CONTINUAL LEARNING VIA EXPLICIT STRUCTURE LEARNING

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ABSTRACT

Despite recent advances in deep learning, neural networks suffer catastrophic forgetting when tasks are learned sequentially. We propose a conceptually simple and general framework for continual learning, where structure optimization is considered explicitly during learning. We implement this idea by separating the structure and parameter learning. During structure learning, the model optimizes for the best structure for the current task. The model learns when to reuse or modify structure from previous tasks, or create new ones when necessary. The model parameters are then estimated with the optimal structure. Empirically, we found that our approach leads to sensible structures when learning multiple tasks continuously. Additionally, catastrophic forgetting is also largely alleviated from explicit learning of structures. Our method also outperforms all other baselines on the Visual Domain Decathlon Dataset with reasonable parameter overhead.

1 INTRODUCTION

Learning different tasks continuously is a common and practical scenario that happens all through the course of human learning. The learning of new skills from new tasks usually does not have negative impact on the previously learned tasks. Furthermore, with learning multiple tasks that are highly related, it often helps to advance all related skills. However, this is commonly not the case in current deep learning models. When presented a sequence of learning tasks, the model experiences so called "catastrophic forgetting" problem (McCloskey & Cohen, 1989; Ratcliff, 1990), where the model "forgets" the previous learned task while learning the new task. This is an interesting phenomenon that has attracted lots of research recently.

Many efforts have been tried to overcome catastrophic forgetting. Common approaches such as Elastic weight consolidation (EWC Kirkpatrick et al., 2017) and synaptic intelligence (Zenke et al., 2017) focuses on alleviating catastrophic forgetting by applying constraints on the update of the parameters. However, forgetting is still non-negligible with these approaches, especially when the number of tasks increases. Forgetting could also be alleviated with memory-based methods, where certain information regarding learned tasks are stored to help retaining the performance of the learned tasks (see Lopez-Paz et al., 2017; Sener & Savarese, 2018, for example). Additionally, there are also methods (Mallya & Lazebnik, 2018; Rebuffi et al., 2017a; 2018; Mancini et al., 2018) that could learn multiple domains and completely avoid forgetting by adding a small portion of parameters while the original weights is kept fixed. However, these kind of models rely on a strong base network and knowledge can only be transferred from the one task to another.

Most of the current approaches in continual learning employ a model with a fixed structure, and apply the same model to learn all tasks. We believe that a more intuitive and sensible approach is to learn task specific model structure *explicitly* along with learning of the model parameters[1]. Since each task may require different architecture. In case two tasks are not quite relevant, it may not make much sense to employ the same structure for learning. For example, in case of learning digit and face recognition models, the lower level features required is likely to be drastically different, and similarly for the required structure. Forcing the same structure for these tasks is likely to prevent

[1]The structure that referred here is more fine-grained, such as number of layers, type of operations at each layer, etc. It does not refer to generic structure names like convolutional nerual networks or recurrent neural networks.

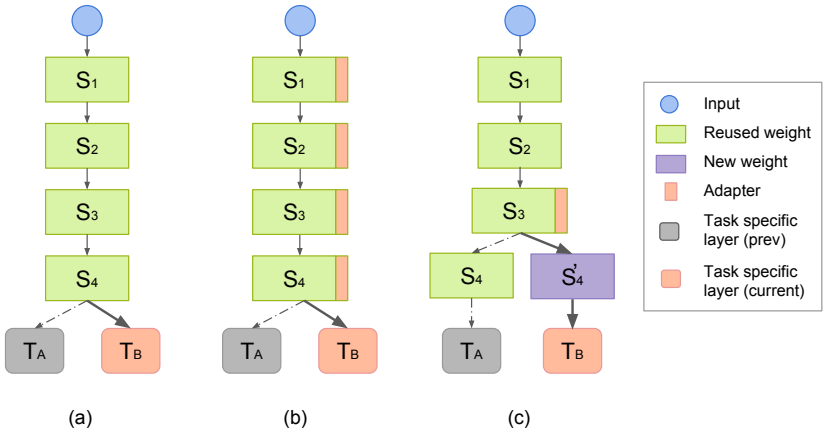

Figure 1: Illustration of different approaches for continuous learning. a) All but the task specific layer are shared, catastrophic forgetting is countered by techniques that prevents parameters to move to lower energy regions of previous tasks. b) Each task will add some fixed task specific parameters, all layers' original weights are not tuned, and thus prevents forgetting. c) Our approach, where network structure is determined by architecture search. In this example, the search results decide to "reuse" the first two layer, do "adaptation" for the third layer and allocate "new" weight for the fourth layer.

