PlaStIL: Plastic and Stable Memory-Free Class-Incremental Learning

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Abstract

Plasticity and stability are needed in class-incremental learning in order to learn from new data while preserving past knowledge. Due to catastrophic forgetting, finding a compromise between these two properties is particularly challenging when no memory buffer is available. Mainstream methods need to store two deep models since they integrate new classes using fine tuning with knowledge distillation from the previous incremental state. We propose a method which has similar number of parameters but distributes them differently in order to find a better balance between plasticity and stability. Following an approach already deployed by transfer-based incremental methods, we freeze the feature extractor after the initial state. Classes in the oldest incremental states are trained with this frozen extractor to ensure stability. Recent classes are predicted using partially fine-tuned models in order to introduce plasticity. Our proposed plasticity layer can be incorporated to any transfer-based method designed for memory-free incremental learning, and we apply it to two such methods. Evaluation is done with three large-scale datasets. Results show that performance gains are obtained in all tested configurations compared to existing methods.

1. Introduction

Class-incremental learning (CIL) enables the adaptation of artificial agents to dynamic environments in which data occur sequentially. CIL is particularly useful when the training process is performed under memory and/or computational constraints \cite{24}. It is affected by catastrophic forgetting, i.e. the tendency of neural networks to forget past information when learning new data \cite{19, 25}. Most recent CIL methods \cite{11, 16, 18, 34, 42} use fine tuning with knowledge distillation \cite{15} from the previous model to preserve past information. Distillation was progressively refined \cite{16, 18, 41, 45, 46} to improve CIL performance. An alternative approach to CIL is inspired by transfer learning \cite{33}. These methods use a feature extractor which is frozen after the initial CIL state \cite{2, 12, 13, 34}. They become competitive in memory-free CIL, a difficult setting due to a strong effect of catastrophic forgetting \cite{24}. The main challenge is to find a good plasticity-stability balance because fine-tuning methods favor plasticity, while transfer-based methods only address stability.

In this work, we tackle memory-free CIL (MFCIL) by combining the two types of approaches described above. Building on the strong performance of transfer-based methods \cite{4, 13}, we introduce a plasticity component by partially fine-tuning models for recent classes. The results from Figure \ref{fig:results} show that our method gives a better global accuracy compared to \textit{DecSIL} \cite{2} and \textit{LUCIR} \cite{16}, two representative methods focused on stability and plasticity, respectively. Accuracy is presented separately for past and new classes for existing methods to examine the plasticity-stability balance offered by each method. \textit{LUCIR} has optimal plasticity (best accuracy of new classes), while \textit{DecSIL} has optimal stability (best accuracy for past classes). However, the performance of both methods is strongly degraded on the complementary dimensions. Our method is close to \textit{LUCIR} in terms of plasticity and to \textit{DecSIL} in terms of stability. Consequently, it ensure a better balance between these two properties of MFCIL.

\textit{PlaStIL} is inspired by transfer learning but adds a partial fine tuning component to boost plasticity. It is appli-
Figure 1. Accuracy of past and new classes in memory-free CIL for three large-scale datasets with $K = 10$ incremental states. 

\textit{LUCIR} \cite{16} uses distillation to preserve past knowledge and favors plasticity. \textit{DeeSIL} \cite{2} transfers features from the initial frozen model to all subsequent states and focuses on stability. \textit{PlaStIL} offers a better plasticity-stability balance. Note that the proportion of past classes increases as the incremental process advances and so does their weight in global accuracy.

cable to any transfer-based method and we implement it for two such methods, \textit{DSDLDA} \cite{15} and \textit{DeeSIL} \cite{2}. A hybrid classification layer which combines classification weights learned with the initial model for past classes and with the fine-tuned models for recent classes. We evaluate the proposed approach on three datasets which contain 1000 classes each. The number of incremental states is varied to assess the robustness of the tested methods. Results show that performance gains are obtained by adding the proposed plasticity component to transfer-based methods. Equally interesting, important performance improvements are obtained over distillation-based methods, which are the mainstream methods deployed to tackle CIL \cite{16,18,34,37,41}. The code will be open-sourced to facilitate reproducibility.

