Incremental Learning Through Deep Adaptation

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Abstract

Given an existing trained neural network, it is often desirable to be able to add new capabilities without hindering performance of already learned tasks. Existing approaches either learn sub-optimal solutions, require joint training, or incur a substantial increment in the number of parameters for each added task, typically as many as the original network. We propose a method which fully preserves performance on the original task, with only a small increase (around 20%) in the number of required parameters while performing on par with more costly fine-tuning procedures, which typically double the number of parameters. The learned architecture can be controlled to switch between various learned representations, enabling a single network to solve a task from multiple different domains. We conduct extensive experiments showing the effectiveness of our method and explore different aspects of its behavior.

1 Introduction

While deep neural networks continue to show remarkable performance gains in various areas such as image classification [16], semantic segmentation [20], object detection [8], speech recognition [10] medical image analysis [19] - and many more - it is still the case that typically a separate model needs to be trained for each new task. Given two tasks of a totally different modality or nature, such as predicting the next word in a sequence of words versus predicting the class of an object in an image, it stands to reason that each would require a different architecture or computation. However, for a set of related tasks such as classifying images from different domains it is natural to expect that solutions will:

1. Utilize the same computational pipeline
2. Require a modest increment in the number of required parameters for each added task
3. Be learned without hindering performance of already learned tasks
4. Be learned incrementally, dropping the requirement for joint training such as in cases the training data for previously learned tasks is no longer available

Our goal is to enable a network to learn a set of related tasks one by one while adhering to the above requirements. We do so by augmenting a network learned for one task with controller modules which utilize already learned representations for another. The parameters of the controller modules are optimized to minimize a loss on a new task. The training data for the original task is not required at this stage. The network’s output on the original task data stays exactly as it was; any number of controller modules may be added to each layer so that a single network can simultaneously encode multiple distinct tasks, where the transition from one task to another can be done by setting a binary switching vector. We demonstrate the effectiveness of our method on 8 image classification datasets with images from various domains and non-overlapping output classes. We show that despite adding only 22% number of original parameters for each newly learned task (the specific number depends on the network architecture) , the average performance closely approaches that of fine tuning all
parameters - without the negative side effects of doubling the number of parameters and catastrophic forgetting.

Our main contribution is the introduction of a knowledge transfer method which is as effective as fine-tuning all network parameters towards a new task, precisely preserves old task performance, requires a fraction (network dependent, typically 22%) of the cost in terms of new weights and is able to switch between any number of learned tasks.

In the next section, we review some related work. Sec. 3 details the proposed method. In Sec. 4 we present various experiments, including comparing our method to more costly baselines, as well as exploring various strategies on how to make our method more effective. We finish with some concluding remarks.

2 Related Work

Multi-task Learning. In multi-task learning, the goal is to train one network to perform several tasks simultaneously. This is usually done by jointly training on all tasks. Such training is advantageous in that a single representation is used for all tasks. In addition, multiple losses are said to act as an additional regularizer. Some examples include facial landmark localization [30], semantic segmentation [11], 3D-reasoning [5], object and part detection [1] and others. While all of these train different tasks on the same dataset, the recent work of [2] explores the ability of a single network to perform tasks on various image classification datasets. We also aim to classify images from multiple datasets but we propose doing so in a manner which learns them one-by-one rather than jointly. Our work bears some resemblance to that of [21], where two networks are trained jointly, with additional “cross-stitch” units, allowing each layer from one network to have as additional input linear combinations of outputs from a lower layer in another. However, our method does not require joint training and requires significantly fewer parameters.

Incremental Learning. Adding a new ability to a neural net often results in so-called “catastrophic forgetting” [7], hindering the network’s ability to perform well on old tasks. The simplest way to overcome this is by fixing all parameters of the network and using the output of its penultimate layer as a feature extractor, upon which a classifier may be trained [4, 27]. While guaranteed to leave the old performance unaltered, it is observed to yield results which are substantially inferior to fine-tuning the entire architecture [8]. The work of [18] provides a succinct taxonomy of various variants of such methods. In addition, they propose a mechanism of fine-tuning the entire network while making sure to preserve old-task performance by incorporating a loss function which encourages the output of the old features to remain constant on newly introduced data. While their method adds a very small number of parameters for each new task, they do not guarantee that the model retains its full ability on the old task. In [26], new representations can be added along old ones, enabling free adaption to new tasks while leaving the old task performance unaffected. However, this comes at a cost of duplicating the number of parameters of the original network for each added task. In [14], the learning rate of neurons is lowered if they are found to be important to the old task. Our method fully preserves the old representation while causing a modest increase in the number of parameters for each added task.