sharing as very less information is relevant between the tasks. On the other hand, if tasks were allowed to use different structure, it has the potential to encourage information sharing. Since now the irrelevant part can be handled by the new/different structure.

Therefore, in this work we propose a framework that explicitly separate the learning of model structure and model parameters. In particular, we employ architecture search for each of the sequential tasks to find the optimal structure for the current task. The search considers various options, such as share previous layer's parameter, spawn new parameters, and so on. The model parameters are then learned correspondingly. We found that 1) qualitatively, the learned structure is sensible – similar tasks tends to share more parameters and structure, whereas distant tasks share less; 2) quantitatively, separating the structure and parameter learning significantly reduced catastrophic forgetting. Additionally, we propose a new approach for doing continuous learning with architecture search.

2 Explicit Structure Learning

The continual learning task that we are concerned with in this work is defined as follows. N tasks $T_1, T_2, \ldots, T_N$ forms a task sequence $\mathbf{T} = (T_1, T_2, ..., T_N)$. Each task T_i is composed of dataset $\mathcal{D}_i = \{(x_1^{(i)}, y_1^{(i)}), (x_2^{(i)}, y_2^{(i)}), \ldots, (x_{N_{T_i}}^{(i)}, y_{N_{T_i}}^{(i)})\}$, where each dataset is of size N_{T_i}. The model gets to observe tasks from 1 to N sequentially. After the model finished learning on task T_i, the model can no longer access this task, i.e. all data from $\mathcal{D}_i$ will not be available when learning tasks T_{i+1} to T_N.

Ideally, we would like to minimize the following loss function in this continuous learning setting

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} \mathcal{L}_i(\theta) \tag{1}$$

$$\mathcal{L}_i(\theta) = \frac{1}{N_{T_i}} \sum_{n=1}^{N_{T_i}} \ell_i(f_\theta(x_n^{(i)}), y_n^{(i)}) \tag{2}$$

where f_θ is the model and ℓ_i is the loss function for task T_i. However, since we do not have access to all dataset at the same time, the above loss in equation 1 is very hard to minimize. In case we ignore the access issue and train each task separately, this will result in catastrophic forgetting. Additionally, the above loss definition clearly does not account for structure changes explicitly in the

formulation. As motivated earlier, we believe explicit learning of structure is important for continuous learning. The key intuition for explicit learning structures for new tasks is that in case there is high dissimilarity between the current and previously seen tasks, optimizing model parameter may inevitably cause forgetting. This is because the model is been asked to function very differently, and it is very unlikely that the new optimal parameters will also be a good solution for the previous tasks. Even in case where the tasks are similar, it may not be ideal to share all of the structure, as there might be fine grained details in tasks that make the part of the model focus on extracting different types of representations. Therefore, we introduce here $s_i(\theta)$ to indicate the structure for task T_i. The updated loss for individual task is then

$$\mathcal{L}_i(\theta) = \frac{1}{N_{T_i}} \sum_{n=1}^{N_{T_i}} \ell_i(f_{s_i(\theta)}(x_n^{(i)}), y_n^{(i)}) \tag{3}$$