2. Related Work

Incremental learning is interesting when artificial agents need to learn under memory or computational constraints \cite{24,30,34}. The main challenge in CIL is to tackle the catastrophic forgetting phenomenon \cite{19,25}. A suitable balance between plasticity and stability of the learned models is sought \cite{27}. Plasticity and stability are needed in order to accommodate new data and preserve previously learned knowledge, respectively \cite{6}. As noted in a recent survey \cite{24}, a large majority of CIL-related works use a memory buffer which stores samples of past classes in order to improve overall performance. Replaying these samples facilitates the preservation of past knowledge, thus making the incremental learning process akin to imbalanced learning \cite{4}. However, the assumption that past samples are available is strong and limits the applicability of CIL. A growing research effort was devoted to memory-free CIL \cite{4,24}. The plasticity-stability dilemma is particularly challenging without memory since the effects of catastrophic forgetting are stronger in this case \cite{3,34,37,41}.

Here, we focus on methods which keep the network architecture constant. According to \cite{4,24}, most methods update learned models in each IL state using fine tuning for plasticity and different flavors of knowledge distillation \cite{15} for stability. Alternatively, a few works \cite{2,9,12,13,34} use a hybrid classification layer which combines classification scores to preserve the geometry of past classes, and an inter-class separation to maximize the distances between past and new classes. \textit{LwF} \cite{22} optimizes distillation by using a representation that provides proxy vectors at each state. An interesting solution is proposed in \cite{45}, where the feature drift between incremental steps is estimated based on features of samples associated to new classes. Feature drift was also tackled in \cite{17} by applying feature transformation to restore previous feature distribution. However, this method has a large footprint since it needs a large multi-layer perceptron and also stores past features to learn the transformation. A feature transformation method is designed for task-incremental learning and adapted for CIL by predicting the task associated to each test sample \cite{40}. The authors of \cite{37} combined feature drift minimization and class separability to improve distillation. Alternatively, the authors of \cite{20} modified distillation by using uncertainty of past classes to reflect their information in the current
state. Besides, they used a self-attention mechanism that adapts non-local model information using the residual connections. Very recently, the authors of [4] proposed an approach which stabilizes the fine-tuned model, adds reciprocal adaptive weights to weigh past and new classes in the loss, and introduces multi-perspective training set augmentation. They reported important gains in memory-free CIL compared to LUCIR [16] and SDC [45] using a protocol in which half of the dataset is available initially [16]. Distillation is widely used but a series of recent studies question its usefulness [4][24][32], especially for large-scale datasets. One explanation for the lack of scalability of distillation is that inter-class confusion becomes too strong when the number of past classes is high. Another challenge is that distillation needs to the previous deep model to preserve past knowledge. The total footprint of these methods is the double of the footprint of the backbone model used.

A second group of methods learns a deep representation in the initial state and uses it as feature extractor for the remainder of the incremental process. They are inspired by transfer learning [38] and clearly favor stability since the representation does not evolve at all. An early example of such an approach was proposed in [34] but it is not applicable in the memory-free setting since past classifiers were learned at each incremental state with the contents of the memory buffer. Usually, these methods learn shallow external classifiers on top of the initial deep representation. The nearest class mean (NCM) [26] was introduced in [34], linear SVCs [7] were used in [2] and extreme value machines [55] were recently tested by [9]. REMIND [12] uses a vector quantization technique to save compressed image representations which are later reconstructed for memory consolidation. DSLDA [13] updates continuously a class-specific mean vector and a shared covariance matrix. The predicted label is the one having the closest Gaussian in the feature space defined by these vectors and matrix. These methods are simple and suited for memory-free CIL, particularly for large-scale datasets where they outperform distillation-based methods [4][24]. Also important, they only use the initial model and thus have a smaller footprint. Their main drawbacks are the genericity of the initial representation and the sensitivity to strong domain variations. Their performance drops if a small number of classes is initially available [4] and if the incremental classes have a large domain shift with classes learned initially [21].

