Shapeshifter Networks: Cross-layer Parameter Sharing for Scalable and Effective Deep Learning

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Abstract

We present Shapeshifter Networks (SSNs), a flexible neural network framework that improves performance and reduces memory requirements on a diverse set of scenarios over standard neural networks. Our approach is based on the observation that many neural networks are severely overparameterized, resulting in significant waste in computational resources as well as being susceptible to overfitting. SSNs address this by learning where and how to share parameters between layers in a neural network while avoiding degenerate solutions that result in underfitting. Specifically, we automatically construct parameter groups that identify where parameter sharing is most beneficial. Then, we map each group's weights to construct layers with learned combinations of candidates from a shared parameter pool. SSNs can share parameters across layers even when they have different sizes, perform different operations, and/or operate on features from different modalities. We evaluate our approach on a diverse set of tasks, including image classification, bidirectional image-sentence retrieval, and phrase grounding, creating high performing models even when using as little as 1% of the parameters. We also apply SSNs to knowledge distillation, where we obtain state-of-the-art results when combined with traditional distillation methods.

1 Introduction

Many neural networks already contain hundreds of millions, or even billions, of parameters. However, since performance continues to improve as the number of parameters increases, networks are still continuing to grow. Scaling to train and evaluate these models is becoming increasingly infeasible with the doubling of necessary compute resources every 3.4 months at the top end [4]. Furthermore, the sheer size of the models may necessitate expensive model parallelism [7,18,43,44] or memory management techniques [10,21,29] to simply fit parameters and training variables into device memory. To minimize overhead and thus costs, researchers have introduced techniques to reduce the number of parameters in a network by reusing the same parameters in multiple layers of a neural network [6,12,23,42]. Notably, and potentially related to Occam’s razor, in some settings these cross-layer parameter sharing approaches lead to better performance than the original network [12,42].

However, as shown in Figure 1(a), previous works were limited to handcrafted parameter sharing strategies, and only share weights between identical layers (e.g., same-size convolutional layers applied to images).

We introduce Shapeshifter Networks (SSNs), a new neural network representation that generalizes and automates parameter sharing techniques to derive powerful and efficient models that can use less
We demonstrate the effectiveness of our approach on both single- (e.g., vision/language) tasks. For example, our SSNs trained for image classification on ImageNet [13] report a 3% reduction in Error@5 compared to a network of a similar parameter size. Furthermore, since our parameter selector and combiner strategies do not depend on network connections or layer input, we can precompute the model weights for each layer when training is complete, making the runtime overhead zero. We can also perform a type of knowledge distillation [26], where the knowledge learned in a large teacher network is transferred to a smaller, more efficient student network. Prior work primarily focused on transferring the knowledge present in the output feature representation of the teacher at different points in the student (e.g., [9, 25, 26, 32, 41, 55]). In contrast, we require no teacher since we can simply use an SSN to increase the capacity of the student during training by using additional parameters, which can be eliminated at inference time. SSNs can also be used in conjunction with traditional knowledge distillation methods to further boost performance.

In summary, our key contributions are:

- We propose Shapeshifter Networks, a flexible neural network representation that learns how to share parameters across multiple layers of a neural network, improving memory efficiency and performance over traditional neural networks.
- We explore different methods for our parameter selector, combiner, and grouping strategies, demonstrating that our SSNs can automate the sharing process, providing greater flexibility, and without sacrificing performance compared to hand-crafted methods.
- We benchmark our approach on image classification, phrase grounding, and bidirectional image-sentence retrieval tasks, illustrating our model’s ability to create high performing networks even when using as few as 1% of the parameters.
- We show that SSNs can also be used for knowledge distillation, and obtain state-of-the-art performance when combining them with traditional distillation methods.

![Diagram](image.png)
2 Related Work

Parameter sharing has been widely used when learning neural networks (e.g., recurrent or convolutional networks). Savarese et al. [42] is the closest in spirit to our work, it manually creates parameter groups and then learns to combine multiple candidates using a weighted average strategy that they evaluate on convolutional layers for image classification. Lan et al. [34] introduce ALBERT, which shares parameters through all layers in a transformer that performs better, converges faster, and increases efficiency over standard transformers. Hao et al. [23] boosts performance by combining a parameter sharing transformer with a normal one. Many other papers have learned how to improve parameter sharing for multi-task training [30, 36, 37, 46], pruning, and/or tying parameters to create more efficient networks [1, 3, 20, 22, 56], and many other applications. However, just as with standard neural networks, these methods can be considered a special case of SSNs that typically use hand-crafted parameter groups and sharing strategies and where shared weights exist only between layers of similar sizes, operations, and input feature types. Our approach is far more flexible and simple, learning when to use parameter sharing in any scenario and with any network architecture.

SSNs share some similarities to neural architecture search (e.g., [7, 16, 47, 52, 57]). Notably, Pham et al. [38] shared parameters between child models to improve search efficiency, but also falls under the same special case of SSNs referenced earlier. SSNs are also similar to modular neural networks (e.g., [2, 14, 19]), which learn parts of a network that can be reused for multiple tasks. However, these methods are designed to search for an architecture given a set of hand-crafted search parameters. In contrast, our SSNs learn how to improve the performance of a particular neural network, which we believe will be useful in future work addressing architecture search and modular networks.