3 Approach

We begin by some notation. Let $T$ be some task to be learned. Specifically, we use a deep convolutional neural net (DCNN) in order to learn a classifier to solve $T$. Most contemporary DCNN’s follow a common structure: for each input $x$, the DCNN computes a representation of the input by passing it through a set of $l$ layers $\phi_i, i \in 1 \ldots l$ interleaved with non-linearities. The initial (lower) layers of the network are convolutions. The output of the network is created by attaching at least one fully connected layer $f_i, i \in 1 \ldots c$ to the output of the last convolutional layers. Let $\Phi_{F_N} = \sigma(\phi_1) \circ \ldots \circ \sigma(\phi_2) \circ \sigma(\phi_1)$ be the composition of all of the convolutional layers of the network $N$, interleaved by non-linearities. For simplicity, we assume an architecture where all non-linearities $\sigma$ are the same function, with no tunable parameters. Denote by $\Phi_{F_N}(x)$ the feature representation of $x$. Similarly, let the classifier part of $N$ be denoted $\Phi_{C_N} = f_c \circ \ldots \sigma(\phi_2) \circ \sigma(\phi_1)$ be the composition of all of the fully-connected layers of $N$. The final output of the network $N$ is then simply defined as

\[ N(x) = \Phi_{C_N} \circ \Phi_{F_N}(x) \]
Note that batch-normalization layers may be also interleaved between \( \phi_l \) but we dropped them from the above notation for brevity. It is also possible to drop the \( \Phi_{\mathcal{CN}} \) term, if the network is fully convolutional, as in [20].

### 3.1 Adapting Representations

Assume that we are given two tasks, \( T_1 \) and \( T_2 \), to be learned, and that we have learned a base network \( N \) to solve \( T_1 \). We augment \( N \) so that it will be able to solve \( T_2 \) as well. One way to do so is to extend the penultimate layer of \( N \) with a new output layer whose weights are then trained for the new task, keeping all of the old weights of \( N \) fixed. However, we wish to avoid the sub-optimal solution likely caused by failing to adapt all of the layers of \( N \). Hence, in addition to adding a new "head" to the network, we also attach a controller module to each of its convolutional layers. Each controller module uses the existing weights of the corresponding layer of \( N \) to create new convolutional filters adapted to the new task \( T_2 \). For each convolutional layer \( \phi_l \) in \( N \), let \( F_l \in \mathbb{R}^{C_l \times C_l \times k \times k} \) be the set of filters for that layer, where \( C_l \) is the number of output features, \( C_l \) the number of inputs, and \( k \times k \) the kernel size (assuming a square kernel), and let \( b_l \in \mathbb{R}^{C_l \times 1} \) be the bias. Denote by \( \tilde{F}_l \in \mathbb{R}^{C_l \times D} \) the matrix whose rows are the flattened versions of the filters of \( F_l \), where \( D = C_l \cdot k \cdot k \); let \( f \in \mathbb{R}^{C_l \times k \times k} \) be a filter from \( F_l \) whose values are

\[
\begin{pmatrix}
    f_{11} & \cdots & f_{1k} \\
    \vdots & \ddots & \vdots \\
    f_{k1} & \cdots & f_{kk}
\end{pmatrix}
\]

The flattened version of \( f \) is a row vector \( \tilde{f} = (f_{11}, \ldots, f_{1k}, \ldots, f_{k1}, \ldots, f_{kk}) \in \mathbb{R}^D \). "Unflattening" a row vector \( \tilde{f} \) reverts it to its tensor form \( f \in \mathbb{R}^{C_l \times k \times k} \). This way, we can write

\[
\tilde{F}_l = W_l \cdot \tilde{F}_l
\]

where \( W_l \in \mathbb{R}^{C_l \times C_l \times 1} \) is a weight matrix defining linear combinations of the flattened filters of \( F_l \), resulting in \( C_l \), new filters. Unflattening \( \tilde{F}_l \) to its original shape results in \( F_l^a \in \mathbb{R}^{C_l \times C_l \times k \times k} \), which we call the adapted filters of layer \( \phi_l \). Using the symbol \( a \otimes b \) as shorthand for flatten b→matrix multiply by a→unflatten, we can write:

\[
F_l^a = W_l \otimes F_l
\]

