Abstract

Deep learning has achieved state-of-the-art performance on several computer vision tasks and domains. Nevertheless, it still demands a high computational cost and a significant amount of parameters that need to be learned for each new domain. Such requirements hinder the use in resource-limited environments and demand both software and hardware optimization. Multi-domain learning addresses this problem by adapting to new domains while retaining the knowledge of the original domain. One limitation of most multi-domain learning approaches is that they usually are not designed for taking into account the resources available to the user. Recently, some works that can reduce computational complexity and amount of parameters to fit the user needs have been proposed, but they need the entire original model to handle all the domains together. This work proposes a method capable of adapting to a user-defined budget while encouraging parameter sharing among domains. Hence, filters that are not used by any domain can be pruned from the network at test time. The proposed approach innovates by better adapting to resource-limited devices while being able to handle multiple domains at test time with fewer parameters and lower computational complexity than the baseline model.

1 Introduction

Deep learning has brought astonishing advances to computer vision, being used in several application domains, such as medical imaging, autonomous driving, road surveillance, and many others [3, 5]. However, to increase the performance of such methods, increasingly deeper architectures have been used [6], leading to models with a high computational cost. Also, for each new domain (or task to be addressed), a new model is usually needed [1]. The significant amount of model parameters to be stored and the high GPU processing power required for using such models can prevent their deployment in computationally limited
devices, like mobile phones and embedded devices [3]. Therefore, specialized optimizations at both software and hardware levels are imperative for developing efficient and effective deep learning-based solutions [4].

For these reasons, there has been a growing interest in the Multi-Domain Learning (MDL) problem. The basis of this approach is the observation that, although the domains can be very different, it is still possible that they share a significant amount of low and mid-level visual patterns [5]. Therefore, to tackle this problem, a common goal is to learn a single compact model that performs well in several domains while sharing the majority of the parameters among them with only a few domain-specific ones. This reduces the cost of having to store and learn a whole new model for each new domain.

Berriel et al. [1] point out that one limitation from MDL methods is that their computational complexity is at best equal to that of the backbone model used. Therefore, they are not capable of adapting their complexity to custom hardware constraints or user-defined budgets. To address this issue, they proposed the modules named Budget-Aware Adapters (BA²) that were designed to be added to a pre-trained model in order to allow them to handle new domains and to limit the network complexity according to a user-defined budget. They act as switches, selecting the convolutional channels that will be used in each domain. However, as mentioned in [1], although the use of this method reduce the amount of parameters required for each domain, the entire model is still required at test time if it aims to handle all the domains. The main reason is that they share few parameters among the domains, which forces loading all potentially needed parameters for all the domains of interest.

This work builds upon the BA² [1] by encouraging multiple domains to share convolutional filters. Figure 1 shows an overview of the problem addressed by our method, comparing it to previous MDL solutions and emphasizing their limitations. As it can be seen, standard adapters use the entire model, while BA² [1] reduces the number of parameters used in each domain, but requiring a different set of parameters per domain. Therefore, the entire model is needed for handling all the domains together. Our improved version of BA² increases the probability of using a similar set of parameters for all the domains. In this way, the parameters that are not used for any of the domains can be effectively pruned at test time. These compact models have a lower number of parameters and computational complexity than the original backbone model, which facilitates their use in resource-limited environments. To enable the generation of the compact models, we propose a new loss function that encourages the sharing of convolutional features among distinct domains. Our proposed approach was evaluated on the Visual Decathlon Challenge [11], a well-known benchmark comprising 10 different image domains. Results show that our approach is comparable to the state-of-the-art methods in terms of classification accuracy, with the advantage of having considerably lower computational complexity and number of parameters than the backbone.

2 Related Work

Previous approaches to adapt an existing model to a new domain used strategies like fine-tuning and pre-training, but faced the problem of catastrophic forgetting, in which the new domain is learned, but the old one is forgotten [1]. More recent MDL approaches usually leverage a pre-trained model as backbone. The backbone parameters are basically frozen and shared among all domains, while attempting to learn a limited and much lower amount of new domain-specific parameters [1]. Approach mostly differ from each other according to the manner the domain-specific parameters are designed, for example, domain-specific
Figure 1: The multi-domain learning (MDL) problem, where a pre-trained model is adapted to handle new domains. In standard adapters, the amount of parameters from the domain specific models (indicated in colored $C$) is equal or greater than the backbone model (due to the mask represented in black). Budget-Aware Adapters can reduce the amount of parameters required for each domain (not-used parameters are denoted in gray). However, the whole model is needed at test time if handling distinct domains (colored areas share few parameters). Our improved version with parameters sharing encourages different domains to use the same parameters (colored areas share most of the parameters). Thus, when handling multi-domains at test, the unused parameters can be pruned without affecting the domains.

residual blocks and binary masks [1].