3 Shapeshifter Networks (SSNs)

We now describe Shapeshifter Networks in detail. A simple feed-forward network like in Figure 1 (left) can be thought of as applying $L$ layer operations $f_1, \ldots, f_L$ to input data $x$ given model parameters $\theta$. For simplicity, we present this case and also neglect layers that do not require parameters, but our approach is applicable to any architecture. A traditional neural network would implicitly choose the layer parameters for each learnable operation $f_i$. In contrast, SSNs decouple the $f_i$ from their parameters, and instead manage them with a parameter selector and combiner (Section 3.1). The parameter selector identifies a set of candidates of the appropriate size to implement a layer, while the combiner fuses the candidates, enabling it to identify different concepts in different candidates and to learn which layers to use them in. This strategy supports weight sharing among any set of layers where appropriate. However, some layers may find sharing parameters detrimental to performance, and so we learn to split layers into parameter groups (Section 3.2) that do not share any parameters with each other. SSNs make no prior assumptions about the network architecture or input data, and can be used to implement any neural network for a wide variety of tasks.

3.1 Generating Model Weights with Parameter Selection and Combination

Given a layer belonging to the $j$th parameter group requesting an $M \times N$ matrix of parameters $\theta$ to perform some operation, the parameter selector $q(i)$ returns a set of candidates $C$ of compatible parameters. The combiner $c(i)$ reduces $C$ into the final set of parameters used for evaluating the layer. The candidate set consists of up to $P$ nonoverlapping parameter blocks (a hyperparameter) of size $M \times N$ from a parameter group $T_j$. As illustrated in Figure 2(a), the parameter selector divides $T_j$ into sub-blocks sized based on the smallest block a layer using the group will request. Blocks are then constructed by concatenating the fewest number of contiguous sub-blocks necessary to form it (we ignore excess parameters due to divisibility issues). If $T_j$ has more parameter blocks than necessary, then the selector returns them in a round-robin fashion across the layers 1, \ldots, $L$ to use all parameters in the group efficiently. When a layer requests more parameters than available in $T_j$, we extract the largest matrix possible that has the same aspect ratio as $\theta$, and then use bilinear interpolation to upsample the matrix to have size $M \times N$.

We found that layers such as Batch Normalization [28], which help regularize feature maps at specific locations, do not benefit from parameter sharing—thus we keep their parameters separate in our experiments. Note that these normalization layers typically have a negligible contribution to the number of parameters in a neural network, but all other operations requiring parameters may end up
Sharing weights. We benchmark four strategies for implementing the combiner, which we categorize into simple methods that extract parameters directly from $T_j$ (Section 3.1.1) and methods that learn a unique combination of the candidates $C_j$ for each layer to obtain $\theta$ (Section 3.1.2). See Figure 2(b) for an overview of the four strategies we explore. We also reiterate that all parameter selection and combination strategies, including learned ones, do not depend on any specific input data, so any layer’s weights $\theta$ can be precomputed for inference.

### 3.1.1 Direct Candidate Combination

In this section we describe the strategies we employ that require no parameters to be learned by the parameter combiner, i.e., they operate directly on the candidate model weights. The only hyperparameter that influences the selection is $P$, the maximum size of the candidate set $C$.

**Round Robin (RR)** reuses parameters of each candidate set (and thus each group) as few times as possible. The scheme simply returns the weights at index $i \bmod |C_j|$ in the (ordered) candidate set $C_j$ at the $i$th query and $j$th parameter group.

**Candidate averaging (Avg)** averages all candidates in $C_j$ to provide a naive baseline for using multiple candidates. A significant drawback of this approach is that, if $|C_j|$ is large this can result in reusing parameters (across combiners) many times with no way to adapt to a specific layer, especially when the size of the parameter group is small.

### 3.1.2 Learned Candidate Combination

We now describe strategies that use learned coefficients $\alpha_j$ to combine the candidates in set $C_j$. Essentially, the goal is to use a soft-attention mechanism over $C$ to obtain the layer parameters. Each strategy begins with features $\phi_j$ representing each layer $i$. These features use an orthogonal initialization so that they begin as far from other layers’ features as possible. Unlike the methods from Section 3.1.1 these allocation strategies require the parameter combiner, $c(i)$, to use additional model parameters (typically less than 0.1% of the total number of parameters in our experiments).

**Candidate weighted averaging (WAvg)** uses a weighted average over available candidates. The coefficients used to combine the candidates are directly learned for each layer and are forced to sum to 1, i.e., $\alpha_j = \text{softmax}(\phi_i)$. Then, the model weights are computed via:

$$\theta_i = \sum_{k=1}^{|C_j|} \alpha_{jk} C_{jk} \tag{1}$$

where $\theta_i$ is the sum of each $k$th candidate in parameter group $j$, $C_{jk}$, weighted by $\alpha_{jk}$.

