Abstract

Incremental learning targets at achieving good performance on new categories without forgetting old ones. Knowledge distillation has been shown critical in preserving the performance on old classes. Conventional methods, however, sequentially distill knowledge only from the last model, leading to performance degradation on the old classes in later incremental learning steps. In this paper, we propose a multi-model and multi-level knowledge distillation strategy. Instead of sequentially distilling knowledge only from the last model, we directly leverage all previous model snapshots. In addition, we incorporate an auxiliary distillation to further preserve knowledge encoded at the intermediate feature levels. To make the model more memory efficient, we adapt mask based pruning to reconstruct all previous models with a small memory footprint. Experiments on standard incremental learning benchmarks show that our method preserves the knowledge on old classes better and improves the overall performance over standard distillation techniques.

1. Introduction

Deep neural networks perform well on many visual recognition tasks [5, 19, 15] given specific training data. However, problem arises when adapting networks to unseen categories while remembering seen ones, which is known as catastrophic forgetting [22, 7, 13]. To tackle this issue, there is a growing research attention on incremental learning where the new training data is not provided upfront but added incrementally. The target of incremental learning is to achieve good performance on new data without sacrificing the performance on old and it has been widely explored across different tasks such as classification [17, 25] and detection [28].

To alleviate catastrophic forgetting in incremental learning, one possibility is to maintain a subset of old data to avoid over fitting on new data [25, 2, 16]. However, an issue in practice is that when models embedded in a product are delivered to customers, they no longer have access to trained data for privacy purposes. To tackle the situation, a stricter exemplar-free setting was introduced in [17], which requires no exemplar set for previous categories and only distills previous knowledge from the current categories.

Prior methods typically apply knowledge distillation sequentially during the incremental procedure to preserve previous knowledge. Since they apply distillation only to the last model, it is difficult to maintain all past knowledge completely (the left side of Figure 1). From that observation, we propose using all the model snapshots. Prior knowledge is preserved better through our approach (the right side of Figure 1). In addition, we enhance the distillation process from different feature levels to further improve the performance. However, saving all previous models may...
incurs a great penalty in memory storage and without somehow compressing this historical information would not be practical. To address this, we reconstruct previous outputs using only "necessary" parameters during training. These parameters are determined by applying a compression algorithm to the series of models. With this pipeline, our approach only requires storing necessary parameters on-the-fly and avoids saving all previous model snapshots.

To this end, we propose an end-to-end Multi-model and Multi-level Knowledge Distillation (M²KD) framework as depicted in Figure 2 for incremental learning. We introduce a multi-model distillation loss which leverages the snapshots of all previous models to serves as teacher models during distillation, and then directly matches the outputs of a network with those from the corresponding teacher models. To make the pipeline more efficient, we adapt mask based pruning methods to reconstruct the previous models. We prune the network after each incremental training step and identify significant weights to reconstruct the model. This allows us to reconstruct previous models and utilize them as teacher models in our multi-model distillation. To further enhance the distillation process, we also include an auxiliary distillation loss to preserve more intermediate features of previous models. Additionally, our approach addresses catastrophic forgetting in sequential distillation, and thus generalizes well for both exemplar based and exemplar-free settings. (See Section 4)

To show the effectiveness of our approach, we evaluate our model on Cifar-100 [14] and a subset of ImageNet [15]. We achieve state-of-the-art performance for all the datasets in the exemplar-free setting. We also show improvement when adapting to exemplar-based incremental learning and our exemplar-free setting outperforms [25] with a 200 exemplar budget.

In summary, our contributions are three fold. First, we propose a multi-model distillation loss, which directly matches logits of the current model with those from the corresponding teacher models. Secondly, for efficiency, we reconstruct historical models via mask based pruning such that model snapshots can be reconstructed with low memory footprint. Experiments on standard incremental learning benchmarks show that our method achieves state-of-the-art performance in exemplar-free incremental setting.