Now the structure is explicitly taken into consideration when learning all the tasks. When optimizing the updated loss in equation 3, one needs to determine the optimal parameter based on the structure s_i. This loss can be viewed in two ways. One can interpret the above loss as selecting a task specific network from a 'super network' that has parameter θ using s_i, or for each task we train a new model with parameter $s_i(\theta)$. There is a subtle difference between this two views. The former one has an constraint on the total model size, where as the latter one does not. So in worst case scenario, the model size will grow linearly as we increase the number of tasks. This would lead to a trivial solution – training completely different models for different tasks and is no longer continuous learning! To address this problem, we propose the following loss

$$\mathcal{L}_i(\theta) = \frac{1}{N_{T_i}} \sum_{n=1}^{N_{T_i}} \ell_i(f_{s_i(\theta)}(x_n^{(i)}), y_n^{(i)}) + \beta_i \mathcal{R}_i^s(s_i) + \lambda_i \mathcal{R}_i^p(\theta) \tag{4}$$

where $\beta_i > 0$, $\lambda_i \geq 0$, $\mathcal{R}_i^s$ and $\mathcal{R}_i^p$ indicate regularizer for structure and parameter, respectively. In this way, the total number of parameters are upper bounded, and the degenerate case is thus avoided.

3 Our Implementation

It is a challenging problem to optimize the loss described in equation 4, since it involves explicit optimization of the structure of the model. In our implementation, we choose to separate this optimization problem to two steps: structure optimization and model parameter learning. In particular, we employ neural architecture search to deal with structure optimization, and then gradient based method for learning model parameters after the structure is fixed. We explain our implementation in detail in the following section.

3.1 Structure Optimization

We employ neural architecture search for structure optimization. Before we move on to further details, we make a further simplification, where we assume that one already have in mind a global structure that may work for all tasks, and we are only selecting connectivity pattern between layers and their corresponding operator. It is straight forward to adapt this to more complicated cases, we make the simplification because: 1) it is common in a multi-task continual learning scenario that one has some rough clue regarding the overall model structure; 2) this simplifies the optimization problem significantly.

Let's define a certain network with L shareable layers and one task-specific layer (i.e. last layer) for each task. A super network $\mathcal{S}$ is maintained so that all the new task-specific layers and new shareable layers will be stored into $\mathcal{S}$.

The goal of search is trying to find out the optimal choice for each of the L layers, given the current task data $\mathcal{D}_i$ and all the shareable layer's weights stored in $\mathcal{S}$. The candidate choices for each layer could be "reuse", "adaptation" and "new". The reuse choice will make new task use the same parameter as the previous task. The adaptation option adds a small parameter overhead that trains an additive function to the original layer output. The new operator will spawn new parameters of exactly the size of the current layer parameters. Here, we denote the size of the l_{th} layer in super network $\mathcal{S}$ as $|\mathcal{S}^l|$. The total number of choices in the l_{th} layer C_l is $2|\mathcal{S}^l| + 1$, because we will have

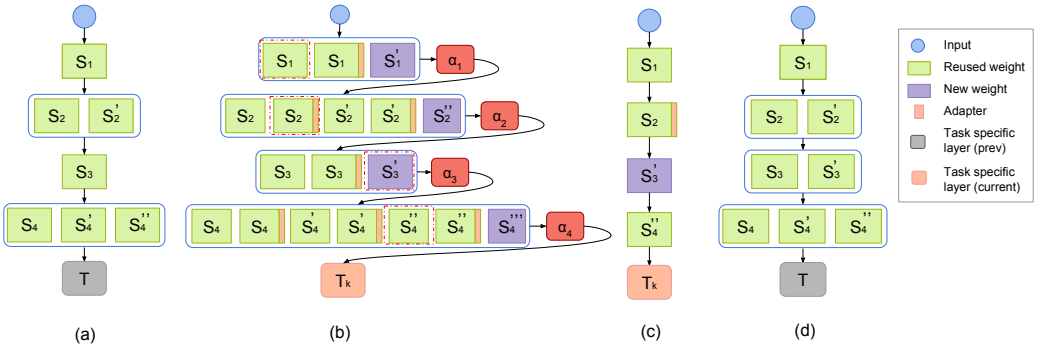

Figure 2: Illustration of the training pipeline of our framework. a) Current state of super model. In this example, the 1st and 3rd layers have single copy of weight, while the 2nd and 4th has two and three respectively. b) During search, each copy of weight for each layer will have a "reuse" and an "adaptation" options plus a "new" option, thus totally $2|S^l|+1$ choices. α is the weight parameters for the architecture. c) Parameter optimization with selected architecture on the current task k. d) Update super model to add the newly created $S_3^{'}$.