**Layer embeddings (Emb)** represent each layer by an embedding $\phi_j$ resulting in a $L \times |C_j| \times 24$ feature tensor. From these embedding we learn to predict the coefficients $\alpha$ for combing the candidates using Eq. (1) using a fully connected layer. Layers that operate over the same set of candidates use the same fully connected layer, which enables us to identify when layers can be implemented using similar parameters as their embeddings will end up near each other. More formally, let $p$ identify the weights of a fully connected layer $W, b$ where the layer’s output dimension is $|C_j|$, then we obtain coefficients with:

$$\alpha_j = \text{softmax}(\phi_i W_p + b_p) \tag{2}$$
3.2 Learning Parameter Groups

Some layers in a neural network may perform very similar operations, which enables parameter sharing with little performance loss. However, the inputs to some layers may vary drastically, requiring very different model parameters, which can lead to performance degradation if the same parameters are used to represent all of them. For example, early layers, which are typically associated with learning low-level features, may hurt performance if shared with late layers that are often associated with higher-level concepts. Savarese et al. [42] addresses this by manually creating parameter groups that do not share between operations of different type or size. However, this kind of approach is overly restrictive by requiring a specific number of parameter groups, and may significantly reduce performance if the groups it chooses have too few parameters for their layers, resulting in frequent weight upsampling. Instead, we adapt the learned combination methods from Section 3.1.2 to identify how compatible different layers are when sharing parameters. Our approach is guided by the hypothesis that if two layers learn a similar layer representation $\phi$ when they operate on the same set of candidates, so that the weights used by each layer end up being similar, then we can share weights between them with little (or no) performance degradation.

We begin by grouping together all layers in the network into a single parameter group. To ensure each layer operates on the same set of candidates, the Parameter Selector splits its parameters into equal-sized candidates $C$ (we found $|C| = 4$ worked well). For each layer we use bilinear interpolation to resize each candidate so that it is the same size as the desired weights $\theta$, and then learn to combine them using Eq. (1) with either the Emb or WAvg strategies from Section 3.1.2. Since each layer has the same number of candidates, only a single fully connected layer is needed for Eq. (2) using the Emb approach. After a few epochs, we perform K-means clustering on all the layer representations $\phi$ (not the weights $\theta$) and use the clusters as our parameter groups for training. Each group is allocated a proportional number of parameters that is equivalent to its portion of the weights the group’s layers represent. For example, if a parameter group has two layers that each require 10K weights (20K total), and the total number of weights required by the entire network is 100K, then it would receive 20% of the parameters allocated in the SSN. After we create our parameter groups and allot weights to groups, we train our SSN on our target task from scratch. As our experiments will show, this typically performs at least on par, and often better than manually created groups, while providing much greater flexibility in the number and makeup of the groups that are produced.

4 Experiments

We provide experiments across a wide variety of tasks and networks in order to demonstrate the broad applicability of our SSNs. We adapt code and data splits made available by the authors and report the average of five runs for all comparisons except ImageNet, which average three runs.
4.1 Compared Tasks

Below we briefly describe each task, datasets, and evaluation metrics.

4.2 Image-Sentence Retrieval

In bidirectional image-sentence retrieval when a model is provided with an image the goal is to retrieve a relevant sentence and vice versa. This task is evaluated using Recall@K={1, 5, 10} for both directions (resulting in 6 numbers), which we average for simplicity. We benchmark methods on two common datasets: Flickr30K \[53\] which contains 30K/1K/1K images for training/testing/validation, each with five descriptive captions, and MSCOCO \[35\], which contains 123K/1K/1K images for training/testing/validation, each image having roughly five descriptive captions.

EmbNet \[50\]. This network learns to embed visual features for each image computed using a 152-layer Deep Residual Network (ResNet) \[24\] that has been trained on ImageNet \[13\] and the average of MT GrOvLE \[8\] language features representing each word into a shared semantic space using a triplet loss. The network consists of two branches, one for each modality, and each branch contains two fully connected layers (for a total of four layers as shown in Figure 3(a)). We adapted the implementation of Burns \textit{et al.} \[8\] and left all hyperparameters at the default settings. This architectures provides a simple baseline for parameter sharing with our Shapeshifter Networks (SSNs), where layers operate on two different modalities.

ADAPT-T2I \[51\]. In this approach word embeddings are aggregated using a bidirectional GRU \[11\] and its hidden state at each timestep is averaged to obtain a full-sentence representation. Images are represented using 36 bottom-up image region features \[5\] that are passed through a fully connected layer. Then, each sentence calculates scaling and shifting parameters for the image regions using a pair of fully connected layers that both take the full-sentence representation as input. The image regions are then averaged, and a similarity score is computed between the sentence-adapted image features and the fully sentence representation. Thus, as shown in Figure 3(c), there are four layers total (3 fully connected, 1 GRU) that can share parameters, including the two parallel fully connected layers (i.e., they both take the full sentence features as input, but are expected to have different outputs). We adapted the author’s implementation and kept the default hyperparameters \[2\]. This method was selected since it achieves high performance and also included fully connected and recurrent layers, as well as having a set of parallel layers that make effectively performing cross-layer parameter sharing more challenging.