For bias, we instantiate a new weight vector \( b_l^a \) instead of the original \( b_l \). The output of layer \( \phi_l \) is computed as follows: let \( x_{l-1} \) be the input of \( \phi_l \) in the adapted network. For a given switching
The fully connected layers $f^o_i$ are learned from scratch. Throughout training & testing, the weights $F$ of the base network as fixed and only used as basis functions for the creation of $F^a$. The weights of the controller modules are learned via back-propagation given the loss function. Weights of any batch normalization (BN) layers, are either kept fixed or learned separately normalization layers for the controller augmented network. The batch-normalized output is switched between the values of the old and new BN layers, similarly to Eq. 4. A visualization of a network augmented with controller-modules can be seen in Fig. 1.

While we test our method on image classification tasks, it can be applied to any architecture with convolutions, i.e., the majority of to-date architectures. However, the choice of filter dimensions can render it less effective in some cases (see next section).

In the following, we denote a network learned for a dataset/task $S$ as $N_S$. A controller learned using $N_S$ as a base network for the purpose of task $T$ will be denoted as $N_{S \rightarrow T}$.

**Parameter Efficiency** The number of new parameters added for each task is dependent on two factors: the number of filters in each layer and the number of parameters in the fully-connected layers. As the fully connected layers are not reused, they are fully duplicated. Let $M = C_o \times D$ be the filter dimensions for some layer in the base network, where $D = C_i \times k \times k$. A controller module for this layer requires $C_o \times C_o$ new coefficients to define the adapted filters and an additional $C_o$ for the new bias. Hence the ratio of new parameters added w.r.t to the old ones for this layer is

$$\frac{C_o \times (C_o + 1)}{C_o \times (C_i + 1)} = \frac{C_o + 1}{C_i + 1} \approx \frac{C_o}{C_i}$$

(the approximation is for a large enough $C_o$ and $D$). Example: for a layer with $C_o = C_i = 256$ input and output units and a kernel size $k = 5$ the ratio of new parameters will be $\frac{256+1}{5+1} \approx 0.04$. In the architecture we use (see Experiments, Sec. 4), the total number of features added to the convolutional layers is about 11% of the number of original features, and the fully-connected parameters also add another 11% of the total number of weights, leading to a total addition of 22% of the parameters of the base network for each newly learned task. The fraction of added parameters is dependent on the chosen network architecture. Our method can be applied to any network with convolutional layers. If, however, $C_o \geq D$, e.g., the number of output filters is greater than the dimension of each input filter, we our method would only increase the number of parameters.
Table 1: Mean transfer learning performance. We show the mean top-1 accuracy (%) attained by fine-tuning a network from each domain to all domains. The last layer of Caltech-256 is most generic. However, fine tuning is best when initially training on the Sketch dataset.

| Dataset     | Daimler | SVHN   | GTSR | CIFAR-10 | Omniglot | Plankton | Sketch | Caltech |
|-------------|---------|--------|------|----------|----------|----------|--------|---------|
| ft-full     | 60.1    | 60     | 65.8 | 70.9     | 80.4     | 81.6     | 84.2   | 82.3    |
| ft-full-bn-off | 61.8    | 64.6   | 66.2 | 72.5     | 78       | 80.2     | 82.5   | 81      |
| ft-last     | 24.4    | 33.9   | 42.5 | 44       | 44.1     | 47       | 50.3   | 55.6    |

3.1.1 Multiple Controllers

The above description mentions one base network and one controller network. However, any number of controller networks can be attached to a single base network, with independently trained controller modules. The amortized number of parameters per task decreases inversely with the number of added controllers. For instance, we construct 7 controllers using one base network, we require \((1 + 0.22 \times 7) \times P = 2.54 \times P\) parameters where \(P\) is the number for the base network alone. Had each network been trained independently, the total number of parameters would be \(8 \times P\), i.e., we use a ratio of \(31\%\) of the number of required parameters, had each network been trained independently. In this case, \(\alpha\) is extended to a one-hot vector of values determined by another sub-network, allowing each controller network to have a varying effect on the final output (see refsub:A-Unified-Network).