An emerging trend is to learn a feature extractor per IL step, and concatenate resulting features in a single classifier [23][43]. Pruning is applied at the end of each task in order to slow the parametric overhead, but it still occurs. The authors of tune [43] the hyperparameters for each experiment to optimize accuracy, which is impractical in practical IL scenarios. The method proposed in [23] is less sensitive to hyperparameters, but it needs stronger parameter growth. Equally important, the methods from [23][43] require the storage of image samples for past classes, and this makes them impractical for MFCIL.

3. Proposed Method

3.1. Problem Formalization

The class-incremental learning process is divided in $K$ states, with $n$ classes being learned in each state. In the memory-free CIL, no data of past classes can be stored for future use. The predictions associated to observed classes are noted $p$. We write the structure of a deep model as:

$$\mathcal{M} = \{B, \mathcal{T}, \mathcal{W}\}$$

(1)

with: $\mathcal{M}$ - the full model; $B$ - the model base which includes the initial layers; $\mathcal{T}$ - the model top which includes the subsequent layers up to the classification one; $\mathcal{W}$ - the classification layer which provides class predictions.

Assuming that the CIL process includes $K$ states, the objective is to learn $K$ models in order to incorporate all classes which arrive sequentially. The incremental learning process can be written as:

$$\mathcal{M}_1 \rightarrow \mathcal{M}_2 \rightarrow ... \rightarrow \mathcal{M}_k \rightarrow ... \rightarrow \mathcal{M}_{K-1} \rightarrow \mathcal{M}_K$$

(2)

Each incremental model needs to integrate newly arrived data, while also preserving past knowledge. Assuming that the current state is $k \geq 2$, the majority of existing CIL methods [5][16][34][37][41][42] fine tune the entire current model $\mathcal{M}_k$ by distilling knowledge from $\mathcal{M}_{k-1}$. Their classification layer is written as:

$$\mathcal{W}^{ft}_k = \{w^1_k, ..., w^n_k, ..., w^{(k-1)\times n}_k, w^{(k-1)\times n+1}_k, ..., w^{k\times n}_k\}$$

(3)

Classifier weights $w^1_k$ to $w^{(k-1)\times n}_k$ correspond to past states 1 to $k - 1$, while classifier weights $w^{(k-1)\times n+1}_k$ to $w^{k\times n}_k$ belong to the new state $k$. They are all trained using $\mathcal{T}_k$, the model top learned in the $k^{th}$ state. The $\mathcal{W}^{ft}_k$ layer is biased toward new classes since it is learned with all samples from the current state, but only with the representation of past classes stored in $\mathcal{M}_{k-1}$ [16][34][42]. This group of methods focuses on CIL plasticity at the expense of stability [4][24].

Transfer-based methods [2][12][13] freeze the feature extractor $\mathcal{F}_1 = \{B_1, \mathcal{T}_1\}$ after the initial non-incremental state. All the classes observed during the CIL process are learned with $\mathcal{F}_1$ as feature extractor. The classification layer can be written as:

$$\mathcal{W}^{fix}_1 = \{w^1_1, ..., w^n_1, ..., w^{(1)\times n}_1, w^{(1)\times n+1}_1, ..., w^{1\times n}_1\}$$

(4)

All classifier weights from Eq. 4 are learned with image features provided by $\mathcal{F}_1$, the feature extractor learned initially, inducing a bias toward initial classes. It is suboptimal.
for classes learned in states \( k \geq 2 \) because their samples were not used to train \( \mathcal{F}_1 \). These methods focus on CIL stability at the expense of plasticity \([4, 24]\).

