Piggyback: Adding Multiple Tasks to a Single, Fixed Network by Learning to Mask

Technical Report

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Abstract

This work presents a method for adding multiple tasks to a single, fixed deep neural network without affecting performance on already learned tasks. By building upon concepts from network quantization and sparsification, we learn binary masks that “piggyback”, or are applied to an existing network to provide good performance on a new task. These masks are learned in an end-to-end differentiable fashion, and incur a low overhead of 1 bit per network parameter, per task. Even though the underlying network is fixed, the ability to mask certain weights allows for the learning of a large number of filters. We show improved performance on a variety of classification tasks, including those with large domain shifts from the natural images of ImageNet. Unlike prior work, we can augment the capabilities of a network without suffering from catastrophic forgetting or competition between tasks, while incurring the least overhead per added task. We demonstrate the applicability of our method to multiple architectures, and obtain accuracies comparable with individual networks trained per task.

1. Introduction

Deep convolutional networks have shown remarkable performance on a variety of tasks including image classification [18, 33], object detection [8], and semantic segmentation [22]. The most popular method used in prior work [7, 8, 14, 22] for training a deep network for a new task or dataset is fine-tuning an established pre-trained model, such as the VGG-16 [33] trained on ImageNet classification [29]. A major drawback of fine-tuning is the phenomenon of “catastrophic forgetting” [6], by which performance on the old task degrades significantly as the new task is learned, necessitating one to store specialized models for each task or dataset. For achieving progress towards continual learning [15, 26], considered to be a key requirement for Artificial General Intelligence (AGI) [24], the ability to add new tasks to an existing network while avoiding catastrophic forgetting and requiring as few additional parameters as possible is of key importance.

Prior methods for avoiding catastrophic forgetting, such as Learning without Forgetting (LwF) [21] and Elastic Weight Consolidation (EWC) [15], maintain performance on older tasks through proxy losses and regularization terms while modifying network weights. Another recent work, PackNet [23], adopts a different route of iteratively pruning unnecessary weights and fine-tuning them for learning new tasks. Our key intuition develops on two observations made by PackNet: 1) It is necessary to be able to change parameters of all layers, and 2) Not a lot of parameters have to be modified to learn a new task. We question whether the weights of a network have to be changed at all to learn a new task, or whether we can get by with just selectively masking, or setting certain weights to 0, while keeping the rest of the weights the same as before. Based on this idea, we propose a new approach, termed “piggyback”, for adding new tasks to an existing network, without changing any of the weights of this network. We learn to mask weights of an existing “backbone” network for obtaining good performance on a new task, as shown in Figure 1. Binary masks that take values in \{0, 1\} are learned in an end-to-end differentiable fashion while optimizing for the task at hand. These masks are elementwise applied to backbone weights, allowing us to learn a large range of different filters, even with fixed weights. A well-initialized backbone network is crucial for good performance and we find the ImageNet pre-trained network to generalize well to new tasks. After training for a new task, we obtain a per-task mask that essentially piggybacks onto the backbone network and provides performance close to state-of-the-art methods on multiple datasets as well as the newly introduced Visual Decathlon challenge [27].

Our experiments conducted on image classification show
that this proposed method obtains performance similar to using a separate network per task, for a variety of datasets considered in prior work [23] such as CUBS birds [34], Stanford cars [17], Oxford flowers [25], as well datasets with a significant departure from the natural image domain of the ImageNet dataset such as WikiArt paintings [31] and human sketches [4]. We also obtain performance competitive with the best methods [28] on the Visual Decathlon challenge [27] while using the least amount of additional parameters. Further, we demonstrate the applicability of our method to multiple network architectures including VGG-16 [33], ResNets [11, 35], and DenseNets [12].

