms the Baseline model up to 1% to 3% by considering the data imbalance problem and applying proper techniques to tackle the long-tailed classification problem to improve performance. Hence, it is reasonable to use cRT as the approximate upper bound of IFL. **(3)** F2M outperforms all state-of-the-art algorithms and the Baseline model. Moreover, the performance of F2M is very close to the approximate upper bound, i.e., the gap with cRT is only 0.2% in the last session on *mini*ImageNet. The results illustrate that although strong constraints are added in [20, 41, 35] and examplars of base classes are saved in [20, 41, 8], they cannot prevent the catastrophic forgetting problem. In contrast, finding flat minima provides a new promising direction to overcome such a fundamental problem of deep neural networks.

5.3 Ablation Study

To verify the effectiveness of our methods, we remove each component of our methods separately, including searching for b-flat local minima in the base classes (**FM**), prototype fixing (**PF**), parameter clamping (**PC**) and prototype normalization (**Normalize**). The experimental results are shown in Table 4.

Table 3: Classification accuracy on CUB-200-2011 for 10-way 5-shot incremental learning.* indicates our re-implementation.

Method	sessions											The gap with cRT
	1	2	3	4	5	6	7	8	9	10	11	
cRT [25]*	80.83	78.51	76.12	73.93	71.46	68.96	67.73	66.75	64.22	62.53	61.08	-
Joint-training*	80.83	77.57	74.11	70.75	68.52	65.97	64.58	62.22	60.18	58.49	56.78	-4.30
Baseline	80.87	77.15	74.46	72.26	69.47	67.18	65.62	63.68	61.30	59.72	58.12	-2.96
iCaRL [41]*	79.58	67.63	64.17	61.80	58.10	55.51	53.34	50.89	48.62	47.34	45.60	-15.48
Rebalance [20]*	80.94	70.32	62.96	57.19	51.06	46.70	44.03	40.15	36.75	34.88	32.09	-28.99
FSLL [35]*	80.83	77.38	72.37	71.84	67.51	65.30	63.75	61.16	59.05	58.03	55.82	-5.26
iCaRL [41]	68.68	52.65	48.61	44.16	36.62	29.52	27.83	26.26	24.01	23.89	21.16	-39.92
Rebalance [20]	68.68	57.12	44.21	28.78	26.71	25.66	24.62	21.52	20.12	20.06	19.87	-41.21
TOPIC [49]	68.68	62.49	54.81	49.99	45.25	41.40	38.35	35.36	32.22	28.31	26.28	-34.80
FSLL [35]	72.77	69.33	65.51	62.66	61.10	58.65	57.78	57.26	55.59	55.39	54.21	-6.87
FSLL+SS [35]	75.63	71.81	68.16	64.32	62.61	60.10	58.82	58.70	56.45	56.41	55.82	-5.26
IDLVQ-C [8]	77.37	74.72	70.28	67.13	65.34	63.52	62.10	61.54	59.04	58.68	57.81	-3.27
F2M	**81.07**	**78.16**	**75.57**	**72.89**	**70.86**	**68.17**	**67.01**	**65.26**	**63.36**	**61.76**	**60.26**	**-0.82**

Table 4: Ablation study on CIFAR-100 to analyze the effectiveness of different designs in F2M. **PD** refers to the performance dropping rate.

FM	PF	PC	Normalize	sessions									PD↓
				1	2	3	4	5	6	7	8	9	
				65.18	60.83	53.13	43.57	23.75	10.76	08.26	07.24	06.45	58.73
		✓		**65.18**	59.48	56.77	52.99	50.09	47.80	45.92	44.20	42.55	22.63
✓	✓		✓	64.71	59.54	53.03	45.09	41.68	39.04	38.64	37.19	36.01	28.70
✓		✓	✓	64.55	61.27	58.33	54.82	51.60	49.22	47.48	45.78	44.08	20.47
✓	✓	✓		64.71	61.75	58.80	55.33	52.27	49.75	47.72	46.01	44.43	20.28
✓	✓	✓	✓	64.71	**61.99**	**58.99**	**55.58**	**52.55**	**49.96**	**48.08**	**46.28**	**44.67**	**20.04**

Finding b-flat local minima. Standard supervised training with SGD as the optimizer tends to converge to a sharp local minima. It leads to a significant drop in performance because the loss drops quickly in the neighborhood of the sharp local minima. Although we clamp the parameters to restrict them within a small region as in F2M in later incremental learning sessions, the performance still drops. However, restricting the parameters in a small region can mitigate forgetting to some extent.

Prototype fixing. Without fixing the prototypes after injecting noise to selected layers during finding the $\mathbf{b}$-flat local minima, i.e. removing the second term of Eq. 4, the old classes are still well separated by tuning the model within the flat region; however, the embedding of old samples suffers from semantic drift [56], which causes the saved prototypes of old classes to become less accurate after tuning the model even within the flat region. It results in a performance drop of nearly 0.6%.

Parameter clamping. Clamping parameters limits the model parameters after incremental learning to the $\mathbf{b}$-flat region. Outside the $\mathbf{b}$-flat region, the performance drops quickly. Removing parameters clamping procedure leads to a significant drop in performance (nearly 8.7%).

Prototype normalization. We have an interesting empirical observation on the norm of embeddings – the norm of the prototypes of different classes tend to be similar after standard training over balanced dataset, however, in few-shot incremental learning, the norm of the prototypes of unseen novel classes are smaller than that of the old classes after fine-tuning (see Appendix A.3). In order to avoid the effect of the norms of prototypes on the evaluation, we normalize and scale the prototypes to calibrate the probability. As shown in Table 4, normalizing the class prototypes before evaluation can slightly enhance the performance.

6 Conclusion

We have proposed a novel approach to overcome catastrophic forgetting in incremental few-shot learning by finding flat local minima of the objective function in the base training stage and then fine-tuning the model within the flat region on new tasks. Extensive experiments on benchmark datasets show that our model can effectively mitigate catastrophic forgetting and adapt to new classes.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] Our approach may not work very well in the medium- or high-shot setting. Because it limits the model parameter vectors within the flat region, which is relatively small.
   (c) Did you discuss any potential negative societal impacts of your work? [No]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] See Section 4.3.
   (b) Did you include complete proofs of all theoretical results? [Yes] See Appendix A.1.
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] In supplemental material.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 5.1 and Appendix A.2.

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See Appendix A.4.

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See "Readme" in supplemental materials.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

(a) If your work uses existing assets, did you cite the creators? [Yes] We have cited [29, 51, 52].

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(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

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(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]