### 3.2. PlaStIL Description

PlaStIL, the proposed method, is motivated by recent studies which question the role of distillation in class-incremental learning, particularly for large-scale datasets \([4, 24, 32]\). Instead of \( \mathcal{M}_{k-1} \) needed for distillation, PlaStIL uses two or more model tops \( \mathcal{T} \) which have an equivalent number of parameters at most. PlaStIL is inspired by feature transferability works \([28, 44]\) which show that higher layers of a model, included in \( \mathcal{T} \), are the most important for successful transfer learning. Consequently, the initial layers \( \mathcal{B} \) are frozen and shared throughout the incremental process. A combination of model tops which includes \( \mathcal{T}_1 \), the one learned in the first incremental state, and those of the most recent state(s) is used in PlaStIL. Similar to transfer-based CIL methods \([2, 12, 13]\), \( \mathcal{T}_1 \) ensures stability for classes first encountered in past states for which a dedicated top model is not available. Different from existing methods, model top(s) are available for the most recent state(s), thus improving the overall plasticity of PlaStIL. The number of different model tops which can be stored instead of \( \mathcal{M}_{k-1} \) depends on the number of higher layers which are fine tuned in each incremental state. The larger the number of layers in \( \mathcal{T} \), the larger its parametric footprint is and the lower the number of storable model tops will be.

The method is illustrated in Figure 2 with a toy example which includes \( K = 4 \) IL states, with \( n = 2 \) new classes per state and which assumes that up to three model tops can be stored. Up to the third state, PlaStIL stores a model top per state and corresponding classifier weights are learned for each model top. In the fourth state, one of the model tops needs to be removed in order to keep the parameters footprint bounded. Consequently, \( \mathcal{T}_2 \) is removed and the initial model top \( \mathcal{T}_1 \) is used. Note that \( \mathcal{T}_1 \) is used to learn classifier weights for all classes when they occur initially. These initial weights are stored for usage in later incremental states in order to cover all past classes for which dedicated model tops cannot be stored. The storage of the initial weights generates a small parameters overhead but its size is small and does not increase over time. If the classifier weights are \( d \)-dimensional, the number of supplementary parameters is \( n \times d \). Moreover, this overhead can be easily compensated by the choice of number of parameters in \( \mathcal{T} \) and the number of such model tops which are stored. In Figure 2, initial classifier weights \( w_7^1 \) and \( w_8^4 \) are first learned in state 2 but only used in state 4, when \( \mathcal{T}_2 \) is no longer available. In state 4, \( \mathcal{T}_1 \) is used for classes which first occurred in states 1 and 2 (classifiers weights \( w_1^1 \) to \( w_4^1 \)). \( \mathcal{T}_3 \) is reused along with its classifier weights \( w_5^2 \) and \( w_6^4 \), learned for the classes which were learned in state 3. Finally, classifier weights of new classes \( w_7^2 \) and \( w_8^4 \) are learned with \( \mathcal{T}_4 \). This results into a hybrid classification weights layer which is defined as:

\[
W_{\text{hyb}}^k = \{ w_1^{1 \times n}, \ldots, w_{j}^{j \times n}, \ldots, w_{j+1}^{(j+1) \times n}, \ldots, w_{k}^{(k-1) \times n}, \ldots, w_{k}^{k \times n} \}
\]

where we assume that \( k - j + 1 \) models can be stored, with \( 2 \leq j \leq k \); the blocks of classes learned with features from different model tops are color coded.

In Equation 5 classifier weights of the first \( j \) incremental states are learned with the features provided by initial model top \( \mathcal{T}_1 \). Those of the most recent states \((j + 1) \) to \( k \) are learned with features provided by model tops \( \mathcal{T}_{j+1} \) to \( \mathcal{T}_k \). An advantage of the classification layer from Equation 5 is that it ensures a good balance between stability, via \( \mathcal{T}_1 \) and plasticity, via \( \mathcal{T}_{j+1} \) to \( \mathcal{T}_k \). The number of storable model tops varies inversely with the number of layers that they include. We report results with three different configurations of PlaStIL in Section 4. A choice between internal and external classifiers has to be made for the implementation of this classification layer. Experiments from \([4]\) indicate that external classifiers are easier to optimize when transferring features from \( \mathcal{M}_1 \) to subsequent incremental states. Following \([13]\) and \([2]\), we implement \( W_{\text{hyb}}^k \) with a compressed version of \text{NCM} \([26]\) and with linear SVCs \([17]\).

### 4. Experiments

We evaluate PlaStIL with three public large-scale datasets which are designed for different visual tasks. We compare it to a set of recent methods which tackle memory-free CIL either by using model updates or initial models. We vary the total number of states using \( K = \{5, 10, 20\} \) because state size has a strong influence on the method performance in MFCL \([24]\). The evaluation metric is the top-1 accuracy averaged over all incremental states. Following a common practice in CIL \([5, 16, 42]\), the performance on the initial state is excluded because it is not incremental.