2. Related Work

While multiple prior works [1, 2, 16] have explored multi-task training, wherein data of all tasks is available at the time of training, we consider the setting in which new tasks are available sequentially, as this is a more realistic and challenging scenario. Prior work that tackles this setting is based on Learning without Forgetting (LwF) [21, 26, 32] and Elastic Weight Consolidation (EWC) [15, 19]. LwF uses initial network responses on new data as regularization targets during new task training, while EWC imposes a smooth penalty on changing weights deemed to be important to prior tasks. An issue with these methods is that it is not possible to determine the change in performance on prior tasks beforehand since all weights of the network are allowed to be modified to varying degrees. PackNet [23] avoids this issue by identifying weights important for prior tasks through network pruning, and keeping the important weights fixed after training for a particular task. Additional information is stored per weight parameter of the network to indicate which tasks it is used by. However, for each of these methods, performance begins to drop as many tasks are added to the network. In the case of LwF, a large domain shift for a new task causes significant drop in prior task performance [21]. For PackNet, performance on a task drops as it is added later to the network due to the lack of available free parameters, and the total number of tasks that can be added is ultimately limited due to the fixed size of the network [23]. Our proposed method does not change weights of the initial backbone network and learns a different mask per task. As a result, the addition of a task does not affect performance on any other task, and is agnostic to task ordering. Further, an unlimited number of tasks can piggyback onto a backbone network by learning a new mask.
The parameter usage masks in PackNet were obtained as a by-product of network sparsification [10], but we choose to learn appropriate masks based on the task at hand. This idea of masking is related to PathNet [5], which learns selective routing through neurons using evolutionary strategies. We achieve similar behavior through an end-to-end differentiable method, which is less computationally demanding. The learning of separate masks per task decouples the learning of multiple tasks, freeing us from having to choose hyperparameters such as batch mixing ratios [16], pruning ratios [23], and cost weighting [21].

Similar to our proposed method, another set of methods adds new tasks by learning additional task-specific parameters. At one extreme is Progressive Neural Networks [30], which duplicates the base architecture while adding lateral connections to layers of the existing network. The newly added parameters are optimized for the new task, while keeping old weights fixed. This method incurs a large overhead as the size of the full network is directly proportional to the number of tasks added. The method of Residual Adapters [27] develops on the observation that linearly parameterizing a convolutional filter bank of a network is the same as adding an additional per-task convolutional layer to the network. The most recent Deep Adaptation Networks (DAN) [28] allows for learning new filters that are linear combinations of existing filters. Similar to these methods, we enable the learning of new per-task filters. However, these new filters are constrained to be masked versions of existing filters. Our learned binary masks incur an overhead of 1 bit per network parameter, smaller than all of the prior work. Further, we do not find it necessary to learn task-specific layer biases and batch normalization parameters.

Our method is based on the technique introduced by Courbariaux et al. [3, 13] for the training of a neural network with binary-valued weights from scratch. The authors maintain a set of real-valued weights that are passed through a binarizer function during the forward pass. Gradients are computed with respect to the binarized weights during the backward pass through the application of the chain rule, and the real-valued weights are updated using the gradients computed for the binarized versions. In [3], the authors argue that even though the gradients computed in this manner are noisy, they effectively serve as a regularizer and quantization errors cancel out over multiple iterations. Subsequent work including [20, 37] has extended this idea to ternary-valued weights. Unlike these works, we do not train a quantized network from scratch but instead learn quantized masks that are applied to fixed, real-valued filter weights. Work on sparsifying dense neural networks, specifically [9], has used the idea of masked weight matrices. However, only their weight matrix was trainable and their mask values were a fixed function of the magnitude of the weight matrix and not explicitly trainable. In contrast, we treat the weight matrix of the backbone network as a fixed constant, and our proposed approach combines the key ideas from these two areas of network binarization and masked weight matrices to learn piggyback masks for new tasks.

3. Approach

The key idea behind our method is to learn to selectively mask the fixed weights of a base network, so as to improve performance on a new task. By learning different binary-valued (0, 1) masks per task, which are element-wise multiplied/masked with network parameters, we can re-use the same underlying base network for multiple tasks, with minimal overhead. Even though we do not modify the weights of the network, a large number of different filters can be obtained through masking. For example, a dense weight vector such as [0.1, 0.9, −0.5, 1] can give rise to filters such as [0.1, 0, 0, 1], [0, 0.9, −0.5, 0], and [0, 0.9, −0.5, 1]. This process is illustrated in Figure 1. In practice, we begin with a network such as the VGG-16 or ResNet-50 pre-trained on the ImageNet classification task as our base network, referred to as the ‘backbone’ network, and associate a real-valued mask variable with each weight parameter of all the convolutional and fully-connected layers. By combining techniques used in network binarization [3, 13] and sparsification [9], we train these mask variables to learn the task at hand in an end-to-end fashion, as described in detail below. The choice of the initialization of the backbone network is crucial for obtaining good performance, and is further analyzed in Section 5.1.