4 Experiments

We conduct several experiments to verify our method and explore different aspects of its behavior. We begin by establishing a baseline performance by training a separate module for each of several benchmark datasets (4.1.1). Next, we evaluate the merit of transfer learning between pairs of datasets (4.2). We then proceed to learn several variants of a single network which is able to simultaneously, yet effectively classify images from all datasets with only a modest increase in the number of required parameters and compare it to more costly alternatives (4.3). Finally, we show how to augment this network with the ability to discern the input domain and output a proper classification (4.3.4).

4.1 Datasets and Evaluation

Our evaluation protocol resembles that of [2], in the following ways: first, we test our network on a variety of datasets\(^1\), namely: Caltech-256 [9], CIFAR-10 [15], Daimler [23], GTSR [29], Omniglot [22], Plankton imagery data [3], Human Sketch dataset [6] and SVHN [24]. We resize all images to a common size of 64 × 64 pixels, duplicating the gray-scale images so that they have 3 channels as do the RGB ones. We whiten all images by subtracting the mean pixel value and dividing by the variance per channel. This is done for each dataset separately. Like [2], we select 80\% for training and 20\% for validation in datasets where no fixed split is provided. Unlike them, we use a simpler network architecture, allowing us to conduct a wide range of experiments within reasonable computational resources. Our network architecture is the B architecture described in [28]. We refer to this architecture as VGG-B. Each convolutional layer is followed by a batch-normalization layer. With roughly 10 million parameters, it performs quite well on the various datasets when trained from scratch (See Tab. 2). Following is a brief description of each dataset.

Caltech-256 is a well-known object classification benchmark with 256 object classes and an additional background class. CIFAR-10 - 10 object classes depicted in a total of 60,000 32x32 color images. The Daimler Mono Pedestrian Classification Benchmark - a collection of pedestrian and non-pedestrian images, cropped and resized to 18 × 36 pixels. GTSR - cropped images of 43 traffic signs. Omniglot - 1623 different handwritten characters from 50 different alphabets. As in [2] we include all the character categories in train and test time. Plankton imagery data - a classification benchmark with 30336 images of various organisms ranging from the smallest single-celled protists to copepods, larval fish, and larger jellies. Human Sketch dataset - 20000 human sketches of everyday objects such as “book”, “car”, “house”, “sun”. The Street View House Numbers (SVHN) - a

\(^1\)The Animals with Attributes dataset [17] was excluded since at the time of writing of this paper, copyright issues prevented accessing the benchmark’s images
| Type     | Net          | CIFAR-10 | GTSR | SVHN | Caltech | Daimler | Omniglot | Plankton | Sketch | Mean |
|----------|--------------|----------|------|------|---------|---------|----------|----------|--------|------|
| Indep    | VGG-B        | 92.3     | 95.2 | 90.4 | 88.2    | 92.9    | 86.7     | 78.3     | 89.2   | 87.3 |
|          | ResNet-38†   | 90.6     | 95.8 | 96.3 | 14.9    | 89.6    | 87.0     | 74.3     | 68.9   | 77.1 |
| Control  | Ncaltech−256 | 77.9     | 93.6 | 91.8 | 88.2    | 93.8    | 81.0     | 63.6     | 49.4   | 79.9 |
|          | Nsketch      | 77.9     | 92.3 | 93.2 | 86.9    | 94.0    | 85.5     | 65.6     | 45.2   | 83.7 |
|          | Nnoise       | 68.1     | 90.0 | 90.4 | 84.6    | 91.3    | 80.0     | 61.7     | 42.7   | 76.4 |
| Pre-Ctrl | Nimagenet(B) | 91.6     | 97.6 | 94.6 | 92.2    | 98.7    | 81.3     | 72.5     | 63.2   | 86.4 |
|          | VGG-B        | 97.2     | 99.0 | 95.8 | 92.6    | 96.7    | 83.8     | 74.2     | 65.4   | 87.7 |
|          | Nimagenet(B) | 91.0     | 97.6 | 95.0 | 92.2    | 98.6    | 83.0     | 72.3     | 69.4   | 86.9 |

Table 2: Top two rows independent baseline performance. Top-1 accuracy (%) on various datasets by training from scratch.† according to [2]. Third, fourth controller Network performance. Using Nsketch as a base network outperforms Ncaltech−256 for most tasks. Learning a controller network based on random weights (Nnoise) works quite well given that its number of learned parameters is a tenth of the other methods. Sixth row Nimagenet(B) - controller networks initialized VGG-B model pretrained on ImageNet. Seventh row: pre-trained VGG-B, fine-tuned on each dataset. Last row: selective Control Network based on both ImageNet & Sketch. We emphasize with color the first, second and third highest values in each column.

real-world digit recognition dataset with around 70,000 images which are centered around a single character and resized to 32 × 32 pixels.