$|\mathcal{S}^l|$ "reuse", $|\mathcal{S}^l|$ "adaptation" and 1 "new". Thus, the total search space is $\prod_l^L C_l$. One potential issue here is that, in worst case, the search space may grow exponentially with respect to the number of tasks. One way of dealing with this is to limit the total number of possible choices, and make use a priority queue for managing the options. However, we do not find this necessary in all of our experiments.

Similar to DARTS (Liu et al., 2018), to make the search space continuous, we relax the categorical choice of the l_{th} layer as a softmax over all possible C_l choices:

$$x_{l+1} = \sum_{c=1}^{C_l} \frac{\exp(\alpha_c^l)}{\sum_{c'=1}^{C_l} \exp(\alpha_{c'}^l)} g_c^l(x_l) \tag{5}$$

Here, the vector α^l of dimension C_l is the architecture weights that are used for mixing the choices for each sharealbe layer. And g_c^l here is the operator for the choice c at layer l which is expressed as:

$$g_c^l(x_l) = \begin{cases} S_c^l(x_l) & \text{if } c \leq |\mathcal{S}^l|, \\ S_c^l(x_l) + \gamma_{c-|\mathcal{S}^l|}^l(x_l) & \text{if } |\mathcal{S}^l| < c \leq 2|\mathcal{S}^l|, \\ o^l(x_l) & \text{if } c = 2|\mathcal{S}^l|+1 \end{cases} \tag{6}$$

Here, γ is the adapter operator and o is the new operator training from scratch. After this relaxation, the task of discrete search become optimizing a set of continuous weights $\alpha = \{\alpha^l\}$. After finishing the searching, the optimal architecture could be obtained by taking the index with the largest weight α_c^l for each layer l, i.e. $c_l = \arg\max \alpha^l$.

Adopting the training strategy from DARTS. We use validation loss L_{val} to update the architecture weights α, while the operator weights are optimized by the training loss L_{train}. The architecture weights and operator weights are updated alternately during the search process. Because it is a nested bi-level optimization problem, the original DARTS provide a second-order approximation for more accurate optimization. In this work, we find it is sufficient to use the simple alternately update approach, which was referred as the first-order approximation in (Liu et al., 2018).

To make it clear how "reuse", "adaptation" and "new" operator works, we walk through a concrete example in the following. Let us take a convolutional neural network (CNN) with all the layers using 3x3 kernel size as an example. The choice of "reuse" is just using the existing weight and keep it fixed during learning, thus there is no additional parameter cost. For "adaptation", it could be a 1x1 conv layer added to the original 3x3 conv layer in parallel (i.e. similar to the adaptor used in paper (Rebuffi et al., 2017a)). During training, the weight of the original 3x3 conv is kept fixed, while the parameters of the 1x1 conv adapter is modified. In this case, the additional parameter cost is only 1/9 of the original parameter size. In case of "new", it is literally start with a new operator that initialized randomly and train from scratch. We make use of the loss function L_{val} to implement the

regularizer for the structure $\mathcal{R}_i^s(s_i)$. The value of the loss function is set proportional to the product of the additional parameter size z_c^l and its corresponding weight α_c^l. The architecture weights α is optimized in terms of both accuracy and parameter efficiency at the same time.

3.2 Parameter Optimization

After we get the optimal choices for each layer from the search procedure, we retrain the optimal architecture on the current task. There are two strategies to deal with "reuse", we can either fix it unchanged during retraining just as in search, or we can tune it with some regularization – simple ℓ_2 regularization or more sophisticated regularizations like elastic weight consolidation (Kirkpatrick et al., 2017). The former strategy could avoid forgetting completely, however it will lose the chance of getting positive backward transfer, which means the learning of new task may help previous tasks performance. When the search process select "reuse" at layer l, it means that the l_{th} layer tends to learn very similar representation as it learned from one of the previous tasks. This is an indication of semantic similarity learned at this layer l between the two tasks. Thus, we conjecture that tuning the l_{th} layer with some regularization could also benefit the previous tasks, or at least reduce catastrophic forgetting due to the semantic relationships. In the experiment section, we investigate this hypothesis in more detail. Finally, After retrained on the current task, we need to update/add the created and tuned layers, task-specific adapters and classifiers in the maintained super network. It will be used for model inference and also can be the basis for future architecture search on new tasks.