For simplicity, we describe the mask learning procedure using the example of a fully-connected layer, but this idea can very easily be extended to a convolutional layer as well. Consider a vanilla fully-connected layer in a neural network. Let the input and output vectors be denoted by \( \mathbf{x} = (x_1, x_2, \ldots, x_m)^T \) of size \( m \times 1 \), and \( \mathbf{y} = (y_1, y_2, \ldots, y_n)^T \) of size \( n \times 1 \), respectively. Let the weight matrix of the layer be \( \mathbf{W} = [w_{ji}] \) of size \( n \times m \). The input-output relationship is then given by \( \mathbf{y} = \mathbf{Wx} \), or \( y_j = \sum_{i=1}^m w_{ji} \cdot x_i \). The bias term is ignored for ease of notation. Let \( \delta \nu \) denote the partial derivative of the error function \( E \) with respect to the variable \( v \). The backpropagation equation for the weights \( \mathbf{W} \) of this fully-connected layer is given by

\[
\delta w_{ji} \triangleq \frac{\partial E}{\partial w_{ji}} = \left( \frac{\partial E}{\partial y_j} \right) \cdot \left( \frac{\partial y_j}{\partial w_{ji}} \right) = \delta y_j \cdot x_i 
\]

(1)

\[
\delta \mathbf{W} \triangleq \left[ \frac{\partial E}{\partial w_{ji}} \right] = \delta \mathbf{y} \cdot \mathbf{x}^T, \tag{2}
\]

where \( \delta \mathbf{y} = (\delta y_1, \delta y_2, \ldots, \delta y_n)^T \) is of size \( n \times 1 \). Our modified fully-connected layer associates a matrix of
real-valued mask weights \( m^r = [m^r]_{ji} \) with every weight matrix \( W \), of the same size as \( W \) \((n \times m)\), as indicated by the rightmost filter in Figure 1. We obtain thresholded mask matrices \( m = [m]_{ji} \) by passing the real-valued mask weight matrices \( m^r \) through a hard binary thresholding function given by

\[
m_{ji} = \begin{cases} 1, & \text{if } m^r_{ji} \geq 0 \\ 0, & \text{otherwise} \end{cases}
\]

The binary-valued matrix \( m \) activates or switches off contents of \( W \) depending on whether a particular value \( m_{ji} \) is 0 or 1. The layer’s input-output relationship given by the equation \( y = (W \odot m)x \), or \( y_j = \sum_{i=1}^{m} w_{ji} \cdot m_{ji} \cdot x_i \), where \( \odot \) indicates elementwise multiplication or masking. In practice, we set the weights \( W \) of our modified layer to those from the same architecture pre-trained on a task such as ImageNet classification. We keep the weights \( W \) fixed as constants throughout, while only training the real-valued mask weights \( m^r \). The backpropagation equation for the thresholded mask weights of this fully-connected layer is given by

\[
\delta m_{ji} \triangleq \frac{\partial E}{\partial m_{ji}} = \left( \frac{\partial E}{\partial y_j} \right) \cdot \left( \frac{\partial y_j}{\partial m_{ji}} \right) = \delta y_j \cdot w_{ji} \cdot x_i \label{eq:delta_m}
\]

\[\therefore \delta m \triangleq \left[ \frac{\partial E}{\partial m} \right]_{ji} = (\delta y \cdot x^T) \odot W. \label{eq:delta_m_full}
\]

Even though the hard thresholding function is non-differentiable, the gradients of the thresholded mask values serve as a noisy estimator of the gradients of the real-valued mask weights, and can even serve as a regularizer, as shown in prior work [3, 13]. We thus update the real-valued mask weights \( m \) using gradients computed for \( m^r \), the thresholded mask weights. After adding a new classification layer for the new task, the entire system can be trained in an end-to-end differentiable manner. In our experiments, we did not train per-task bias terms as prior work [23] showed that this does not have any significant impact on performance. We also did not train per-task batch normalization parameters for simplicity. Section 5.3 analyzes the impact of training per-task batchnorm parameters, especially for tasks with large domain shifts.