4.3 Phrase Grounding

Given a phrase the goal of a phrase grounding model is to identify the image region described by the phrase. Success is achieved if the predicted box has at least 0.5 intersection over union with the ground truth box. Performance is measured using the percent of the time a phrase is accurately localized. We evaluate on two datasets: Flickr30K Entities \[40\] which augments the Flickr30K dataset with 276K bounding boxes associated with phrases in the descriptive captions, and ReferIt \[31\] which contains 20K images that are evenly split between training/testing and 120K region descriptions.

SimNet \[49\]. This network contains three branches that each operate on different types of features as shown in Figure 3(b). One branch passes image regions features computed with a 101-layer ResNet that have been fine-tuned for phrase grounding using two fully connected layers. A second branch passes MT GrOvLE features through two fully connected layers. Then, a joint representation is computed for all region-phrase pairs using an elementwise product. Finally, the third branch passes these joint features through three fully connected layers (7 total), where the final layer acts as a classifier indicating the likelihood that phrase is present in the image region. We adapt the code from Plummer \textit{et al.} \[39\] and keep all hyperparameters at their default settings. This enables us to test how well our SSNs generalize to another task and how well it can adapt to sharing parameters with layers operating on three types of features (just vision, just language, and a joint representation).
Table 1: Parameter combiner comparison (see Section 3.1 for combiner descriptions). All models in the same row use the same (reduced) number of parameters. For example, our SSN is emulating WRN-28-10 using only about 4M parameters. “Reduced Baseline” uses no parameter sharing, but adjusts the number and/or size of filters so they have the same number of parameters as our SSNs. The original model’s performance is reported in the first column of results in Table 2. Results with standard deviations are provided in Appendix A.

| Method           | Orig Num Params (M) | % of Params Used | Dataset         | Reduced Baseline | RR Avg | W Avg | Emb  |
|------------------|---------------------|------------------|-----------------|------------------|--------|-------|------|
| **Image-Sentence Retrieval** |                     |                  |                 |                  |        |       |      |
| EmbNet [50]      | 7                   | 57.1%            | F30K [53]       | 72.8             | 74.1   | 73.5  | 74.0 | 74.3 |        | 81.5 |
|                  |                     |                  | MSCOCO [55]     | 80.9             | 80.8   | 80.9  | 81.2 |      |        |      |
| ADAPT-T2I [51]  | 14                  | 70.9%            | F30K [53]       | 80.6             | 81.2   | 80.5  | 81.6 | 81.7 |        |      |
|                  |                     |                  | MSCOCO [35]     | 85.2             | 85.6   | 85.8  | 86.2 | 85.9 |        |      |
| **Phrase Grounding** |                     |                  |                 |                  |        |       |      |
| SimNet [49]      | 6                   | 33.1%            | F30K Entities [40] | 71.1         | 72.3   | 72.1  | 72.3 | 72.5 |        |      |
|                  |                     |                  | ReferIt [31]    | 59.4             | 60.5   | 60.2  | 60.5 | 60.4 |        |      |
| **Image Classification** |                     |                  |                 |                  |        |       |      |
| WRN-28-10 [54]  | 36                  | 11.3%            | CIFAR-10 [33]   | 4.22             | 4.09   | 4.19  | 4.00 | 3.84 |        |      |
|                  |                     |                  | CIFAR-100 [33]  | 22.34            | 21.91  | 22.78 | 21.78| 21.78|        |      |
| WRN-50-2 [54]   | 69                  | 27.5%            | ImageNet [13]   | 10.08            | 6.69   | 7.61  | 7.38 | 6.69 |        |      |

4.4 Image Classification

For image classification the goal is to be able to recognize if an object is present in an image. Typically this task is evaluated using Error@K, or the portion of times that the correct category doesn’t appear in the top k most likely objects. We evaluate our Shapeshifter Networks on three datasets: CIFAR-10 and CIFAR-100 [33], which are comprised of 60K images of 10 and 100 categories, respectively, and ImageNet [13], which is comprised of 1.2M images containing 1,000 categories. We report Error@1 for both CIFAR datasets and Error@5 for ImageNet.

**Wide Residual Network (WRN) [54].** WRN modified the traditional ResNets by increasing the width k of each layer while also decreasing the depth d, which they found improved performance. Different variants are identified using WRN-d-k. Following Savarese et al. [42], we evaluate our Shapeshifter Networks using WRN-28-10 for CIFAR and WRN-50-2 for ImageNet. We adapt the implementation of Savarese et al. [42] and use cutout [15] for data augmentation. Unlike the vision-language models discussed earlier, these architecture include convolutional layers in addition to a fully connected layer used to implement a classifier, and also have many more layers than the shallow vision-language models. An illustration of this model is provided in Figure 3(d).

**DenseNet [27].** Unlike traditional neural networks where each layer in the network is computed in sequence, every layer in a DenseNet using feature maps from every layer which came before it. We adapt PyTorch’s official implementation using the hyperparameters as set in Huang et al. [27]. These networks provide insight into the effect depth has on learning SSNs, as we use a 190-layer DenseNet-BC configuration for CIFAR. However, due to their high computational cost we provide limited results testing only some settings.