4 How Explicit Structure Learning Affects Continuous Learning

In this section, we test two main hypothesis that leads to our framework. First, does making structure learning explicit leads to discovery of sensible model architectures for corresponding tasks? Second, if so, does this leads to better continuous learning? We test these two hypothesis on two datasets: permuated MNIST and the visual domain decathlon dataset (Rebuffi et al., 2017a). The permutated MNIST dataset is a simple image classification problem that derived from the MNIST handwritten digit dataset (Yann LeCun, 1998), which is commonly used as benchmark in continual learning literature (Kirkpatrick et al., 2017; Lopez-Paz et al., 2017; Zenke et al., 2017). For each task, a unique fixed random permutation is used to shuffle the pixels of each image, but the label corresponding to the image is kept fixed. The visual decathlon dataset consists of 10 image classification tasks – ImageNet, CIFAR100, Aircraft, DPed, Textures, GTSRB, Omniglot, SVHN, UCF101 and VGG-Flowers. The images of all the tasks are resized to lower-edge be 72 pixels. And the tasks are across multiple domains and dataset sizes are highly imbalanced, which makes it a good candidate to investigate the continual learning problem with potential inter-task transfer.

For all MNIST experiments, we use a 6-layer fully-connected neural networks with 5 feed-forward layers and the $6th$ layer is the task-specific softmax classification layer, as shown in Figure 3(a). We apply our implementation of the framework for learning 10 permuated MNIST tasks in sequence. For simplicity, we only use two choices, "reuse" and "new", during the structure optimization.

For experiments on visual decathlon dataset, we use a 26-layer ResNet (He et al., 2016) as the base network to learn the first task. This network consists of 3 residual blocks, each output 64, 128, 256 channels. Each residual block contains 4 residual units, each of which consists of two convolutional layers with 3×3 kernels and a skip connection. At the end of each residual block, the feature resolution is halved by average pooling. We adopt three type of choices during the search, i.e. "reuse", "adaptation" and "new". For "adaptation", a 1×1 convolution layer with channels equal to the current layer output channels is added for the corresponding layer. The convolved results are then added back to the convolution output. During training, the weight of the original layer is kept fixed, while the 1×1 layer is adjusted.

4.1 Does Explicit Structure Learning Leads to Sensible Structures?

We first experimented on the permutated MNIST dataset. One would expect a sensible architecture for these tasks tends to share higher level structures but differs at lower layers. This is because the high level semantic information of digits is identical throughout, which should imply similar high

level structures. However, since the input pixels are all shuffled differently, the lower level features would need to be different. This implies different parameter values should be used in lower layers. Interestingly, our experiments show that the structure optimization chooses the same configuration that make brand new first layer and reuse all of the following four layers in all the 10 tasks (see Figure 3 b). This exactly confirms the prediction that we had before, which is a good indication that the structure optimization is working properly.

To further demonstrate that the learned structure indeed make sense, we performed additional experiments. Since during the search process on each new task, our model always trying to "new" the first layer and "reuse" the other layers. So, the simple question could be raised here is that what if we use new parameters for other layers? Because the five feed-forward layers has similar input and output dimensions, it's fair to compare the five setups that the ith layer is "new" and others are "reuse". In the results, we found that using new parameters in the first layer is actually the best choice compared with other situations (see Fig. 3 d). Making the second layer as "new" also results in less forgetting compared with making one of the last three layers as "new".