After training a mask for a given task, we no longer require the real-valued mask weights. These are then discarded, and only the binary masks associated with the backbone network weights are stored. A typical neural network parameter is represented using a 32-bit float value (including in our implementation that uses PyTorch). A binary mask only requires 1 extra bit per parameter, leading to an approximate per-task overhead of 3.12% of the backbone network size. For adding \( N \) tasks to a network, PackNet incurs an overhead of \( \log_2(N) \) bits per network parameter, whereas a binary-valued piggyback mask incurs an overhead of \( N \) bits per network parameter.

**Practical optimization details.** From Equation 7, we observe that \( |\delta m|, |\delta m^r| \propto |W| \). The magnitude of pre-trained weights varies across layers of a network, and as a result, the mask gradients would also have different magnitudes at different layers. This relationship requires us to be careful about the manner in which we initialize and train mask weights \( m^r \). We could go about this in two ways:

1) Initialize \( m^r \) with values proportional to the weight matrix \( W \) of the corresponding layer. In this case, the ratio \( (|\delta m^r|/|m^r|) \) will be similar across layers, and a constant learning rate can be used for all layers.

2) Initialize \( m^r \) with a constant value, such as 0.001, for all layers. This would require a separate learning rate per layer, due to the scaling of the mask gradient by the layer weight magnitude. While using SGD, scaling gradients obtained at each layer by a factor of 1/\( \text{avg}(|W|) \), while using a constant learning rate, has the same effect as layer-dependent learning rates. Alternatively, one could use adaptive optimizers such as Adam, which would learn appropriate scaling factors.

The second initialization approach combined with the Adam optimizer produced the best results, with a consistent gain in accuracy by \( \sim 2\% \) compared to the alternatives and we used this setting in all our experiments.

### 4. Experiments and Results

#### 4.1. Datasets

We consider a wide variety of datasets to evaluate our proposed method, samples from which are displayed in Figure 2, and statistics are summarized in Table 1. Similar to PackNet [23], we evaluate our method on two large-scale datasets, the ImageNet object classification dataset [29] and the Places365 scene classification dataset [36], each of which has over a million images, as well as the CUBS [34], Stanford Cars [17], and Flowers [25] fine-grained classification datasets. Further, we include two more datasets with significant domain shifts from the natural images of ImageNet, the WikiArt Artists classification dataset, created from the WikiArt dataset [31], and the Sketch classification dataset [4]. The former includes a wide genre of painting styles, as shown in Figure 2(f), while the latter includes black-and-white sketches drawn by humans, as shown in Figure 2(g). For all these datasets, we use networks with an input image size of 224 \( \times \) 224 px.

We also evaluate our proposed method on the newly introduced Visual Decathlon challenge [27] consisting of 10 classification tasks. Evaluation on this challenge reports per-task accuracies, and assigns a cumulative score with a maximum value of 10,000 (1,000 per task) based on the per-task accuracies. The goal is to learn models for max-
Figure 2: Randomly chosen images from the classification datasets used show the wide variety of inputs considered. The WikiArt (f) and Sketch (g) datasets have images whose distributions are significantly different from that of ImageNet.

| Dataset            | #Train  | #Eval  | #Classes |
|--------------------|---------|--------|----------|
| ImageNet [29]      | 1,281,144 | 50,000 | 1,000    |
| Places365 [36]     | 1,803,460 | 36,500 | 365      |
| CUBS [34]          | 5,994   | 5,794  | 200      |
| Stanford Cars [17] | 8,144   | 8,041  | 196      |
| Flowers [25]       | 2,040   | 6,149  | 102      |
| WikiArt (Artists) [31] | 42,129 | 10,628 | 195      |
| Sketch [4]         | 16,000  | 4,000  | 250      |

Table 1: Summary of datasets used.