For methods that use residual blocks to learn new domains, an example is the work of Rebuffi et al. [11] that adds domain-specific parameters to the ResNet network in the form of serial residual adapter modules, and another is the extended version presented in [12] that proposes switching to parallel residual adapters. These modifications lead to an increase in accuracy and also a reduction in domain-specific parameters.

Following a different path, some works make use of binary masks to prune different convolutional filters of the network for each domain, like the Piggyback method proposed by Mallya et al. [7]. The mask is initially learned with real values during training and then is thresholded to obtain binary values. In test time, the learned binary mask is multiplied by the weights of the convolutional layer, keeping the value of some of them and setting the others to zero, generating a selection of different weights for each domain learned. Expanding on this idea, Mancini et al. [8] also makes use of masks, however, unlike Mallya et al. [7], that performs a multiplication, this approach learns an affine transformation of the weights through the use of the mask and some extra parameters. This work is further extended in [9] by using a more general affine transformation and combining it with the strategy used by Mallya et al. [7]. Focusing on increasing the accuracy with masks, Chattopadhyay et al. [2] proposes a soft-overlap loss to encourage the masks to be domain specific by minimizing the overlap between them. They were motivated by the fact that most domain generalization methods focus mainly on domain-invariant features, but domains usually have unique characteristics.

The works mentioned so far mainly focused on improving accuracy while attempting to add a small number of new parameters to the model, but they do not take into consideration the computational cost and memory consumption, making their utilization on resource-limited devices difficult [14]. Trying to address that, recent works have attempted to tackle the multiple-domain learning problem while taking into account resource constraints.
In regards to the parameters sharing, Wallingford et al. [13] proposed the Task Adaptive Parameter Sharing (TAPS), which learns to share layers of the network for multiple tasks while having a sparsity hyperparameter defined by the user. This is performed by adding a scoring parameter to each shared layer. If this learnable parameter is greater than a specific threshold, the layer becomes task specific by adding a learnable perturbation to their weights.

As pointed out by Berriel et al. [1], all the methods presented so far have computational complexity at best equal to the backbone model. They addressed this issue by proposing Budget-Aware Adapters (BA2), which are added to a backbone model, enabling it to learn new domains while limiting the computational complexity according to the user budget. The BA2 modules are similar to the approach from Mallya et al. [7], that is, masks are applied to the convolutional layers of the network, selecting a subset of filters to be used in each domain. The masks are made of real values that are binarized during the forward pass but are used as real values during backpropagation. The network is encouraged to use a smaller amount of filters per convolution layer than a user-defined budget, being implemented as a constraint to the loss function that is optimized by constructing a generalized Lagrange function. During test time, for a specific domain, the unused filters can be discarded reducing the computational complexity of the model. Also, the parameters from batch normalization layers are domain-specific, since they perform poorly when shared. This is the only method presented so far that is capable of achieving a lower computational complexity than the original backbone model, being able to adapt to the user and task needs. However, the entire model is still required to handle all the domains at test time, since each domain might use a different subset of parameters hindering the pruning of the unused ones [1].

3 Budget-Aware Adapters with Parameter Sharing

This work was built upon the BA2 modules from Berriel et al. [1] by adding an extra loss to encourage parameter sharing among domains and by performing a simultaneous training in order to enable handling all the domains together at test time. As a result, the proposed method is able to prune and reduce the amount of parameters from the original backbone model even when dealing with multiple domains at test time, while also reducing the computational complexity (see Figure 2 for an overview).
3.1 Problem Formulation

The main goal of MDL is to learn a single model that can be used in different domains. One possible approach is to have a fixed pre-trained backbone model with frozen weights that are shared among all domains, while learning only a few new domain-specific parameters. Equation 1 describes this approach, where \( \Psi_0 \) is the pre-trained backbone model that when given input data \( x_0 \) from the domain \( X_0 \) return a class from domain \( Y_0 \) considering \( \theta_0 \) as the models weights. Our goal is to have a model \( \Psi_d \) for each domain \( d \) that attributes classes from the domain \( Y_d \) to inputs \( x_d \) from the domain \( X_d \) while keeping the \( \theta_0 \) weights from the backbone model and learning as few domain-specific parameters \( \theta_d \) as possible.