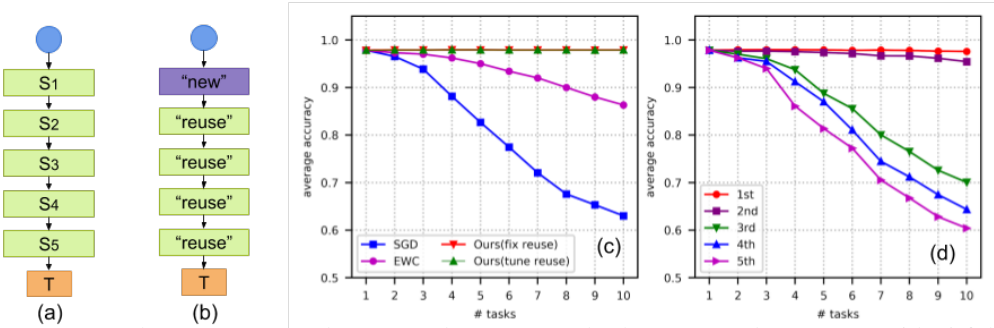

Figure 3: Results on permutated MNIST dataset. a) The base network structure with 5 fully-connected layers and 1 task specific classifier. b) The searched architecture results from running 10 permutated MNIST sequentially. The first layer always choose to "new", while other layers choose to "reuse". c) Comparing our method (both fix reuse and tune reuse) with SGD and EWC on the average accuracy over the seen tasks. d) Ablation experiments of "new" different layers in terms of average accuracy over the seen tasks.

Next, we run experiments on the visual decathlon dataset, which is a more realistic image dataset. To see if the results from structure optimization is consistent with what we have previously, we did two experiments. We first test on a similary task pair, i.e. ImageNet and CIFAR-100. In this case, the images are all natural images, although the size of objects are largely different, most of the representation should still be very similar. Indeed, as we can see from left of Fig. 5, most of the layers are shared for these two tasks. Next, we tested on two drastically different tasks, i.e. ImageNet and Omniglot. Since these are two very different visual tasks, we would expect minimal sharing in the resulting structure. As can be see from right of Fig. 5, most of the resulting structure leads to use option "new".

The above experiments suggest that structure optimization indeed resulting in sensible task specific structures. The learned task structure tends to share when the semantic representation of corresponding layers are similar, and spawn new parameters when the required information is very different.

4.2 Does Explicit Structure Learning Affects Forgetting?

With first hypothesis confirmed, the next natural question is – do sensible structures lead to better continuous learning capability. More specifically, will explicit structure learning help catastrophic forgetting in any way?

First, we run experiments on the permutated MNIST dataset. As mentioned in Section 3.2, we have two strategies when the search result gives "reuse" for a certain layer. We can either fix the reused weight during retraining without the risk forgetting, or we can apply tuning on the "reused" layers. As a baseline, we shown that simply updating all the layers with stochastic gradient descent (SGD) results in catastrophic forgetting (see Fig. 3 c). After training 10 tasks, the average accuracy dropped from 97.9% to 63.0%. With the elastic weight consolidation

(EWC) (Kirkpatrick et al., 2017), the forgetting was alleviated to 86% average accuracy over 10 tasks. For our approach, we found that tuning the "reuse" layers by using simple ℓ_2 based regularization on previous task parameter is safe enough in terms of forgetting and both strategies can keep the overall accuracy as high as training each task individually (see Fig. 3). Although our method costs about 1/5 additional parameters (the first fc layer) starting from the second task.

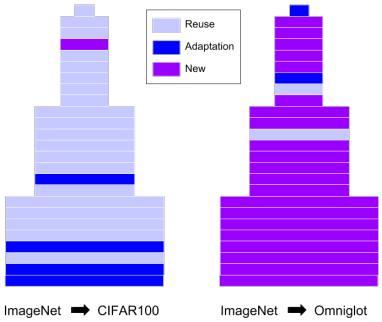

Figure 4: Visualization of searched architecture with learning two tasks sequentially. The search are based on the super model obtained by training ImageNet as first task. (a) and (b) shows searched architecture on CIFAR100 and Omniglot task respectively.