4.5 Results

Table 1 compares the strategies for the parameter combiner discussed in Section 3.1. In these experiments we use a single parameter group and each combiner method only allocates the number of parameters that are required to implement the largest layer in its network. For example, the ADAPT-T2I model requires 14M parameters, but its bidirectional GRU accounts for 10M of those parameters, so all SSN variants in this experiment allocate 10M parameters. This also means that networks share parameters between layers of different types and data modalities. Comparing to the "reduced
Table 2: Parameter bank grouping comparison. Each method uses the same number of parameters and the baseline represents no parameter sharing. The manual groups are illustrated in Figure 3 and the learned grouping methods (WAvg, Emb) are described in Section 3.2. Results with standard deviations are provided in Appendix A.

| Method                | #Groups | Dataset     | Baseline | Single | Random | Manual | WAvg  | Emb  |
|-----------------------|---------|-------------|----------|--------|--------|--------|-------|------|
| **Image-Sentence Retrieval** |         |             |          |        |        |        |       |      |
| EmbNet [50]           | 2       | F30K [53]   | 74.1     | 74.4   | 74.0   | 74.3   | 74.2  | 74.3 |
|                       |         | MSCOCO [35] | 81.4     | 82.1   | 81.5   | 81.7   | 81.7  | 81.9 |
| ADAPT-T2I [51]        | 2       | F30K [53]   | 83.3     | 82.1   | 81.9   | 82.0   | 82.6  | 82.9 |
|                       |         | MSCOCO [35] | 86.8     | 86.1   | 86.3   | 86.1   | 86.4  | 87.0 |
| **Phrase Grounding**  |         |             |          |        |        |        |       |      |
| SimNet [49]           | 3       | F30K Entities [40] | 71.7     | 71.4   | 71.8   | **72.4** | 72.2  | 72.1 |
|                       |         | ReferIt [51] |         |        |        |        |       |      |
|                       |         |             |          |        |        |        | **61.1** |      |
|                       |         |             |          |        |        |        | 60.9  | 60.0 |
|                       |         |             |          |        |        |        | 60.2  | 60.2 |
|                       |         |             |          |        |        |        | 61.0  | 60.5 |
| **Image Classification** |       |             |          |        |        |        |       |      |
| WRN-28-10 [54]        | 14      | CIFAR-10 [33] | 3.57     | 3.71   | 3.63   | **3.38** | 3.51  | 3.42 |
|                       |         | CIFAR-100 [33] | 19.44    | 19.99  | 20.36  | 19.29  | 19.47 | **19.24** |
| WRN-50-2 [54]         | 32      | ImageNet [13] | 5.84     | 6.18   | 5.91   | **5.82** | 5.86  | 5.96 |

Figure 4: Comparison of reducing the parameter parameters by adjusting layer sizes vs. our SSNs using the same number of parameters. For SSN-EmbNet we use a single parameter bank, but automatically learn 3 groups for all image classification results. SSN configurations with fewer than 4M/4M/2M parameters for EmbNet/WRN/DenseNet, respectively, requires some parameter upsampling as detailed in Section 3.1. See text for additional discussion.

Table 2 reports the effect of using different methods of creating parameter bank groups. As alternate methods we also include a single group (Single) and a random assignment of layers to groups (Random). We see a small, but consistent improvement over the baseline, i.e., the original model without any parameter sharing. Notably, our learned grouping strategies (WAvg, Emb) perform on par, and sometimes better than the manual groups like those used in prior work [42]. These learned grouping methods also provide additional flexibility to learn any number of parameter groups without requiring manual intervention, which can lead to more optimal groups and improve performance.

For example, in Figure 4 we compare using an SSN vs. changing the model architecture to reduce the size/number of layers to obtain a similar parameter reduction. In addition to using WRN, we also
Table 3: Comparison of different Wide Resnet [54] configurations under different Shapeshifter Network settings on the image classification task. (a) contains baseline results without parameter sharing, while (b) demonstrates that using SSNs enable us to improve performance by increasing the required floating point operations without also increasing memory consumed, and (c) shows that the gap between SSNs with few model weights and fully-parameterized baselines in (a) gets smaller as the networks get larger. Note that the number of parameters in (c) was set by summing together the number of parameters required to implement the largest layer in the learned parameter groups for each network (e.g., four parameter groups would result in summing four numbers).