#### 4.1. Datasets

We thus select large-scale datasets which provide a more realistic scenario for evaluation compared to medium-scale ones which are still used \([37, 41]\). We run experiments with:

- **ILSVRC** \([36]\) - the well-known subset of ImageNet\([8]\) built for the eponymous competition and also used in CIL \([5, 16, 34, 42]\). The training and testing sets are composed of 1,231,167 and 50,000 images, respectively.
- **Landmarks** - a subset of a landmarks recognition dataset \([29]\) which includes a total of over 30000 classes. We select the 1000 classes having the largest number of images. The training and testing sets are composed of 374,367 and 20,000 images, respectively.
Figure 2. PlaStIL overview with a toy example with $K = 4$ incremental states and with $n = 2$ new classes learned per state. The global memory footprint is equivalent to that of distillation-based methods, but this memory is used differently. Here, we assume that a model base and at most three model tops can be used. A base $B$, is learned in the initial state and then frozen for use in subsequent states. $T_1$, the initial model top is equally frozen and reused in all subsequent states to ensure stability. Initial classifier weights are trained using $T_1$ and $T_2$, and at most three model tops can be used. A base memory footprint is equivalent to that of distillation-based methods, but this memory is used differently. Here, we assume that a model is composed of 300,000 and 10,000 images, respectively. More dataset details are provided in the supp. material.

4.2. State-of-the-art methods

We compare PlaStIL with the following existing ones:

- iNaturalist - a subset of the dataset used for the iNaturalist challenge [39]. The full version includes 10000 fine-grained classes for natural species. We sample 1000 classes from different super-categories to obtain a visually diversified dataset. The training and testing sets are composed of 300,000 and 10,000 images, respectively.

- SIW [3] - uses a vanilla FT backbone and tackles catastrophic forgetting by reusing the past classifiers learned when these classes were first learned.

- LUCIR [10] - adapts distillation to feature vectors instead of raw scores to preserve the geometry of past classes and also pushes for inter-class separation. Note that while initially proposed for CIL with memory, this method showed strong performance in MFCIL too [4].

- SPB-M [41] is a very recent method which focuses on balancing plasticity and stability in memory-free CIL. We report results with the multi-perspective variant, which has the best overall performance in [41]. SPB-M was provides very competitive performance compared to LUCIR when half of the dataset is initially available.

- DSLDA [13] - is based on Gaussian functions defined in the features space by specific mean class vectors and a covariance matrix which is shared among all classes. This method is interesting since its classification layer provides an efficient inter-class separability mechanism.

- DeeSIL [2] - freezes the network after the initial state and uses linear SVCs [7] to learn classifiers afterwards. DeeSIL was initially proposed for CIL with memory but is has interesting performance in MFCIL too [4].

The first four methods fine tune models in each incremental state. The last two methods are transfer-based, and PlaStIL can be applied to them. They were implemented using the optimal parameters reported in the original papers. Whenever the original experimental settings were different from the ones used here, the correct functioning the baselines was carefully checked. The obtained accuracy was coherent with the results reported in the original papers and/or in comparative studies such as [4, 24] in all cases. See details about the reproduced results in the supp. material.

We experiment with three versions of PlaStIL designed to ensure that its parameters footprint is equivalent to (or lower than) that of distillation-based methods. We assume that the incremental process is in the $k$th state and test:

- PlaStIL$_1$ - fine tunes model tops $T$ limited to the last convolutional layer of ResNet-18, which includes approximately 21.45% of the model parameters. Consequently, we can fit $T_1$, $T_{k-3}$, $T_{k-2}$, $T_{k-1}$ and $T_k$ in memory.

- PlaStIL$_2$ - fine tunes $T$ which includes the last two convolutional layers of ResNet-18, which includes approximately 42.9% of the model parameters. We can fit $T_1$, $T_{k-1}$ and $T_k$ in the allowed parameters memory.