Next we run a similar experiment on the visual decathlon dataset. All ten tasks are trained in order of ImageNet, CIFAR-100, SVHN, UCF101, Omniglot, GTSR, DPed, Flower, Aircraft and Textures. As a baseline we also train a model that shares all parts of the structure. Both models are trained with simple ℓ_2 regularization on model weights between tasks. As can be seen from figure 5, the performance from our approach with explicit learning of structure constantly out performs the baseline, suggests a lot less forgetting when transfer between different tasks. We would like to note that simple ℓ_2 based regularization does not prevent forgetting in general in a multi-task setting. This is because using too strong regularization would leads to model parameters that are very close to the original task, which would then prevent the model from learning new tasks. Smaller regularization helps, however, as the number of tasks increase, the distance between the last model parameter and the very first could be significant, even though each successive distances are small. For baseline model we need to use relatively large regularizations, and thus leads to worse performance of new tasks. Using smaller regularization in baseline leads to significant forgetting. Observing significantly less forgetting may suggests that the model parameters does not move much, or moved on the same level set of the loss surface.

4.3 Comparison with Other Methods

In the multi-task continual learning experiments, the 10 tasks was trained in a random sequence except the first task was fixed to be ImageNet. This is just for fair comparison with other works such as Rebuffi et al. (2017a) and Mallya & Lazebnik (2018), they are all using a light weight module to adapt ImageNet pretrained model to other of the 9 tasks. In real case, the tasks can come in any order, thus our framework would be much more flexible. As the tasks are trained in sequence, a super model is maintained that all the newly created weights and task-specific layers are stored. In this ResNet-26 model, all the Batch Normalization (BN) layers are treated as task-specific, which means each task has its own sets of BNs. Here, we fixed the weight during retraining when "reuse" is selected in the search phase. This means that the results of previous tasks would not be affected, i.e. no forgetting. We leave the evaluation of forgetting in the context of VDD dataset as future work.

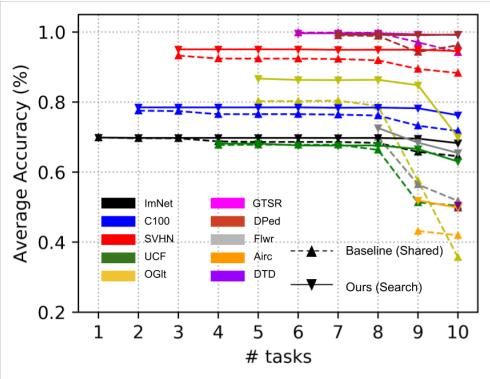

Figure 5: Comparison catastrophic forgetting effect between our proposed approach and baseline on visual decathlon dataset.

In Table 1, we compare the results using our approach with other baselines. "Individual" means that each task is trained individually and weights are initialized randomly. "Classifier" means that only the last layer classifier could be tuned while the former 25 layers are transfer from ImageNet pretrained model and kept fixed during training. In this case, each task only adds a task-specific classifier and BNs, thus the overall model size is small. "Adapter" add a 1x1 conv layer besides

each 3x3 conv layer, and the outputs will be added before proceed to the next layer. Due to the lightweight 1x1 conv layer, each task will add approximately 1/9 of the whole model size. As shown in table 1, the results achieved by our framework is better than other baselines and the total model size is similar to "Adapter" case. We can see that our approach gives best results in five out of nine tasks. Especially in task with small data size, e.g. VGG-Flowers and Aircraft, our method outperforms other baselines by a large margin.

Due to each choice has different parameter cost, we add a parameter loss function to L_{val} to penalize the choices that cost additional parameters. And the value of the loss function is proportional to the product of the additional parameter size and its corresponding weight value α_c^l. In table 2, we test it with three different scaling factor β of the parameter loss. We found that the scaling factor β can control the additional parameter size for each task. And we find that $\beta = 0.1$ gives the best average accuracy and can control the total model size approximate $2.3\times$ compared with the original model size.