As seen in Table 2, training individual networks per task clearly provides a huge benefit over the classifier only baseline for all tasks. PackNet significantly improves over the classifier only baseline, but begins to suffer when more than 3 tasks are added to a single network. As PackNet is sensitive to the ordering of tasks, we try two settings - adding tasks in order from CUBS to Sketch (top to bottom in Table 2), and the reverse. The order of new task addition has
Table 2: Errors obtained by starting from an ImageNet-trained VGG-16 network and then using various methods to learn new fine-grained classification tasks. PackNet performance is sensitive to order of task addition, while the rest, including our proposed method, are agnostic. ↓ and ↑ indicate that tasks were added in the CUBS → Sketch, and Sketch → CUBS order, resp. Values in parentheses are top-5 errors, rest are top-1 errors.

| Dataset      | Classifier Only | PackNet [23] ↓ | Piggyback (ours) ↑ | Individual Networks |
|--------------|-----------------|---------------|-------------------|---------------------|
| ImageNet     | 28.42 (9.61)    | 29.33 (9.99)  | 28.42 (9.61)      | 28.42 (9.61)        |
| CUBS         | 36.49           | 22.30         | 29.69             | 22.22               |
| Stanford Cars| 54.66           | 15.81         | 21.66             | 13.87               |
| Flowers      | 20.01           | 10.33         | 10.25             | 9.33                |
| WikiArt      | 49.53           | 32.80         | 31.48             | 28.84               |
| Sketch       | 58.53           | 28.62         | 24.88             | 23.51               |

# Models (Size) 1 (537 MB) 1 (587 MB) 1 (621 MB) 6 (3,222 MB)

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4.3. Visual Decathlon

Table 5 reports the results obtained on the online test set of the Visual Decathlon challenge. Consistent with prior work [27, 28], we use a Wide Residual Network [35] with a depth of 28, widening factor of 4, and a stride of 2 in the first convolutional layer of each block. We use the ImageNet-trained network of [28] as our backbone network, and train piggyback masks for the remaining 9 datasets. We train for a total of 60 epochs per dataset, with learning rate decay by a factor of 10 after 45 epochs. The base learning rate for final classifier layer which uses SGDm was chosen from \{1e-2, 1e-3\} using cross-validation over the validation set. Adam with a base learning rate of 1e-4 was used for updating the real-valued piggyback masks. Data augmentation by random cropping, horizontal flipping, and resizing the entire image was chosen based on cross-validation.

As observed in Table 5, our method obtains performance competitive with the state-of-the-art, while using the least amount of additional parameters over a single network. Assuming that the base network uses 32-bit parameters, it accounts for a parameter cost of 32n bits, where n is the number of parameters. A binary mask per dataset requires n bits, leading to a total cost of approximately \(32n + 9n = 41n\) bits, or a parameter ratio of \((41/32) = 1.28\), as reported.
## Table 3
Adding a large-scale dataset to an ImageNet-trained VGG-16 network. Values in parentheses are top-5 errors, rest are top-1 errors. ∗ indicates models downloaded from [https://github.com/CSAILVision/places365](https://github.com/CSAILVision/places365), trained by [36].

| Dataset   | Jointly Trained Network\(^{∗}\) | PackNet [23] | Piggyback (ours) | Individual Networks |
|-----------|---------------------------------|---------------|------------------|---------------------|
| ImageNet  | 33.49 (12.25)                   | 29.33 (9.99)  | 28.42 (9.61)     | 28.42 (9.61)        |
| Places365 | 45.98 (15.59)                   | 46.64 (15.92) | 46.71 (16.18)    | 46.35 (16.14)\(^{∗}\) |
| # Models (Size) | 1 (537 MB)   | 1 (554 MB)    | 1 (554 MB)       | 2 (1,074 MB)        |

## Table 4
Results on other network architectures. Values in parentheses are top-5 errors, rest are top-1 errors. ↑ and ↓ indicate order of task addition for PackNet.