\[
\Psi_0(x_0; \theta_0) : X_0 \rightarrow Y_0
\]

\[
\Psi_d(x_d; \theta_0, \theta_d) : X_d \rightarrow Y_d
\]

Our starting point was the BA\(^2\) [1] modules, which are associated with the convolutions layers of the network, enabling them to reduce their complexity according to a user-defined budget. Equation 2 describes one channel of the output feature map \( m \) at the location \((i, j)\) of a convolutional layer, where \( g \) is the activation function, \( K \in \mathbb{R}^{(2K_H+1) \times (2K_W+1) \times C} \) is the kernel weights with height of \( 2K_H + 1 \), width of \( 2K_W + 1 \) and \( C \) input channels, and \( I \in \mathbb{R}^{H \times W \times C} \) is the input feature map with \( H \) height, \( W \) width and \( C \) channels.

\[
m(i, j) = g(C\sum_{c=1}^{C} \phi_c(i, j)) \tag{2}
\]

\[
\phi_c(i, j) = \sum_{h=-K_h}^{K_h} \sum_{w=-K_w}^{K_w} K(h, w, c)I(i-h, j-w, c)
\]

Berriel et al. [1] proposed to add a domain-specific mask that is composed of \( C \) switches \( s_c \) for each input channel, as shown in Equation 3. At training time, \( s_c \in \mathbb{R} \) while, at test time, they are thresholded to be binary values. When \( s_c = 0 \), the weights \( K_c \) (i.e., the filters for the \( c \) input channel for a given output channel) can be removed from the computational graph, effectively reducing the computational complexity of the convolutional layers.

\[
m(i, j) = g(C\sum_{c=1}^{C} s_c \phi_c(i, j)) \tag{3}
\]

The model is trained by minimizing the total loss \( L_{total} \), which is composed of the cross entropy loss \( L \) and a budget loss \( L_B \), as shown in Equation 4, where \( \beta \in [0, 1] \) is a user-defined budget, \( \theta_d^\beta \) are the domain-specific parameters for the budget \( \beta \) and domain \( d \), \( \bar{\theta}_d^\beta \) is the mean value of the switches for all convolutional layers and \( \lambda \) is the Karush-Kuhn-Tucker (KKT) multiplier.

\[
L_{total} = L(\theta_0, \theta_d^\beta) + L_B(\theta_d^\beta, \beta) \tag{4}
\]

The budget loss is given by \( L_B(\theta_d^\beta, \beta) = \max(0, \lambda(\bar{\theta}_d^\beta - \beta)) \). When the constraint \( \bar{\theta}_d^\beta - \beta \) is respected, \( \lambda = 0 \), otherwise, the optimizer increases the value of \( \lambda \) to boost the impact of the budget.
3.2 Encouraging the Sharing of Parameters

Although BA$^2$ can reduce the computational complexity of the model, it can not reduce the number of parameters necessary to handle all the domains together. Switches $s_c$ can only be pruned at test time when they are zero for all domains, but they, in fact, assume different values if not forced to do so.

For this reason, we added an additional parameter sharing loss $L_{PS}$ to $L_{total}$, as described in Equation 5, where $N$ is the number of domains, $\theta^\beta_k$ for $k \in [1, ..., N]$ are the domain-specific parameters (switches) for each domain, $M$ is the total number of switches and $\lambda_{PS}$ is a hyperparameter that defines the importance of this loss component.

$$L_{total} = L(\theta_0, \theta^\beta_d) + L_B(\theta^\beta_d, \beta) + L_{PS}(\theta^\beta_1, ..., \theta^\beta_N, \beta)$$

$$L_{PS}(\theta^\beta_1, ..., \theta^\beta_N, \beta) = \max(0, \lambda_{PS}(1 - \frac{|\theta^\beta_1 \cap \theta^\beta_2 \cap ... \cap \theta^\beta_D|}{M\beta}))$$

The parameter sharing loss calculates the intersection of all the domains masks and encourages it to grow up to the budget limitation. Since the domain-specific weights from all the domains are required by this loss component, it is necessary to train on all of them simultaneously. Finally, the switches $s_c$ and the associated kernel weights $K_c$ can be pruned.

4 Experiments and Results

In this section, we present the experiments that were carried out and their results. First, we describe the experimental setup in detail. Then, the results on the well-known Visual Decathlon Challenge are provided together with discussions. Finally, we perform and report results of an additional analysis.