2. Related Work

The ultimate goal of incremental learning is to achieve good performance on new data while preserving the knowledge about old data. Generally, two types of evaluation settings [3] have been considered. One is multi-head incremental learning which utilizes multiple classifiers at inference, and the other is single-head incremental learning which only utilizes one classifier at inference.

**Multi-head incremental learning.** The evaluation setting in this stream is that a specific classifier is selected during testing according to the tasks or categories. With this prior information, no confusion exists across different classifiers, and thus the target becomes how to adapt the old model for new tasks or categories. Kirkpatrick et al. [13] explore Elastic Weight Consolidation (EWC), which constrains the important weights on the old tasks when adapting to the new ones. Mallya et al. [21, 20] use a mask for pruning to further constrain the weights on the old tasks. Hou et al. [11] rely on a subset of old data and distill the knowledge of the old model when adapting to new tasks. Different from this setting, we do not assume the task or category information is known during inference and follow the setting of single-head incremental learning. Also, even though we apply pruning in our approach, our goal is different from Mallya et al. [21, 20] as the masks are utilized to reconstruct previous models for single-head setting.

**Single-head incremental learning.** Single-head evaluation uses only one classifier to predict both the old and the new classes. This setting is more challenging [3] compared to the multi-head counterpart because of the confusion between old and new categories. Knowledge distillation is frequently utilized to preserve information. Li et al. [17] Learn Without Forgetting (LWF) by distilling the knowledge from the last model. Dhar et al. [4] learn a mask for pruning in the loss function. Rebuffi et al. [25] introduce exemplar set for the old data and match previous logits through distillation. Castro et al. [2] explore the balance between old and new data during training. Li et al. [16] focus on constructing exemplar set and Caselles et al. [1] replay the seen categories with GANs [6]. Instead of saving exemplars, we save the parameters of previous models for reconstruction. With that, this paper can be considered a complement research direction. In fact, as knowledge distillation is an important component in these methods, they can potentially benefit from our approach as well.

**Network pruning.** Considerable research has explored this area to reduce network redundancy. Han et al. [8, 9] propose to compress network through quantization and Huffman coding. Yu et al. [29] compress the weights according to their scores. Other methods [24, 12, 18] explore compression for fast inference. In contrast to these methods, we leverage network redundancy and use pruning to reconstruct all previous models in incremental learning with low memory footprint.

3. Approach

We propose novel distillation losses to preserve previous information without introducing too much memory overhead (See Figure 2). The model is agnostic to the backbone architecture and generalizes well to both exemplar based and exemplar-free methods.
Figure 2. Framework overview. Given images from the current training data, we preserve previous knowledge directly from the reconstructed output through matching the logits with the corresponding model and classifying the current data with its ground truth. As an example, each layer contains a mask matrix $M_t$ at the $t$-th incremental step recording significant weights for previous data. The gray dots represent the weights to be trained on the current data. Red and green dots denote the weights retained from the first and second incremental step respectively—they are fixed during training. The gray dots are fine-tuned for the current data before pruning. After pruning, a subset of the gray dots will be marked as important weights and become blue dots, and remaining weights will be fine-tuned during the next incremental step. Accordingly, $M_{t_2}$ is updated and used as $M_{t_3}$ at the end of this round. In multi-model distillation, the red and green output logits of the current model are matched with the model 1 and 2 respectively while the blue logits are matched with its ground truth.

### 3.1. Multi-model Distillation

The incremental learning process consists of a sequence of incremental class inclusion steps, referred to as incremental steps. Samples from a batch of new classes $C_k$ are added at the $k$-th incremental step. For instance, 20 classes will be added per incremental step in a 20-class batch setting. Accordingly, the network assigns new logits (output nodes) for the incremental classes. At inference, the maximum logit score in the output is treated as the final decision.

