Side-Tuning: Network Adaptation via Additive Side Networks

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Abstract

When training a neural network for a desired task, one may prefer to adapt a pre-trained network rather than starting from randomly initialized weights – due to lacking training data, performing lifelong learning where the system has to learn a new task while being previously trained for other tasks, or wishing to encode priors in the network via preset weights. The most commonly employed approaches for network adaptation are fine-tuning and using the pre-trained network as a fixed feature extractor, among others.

In this paper, we propose a straightforward alternative: Side-Tuning. Side-tuning adapts a pre-trained network by training a lightweight “side” network that is fused with the (unchanged) pre-trained network with summation. This simple method works as well as or better than existing solutions while it resolves some of the basic issues with fine-tuning, fixed features, and several other common baselines. In particular, side-tuning is less prone to overfitting when little training data is available, yields better results than using a fixed feature extractor, and does not suffer from catastrophic forgetting in lifelong learning. We demonstrate the performance of side-tuning under a diverse set of scenarios, including lifelong learning (iCIFAR, Taskonomy), reinforcement learning, imitation learning (visual navigation in Habitat), NLP question-answering (SQuAD v2), and single-task transfer learning (Taskonomy), with consistently promising results.

1. Introduction

The goal of side-tuning (and generally network adaptation) is to capitalize on a pretrained model to better learn one or more novel tasks. The side-tuning framework is straightforward: it assumes access to a given (base) model \(B : \mathcal{X} \rightarrow \mathcal{Y}\) that maps the input \(x\) onto some representation \(y\). Side-tuning then learns a side model \(S : \mathcal{X} \rightarrow \mathcal{Y}\), so that the curated representations for the target task are

\[
R(x) \triangleq B(x) \oplus S(x),
\]

for some combining operation \(\oplus\). In our formulation, we use a learned alpha-blending, \(B(x) \oplus S(x) \triangleq \alpha B(x) + (1 - \alpha)S(x)\) as the combining operation (other options are discussed in Section 3.1). Certain pre-set curricula of \(\alpha\) reduce the side-tuning framework to: fine-tuning, feature extraction, and stage-wise training (see Fig. 2, right). Hence those can be viewed as special cases of the general side-tuning framework. Other curricula suggest (e.g.) a maximum a posteriori estimator that integrates the \(B(x)\) prior with the evidence from \(S(x)\).

Side-tuning is an example of an additive learning approach, one that adds new parameters for each new task. Since side-tuning does not change the base model, it, by design, adapts to a target task without degrading the performance of the base task. A number of existing approaches also adapt the base network by learning new parameters for each new task (e.g. [27]). Unlike these approaches, side-tuning places no constraints on the structure of the side network, allowing for its architecture and size to be independent of that of the base network. In particular, while other approaches require the side network to scale with the base network, side-tuning can use tiny networks when the base requires minor updates. By adding fewer parameters per task, side-tuning can learn more tasks before the model grows large enough to require parameter consolidation.

These approaches stand in contrast to substitutive meth-
ods, which do not increase the number of parameters over time and instead gradually fill up the capacity of a large base model (e.g. fine-tuning). A large body of constraint-based methods focus on how to regularize these updates in order to prevent inter-task interference [13, 29]. Side-tuning does not require such regularization since the base is untouched.

We compare side-tuning to alternative approaches on both the iCIFAR and Taskonomy datasets. iCIFAR consists of ten distinct 10-class image classification problems. Taskonomy covers multiple tasks of varied complexity from across computer vision (surface normal estimation, depth estimation, edge detection, image 1000-way classification, etc.). On these datasets, side-tuning uses side networks that are much smaller than the base. Consequently, even without consolidation, side-tuning uses fewer learnable parameters than the alternative methods.

This simple approach deals with the key challenges of incremental learning. Namely, it does not suffer from either:

- **Catastrophic forgetting**: tendency of a network to abruptly lose previously learned knowledge upon learning new information. Discussed in Sec. 4.2.1.