4.1.1 Baselines
As a baseline, we train our network independently on each of the 8 datasets. All experiments are done with the Adam optimizer [13], with an initial learning rate of 1e-3 or 1e-4, dependent on a few epochs of trial on each dataset. The learning rate is halved after each 10 epochs. Most networks converge within the first 10-20 epochs, with mostly negligible improvements afterwards. The top-1 accuracy (%) is summarized in Table 2. In [2], a more recent architecture was chosen, namely the ResNet-38 [12]. We compare the baseline performance of our chosen architecture those attained by [2] with ResNet-38. Our main goal is not reaching state-of-the-art performance on independently learned datasets. Nevertheless, the relative performance justifies the choice of VGG-B as solid baseline. Admittedly, it is not unlikely that small implementation details (e.g., learning rate selection) are the cause of the gaps in performance in favor of the simpler VGG-B.

4.2 Transferability
We aim to use a network trained on one dataset to perform well on others. As an indicator of the representative power of the features of each independently trained network N, we test the performance on other datasets, using N for fine tuning. We test 3 different scenarios. ft-last: fine-tuning only the last layer, keeping all the rest frozen. ft-full: fine-tuning all layers of the network. ft-full-bn-off: same as ft-full, but freezing the parameters of the batch-normalization layers - this was found to be useful in some cases. We define the transferability of a source dataset S w.r.t a target dataset T as the top-1 accuracy attained by fine-tuning a network trained on S to perform on T. The results are summarized in Fig. 2. The figure shows some interesting phenomena. First, it is very clear that fine-tuning the last layer only is far inferior to fine-tuning the entire network. Second, perhaps due to the small size of the datasets, usually training from scratch is the most beneficial option. Third, we see a distinction between natural images (Caltech-256, CIFAR-10, SVHN, GTSR, Daimler) and unnatural ones (Sketch, Omniglot, Plankton) ; the Plankton images are natural in the rigorous sense, but do seem to exhibit different behavior than the rest. It is evident that features from the natural images are less beneficial for the unnatural images. Interestingly , the converse is not true: training a network starting from Sketch or Omniglot works quite well for most datasets, both natural and unnatural. This is further shown in Table 1 (a): we calculate the mean transferability of each dataset by the mean value of each rows of the transferability matrix from Fig 2; on average, using a network trained on Caltech-256 as a feature-extractor for shallow fine-tuning works best. However, using the Plankton dataset works as the best starting point for full fine-tuning, closely followed by Caltech-256. Hence they make good candidates for base-networks, as we show next.

4.3 Control Networks
We tested the performance of controller networks based on base networks trained initially on the Plankton or Caltech-256 datasets. One question which arises is how to initialize the weights W
of a control-module. We tested several options. (1) Set $W$ to be an identity matrix (diagonal). This is equivalent to the controller module starting with a state which effectively mimics the behavior of the base network (2) Set $W$ to random noise (random) (3) Train an independent network for the new task from scratch; set $W$ to best linearly approximate the new weights with the base weights (linear_approx). To test the best alternative out of the three mentioned, we trained $N_{\text{sketch-caltech256}}$ for one epoch with each initialization and observed the loss function. Each experiment was repeated 5 times and the result averaged. The loss curves can be seen in Fig. 3(a). It is evident that the diagonal initialization is superior - this means that - perhaps counter-intuitively - there is no need to trained a fully parametrized target network; simply starting with the behavior of the base network and tuning it via the control modules results in faster convergence. With this observation, we train controller modules with the diagonal method, starting from Sketch and Caltech-256, for each of the remaining set of datasets. The best overall mean accuracy (83.7%) is attained using $N_{\text{sketch}}$ as a base-network. Note that this is very close to the performance attained by full transfer learning (84.2 %, see Tab. 1 ), at a fraction of the number of parameters. This is consistent with our transferability measure. To further test the ability of the “transferability” measure to predict how well a control network would perform with the base network as a specific dataset, we used each dataset as a basis for control networks for all others and measured the mean overall accuracy. The relation between the two can be seen in Fig. 3 (b).