| Dataset   | Classifier Only | PackNet [23] | Piggyback (ours) | Individual Networks |
|-----------|-----------------|---------------|------------------|---------------------|
| **VGG-16 BN** |                  |               |                  |                     |
| ImageNet  | 26.63 (8.49)    | 27.18 (8.69)  | 26.63 (8.49)     | 26.63 (8.49)        |
| CUBS      | 33.88           | 20.21         | 23.82            | 19.89 (19.57)       |
| Stanford Cars | 51.62       | 14.05         | 17.60            | 11.62 (9.41)        |
| Flowers   | 19.38           | 7.82          | 7.85             | 6.40 (4.55)         |
| WikiArt   | 48.05           | 30.21         | 29.59            | 26.70 (26.68)       |
| Sketch    | 59.96           | 25.47         | 23.53            | 22.42 (21.92)       |
| # Models (Size) | 1 (537 MB)   | 1 (587 MB)    | 1 (621 MB)       | 6 (3,222 MB)        |
| **ResNet-50** |                  |               |                  |                     |
| ImageNet  | 23.84 (7.13)    | 24.29 (7.18)  | 23.84 (7.13)     | 23.84 (7.13)        |
| CUBS      | 29.97           | 19.59         | 28.62            | 19.61 (17.17)       |
| Stanford Cars | 47.20       | 13.89         | 19.99            | 11.89 (8.17)        |
| Flowers   | 14.01           | 6.96          | 9.45             | 6.46 (3.44)         |
| WikiArt   | 44.40           | 30.60         | 29.69            | 26.59 (24.40)       |
| Sketch    | 49.14           | 23.83         | 21.30            | 20.56 (19.22)       |
| # Models (Size) | 1 (94 MB)     | 1 (103 MB)    | 1 (109 MB)       | 6 (564 MB)          |
| **DenseNet-121** |                 |               |                  |                     |
| ImageNet  | 25.56 (8.02)    | 25.60 (7.89)  | 25.56 (8.02)     | 25.56 (8.02)        |
| CUBS      | 26.55           | 19.26         | 30.36            | 20.32 (18.08)       |
| Stanford Cars | 43.19       | 15.35         | 22.09            | 12.85 (8.64)        |
| Flowers   | 16.56           | 8.94          | 8.46             | 5.73 (3.49)         |
| WikiArt   | 45.08           | 33.66         | 30.81            | 28.00 (23.59)       |
| Sketch    | 46.88           | 25.35         | 21.08            | 20.02 (19.48)       |
| # Models (Size) | 1 (28 MB)     | 1 (31 MB)     | 1 (33 MB)        | 6 (168 MB)          |

## 5. Analysis
### 5.1. Does Initialization Matter?

Here, we analyze the importance of the initialization of the backbone network. It is well known that training a large network such as the VGG-16 from scratch on a small dataset such as CUBS, or Flowers leads to poor performance, and the most popular approach is to fine-tune a network pre-trained on the ImageNet classification task. It is not obvious whether initialization is just as important for the piggyback method. Table 6 presents the errors obtained by
training piggyback masks for tasks using the ResNet-50 as the backbone network, but with different initializations. We consider 3 different initializations: 1) a network trained on the ImageNet classification task, the popular initialization for fine-tuning, 2) a network trained from scratch on the Places365 scene classification task, a dataset larger than ImageNet (1.8 M v/s 1.3 M images), but with fewer classes (365 v/s 1000), and lastly 3) a randomly initialized network.

We observe in Table 6 that initialization does indeed matter, with the ImageNet-initialized network outperforming both the Places365 and randomly initialized network on all tasks. In fact, by training a piggyback mask for the Places365 dataset on an ImageNet-initialized backbone network, we obtain an accuracy very similar to a network trained from scratch on the Places365 dataset. The ImageNet dataset is very diverse, with classes ranging from animals, to plants, cars and other inanimate objects, whereas the Places365 dataset is solely devoted to the classification of scenes such as beaches, bedrooms, restaurants, etc. As a result, the features of the ImageNet-trained network serve as a very general and flexible initialization, more so than the Places-trained network.