| Method            | Orig Num | #Params Used (M) | % of Orig Params | % of WRN-28-10 | CIFAR-100  |
|-------------------|----------|------------------|------------------|----------------|------------|
|                   | Params (M) |                  |                  |                | Error@1     |
| (a) WRN-28-10     | 36       | 36               | 100.0            | 100.0          | 19.44 ± 0.21 |
| WRN-40-10         | 56       | 56               | 100.0            | 153.1          | 18.73 ± 0.34 |
| WRN-52-10         | 75       | 75               | 100.0            | 206.2          | 18.85 ± 0.31 |
| WRN-76-12         | 164      | 164              | 100.0            | 449.6          | **18.31 ± 0.22** |
| (b) SSN-WRN-28-10 | 36       | 4                | 11.3             | 11.3           | 21.71 ± 0.13 |
| SSN-WRN-40-10     | 56       | 4                | 6.8              | 10.3           | 21.06 ± 0.11 |
| SSN-WRN-52-10     | 75       | 4                | 5.0              | 10.4           | 20.93 ± 0.25 |
| SSN-WRN-76-12     | 164      | 5                | 3.3              | 14.9           | **20.37 ± 0.21** |
| (c) SSN-WRN-28-10 | 36       | 4                | 10.3             | 10.3           | 21.78 ± 0.16 |
| SSN-WRN-40-10     | 56       | 7                | 13.4             | 20.4           | 20.17 ± 0.32 |
| SSN-WRN-52-10     | 75       | 15               | 19.7             | 40.7           | 19.50 ± 0.21 |
| SSN-WRN-76-12     | 164      | 21               | 13.0             | 58.6           | **18.83 ± 0.19** |

includes some results using DenseNet [27] to further demonstrate our approach’s ability to generalize. Notably, our SSNs consistently obtain better performance on both tasks we compare, even obtaining an 11% gain over EmbNet when using just 0.5M parameters. Note that we found that on the image classification task automatically learning 3 groups performed best (all CIFAR image classification results in Table 2 used 14 groups on WRN for consistency with manual groups). We further explore the effect the number of parameter groups has when using SSNs in the Appendix B.

Table 3 demonstrates the ability of our SSNs to significantly reduce the parameters required, and, thus, the memory required to implement large Wide ResNets so they fall within specific bounds. For example, Table 3(b) shows larger and deeper configurations continue to improve performance even when the number of parameters remains largely consistent. Comparing the first line of Table 3(a) and the last line of Table 3(c) we see that SSN-WRN-76-12 outperforms the fully-parameterized WRN-28-10 network by 0.6% on CIFAR-100 while only using just over half the parameters, and comes within 0.5% of WRN-76-12 while only using 13.0% of its parameters. We do note that using a SSN does not reduce the number of floating point operations, so although our SSN-WRN-76-12 model uses fewer parameters than the WRN-28-10, it is still slower at both test and train time. However, our results help demonstrate that SSNs can be used to implement very large networks with lower memory requirements by effectively sharing parameters. This enables us to train larger, better-performing networks than is possible with traditional neural networks on comparable computational resources.

4.6 Shapeshifter Networks for Knowledge Distillation

The goal of knowledge distillation is to improve the performance of a small and efficient student by transferring knowledge from a large high performing teacher. Our SSNs can accomplish a similar feat without using a teacher network by using extra parameters in our student during training, which can be combined statically for inference with no performance loss or increase in memory.

We began by separating each layer into its own parameter group so it would share no parameters with other layers. We set the number of parameters available to the small student network to be the same as the teacher network in our experimental setup outlined in Table 4. We began by obtaining a good parameter initialization by training the student SSN to use all of the weights available to it rather than combining multiple candidates using one of the strategies from Section 3.1. Then, the student is fine-tuned using WAvg since each parameter group contains a single layer and Emb’s primary benefit is learning relationships between multiple layers in a parameter group. Table 5 shows that our SSNs
Table 4: Experimental setup for our knowledge distillation experiments reported in Table 5.

| Experiment | Teacher  | #Params (M) | Student  | #Params (M) | Dataset          |
|------------|----------|-------------|----------|-------------|-----------------|
| (a)        | WRN-28-4 | 5.87        | WRN-28-2 | 1.47        | CIFAR-100       |
| (b)        | WRN-28-4 | 5.87        | WRN-16-2 | 0.70        | CIFAR-100       |

Table 5: Knowledge distillation results on CIFAR-100 using teacher/student setup in Table 4. Note our SSNs only use a teacher network when combined with OD [25]. See Section 4.6 for discussion.

| Experiment | Teacher | Baseline | AT [55] | Jacobian [45] | FT [32] | AB [9] | OD [25] | SSN (ours) | SSN+OD   |
|------------|---------|----------|---------|--------------|--------|-------|--------|------------|---------|
| (a)        |         | 21.09    | 24.88   | 23.70        | 23.41  | 23.19 | 21.98  | 23.62 ± 0.13 | 21.21 ± 0.21 |
| (b)        |         | 21.09    | 27.32   | 26.56        | 26.71  | 25.91 | 24.08  | 26.53 ± 0.15 | 23.30 ± 0.19  |

obtain competitive performance with other recent knowledge distillation methods, although SSN performs worse than the state-of-the-art. However, whereas our approach can be thought of as adding additional model flexibility during training, most knowledge transfer methods instead regularize the feature representation learned by the student at multiple points in the network. As such, we can combine them, resulting in just under 1% improvement over using knowledge transfer alone as shown in the last column of Table 5. This helps illustrate the significant potential of SSNs to improve performance and efficiency across a wide variety of neural network architectures and tasks.