The knowledge distillation used in incremental learning [17, 25] mainly aims to match the output of the current model to a concatenation of the last model logits and ground truth labels. Formally, it optimizes the cross entropy for both the old and new logits,

$$L_D = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C_o} s'_{ij} \log(s_{ij}) - \frac{1}{N} \sum_{i=1}^{N} \sum_{j=C_o+1}^{C} y_{ij} \log(s_{ij}),$$

(1)

where $N$ and $C$ denotes the number of samples and the total class number so far respectively, and $C_o$ denotes the old classes. $s_{ij}$ is the output score of the network obtained by applying Sigmoid function to the output logits for sample $i$ at logit $j$. $s'_{ij}$ denotes the old score obtained by the most previous model. $y_{ij}$ denotes the ground truth.

Treating the most previous model as the teacher and applying this distillation sequentially helps preserve historical information, especially when no previous exemplar set is stored, which is the protocol for prior methods [25, 2, 17, 4]. However, the historical information will be gradually lost in this sequential pipeline as the current model must reconstruct all the prior information from the penultimate model alone. To address this limitation, we propose multi-model distillation, which directly leverages all previous models as our teacher model set. Since we mainly have current training data and labels for both settings, the network is more confident on current classes than old ones. Therefore, matching the previous logits of the current model directly with their corresponding old models preserve information better than always using the last model. Formally, we minimize the cross entropy for the logits between the current model and corresponding teacher models from previous in-
Figure 3. Illustration of auxiliary distillation. We extract the intermediate features and connect directly with an auxiliary classifier to preserve middle level knowledge.

incremental steps,

\[
L_{MMD} = - \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{P-1} \sum_{j=C_{k-1}+1}^{C_k} s_{ijk} \log(s_{ijk})
- \frac{1}{N} \sum_{i=1}^{N} \sum_{j=C_{P-1}+1}^{C} y_{ij} \log(s_{ij}),
\]

(2)

where classes from \(C_{k-1} + 1\) to \(C_k\) belong to the \(k\)-th incremental step and \(P\) denotes the number of incremental steps. Classes from \(C_{P-1} + 1\) to \(C\) belong to the current categories. \(s_{ijk}\) is the output score of the current model for sample \(i\) at logit \(j\) in the \(k\)-th incremental step. \(s'_{ijk}\) denotes the output score of the \(k\)-th previous model.

Multi-model distillation matches the logits in the current model with the corresponding teacher model directly, reducing the information loss between incremental steps. At inference, we directly choose the maximum among the output logits, which acts as an ensemble of all the previous teacher models and the current model.

### 3.2. Auxiliary Distillation

Previous incremental learning methods preserve old class information through matching the final output. However, the features from intermediate layers also contain useful information. Inspired by the auxiliary loss in segmentation task \([30]\), we propose an auxiliary distillation loss to preserve the intermediate statistics of previous models. Similar to using the final output to represent network statistics, the prediction made by lower level features also represents intermediate feature statistics. Following the main branch classification, we extract lower level features and use an auxiliary classifier to conduct classification based on intermediate features (See Figure 3).

Also, a multi-model distillation loss is added on this auxiliary classifier for the purpose of preserving prior lower level features, and a standard cross entropy loss is also included for classifying the current data. Formally, the loss function becomes

\[
L_{AD} = - \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{P-1} \sum_{j=C_{k-1}+1}^{C_k} a'_{ijk} \log(a_{ijk})
- \frac{\alpha}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log(a_{ij}),
\]

(3)

where \(a'_{ijk}\) denotes the output score from previous auxiliary classifiers, \(a_{ijk}\) or \(a_{ij}\) is the output score of the auxiliary branch, \(\alpha\) is the ratio between the distillation and cross entropy loss. Notice that all the logits in ground truth labels are utilized in the classification cross entropy to enforce the correct prediction of current data.

The total loss function of the network becomes,

\[
L_{total} = L_{MMD} + \lambda L_{AD},
\]

(4)

where \(\lambda\) is the ratio between the main classification multi-model distillation and the auxiliary classification distillation. This auxiliary classification branch is only used during training. At inference time, we only use the main branch classifier for prediction.

### 3.3. Model Reconstruction

One drawback of multi-model distillation in its original form is that it utilizes all previous models, requiring additional memory storage for the models. However, we observe that distillation aims to match logits. Therefore it is only necessary to preserve the outputs of previous networks, not the entire networks themselves. Our key idea is to save only a small set of the most important parameters of the networks from which we can approximate the output. By that way, all the models can be recovered on-the-fly without large memory penalty.