4.1 Experimental Setup

Our approach was validated on the Visual Decathlon Challenge [11], a well-known MDL benchmark. It comprises classification tasks on ten diverse well-known image datasets from different visual domains: ImageNet, Aircraft, CIFAR-100, Daimler Pedestrian (DPed), Describable Textures (DTD), German Traffic Signs (GTSR), VGG-Flowers, Omniglot, SVHN and UCF-101. Such visual domains are very different from each other, ranging from people, objects, and plants to textural images. The goal of this challenge is to reward methods that have a good performance over all the domains. To assess the performance of each method, it was proposed an evaluation metric named S score [11], which is given by Equation 6:

$$S = \sum_{d=1}^{10} \alpha_d \max\{0, Err_d^{max} - Err_d\} \gamma_d$$

where $Err_d$ is the classification error obtained on the dataset $d$, $Err_d^{max}$ is the maximum allowed error from which points are no longer added to the score and $\gamma_d$ is a coefficient to ensure that the maximum possible $S$ score is 10.000 [11]. In addition to the $S$ score, we also reported the classification accuracy on each domain and the mean accuracy over all of them.

To assess the computational cost of a model, we considered its amount of parameters and computational complexity. For the number of parameters, we measured their memory usage,
excluding the classifier and encoding float numbers in 32 bits and the mask switches in 1 bit. For the computational complexity, we used the THOP library to calculate the amount of multiply-accumulate operations (MACs) for our approach, while we reported the values from [1] for the original BA$^2$. All reported values are relative to the backbone size, as in [1].

In addition to such performance metrics, we also reported the sparsity among all domains, which is given by the average amount of filters that are discarded per layer, not being used in any domain. This leads to an effective reduction in the amount of parameters and computational complexity. Similar to [1], in order to assess the trade-off between effectiveness on the MDL problem and computational efficiency, we consider two variations of the S score, named as $S_O$, which is the S score per operation; and $S_P$, the S score per parameter.

We adopted the same experimental protocol of Berriel et al. [1], only making the necessary adjustments for our objective of sharing filters among different domains. The Wide ResNet-28 [15], pre-trained on ImageNet was used as the backbone model, keeping all of the weights frozen and only training the domain-specific parameters (i.e., classifiers and masks). SGD with a momentum of 0.9 and a learning rate of $10^{-3}$ was used for the classifier, while Adam with learning rate of $10^{-4}$ was used for the masks. The model was trained using a mini-batch size of 32 for 60 epochs. Step-decay is used to reduce the initial learning rates by a factor of 10 at the epoch 45. The switches from the masks are initialized with the value $10^{-3}$. Data augmentation with random crop and horizontal mirroring with a probability of 50% was used on the training phase, except for DTD, GTSR, Omniglot and SVHN, where mirroring did not improve results or was harmful. For testing, we used five crops (center and 4 corners) for the datasets without mirroring, and 10 crops for the others (5 crops and their mirrors). The final prediction is an average of all crops.

Differently from Berriel et al. [1], we needed to train all the domains simultaneously, since we want to encourage the sharing of weights among them. In order to do so, we run one epoch of each dataset in a round robin fashion. We repeat this process until 60 epochs of each dataset have been run. After obtaining the best hyperparameter configuration, we trained our model on both train and validation sets and evaluated them on the test set, comparing our results with other state-of-the-art methods. Experiments were run using V100 and GTX 1080 TI NVIDIA GPUs, Ubuntu 20.04 distribution, CUDA 11.6, and PyTorch 1.12.

4.2 Results on Visual Decathlon Challenge

Before running the main experiments on the on the test set, a hyperparameter optimization procedure was performed on the validation set, and the remaining experiments were carried out using the best model. Additionally, ablation studies reporting the influence of the simultaneous task training of the model can also be found in the supplementary material.

After obtaining the best hyperparameter configuration, the model was trained on both training and validation sets and evaluated on the test set of the Visual Domain Decathlon. The comparison of the results with state-of-the-art method, BA$^2$, is shown in Table 1.