The randomly initialized network fails to learn useful classifiers for the smaller fine-grained datasets considered. A very interesting observation is that for the large-scale ImageNet and Places datasets, we are able to obtain non-trivial accuracies even with random initialization. Places365 has a larger number of total examples compared to ImageNet as well as fewer classes, leading to a larger number of examples per class (1.8 M for 365 classes compared to 1.3 M for 1000 classes for ImageNet). The obtained results show that having a large number of training examples, especially per class in the dataset, can help learn piggyback models that achieve meaningful accuracies even with a backbone network having completely random initialization.

### 5.2. Learned sparsity and distribution across layers

Table 7 reports the total sparsity, or the number of mask values set to 0 in a binary piggyback mask learned for the corresponding choice of dataset and network architecture. This measures the amount of change that is required to be made to the backbone network, or the deviation from the ImageNet-trained initialization, in order to obtain good performance on a given dataset. We note that the amount of sparsity obtained on fine-grained datasets seems to be proportional to the errors obtained by the Classifier Only method on the respective datasets. The easiest Flowers dataset requires the least number of changes, or a sparsity of 0.39%, while the harder WikiArt dataset leads to a 22.76% sparsity for a VGG-16 network mask. Across network architectures, we observe a similar pattern of sparsity based on the inherent difficulty of the tasks.

It is interesting to note that a Places365-initialized network requires more changes as compared to an ImageNet-initialized network (refer to the ResNet-50 column of Table 7). This once again shows that features learned on Im-

| Method                  | #par | ImNet. | Airc. | C100 | DPed | DTD | GTSR | Flwr | Ogtl | SVHN | UCF | Mean | Score |
|-------------------------|------|--------|-------|------|------|-----|------|------|------|------|-----|------|-------|
| Scratch [27]            | 10   | 59.87  | 57.1  | 75.73| 91.2 | 37.77| 96.55| 56.3 | 88.74| 96.63| 43.27| 70.32| 1625  |
| Feature [27]            | 1    | 59.67  | 23.31 | 63.11| 80.33| 45.37| 68.16| 73.69| 58.79| 43.54| 26.8 | 54.28| 544   |
| Finetune [27]           | 10   | 59.87  | 60.34 | 82.12| 92.82| 55.53| 97.53| 81.41| 87.69| 96.55| 51.2 | 76.51| 2500  |
| Res. Adapt. [27]        | 2    | 59.67  | 56.68 | 81.2 | 93.88| 50.85| 97.05| 66.24| 89.62| 96.13| 47.45| 73.88| 2118  |
| Res. Adapt. (J) [27]    | 2    | 59.23  | 63.73 | 81.31| 93.3 | 57.02| 97.47| 83.43| 89.82| 96.17| 50.28| 77.17| 2643  |
| DAN [28]                | 2.17 | 57.74  | 64.12 | 80.07| 91.3 | 56.54| 98.46| 86.05| 89.67| 96.77| 49.38| 77.01| 2851  |
| Piggyback (Ours)        | 1.28 | 57.69  | 65.29 | 79.87| 96.99| 57.45| 97.27| 79.09| 87.63| 97.24| 47.48| 76.60| 2838  |

Table 5: Top-1 accuracies obtained on the Visual Decathlon online test set.

| Dataset     | ImageNet-init. | Places365-init. | Random init. |
|-------------|----------------|-----------------|--------------|
| CUBS        | 19.61          | 32.05           | 99.40        |
| Stanford Cars | 11.89          | 16.52           | 99.18        |
| Flowers     | 6.46           | 13.49           | 98.24        |
| WikiArt     | 26.59          | 30.60           | 93.77        |
| Sketch      | 20.56          | 24.29           | 99.42        |
| ImageNet    | **23.84**      | **32.56**       | **71.48**    |
|             | (7.13)         | (11.92)         | (46.73)      |
| Places365   | 45.17          | **45.39**       | 60.41        |
|             | (15.12)        | (15.05)         | (28.94)      |