- PlaStIL$_all$ - trains all the layers of the current model in
The three variants of PlaStIL make different assumptions regarding the balance between model top plasticity and the allowed number of such models. PlaStIL$_1$ fine tunes only the last convolutional layer of model tops and maximizes the number of such storable models. Inversely, PlaStIL$_{alt}$ provides optimal transfer since all layers are trained with new data but can accommodate only the current model. PlaStIL$_2$ provides a compromise between the quality of the transfer process and the number of storable models.

We also provide results for: (1) vanilla fine tuning (FT) - a baseline that does not counter catastrophic forgetting at all, and (2) Joint - an upper bound which consists of a standard training in which all data are available at once.

4.3. Implementation

A ResNet-18 [14] architecture was used as a backbone in all experiments. All methods were run with the published optimal parameters and minor adaptation of the codes to fit our data structuring: FT [3], LwF [34], LUCIR [15], SIW [37], DSLDA [13], and DeeSIL [2]. SPB-M [41] has no public implementation and we reimplemented the method. We verified its correctness by comparing the accuracy obtained with our implementation (60.1) to the original one (59.7) for ILSVRC split tested by the authors [41]. All methods were implemented in PyTorch [31], except for LwF. We adopted the Tensorflow [11] implementation of LwF from [34] because it provides better performance compared to later implementations from [13] [32]. The training procedure from [12] was used to obtain initial models for all transfer-based methods. These initial models were trained for 90 epochs, with a learning rate of 0.1, a batch size of 128, and a weight decay of $10^{-4}$. We used stochastic gradient descent for optimization and divided the learning rate by 10 every 30 epochs. The regularization parameter of the linear SVC classification layer is validated using 10% of training data of new classes. Detailed parameters are presented in the supp. material.

4.4. Main results

The results presented in Table 1 show that all PlaStIL variants improve over the transfer-based methods to which they are added for all tested datasets and CIL configurations. The gains are generally higher for $K = 5$ states, but remain consistent for the $K = \{10, 20\}$. For instance, PlaStIL$_1$ gains 6.9, 6.2 and 4.1 points for ILSVRC split into 5, 10, 20 states, respectively. The best overall performance is obtained with PlaStIL$_1$, followed by PlaStIL$_2$ and PlaStIL$_{alt}$ applied on top of DeeSIL. A combination of recent model tops which fine tune only the last convolutional layer is best here. Gains are equally interesting for DSLDA, and particularly for $K = 20$. The better behavior of DSLDA for longer incremental sequences is expected since this method features a global inter-class separability component. In contrast, DeeSIL only separates classes within each state and its discriminative power is reduced when each state includes a low number of classes.

Distillation-based methods have lower performance compared to transfer-based methods for the tested large-scale datasets. This result is coherent with previous findings regarding scalability problems of distillation [4] [24] [32]. The difference between PlaStIL applied to DeeSIL and DSLDA and distillation-based methods is very consequent. It is in the double-digits range compared to LUCIR, the best distillation-based method, for five configurations out of nine tested. This difference reaches a maximum value of 25.9 top-1 accuracy points for Landmarks with $K = 20$ states and a minimum of 2.5 points for the same dataset with $K = 5$ states. SPB-M is a recent method which compares very favorably with LUCIR when half of the dataset is allowed in the initial state [41]. However, its behavior is globally similar to that of LUCIR, with performance gains for $K = 20$ states and losses for $K = 5$. This happens because SPB-M is more dependent on the representativeness of the initial model compared to LUCIR since it features a strong stability component. LwF and SIW, the two other methods which update models in each incremental state have even lower performance than LUCIR and SPB-M. All MFCIL methods need a supplementary budget to ensure the plasticity-stability balance. The takeaway from the comparison of PlaStIL with mainstream methods is that this budget is much better spent on partially fine-tuned model tops than on storing the previous model needed for distillation.