5 Conclusion

We introduced Shapeshifter Networks that automatically learn parameter sharing strategies by decoupling weights from layers. They allow neural networks to get the benefits of parameter sharing—reduced memory requirements during training and inference, potentially improved accuracy—without any manual tuning. We show SSNs can even be used to train large datasets like ImageNet, where SSNs report a 3 point improvement on Error@5 over a same sized network without parameter sharing. Surprisingly, we also find that parameters can be shared among very different layers. Further, we demonstrate that SSNs can be combined with distillation methods to achieve state-of-the-art results. One could think of SSNs as spreading the same number of parameters across more layers, increasing effective depth, which benefits generalization [48], although this requires further exploration. Future directions also include more extensive studies of parameter grouping and combination methods, as well as studying the performance implications of these methods.

Given that applying SSNs is nearly transparent, we hope that parameter sharing can become a standard part of deep learning workflows.

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A Results with Standard Deviation

The results in the main paper are averaged over five runs, except ImageNet which was averaged over three. In this section we provide standard deviations for our results, which we could not provide in our paper due to space constraints. This includes bidirectional image-sentence retrieval (Table 6), phrase grounding (Table 7), and image classification (Table 8). The inclusion of standard deviation helps to solidify the significance of our reported performance gains using SSNs.

Table 6: Bidirectional image-sentence retrieval results with standard deviations from Table 1 and Table 2 from our paper. Please refer to our paper for number of parameters and groups used for each experiment. Note that “Baseline” refers to using with no parameter sharing, and “Reduced Baseline” adjusts the number and/or size of filters of the baseline so they have the same number of parameters as our SSNs.

| Architecture | EmbNet [50] | ADAPT-T2I [51] |
|--------------|-------------|----------------|
| Dataset      | F30K [53]  | MSCOCO [35]   |
| Reduced Baseline | 72.8 ± 0.19 | 80.9 ± 0.26    |
| RR           | 74.1 ± 0.25 | 80.8 ± 0.25    |
| Avg          | 73.5 ± 0.21 | 80.9 ± 0.28    |
| WAvg         | 74.0 ± 0.18 | 81.2 ± 0.22    |
| Emb          | 74.3 ± 0.27 | 81.5 ± 0.32    |

B Effect of the Number of Parameter Groups

A significant advantage of using learned parameter groups described in Section 3.2 of our paper is that our approach can support any number of parameter groups, unlike prior work that required manual grouping and/or heuristics to determine which layers shared parameters (e.g., [34,42]). In this section we explore how the number of parameter groups effects performance on the image classification task. We do not benchmark bidirectional retrieval and phrase grounding since networks addressing these tasks have few layers, so parameter groups are less important (as shown in Table 6 and Table 7).

Table 9 reports the performance of our SSNs when using different numbers of grouped parameters. We find that training with few parameters (first line) low numbers of parameter groups work best, while when more parameters are available larger numbers of parameter groups work better (second line). In fact, there is a significant drop in performance going from 4 to 8 groups when training with few parameters as seen in the first line of Table 9. This is due to the fact that starting at 8 groups some parameter groups had too few weights to implement their layers, resulting in upsampling parameters as discussed in Section 3.1 of the paper. This suggests that we may be able to further improve performance when there are few parameters by developing better methods of implementing layers when too few parameters are available.

Figure 5 visualizes parameter groups used for SSN-WRN-28-10 to create 14 parameter groups. We observed two trends in our learned parameter groups. First, we found the learned parameter groups tended to share parameters cross layers early in the network, opting for later layers to share no
Table 7: Phrase grounding results with standard deviations from Table 1 and Table 2 from our paper. Please refer to our paper for number of parameters and groups used for each experiment. Note that “Baseline” refers to using no parameter sharing, and “Reduced Baseline” adjusts the number and/or size of filters of the baseline so they have the same number of parameters as our SSNs.

| Architecture | SimNet [49] | Dataset | F30K Entities [40] | ReferIt [31] |
|--------------|-------------|---------|---------------------|--------------|
| Parameter Combiner Comparison | | | | |
| Reduced Baseline | 71.1 ± 0.28 | 59.4 ± 0.49 |
| RR | 72.3 ± 0.28 | **60.5 ± 0.53** |
| Avg | 72.1 ± 0.31 | 60.2 ± 0.53 |
| WAvg | 72.3 ± 0.25 | **60.5 ± 0.48** |
| Emb | **72.5 ± 0.30** | 60.4 ± 0.52 |
| Parameter Bank Grouping Comparison | | | | |
| Baseline | 71.7 ± 0.26 | **61.1 ± 0.39** |
| Single | 71.4 ± 0.33 | 60.9 ± 0.56 |
| Random | 71.8 ± 0.43 | 60.0 ± 0.57 |
| Manual | **72.4 ± 0.29** | 60.2 ± 0.49 |
| WAvg | 72.2 ± 0.34 | 61.0 ± 0.43 |
| Emb | 72.1 ± 0.28 | 60.5 ± 0.57 |

Table 8: Image classification results with standard deviations from Table 1 and Table 2 from our paper. Please refer to our paper for number of parameters and groups in each experiment. Note that “Baseline” refers to using no parameter sharing, and “Reduced Baseline” adjusts the number and/or size of filters of the baseline so they have the same number of parameters as our SSNs.