4.3.1 Starting from a Randomly Initialized Base Network

To check the effectiveness of our method, we checked how well it can perform without any prior knowledge, e.g, using a randomly initialized base network. The total number of parameters for this architecture is 12M. However, as 10M have been randomly initialized and only the controller modules and fully-connected layers have been learned, the effective number is actually 2M. We summarize the results in Tab. 2. Notably, the results of this initialization worked surprisingly well; the mean top-1 precision attained by this network was 76.3 %, slightly worse than of $N_{\text{caltech256}}$ (79.9%). This is better than initializing with $N_{\text{daimler}}$, which resulted in a mean accuracy of 75%.

4.3.2 Pre-trained Networks

We now check how well a network can perform as a base-network, after it has seen ample training examples. We denote by $N_{\text{imagenet}}$ the VGG-B architecture which was pre-trained on the ImageNet [25] dataset. We train control networks for each of the 8 datasets and report the results in Table 2 (Pre-Ctrl). This improves the average performance by a significant amount (83.7 % to 86.5 %), however for both Sketch and Omniglot the performance is in favor of $N_{\text{sketch}}$. Note these are the only two domains of strictly unnatural images. On Caltech256 we see an improvement from 88.2 % (training from scratch) to 92.2 %. Fine-tuning all parameters of VGG-B yield slightly better results, with an average accuracy of 87.7 %, compared to 86.5 % attained by the control networks, but requiring x5 parameters.

4.3.3 Multiple Base Networks

Ideally, a good base network should have features which are generic enough so that a controller network can use them for any target task. In reality (and as we can see from the performance using only a single base network) this is not necessarily the case. To use two base-networks simultaneously, we implemented a dual-controlled network by using both $N_{\text{caltech256}}$ and $N_{\text{sketch}}$ and attaching them controller networks. The outputs of the feature parts of the resulting sub-networks were concatenated before the fully-connected layer. This resulted in the exact same performance as $N_{\text{sketch}}$ alone. However, by using selected controller-modules per group of tasks, we can improve the results dramatically: For each dataset the maximally performing network is the basis for the control module; i.e., we use the pre-trained VGG-B for all the but Omniglot & Sketch. For the latter two we use $N_{\text{sketch}}$ as a base net. While this requires more parameters, it boosts the mean performance to 87.76 % - better than using any single base network.

4.3.4 A Unified Network

Finally, we test the possibility of making a single network which can both determine the domain of an image and classify it. We train a classifier to output which dataset an image originates from, using training images from the 8 different datasets. This turns out to be an extremely simple task compared
We have presented a method to adapt an existing network to new tasks while fully preserving the existing representation. Our method is able to closely approach the average performance of full-transfer learning though requiring a fraction of the parameters (around 22% vs. 100%) for each newly learned task, given a proper selection of a base network, and surpass the performance when using controller parameters based on two networks. Built into our method is the ability to easily switch the representation between the various learned tasks, enabling a single network to perform seamlessly on various domains. We find it surprising that using combinations of existing representations yields ones which are useful for other tasks almost as training the entire network from scratch. The control parameter $\alpha$ can be cast as a real-valued vector, allowing a smooth transition between representations of different tasks. An example of the effect of such a smooth transition can be seen in Fig. 3 (c) where $\alpha$ is used to linearly interpolate between the representation of differently learned tasks, allowing one to smoothly control transitions between different behaviors. Allowing each added task to use a convex combination of already existing controllers will potentially utilize controllers more efficiently and decouple the number of controllers from the number of tasks.

5 Conclusions

We have presented a method to adapt an existing network to new tasks while fully preserving the existing representation. Our method is able to closely approach the average performance of full-transfer learning though requiring a fraction of the parameters (around 22% vs. 100%) for each newly learned task, given a proper selection of a base network, and surpass the performance when using controller parameters based on two networks. Built into our method is the ability to easily switch the representation between the various learned tasks, enabling a single network to perform seamlessly on various domains. We find it surprising that using combinations of existing representations yield ones which are useful for other tasks almost as training the entire network from scratch. The control parameter $\alpha$ can be cast as a real-valued vector, allowing a smooth transition between representations of different tasks. An example of the effect of such a smooth transition can be seen in Fig. 3 (c) where $\alpha$ is used to linearly interpolate between the representation of differently learned tasks, allowing one to smoothly control transitions between different behaviors. Allowing each added task to use a convex combination of already existing controllers will potentially utilize controllers more efficiently and decouple the number of controllers from the number of tasks.

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