To determine the necessary parameters, we adapt mask based pruning \([21]\) for model reconstruction. Specifically, after training each incremental step we sort the magnitude
obtained from its classifier (the last layer) and features, and classifier parameters, we can reconstruct all previous incremental step. With the saved biases, batch normalization each layer for all previous incremental steps. After each notes the activation function and $w$ where $n$ in the $n$-th layer and can be generally written as $f^{(n)} = \sigma(w^{(n)} f^{(n-1)} + b^{(n)})$, (6)
where $w$ and $b$ are weights and biases respectively, $\sigma$ denotes the activation function and $f^{(0)}$ is the input.

With the mask $M_k$ for the $k$-th incremental step, we reconstruct the corresponding feature by:

$$f_{k}^{(n)} = \sigma(w_{k}^{(n)} \delta(M_{k}^{(n)} \leq k) f_{k}^{(n-1)} + b_{k}^{(n)}),$$ (7)

where $M_{k}^{(n)}$ denotes the mask in the $n$-th layer at incremental step $k$, $f_{k}^{(n)}$ denotes the feature in the $n$-th layer in $k$-th incremental step, and $\delta$ denotes delta function.

Thus the output of the $k$-th model is reconstructed by

$$s_{k} = \Psi_{k}(f_{k}^{(n)}),$$ (8)

where $s_{k}$ and $\Psi_{k}$ denotes the output of the network and the classifier for the $k$-th incremental step respectively.

We update masks and save parameters including biases, batch normalization and classifier on-the-fly.

4. Experiments

We evaluate our method in the exemplar-free setting in subsection 4.3. Then we extend our method to the exemplar-based setting in subsection 4.6. We also compare our memory cost with other methods in subsection 4.7.

4.1. Datasets and Evaluation Metrics

The dataset and training strategy for incremental learning are as followed:

**iLSVRC-small[26]:** A small subset of 100 classes out of the 1000-class ImageNet. The evaluation metric is the 5 iteration average accuracy of the 100 classes. The number of classes in every incremental step is determined by the number of steps. We train from scratch and the performance is evaluated on the validation set of ImageNet.

**Cifar-100[14]:** All 100 classes are evaluated. The average result out of 5 random selections of classes for each incremental step is reported. We train from scratch and the evaluation results are based on the test set.

**Evaluation Metrics.** Following the same metrics in prior methods [17, 25], the top-1 classification accuracy is reported for Cifar-100 and top-5 classification accuracy is reported for iLSVRC-small.

4.2. Implementation Details

We use PyTorch for implementation. The network architecture follows prior works [25, 17, 2]: we use ResNet-32 [10] with input size $32 \times 32$ for Cifar-100 and ResNet-18 with input size $224 \times 224$ for iLSVRC-small. We extract the output of the second residual block for auxiliary distillation and empirically set $\alpha$ to 0.5. We train 80 epochs for Cifar-100 and 60 epochs for iLSVRC-small. Following the setting in [25], we use the training batch size of 128 and the initial learning rate of 2.0 to train the model. The learning rate decays by a factor of 5 every 40 epochs for Cifar-100 and 20 epochs for iLSVRC-small. Weight decay with a factor of 1e-5 is applied for the first incremental step and 0 for the rest in our full model to ensure weights from previous models remain the same. We optimize the network using standard Stochastic Gradient Descent (SGD) with a momentum 0.9. The pruning ratio is 0.75 for class batch less than 20 and 0.8 for 20 groups. After cutting off insignificant weights in the pruning stage, we fine tune the network for another half number of the epochs in normal training. $\lambda$ is set to be 1.0 to balance the losses. Only random horizontal flipping is applied as data augmentation for all experiments.

4.3. Exemplar-free setting

We evaluate our methods in exemplar-free single-head setting. For evaluation, we also compare with the following baselines and state-of-the-art approaches.