Our method faced a small drop (up to 2.8%) in mean accuracy compared to [1]. We believe the main reason for this drop in accuracy is the simultaneous training procedure, as a similar drop was observed when switching from individual to simultaneous training (see supplementary material for additional results on the simultaneous training). The simultaneous training is necessary to enable parameter sharing. The individual domains with the biggest accuracy drops were the smaller datasets, like aircraft, DTD, VGG-Flowers and UCF-101. Other works, like Rebuffi et al. [11, 12] also mention subpar performance on these datasets, identifying the problem of overfitting.
Table 1: Accuracy and S-score on the test sets of the Visual Domain Decathlon.

| Method                  | ImNet | Airc. | Cl100 | DPed | DTD  | GTSR | Flwr. | Oglt. | SVHN | UCF  | Mean | S-score |
|-------------------------|-------|-------|-------|------|------|------|-------|-------|------|------|------|---------|
| BA² [1]:                |       |       |       |      |      |      |       |       |      |      |      |         |
| BA² (β = 1.00)          | 56.9  | 49.9  | 78.1  | 95.5 | 55.1 | 99.4 | 86.1  | 88.7  | 96.9 | 50.2 | 75.7 | 3199    |
| BA² (β = 0.75)          | 56.9  | 47.0  | 78.4  | 95.3 | 55.0 | 99.2 | 85.6  | 88.8  | 96.8 | 48.7 | 75.2 | 3063    |
| BA² (β = 0.50)          | 56.9  | 45.7  | 76.6  | 95.0 | 55.2 | 99.4 | 83.3  | 88.9  | 96.9 | 46.8 | 74.5 | 2999    |
| BA² (β = 0.25)          | 56.9  | 42.2  | 71.0  | 93.4 | 52.4 | 99.1 | 82.0  | 88.5  | 96.9 | 43.9 | 72.6 | 2538    |
| Ours (BA² with parameter sharing among domains): |       |       |       |      |      |      |       |       |      |      |      |         |
| Ours (β = 1.00)         | 56.872| 37.294| 80.200| 95.046| 57.926| 98.599| 84.615| 83.820| 95.993| 45.837| 73.620| 2512    |
| Ours (β = 0.75)         | 56.872| 42.574| 75.280| 94.959| 56.064| 98.551| 82.810| 87.234| 95.970| 44.674| 73.499| 2444    |
| Ours (β = 0.50)         | 56.872| 42.094| 73.690| 96.760| 51.277| 98.678| 81.444| 87.123| 96.047| 45.414| 72.940| 2552    |
| Ours (β = 0.25)         | 56.872| 33.633| 67.890| 95.281| 44.894| 98.147| 75.053| 87.381| 96.074| 43.008| 69.823| 1942    |

The S-score also dropped up to 687 points for the same issues. The drop is harsher since the metric was designed to reward good performance across all datasets, and the small datasets we mentioned had subpar performance. Despite facing small drops in accuracy and S-score, our method offers a good trade-off between classification performance and computational cost. Table 2 compares once again the original BA² and our method, taking into account the computational complexity, number of parameters, S-score, $S_O$ and $S_P$.

Table 2: Computational complexity, number of parameters, S-score, $S_O$ and $S_P$ metrics for the original BA² and our approach with parameter sharing on the test sets of the Visual Domain Decathlon.

| Method                  | Complexity | Params | S-score | $S_O$ | $S_P$ |
|-------------------------|------------|--------|---------|-------|-------|
| BA² [1]:                |            |        |         |       |       |
| BA² (β = 1.00)          | 0.646      | 1.03   | 3199   | 4952  | 3106  |
| BA² (β = 0.75)          | 0.612      | 1.03   | 3063   | 5005  | 2974  |
| BA² (β = 0.50)          | 0.543      | 1.03   | 2999   | 5523  | 2912  |
| BA² (β = 0.25)          | 0.325      | 1.03   | 2538   | 7809  | 2464  |
| Ours (BA² with parameter sharing among domains): |            |        |         |       |       |
| Ours (β = 1.00)         | 0.837      | 1.03   | 2512   | 3001  | 2438  |
| Ours (β = 0.75)         | 0.645      | 0.921  | 2444   | 3789  | 2654  |
| Ours (β = 0.50)         | 0.447      | 0.783  | 2552   | 5709  | 3259  |
| Ours (β = 0.25)         | 0.238      | 0.531  | 1942   | 8159  | 3657  |

When comparing computational complexity (column Complexity of Table 2), for the budgets of $\beta = 1.00$ and 0.75, the original BA² had lower values, but for the harsher budgets of $\beta = 0.50$ and 0.25, our methods obtained the lower complexity. This happens due to the fact that the original BA² tends to discard more weights than the demanded when the budget is higher, while our methods tend to stay closer to the amount defined by the budget. It also must be noted that all our methods obtained lower complexity than the value defined by the budget, showing that it is a great tool to adapt a backbone model to the resources available to the user.