| Architecture | WRN-28-10 [54] | WRN-50-2 [54] | Dataset | CIFAR-10 [33] | CIFAR-100 [33] | ImageNet [13] |
|--------------|----------------|----------------|---------|---------------|----------------|---------------|
| Parameter Combiner Comparison | | | | | | |
| Reduced Baseline | 4.22 ± 0.16 | 22.34 ± 0.12 | 10.08 ± 0.02 |
| RR | 4.09 ± 0.34 | 21.91 ± 0.24 | **6.69 ± 0.08** |
| Avg | 4.19 ± 0.11 | 22.78 ± 0.29 | 7.61 ± 0.07 |
| WAvg | 4.00 ± 0.08 | **21.78 ± 0.26** | 7.38 ± 0.02 |
| Emb | **3.84 ± 0.13** | 21.92 ± 0.30 | **6.69 ± 0.11** |
| Parameter Bank Grouping Comparison | | | | | | |
| Baseline | 3.57 ± 0.19 | 19.44 ± 0.21 | 5.84 ± 0.06 |
| Single | 3.71 ± 0.17 | 19.99 ± 0.22 | 6.18 ± 0.05 |
| Random | 3.63 ± 0.11 | 20.36 ± 0.50 | 5.91 ± 0.08 |
| Manual | **3.38 ± 0.14** | 19.29 ± 0.26 | **5.82 ± 0.01** |
| WAvg | 3.51 ± 0.11 | 19.47 ± 0.30 | 5.86 ± 0.06 |
| Emb | 3.42 ± 0.06 | **19.24 ± 0.29** | 5.96 ± 0.06 |

Table 9: Effect the number of learned parameter groups has on performance for a SSN-WRN-28-10 model when training on CIFAR-100 using the Emb strategy. See Section B for discussion.

| #Groups | 1 | 2 | 4 | 8 | 12 | 14 | 16 |
|---------|---|---|---|---|----|----|----|
| 4M Params | 21.92 ± 0.30 | 21.77 ± 0.16 | **21.71 ± 0.13** | 23.30 ± 0.36 | 23.82 ± 0.47 | 24.13 ± 0.41 | 25.76 ± 0.45 |
| 36M Params | 19.99 ± 0.22 | 19.80 ± 0.38 | 19.75 ± 0.29 | 19.69 ± 0.28 | 19.27 ± 0.10 | **19.24 ± 0.29** | 19.40 ± 0.14 |
Figure 5: Comparison grouping parameters into 14 groups for a SSN-WRN-28-10 network trained on CIFAR-100, where the groups are create (a) manually, as done in Savarese et al. [42], or (b) automatically using our approach. Similar colors indicate layers that share parameters, except green layers which share no parameters with any other layer. See Section B for discussion.
Table 10: Effect the number of candidates returned by the parameter selector has on performance. Share type is set using the best results from Section A. Due to the computational cost, we set the number of candidates for ImageNet experiments in our paper using CIFAR results.

| Method                        | #Candidates | 2     | 4     | 6     | 8     | 10    |
|-------------------------------|-------------|-------|-------|-------|-------|-------|
| **Image-Sentence Retrieval**  |             |       |       |       |       |       |
| EmbNet [50]                   | F30K [53]   | 73.7 ± 0.55 | **74.3 ± 0.25** | 73.9 ± 0.18 | **74.3 ± 0.14** | 74.1 ± 0.16 |
| MSCOCO [35]                   | 81.7 ± 0.26 | **81.9 ± 0.30** | 81.6 ± 0.23 | 81.7 ± 0.16 | 81.5 ± 0.19 |
| **Phrase Grounding**          |             |       |       |       |       |       |
| SimNet [49]                   | F30K Entities [40] | 72.1 ± 0.18 | **72.2 ± 0.34** | 72.0 ± 0.33 | 71.6 ± 0.29 | 71.8 ± 0.25 |
| ReferIt [31]                  | 60.7 ± 0.37 | **61.0 ± 0.43** | 60.8 ± 0.39 | 60.4 ± 0.45 | 60.5 ± 0.43 |
| **Image Classification**      |             |       |       |       |       |       |
| WRN-28-10 [54]                | CIFAR-100 [33] | 19.66 ± 0.23 | 19.59 ± 0.21 | 19.48 ± 0.24 | **19.24 ± 0.29** | 19.32 ± 0.27 |

parameters. Second, the early layers tended to group layers into 3-4 parameter groups across different runs, with the remaining 10-11 parameter groups containing a single layer.

C Effect of the Number of Candidates Retrieved by the Parameter Selector

Table 10 reports the results using different numbers of candidates. We find that varying the number of candidates only has a minor impact on performance most of the time. We note that more candidates tends to lead to reduced variability between runs, making results more stable. As a reminder, however, the number of candidates does not guarantee that each layer will have enough parameters to construct them. Thus, parameter groups only use this hyperparameter when many weights are available to it (i.e., it can form multiple candidates for the layers it implements). This occurs for the phrase grounding and bidirectional retrieval results at the higher maximum numbers of candidates.