- **Rigidity**: Increasing inability of a network to adapt to new problems as it accrues constraints from previous problems. Discussed in Sec. 4.2.2.

Side-tuning avoids these problems using a straightforward mechanism while remaining highly performant, which we demonstrate in Section 4.2.3. Side-tuning is significantly simpler than most existing lifelong learning approaches.

2. Related Work

Broadly speaking, network adaptation methods either overwrite existing knowledge (substitutive methods) or save it and add new parameters (additive learning). In incremental (lifelong, continual) learning, substitutive methods like fine-tuning are at risk of forgetting early tasks. To this end, existing methods constrain the learning procedure, leading to undesirable trade-offs. By design, additive approaches are able to circumvent forgetting, reuse knowledge, and scale to more tasks. Side-tuning is one of the simplest additive methods which takes this family of methods and captures a small yet core component that makes them work. We show this experimentally on various tasks and datasets, including iCIFAR [23], Habitat [28], SQuAD v2 [21], and Taskonomy [31]. In the remainder of this section we overview sidetuning’s connection to related fields.

**Incremental learning**’s objective is to learn a sequence of tasks $T_1, \ldots, T_m$ and perform well on the entire set at the end of training. Two problems arise from this sequential presentation: catastrophic forgetting (see Sec. 4.2.1) and rigidity (see Sec. 4.2.2). Incremental learning methods fall under two paradigms: substitutive and additive.

**Substitutive** methods modify an existing network to solve a new task by updating some or all of the network weights (simplest approach being fine-tuning). There are many alternatives that attempt to avoid catastrophic forgetting. [13] adds constraints on how the parameters are updated and [29, 13, 14] add a parameter regularization term per task. These approaches tend to impose constraints which slow down learning on later tasks (see Sec. 4.2.2 on rigidity, [2]). [3] relegates each task to approximately orthogonal subspaces but is unable to transfer information across tasks.

**Additive** methods circumvent the aforementioned problems by freezing the weights and adding a small number of new parameters per task (simplest approach being fixed features). One economical approach is to use off-the-shelf-features with one or more readout layers [22], [16, 26] modulate the output by applying learned weight masks. [1, 25] learn across different tasks with additional task-specific parameters. Perhaps the most comparable work to side-tuning is Progressive Neural Networks (PNN) [27] which, for each new task, learn a new network utilizing dense lateral connections from neural networks of earlier tasks. Side-tuning drops these lateral connections, making it significantly simpler and applicable on a larger variety of problems. Furthermore, the results suggest that side-tuning offers similar or better performance to these methods.

**Meta-learning** seeks to create agents that rapidly adapt to new problems by first training on tasks sampled from a standing distribution of tasks. Side-tuning is fundamentally compatible with this formulation and with existing approaches (e.g. [6]). Moreover, recent work suggests that these approaches work primarily by feature adaptation rather than rapid learning [20], and feature adaptation is also the motivation for our method.

**Fusion.** Many problems are easier to solve when using a suite of sensors providing complementary sources of information [5]. We combine both a base and a residual side network via a simple summation mechanism. This has been successfully used in computer vision (ResNets [8]) and in robotics, where residual RL [10, 30] learns a single task by combining a coarse policy (e.g. hand-coded optimal control) and with a learned residual network. Alternatively,
multiplication can be thought of as a measure of agreement among sensors, and multiplication for fusion has been explored in \([5, 16]\). FiLM [18] defines a combination operator that combines both multiplicative and summation transformations.

3. The Side-tuning Framework

Given a pre-trained base model \(B(x)\), \textit{Side-tuning} learns a side model \(S(x)\) and combines it with \(B(x)\) so that the representation for the target task is computed as \(R(x) \doteq B(x) \oplus S(x)\).

3.1. Architectural Elements

\textbf{Base Model.} The base model \(B(x)\) provides some core cognition or perception, and we put no restrictions on how \(B(x)\) is computed. We never update \(B(x)\), and in our approach it has zero learnable parameters. We consider several choices for \(B(x)\) in Section 4.4, but the simplest choice is a pre-trained network.