**FT:** A baseline approach that fine-tunes the whole model on new coming incremental classes without applying knowledge distillation.

**LWF-MC** [25]: A multi-class classification version of [17] as described in [25], applying distillation to the logits from the last previous model sequentially.

**M^2-KD (ours):** Our full model applying multi-model, auxiliary distillation along with pruning procedure to save memory storage.

**M^2-KD (no pruning):** The upper bound of our model which directly loads all the previous snapshots for multi-model distillation.

Figure 4 highlights our performance compared to state-of-the-art methods. For Cifar-100, our methods consistently
outperforms LWF-MC and FT from 5-classes to 20-classes per incremental step. The margin becomes larger as more incremental steps are added. This demonstrates the advantage of multi-model distillation as it avoids accumulating loss of historical information. Similar observation can be made when evaluating on iILSVRC-small. It is interesting to note that our model with pruning achieves comparable performance with the no-pruning version. This indicates the effectiveness of the pruning procedure in terms of saving memory while maintaining performance. Even though the residual active weights decrease gradually due to pruning, we still preserve the performance up to 20 incremental steps. See Section 4.4 for more detailed discussions of each component of our approach.

4.4. Ablation Studies

We investigate the effectiveness of each component of our method in this section. In particular, we compare our full model with the following baselines.

**LWF-MC aux**: Add auxiliary distillation to LWF-MC.

**LWF-MC MMD**: Change the original loss to our multi-model distillation. No auxiliary distillation is applied.

**Ours skip1**: Instead of using all previous models, we study the case when skipping some snapshots. Starting from the last previous model, we skip the first model in multi-model distillation. The skipped model is replaced by the next model for multi-model distillation. **Ours skip2**: Skip the first two models instead of one compared to **Ours skip1**.

Figure 5 shows the comparison for each of the component in our approach. **LWF-MC aux** improves our baseline model **LWF-MC** on all the datasets after adding auxiliary distillation, indicating that the intermediate level information also contributes to preserving previous knowledge. With only multi-model distillation (**LWF-MC MMD**), the performance gradually improves for both datasets as more incremental steps are involved, which demonstrates that directly distilling knowledge from the corresponding model helps to reduce the lost in sequential distillation. Note that our multi-model distillation reduces to the standard distillation used in [17] if only one or two incremental steps are added. By incorporating the auxiliary distillation, however, our method still shows improved performance. Lastly, our model achieves nearly the same performance as our upper bound which saves all previous snapshots, showing the effectiveness of our pruning based approach. See Section 4.5 for more experiments about the pruning ratio.

Figure 7 compares how multi-model distillation is affected by the number of models. **LWF-MC** can be regarded as a special case which skips 3 models in the last round. The
Figure 5. Ablation Studies for our approach. a) Top-1 accuracy comparison on Cifar-100 (20-class batch). b) Top-5 accuracy performance on iLSVRC-small (20-class batch).

| Step | 1 | 2 | 3 | 4 | 5 |
|------|---|---|---|---|---|
| Ratio 0 | 83.5 | 61.8 | 52.5 | 51.5 | 42.1 |
| Ratio 0.6 | 82.9 | 59.6 | 52.2 | 46.5 | 40.1 |
| Ratio 0.7 | 83.5 | 61.7 | 52.5 | 50.0 | 42.8 |
| Ratio 0.8 | 83.5 | 58.5 | 52.0 | 49.3 | 42.0 |
| Ratio 0.9 | 83.0 | 58.0 | 49.7 | 47.3 | 39.9 |

Table 1. Top1 accuracy comparison among different pruning ratios on Cifar-100 (20 classes per incremental step).

performance trend from LWF-MC to Ours shows that the performance improves as the number of model preserved increases, confirming the values of multi-model distillation.

To further analyze the performance behind our model, we show the resulting confusion matrices in Figure 6. It can be observed from the confusion matrix that LWF-MC has a strong bias to the data from the newly added classes while the performance on the old classes degrades dramatically. With the knowledge from the intermediate level, the confusion of previous data gets reduced. More clearly, with the favor of multi-model distillation, the knowledge from all the previous data preserves better and cause less confusion. Also, if we skip some previous models in the distillation and use other models to guide the network, the skipped logits become less confident than directly using the corresponding model for distillation. In short, the comparison from confusion matrices confirm the advantage on preserving previous knowledge via multi-model distillation.