By comparing the $S_O$ metric, we can observe that both methods have a good trade-off between computational complexity and S-score, as this metric greatly increases as the budget is reduced, showing that the reduction in computational complexity is considerably greater than the loss in S-score. As expected, our method had better $S_O$ for the harsher budgets of $\beta = 0.50$ and 0.25 while BA² achieved superior results on the budgets of $\beta = 1.00$ and 0.75.

The main advantage of our proposed method is the reduction on the number of parameters of the model, as it is, to our knowledge, one of the only methods that is capable of tackling the problem of multiple-domain learning, while also reducing the number of pa-
parameters in relation to the backbone model. As we can see (column Params of Table 2), the original BA\(^2\) had similar amount of parameters to the backbone model, being 3% more for all budgets. For the budget of \(\beta = 1.00\), we obtained the same result, while for the budget of \(\beta = 0.75\) we reduce the amount of parameters compared to the backbone model in 7.9%, for budget \(\beta = 0.50\), the reduction was of 22.7% and for the for budget of \(\beta = 0.25\) there were 49.9% less parameters. This results shows that our method was successfully in encouraging the sharing of parameters among domains and that this approach can lead to considerable reductions on the amount of parameters of the network. The \(S_P\) metric also show this results, as for the budgets of \(\beta = 0.50\) and 0.25 our method was able to outperform BA\(^2\) by considerably reducing the amount of parameter.

### 4.3 Additional Analysis

Table 3 shows the shared sparsity among different budgets of our model. For reference, the upper bound for such values are also indicated. Notice that the budgets of \(\beta = 0.25\) and 0.50 discard a lot of the same weights, around 33% of 50%. As the budgets increase, the shared sparsity decreases, being 16% for \(\beta = 0.50\) and 0.75 and 14% for all budgets together.

| Budgets          | Shared sparsity / Max shared sparsity |
|------------------|--------------------------------------|
| \(\beta = 0.25\) and 0.50 | 33 / 50                            |
| \(\beta = 0.50\) and 0.75 | 16 / 25                            |
| \(\beta = 0.75\), 0.50 and 0.25 | 14 / 25                            |

Motivated by these results, we also tested to run our experiment incrementally from one budget to the other, starting with the \(\beta = 1.00\) and then transferring the weights and training the model with a restriction of \(\beta = 0.75\), repeating the process sequentially to the budgets of \(\beta = 0.50\) and \(\beta = 0.25\). But none of the models were able to increase sparsity of the network. We believe this occurs because the initial budgets with smaller restrictions found local minimums, and the next more strict budget was not able to optimize the sparsity while forced to discard the same weights.

To verify the robustness of our method to the training stochasticity, we did 5 runs of our best method. The results can be seen in Table 4. Overall, the standard deviation was small for both mean accuracy and sparsity, being a maximum of approximately 1% and 1.4%, respectively. This results show that our method is robust to variance in the training phase.

| Method       | Accuracy       | Sparsity       |
|--------------|----------------|----------------|
| Ours (\(\beta = 1.00\)) | 73.595 ± 0.508 | 0.001 ± 0.000 |
| Ours (\(\beta = 0.75\)) | 71.919 ± 0.486 | 17.767 ± 0.738|
| Ours (\(\beta = 0.50\)) | 69.994 ± 0.758 | 37.668 ± 1.432|
| Ours (\(\beta = 0.25\)) | 67.326 ± 1.045 | 60.554 ± 0.983|
5 Conclusions

In this paper, we addressed the multiple-domain learning problem while taking into account a user defined budget for computational resources. We propose to encourage the sharing of parameters among domains, allowing us to effectively prune the weights that are not used in any of them, reducing both the computational complexity and amount of parameters to values lower than the original baseline for a single domain. To the best of our knowledge, our work is one of the only ones to do so. Performance-wise, our results were competitive with other state-of-the-art methods while offering good trade-offs between classification performance and computational cost according to the user’s needs. As future work, we intend to evaluate different strategies for encouraging parameter sharing, as well as, testing our method on different network models and benchmarks.

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Parameter Sharing in Budget-Aware Adapters for Multi-Domain Learning: Supplementary Material

In this supplementary material, we include additional analysis of our achievements. Section A discusses the results of training our approach simultaneously on all the domains without our loss function, comparing with the original BA\(^2\) that trains independently on each domain. In Section B, we added our parameter sharing loss to the model and tested different values for the hyperparameter \(\lambda_{PS}\), which weighs the contribution of our loss term. And finally, Section C presents the sparsity values for each domain individually and for all the domains together.