The results per dataset show that ILSVRC and iNaturalist are harder to solve compared to Landmarks. The gains obtained by PlaStIL are smaller for Landmarks since the progress margin is more reduced for this simpler dataset. The performance gap between the evaluated methods and Joint is large. The fact that the gap widens with the number of incremental states has specific explanations for the two types of methods. Past knowledge becomes harder to preserve when the number of fine-tuning rounds increases in LUCIR, SPB-M, SIW, LwF. For transfer-based methods, past knowledge is encoded using a weaker feature extractor, learned on a smaller set of initial classes. PlaStIL reduces the gap with Joint, but the results reported here show that memory-free class-incremental learning remains a very challenging problem.

We complement the results from Table 1 with a more detailed presentation of the incremental accuracy of the best methods in Figure 5. PlaStIL$_1$ and PlaStIL$_2$ are presented for DeeSIL and DSLDA since they provide the best performance for these methods. The detailed results confirm the large gap between the proposed methods and distillation-based ones. We note that PlaStIL applied on top of DeeSIL is initially better than that applied to DSLDA.
but the difference is reduced towards the end of the CIL process. SPB-M has lower performance at the start of the process, but then becomes better than LUCIR.

4.5. Method analysis

We conduct an analysis of PlaStIL in terms of model footprint and number of operations needed to infer test image predictions. These experiments are run using PlaStIL applied on top of DeeSIL since this variant has the best overall results. They are important in order to highlight the merits and limitations of the proposed method.

**Model footprint.** Incremental learning algorithms are particularly useful in memory-constrained environments. Their model footprint is thus an important characteristic. Distillation-based methods require the storage of models $M_k$ and $M_{k-1}$ to preserve past knowledge. Transfer-based methods only need $M_1$, but they optimize stability at the expense of plasticity. The three versions of PlaStIL, whose performance is presented in Table 1, store $B_1$, the initial model base and a variable number of model tops. Each of the four recent model tops used by PlaStIL$_1$ fine tunes the last convolutional layer of ResNet-18 [14], which accounts for 21.45% of total number of the model’s parameters. The parametric footprint of PlaStIL$_1$ is thus lower than that of distillation-based methods. PlaStIL$_2$ has the same footprint as PlaStIL$_1$ since it stores two model tops which account for 42.9% of total number of the model’s parameters.

As an ablation of PlaStIL, we also present results with a single model top, regardless of its fine-tuning depth in Figure 4. Naturally, PlaStIL$_{all}$ obtains the best results in this configuration, but interesting gains are still obtained with model tops which fine tune one or two final convolutional layers in PlaStIL$_1$ and PlaStIL$_{all}$, respectively.

**Inference complexity.** The classification layer defined in Equation 5 is fed with features from the initial and the updated model top(s), for past and recent classes, respec-

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### Table 1. Average top-1 accuracy with three numbers of states $K$ per dataset. Results of model-tuning baselines are shown in the upper rows. Transfer-based methods and their versions with PlaStIL are shown in the lower rows. Best results - in bold, second best - underlined.

| CIL Method | ILSVRC | Landmarks | iNaturalist |
|------------|--------|-----------|-------------|
|            | $K=5$  | $K=10$    | $K=20$     | $K=5$  | $K=10$    | $K=20$     | $K=5$  | $K=10$    | $K=20$     |
| FT (lower bound) | 26.6 | 18.3 | 12.2 | 31.3 | 21.0 | 13.4 | 25.6 | 17.5 | 11.4 |
| LUCF [34] (CVPR'17) | 24.0 | 21.1 | 17.4 | 36.9 | 34.7 | 28.0 | 23.9 | 21.5 | 16.3 |
| SIW [3] (BMVC'20) | 38.3 | 35.2 | 26.8 | 66.4 | 55.7 | 41.4 | 38.6 | 30.9 | 17.2 |
| LUCIR [16] (CVPR'19) | 30.4 | 37.4 | 24.4 | 89.5 | 75.0 | 50.5 | 54.9 | 39.4 | 24.8 |
| SPB-M [41] (ICCVW'20) | 38.9 | 37.3 | 30.4 | 86.8 | 82.1 | 76.1 | 46.7 | 39.6 | 29.8 |
| DSLDA [14] (CVPRW'20) | 51.3 | 45.4 | 39.2 | 82.7 | 78.5 | 74.5 | 49.7 | 42.1 | 34.8 |
| w/ PlaStIL$_1$ | 56.8 | 50.1 | 42.2 | 86.8 | 82.1 | 76.1 | 53.8 | 45.6 | 36.6 |
| w/ PlaStIL$_2$ | 58.3 | 50.6 | 42.5 | 87.8 | 82.1 | 76.0 | 56.1 | 46.2 | 36.9 |
| w/ PlaStIL$_{all}$ | 57.7 | 49.8 | 41.9 | 86.9 | 81.3 | 75.5 | 56.2 | 46.3 | 37.4 |
| DeeSIL [2] (ECCVW'18) | 52.7 | 45.6 | 37.5 | 88.0 | 81.8 | 73.0 | 54.1 | 43.3 | 32.4 |
| w/ PlaStIL$_1$ | 59.6 | 51.8 | 41.6 | 92.0 | 86.3 | 76.4 | 58.6 | 47.7 | 34.9 |
| w/ PlaStIL$_2$ | 60.0 | 50.6 | 40.3 | 91.9 | 85.3 | 75.3 | 59.4 | 46.9 | 34.0 |
| w/ PlaStIL$_{all}$ | 58.3 | 48.8 | 39.1 | 90.8 | 83.5 | 74.4 | 59.5 | 46.7 | 33.8 |