4.5. Analysis on pruning ratio

We compare the results corresponding to different pruning ratios to investigate the robustness of our approach. Table 1 summarizes the results. Marginal performance variation (around 3%) is observed for different pruning ratios. Even though a higher (0.9) pruning ratio affects the performance as the active weights decrease in the current incremental step and a lower (0.6) ratio affects the performance as available weights decrease in the future steps, the relatively trivial influence indicates that a large redundancy exists in the network architecture. Benefitting from it, our approach shows robustness to different pruning ratios.

4.6. Exemplar Based Setting

Our approach also works for exemplar based incremental learning which use distillation sequentially on the output of networks [25, 2, 16]. To evaluate our model in this setting, we add exemplar selection to our approach and compare with exemplar based methods.

iCaRL [25]: A prominent exemplar based incremental learning approach which constructs exemplar set for the old data according to the feature means and do distillation on the last previous model. An external nearest class mean classifier [23] is applied at inference.

iCaRL aux: Adding auxiliary distillation to iCaRL.

iCaRL $M^2$KD: Change the original distillation function which only match logits from the last previous model to
The results are shown in Figure 8. With the introduction of multi-model and auxiliary distillation, the performance of iCaRL improves. It indicates that with direct access to all the previous models for distillation, the knowledge preserves better even with exemplar set.

### 4.7. Memory Comparison

Starting from the memory footprint of LWF as our baseline, we compare the extra memory storage between exemplar based method such as iCaRL [25] and our approach. The memory is calculated in the 10-class incremental step setting for both iILSVRC-small and Cifar-100. For our approach, we directly calculate the storage difference between the last and the initial step as stored parameters are accumulating along the training procedure. For iCaRL, the memory is approximately calculated by the average size of image for 2000 samples (i.e. the default exemplar size), and the compensation for saving the record of exemplar set. To optimize the memory consumption of iCaRL, we resize the images in iILSVRC-small to $256 \times 256$ and compress to JPG with quality 95 before calculate the image size to match their image size during training.

Table 2 shows the memory compensation for different methods. It indicates that our approach has approximately $7 \times$ smaller memory compensation on iILSVRC-small and $10 \times$ smaller on Cifar-100 than iCaRL. On average, for each incremental step, our approach only take 0.98 MB and 0.08 MB for iILSVRC-small and Cifar-100 respectively. The memory advantage to exemplar based methods might become larger in real scenario as higher resolution images take more storage.

We perform further memory analysis in Figure 9. We compare our approach with iCaRL given the constraint of the same memory on Cifar-100. For fair comparison, we reduce the exemplar set as a penalty of the additional memory we use for network parameters to match with the memory size used for iCaRL. The performance is evaluated by averaging the top-1 accuracy across all the incremental steps. When memory budget limit equals to 200 images, we do not use any exemplar set but still performs better than iCaRL. The reason for this is that the sequential distillation pipeline tends to lose information even when exemplars from old classes are available. Moreover, increasing memory budget makes the performance gap between our approach and iCaRL larger, showing our strength to memorize what has been learned.

### 5. Conclusion and Discussion

This paper presents a novel distillation strategy that mitigate catastrophic forgetting in single-head incremental learning setting. We introduce multi-model distillation which directly guides the model to distill knowledge from the corresponding teacher models. To further improve our performance, we incorporate auxiliary distillation to preserve intermediate features. More efficiently, we avoid to save all the model snapshots through reconstructing all previous models using mask based pruning algorithm. Extensive experiments on standard incremental learning benchmarks demonstrate the effectiveness of our approach. Incremental learning is still far from solved. There’s still a significant gap between one-step training versus incremental training. It remains to be a open question how to reduce the confusion between different incremental steps especially without access to previous data, which might be a future exploration for our research.
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