A Training Simultaneously in Multiple Domains

Table 5 presents the results from our run of the original BA\(^2\) method [1], where each domain is trained independently; and an initial version of our approach, in which all domains are trained simultaneously, but without using the parameter sharing loss.

Table 5: Comparison of mean accuracy and sparsity over all the domains together on the validation set of the Visual Decathlon Challenge for BA\(^2\), that is trained independently, and an initial version of our approach, that is trained simultaneously without the parameter sharing loss.

| Method               | Accuracy | Sparsity |
|----------------------|----------|----------|
| BA\(^2\) [1] (Independent training): |          |          |
| BA\(^2\) (\(\beta = 1.00\)) | 75.584   | 0.121    |
| BA\(^2\) (\(\beta = 0.75\)) | 75.080   | 1.623    |
| BA\(^2\) (\(\beta = 0.50\)) | 74.116   | 2.818    |
| BA\(^2\) (\(\beta = 0.25\)) | 72.435   | 25.187   |
| Simultaneous Training: |          |          |
| Ours (\(\beta = 1.00\)) | 73.780   | 0.183    |
| Ours (\(\beta = 0.75\)) | 73.327   | 1.578    |
| Ours (\(\beta = 0.50\)) | 72.386   | 2.491    |
| Ours (\(\beta = 0.25\)) | 69.983   | 21.625   |

As can be seen, there was a small decrease in the mean accuracy after changing the training procedure to be simultaneous in all the domains, up to 2.4 percent. This indicates that domains can affect each other during the training process and that small changes in the training procedures of the method can have effects on the results. Nevertheless, it is necessary to keep this procedure in order to be able to use our loss function to share parameters among different domains, since it demands information from all the domains to work. We also tested freezing the weights of all other domains except for the one from the input data, but our loss function was not able to encourage the sharing of parameter in this scenario.

Another aspect we tested was different strategies for performing the simultaneous training, like having one batch of each dataset, mixed batches with data from all domains, and a round robin approach where we ran one epoch of each dataset in a random order. We chose to use and report only the latter, as it was slightly faster and the accuracy of all was similar.
Besides the accuracy, we also compared the sparsity over all domains, which indicates the average amount of convolutional filters per layer that are not used by any domain and can be discarded at test time, reducing the amount of parameters of the model. As expected, the sparsity is similar for both approaches, being very low for all budgets, except the lowest one, since there is no direct incentive to share parameters among domains, validating our main proposal to add a loss function for accomplish it. For $\beta = 0.25$, there is a sparsity of about 25% for the baseline $BA^2$ and 22% for our modified version with simultaneous training. This is due to the harsh budget restriction, that only allows up to 25% of the network to be used for each domain. Considering this fact, the amount of shared filters is still low, since 75% of the network would need to be kept while only up to 25% is used in each domain.

B Hyperparameter Tuning

After evaluating the training of our method in all the domains simultaneously, we added our parameter sharing loss function to it. Table 6 show the mean accuracy and sparsity over all domains we obtained testing different values of $\lambda_{PS}$, an hyperparameter used to control the emphasis given to the loss function we added.

Table 6: Comparison of mean accuracy and sparsity over all domains together for $BA^2$ with different values of $\lambda_{PS}$ for our parameter sharing loss $L_{PS}$ on the validation set of the Visual Decathlon Challenge.

| Method       | Accuracy | Sparsity |
|--------------|----------|----------|
| $\lambda_{PS} = 1.000$: |          |          |
| $\beta = 1.00$  | 74.047   | 0.001    |
| $\beta = 0.75$  | 71.915   | 18.175   |
| $\beta = 0.50$  | 70.799   | 38.736   |
| $\beta = 0.25$  | 67.999   | 61.984   |
| $\lambda_{PS} = 0.500$: |          |          |
| $\beta = 1.00$  | 72.220   | 0.003    |
| $\beta = 0.75$  | 72.596   | 17.236   |
| $\beta = 0.50$  | 70.261   | 36.516   |
| $\beta = 0.25$  | 67.502   | 59.856   |
| $\lambda_{PS} = 0.250$: |          |          |
| $\beta = 1.00$  | 70.003   | 0.002    |
| $\beta = 0.75$  | 73.417   | 16.121   |
| $\beta = 0.50$  | 71.474   | 36.043   |
| $\beta = 0.25$  | 68.598   | 57.805   |
| $\lambda_{PS} = 0.125$: |          |          |
| $\beta = 1.00$  | 71.385   | 0.001    |
| $\beta = 0.75$  | 72.934   | 13.187   |
| $\beta = 0.50$  | 72.142   | 32.801   |
| $\beta = 0.25$  | 68.060   | 56.575   |