**Joint (upper bound)** | 97.4 | 75.6 |

Figure 3. Incremental accuracy across all states for $K = 10$. Plots are presented for the best methods from Table 1. Best viewed in color.
Figure 4. Top-1 incremental accuracy of three versions of PlaStIL applied to DeeSIL with variable fine-tuning depth. DeeSIL is a limit case in which the whole feature extractor is frozen. Best viewed in color.

Figure 5. Top-1 accuracy gains obtained with the three variants of PlaStIL applied to DeeSIL with different thresholds for the rank of the top new class among the predictions generated with Equation 4. Results are shown for ILSVRC with $K = 10$ states. The corresponding percentage of supplementary inferences needed for each threshold is also plotted. Interesting gains are obtained starting with a recent class predicted in the second position, which requires approximately $20\%$ of supplementary inferences for PlaStIL$_1$. Best viewed in color.

**Figure 5.** Top-1 accuracy gains obtained with the three variants of PlaStIL applied to DeeSIL with different thresholds for the rank of the top new class among the predictions generated with Equation 4. Results are shown for ILSVRC with $K = 10$ states. The corresponding percentage of supplementary inferences needed for each threshold is also plotted. Interesting gains are obtained starting with a recent class predicted in the second position, which requires approximately $20\%$ of supplementary inferences for PlaStIL$_1$. Best viewed in color.

**5. Conclusion**

We proposed a new method which adds a plasticity layer to transfer-based methods in memory-free CIL. Plasticity is improved by training dedicated model tops which fine tune a variable number of deep models layers for one or more recent incremental states. The predictions of the different model tops used by our method are integrated in a hybrid classification layer. Model tops improve accuracy compared to the transfer-based method to which they are added to in order improve plasticity. These improvements are obtained by introducing supplementary parameters so
as to have a total footprint which remains lower than that of distillation-based methods. The comparison of these methods with PlaSTIL is clearly favorable to the latter. The takeaway is that the parameters allocated to the previous model in distillation-based approaches are better spent on partially fine-tuned model tops. This finding is aligned with those reported in recent comparative studies which question the usefulness of distillation in large-scale CIL with or without memory [4, 24, 32]. We believe that future studies should consider transfer-based methods to assess progress in memory-free CIL in a fair and comprehensive manner.

We plan on working toward optimizing the stability-plasticity compromise for memory-free CIL to further improve the encouraging results reported here. First, we will try to devise a classifier which predicts the most probable initial state for each test sample, following for instance the proposal made in [40]. If successful, this initial prediction would reduce the classification space to individual states and remove the need for a hybrid classification layer. Second, we will investigate the use of stronger initial representations trained on larger amounts of supervised or semi-supervised data, as proposed in [2, 9, 12]. Such models can be seamlessly integrated in the PlaSTIL pipeline.

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