Model	ImNet	C100	SVHN	UCF	OGlt	GTSR	DPed	Flwr	Airc.	DTD	avg.	#params
Individual	69.84	73.96	95.22	69.94	86.05	**99.97**	**99.86**	41.86	50.41	29.88	71.70	58.96
Classifier	69.84	77.07	93.12	62.37	79.93	99.68	98.92	65.88	36.41	48.20	73.14	6.68
Adapter	69.84	**79.82**	94.21	70.72	85.10	99.89	99.58	60.29	50.11	**50.60**	76.02	12.50
Search (Ours)	69.84	79.59	**95.28**	**72.03**	**86.60**	99.72	99.52	**71.27**	**53.01**	49.89	**77.68**	14.46

Table 1: Results of the (top-1) validation classification accuracy (%) on Visual Domain Decathlon dataset. The total model size ("#params") is the total parameter size (in Million) after training the 10 tasks.

		ImNet	C100	SVHN	UCF	OGlt	GTSR	DPed	Flwr	Airc.	DTD	Tot.
$\beta = 0.01$	acc	69.84	78.50	95.33	72.50	86.41	99.97	99.76	66.01	51.37	50.05	76.97
	#params	6.07	0.15	2.74	2.28	6.17	3.59	1.02	0.19	4.15	0.13	26.49
$\beta = 0.1$	acc	69.84	79.59	95.28	72.03	86.60	99.72	99.52	71.27	53.01	49.89	77.68
	#params	6.07	0.34	1.19	1.32	3.19	0.02	0.27	0.16	1.86	0.04	14.46
$\beta = 1.0$	acc	69.84	78.00	93.40	63.83	84.30	99.78	99.01	65.77	39.27	48.77	74.20
	# params	6.07	0.04	0.03	0.12	0.66	0.02	0.01	0.02	0.35	0.02	7.34

Table 2: Comparison of (top-1) validation classification accuracy (%) and total model size (in Million) on Visual Domain Decathlon dataset with parameter loss factor β of 0.01, 0.1, 1.0.

5 Related Work

Continual learning (Thrun & Mitchell, 1995) is a challenging problem, as models have the tendency to forget previously learned knowledge when learning on new information (Thrun & Mitchell, 1995; McCloskey & Cohen, 1989). This is referred as catastrophic forgetting problem in the literature. Early attempts to alleviate catastrophic forgetting often consists of memory system that store previous data and replay the sampled old examples with the new data (Robins, 1995), and similar approaches are still used today (Rebuffi et al., 2017b; Li et al., 2018; Lopez-Paz et al., 2017). Another class of common method for mitigating catastrophic forgetting is through regularization which imposes constraints on the update of neural weights. Kirkpatrick et al. (2017) proposed elastic weight consolidation (EWC), which tries to minimize the change of weights that are important to previous tasks through the use of a quadratic constraint. Zenke et al. (2017) proposed to alleviate catastrophic forgetting by allowing individual synapse to estimate their importance for solving a learned task, then penalize the change on the important weights. One could also completely avoid forgetting by preventing changes to previous task weights (see for example Rusu et al., 2016; Mallya & Lazebnik, 2018; Fernando et al., 2017).

Another class of methods for continuous learning is allowing the model to expand. Dynamically expandable networks (Lee et al., 2017) select whether to expand or duplicate based on certain criteria on the new task. However, the model on the new task is forced to use the old structure from previous tasks. Our framework is more flexible, as it allows model to choose whether to use previous structures.

Our work also relates to neural architecture search (Stanley & Miikkulainen, 2002; Zoph & Le, 2016; Baker et al., 2017; Liu et al., 2018), as we employ search methods for the implementation of structure optimization. In particular, DARTS (Liu et al., 2018), where a continuous relaxation for architecture search is proposed. This allowed more efficient structure optimization, and hence employed in our work.

6 Conclusion

In this work, we propose to explicit take into account structure optimization in a continuous learning setting. Empirically, we found that explicit learning of structure does lead to learning of sensible structures for each of the tasks. In particular, lower level features are shared more in case the input representations are more similar, and higher level representations tends to share when the high level semantic has commonality. Additionally, the catastrophic forgetting problem gets alleviated with structure optimization. We achieved reasonable performance on all tasks, and simultaneously minimized forgetting by only use simple ℓ_2 based regularization. This suggests that structure learning plays a significant role in the catastrophic forgetting problem. Moreover, we achieved competitive or better performance as compared to all baselines on the visual decathlon dataset.

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