As we can see, for $\lambda_{PS} = 1.0$, our method obtained accuracy up to 4.4% lower than the $BA^2$ baseline, while gaining around 16% in sparsity for the budget of $\beta = 0.75$, and increasing in approximately 36% for $\beta = 0.50$ and 0.25. Such results indicate that our method greatly increase the sparsity of the network, leading to considerable decreases in the number of parameters, with a small trade off in accuracy.
All values of $\lambda_{PS}$ obtained similar accuracies, where different values of $\lambda_{PS}$ where better for different budgets. For sparsity, it was possible to notice a decrease from 1 to 2% for each step of reducing the $\lambda_{PS}$. For this reason, we chose the value of 1.0 for $\lambda_{PS}$ in all the next experiments, since it had similar accuracy to the others, while having the highest sparsity.

## C Sparsity on the Visual Domain Decathlon

Finally, we conducted a deeper analysis on the sparsity obtained on our method, comparing it to the ones obtained by the original BA$^2$, as shown on Table 7. The individual sparsity values for each domain indicates the mean amount of parameters per layer that are not used for predicting for that domain, being the main reason for the reduction on computational complexity of the model. The sparsity over all domains together indicates the mean amount of parameters per layer that are not used by any domain. These parameters can be pruned from the model and are the reason of the parameter reduction present on our approach. The values for ImageNet are not reported since the backbone pre-trained model is used.

### Table 7: Sparsity for each domain individually and over all domains together for BA$^2$ on the validation set of the Visual Decathlon Challenge.

| Method | Airc. | C100 | DPed | DTD | GTSR | Flwr. | Oglt. | SVHN | UCF | All |
|--------|-------|------|------|-----|------|-------|-------|------|-----|-----|
| BA$^2$ ($\beta = 1.00$) | 38.878 | 33.827 | 41.024 | 28.321 | 42.475 | 44.414 | 41.069 | 37.988 | 30.395 | 0.121 |
| BA$^2$ ($\beta = 0.75$) | 44.394 | 35.903 | 44.353 | 39.365 | 45.765 | 47.323 | 44.695 | 42.284 | 41.610 | 1.623 |
| BA$^2$ ($\beta = 0.50$) | 50.549 | 50.325 | 50.802 | 51.102 | 50.979 | 51.087 | 50.707 | 50.497 | 51.117 | 2.818 |
| BA$^2$ ($\beta = 0.25$) | 74.823 | 75.179 | 75.467 | 74.722 | 75.573 | 75.330 | 75.319 | 75.047 | 75.124 | 25.187 |
| Ours (BA$^2$ with parameter sharing among domains) | 8.971 | 27.470 | 33.174 | 6.876 | 8.405 | 41.926 | 12.026 | 11.104 | 17.572 | 0.001 |
| BA$^2$ ($\beta = 1.00$) | 8.971 | 27.470 | 33.174 | 6.876 | 8.405 | 41.926 | 12.026 | 11.104 | 17.572 | 0.001 |
| BA$^2$ ($\beta = 0.75$) | 25.638 | 37.188 | 43.805 | 22.539 | 46.116 | 42.499 | 50.110 | 27.410 | 25.351 | 18.175 |
| BA$^2$ ($\beta = 0.50$) | 50.246 | 57.210 | 58.065 | 46.406 | 67.880 | 57.662 | 68.785 | 50.532 | 49.897 | 38.736 |
| BA$^2$ ($\beta = 0.25$) | 74.652 | 76.097 | 75.757 | 71.109 | 86.609 | 75.331 | 85.448 | 75.034 | 73.185 | 61.984 |

Observing the values of the individual sparsity per domain, we can see that our method obtained sparsity closer to the complement of the budget when compared with the original BA$^2$. We believe this is due to the the parameter sharing loss function, that encourages the intersection of weights among different domains to grow up to the limit of the budget.

Due to the aforementioned reasons, for the budgets of $\beta = 1.00$ and 0.75, the individual sparsity of the original BA$^2$ was slightly bigger for most domains, but for the budgets of $\beta = 0.50$ and 0.25, in most domains, our method obtained slightly higher individual sparsity, since the budget restriction is harsher, making both methods stay close the limit, and in some cases, have values bellow the complement of the budget.

The sparsity over all the domains shows the key advantage of our method, since it is very small for most budgets in the original BA$^2$, while being considerably higher in our method, allowing for the pruning of the model and the reduction on the amount of parameters.