Table 6: Errors obtained by piggyback masks for the ResNet-50 backbone network with different initializations. Values in **bold** indicate errors of backbone networks used. Errors in parentheses are top-5 errors, the rest are top-1 errors.
Table 7: Percentage of zeroed out weights after training a binary mask for the respective network architecture and dataset.

| Dataset  | VGG-16  | VGG-16  | ResNet-50 | Dense-Net-121 |
|----------|---------|---------|-----------|---------------|
|          | ImNet-init. | Places-init. |           |               |
| CUBS     | 3.60%   | 3.91%   | 3.46%     | 7.02%         | 3.92%         |
| Stanford Cars | 5.58%   | 6.07%   | 5.95%     | 9.14%         | 6.37%         |
| Flowers  | 0.39%   | 0.61%   | 1.31%     | 2.46%         | 1.36%         |
| WikiArt  | 22.76%  | 21.84%  | 18.93%    | 20.14%        | 18.50%        |
| Sketch  | 13.28%  | 12.82%  | 10.68%    | 13.75%        | 11.47%        |
| ImageNet | –       | –       | –         | 37.59%        | –             |
| Places365 | 43.47%  | –       | 37.99%    | –             | –             |

Figure 3: Percentage of weights masked out per VGG-16 layer.

ageNet are more diverse and serve as better initialization than those learned on Places365.

Figure 3 shows the sparsity obtained per layer of the VGG-16 network, for all the datasets considered. While the total amount of sparsity obtained per dataset is different, we observe a consistent pattern of sparsity across the layers for the fine-grained tasks (CUBS to Sketch). There are generally two peaks of sparsity, a small one in the lower layers (conv1-conv2), and a larger one in the higher level convolutional layers (conv4-conv6). There are minor variations depending on the specific dataset, such as large number of changes in the fully connected layers (fc6, fc7) for the WikiArt and Sketch dataset, and a small number of changes for the Flowers dataset. These plots seem to indicate that most of the changes occur in the low-level and high-level features of the backbone network, for fine-grained tasks. For the large-scale Places365 dataset, the percentage of zeros in the mask keeps increasing with layer index.

5.3. Handling large input domain shifts

In Table 4, we observe that datasets such as WikiArt and Sketch, which have a large domain shift from the ImageNet dataset on which the backbone network was trained on, have a larger gap in performance between the piggyback and individual network methods, especially for the deeper ResNet and DenseNet networks. Those numbers are duplicated in the Piggyback - Fixed BN and Individual Network columns of Table 8. We suspect that keeping batchnorm parameters fixed while training the piggyback masks might be a rea-
Table 8: Effect of task-specific batch normalization layers on the top-1 error.

| Dataset   | Piggyback Fixed BN | Piggyback Trained BN | Individual Network |
|-----------|---------------------|----------------------|--------------------|
|           | 26.59               | 25.06                | 24.40              |
| WikiArt   | 20.56               | 20.21                | 19.22              |
| Sketch    | 28.00               | 25.24                | 23.59              |
|           | 20.02               | 20.31                | 19.48              |

The top-1 error on WikiArt reduces from 26.59% to 25.06% for the ResNet-50 network, and from 28.00% to 25.24% for the DenseNet-121 network if the batchnorm parameters are allowed to update. However, for the Sketch dataset, training separate batchnorm parameters led to a small decrease in performance for the DenseNet-121 network, with an error increase from 20.02% to 20.31%. Task-specific batchnorm parameters might help for some datasets, while causing a small increase in the storage overhead of ∼1 MB for both networks considered.

6. Conclusions

We have presented a novel method for utilizing the fixed weights of a network for obtaining good performance on a new task. The wide range of experiments conducted have empirically shown that the proposed method works for multiple datasets as well as network architectures. We hope that the piggyback method will be useful in practical scenarios where new skills need to be learned on a deployed device without having to download a new and large network. Further, the re-usability of the backbone network will help simplify and scale new task learning across the large number of potential users or devices.

Future extensions to learning ternary masks instead of binary masks might help further improve performance. Another avenue for future work is the mixed learning of newly inserted layers as well as masks, where only certain layers are kept fixed for reasons of size, or other practical requirements.

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