\textbf{Side Model.} Unlike the base model, the side network \(S(x)\) is updated during training; learning a residual that we apply on top of the base encoding. Iteratively learning residuals for a single task is known as \textit{gradient boosting} (see Section 4.4 for a comparison). \textit{Side-tuning} is instead focused on learning multiple tasks.

One crucial component of the framework is that the complexity of the side network can scale to the difficulty of the problem at hand. When the base is relevant and requires only a minor update, a very small network can suffice. Section 4.4 explores the effect of network size, how that changes with the choice of base and target tasks.

While the side network can be initialized using a variety of methods, we initialize the side network with a copy of the base network. When the forms of the base and side networks differ, we initialize the side network with weights distilled from the base network using knowledge distillation [9]. We test alternatives in Section 4.4.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Mechanics of side-tuning. (i) Side-tuning takes some core network \((B)\) and adapts it to a new task by training a side network. (ii) shows the connectivity structure when using side-tuning along with alpha-blending. (iii) Some of the existing common adaptation methods turn out to be special cases of an alpha blending with a side network. In particular: fine-tuning, feature extraction, and other approaches are side-tuning with a fixed curriculum on the blending parameter \(\alpha\), as shown in the plot.}
\end{figure}

Combining Base and Side Representations. The final side-tuning representation is a combination, \(B(x) \oplus S(x)\). What should \(\oplus\) be?

\textit{Side-tuning} admits several options for this combination operator and we compare several operators in Section 4.4. We observe that alpha blending, \(B(x) \oplus S(x) \doteq \alpha B(x) + (1 - \alpha) S(x)\), where \(\alpha\) is treated as a learnable parameter works well and \(\alpha\) correlates with task relevance (see Section 4.4). Our loss function for a single task using supervised learning, is

\[ L(x, y) = \|D(\alpha B(x) + (1 - \alpha) S(x)) - y\| \]

where \(D\) is some readout of the side-tuning representation.

While simple, alpha blending is expressive enough that it encompasses several common transfer learning approaches. As shown in Figure 2(iii), side-tuning is equivalent to feature extraction when \(\alpha = 1\). When \(\alpha = 0\), side-tuning is instead equivalent to fine-tuning if the side network has the same architecture as the base. If we allow \(\alpha\) to vary during training, then switching \(\alpha\) from 1 to 0 is equivalent to the common (stage-wise) training curriculum in RL, where a policy is trained on top of some fixed features that are unlocked partway through training.

Another notable curriculum is \(\alpha(N) = \frac{k}{k + N}\) for \(k > 0\) (hyperbolic decay) where \(N\) is the number of training epochs. In this curriculum, \(\alpha\) controls the weighting of the prior \((B(x))\) with the learned estimate \((S(x))\), and the weight of the evidence scales with the amount of data. This curriculum is suggestive of a maximum a posteriori estimate and, like the MAP estimate, it converges to the MLE (fine-tuning, \(\alpha = 0\)).

3.2. Asymptotic Consistency and Bias/Variance

When minimizing estimation error there is often a trade-off between the bias and variance contributions \([7]\). Choosing between feature extraction or fine-tuning exemplifies this dilemma. Feature extraction \((\alpha = 0)\) locks the weights and corresponds to a point-mass prior that, unless the
weights are already optimal, yields a biased estimator. In fact, the estimator allows no adaptation to new evidence and is asymptotically inconsistent. On the other hand, fine-tuning ($\alpha = 1$), is an uninformative prior yielding a low-bias high-variance estimator. With enough data, fine-tuning can produce better estimates, but this usually takes more data than feature extraction. Side-tuning addresses both these problems. It reduces variance by including the fixed features in the representation, and it is consistent because it allows updating via the residual side network.

3.3. Regularization and Catastrophic Forgetting

While $\alpha$ provides a way to control the importance of the prior, another natural approach for enforcing a prior is to penalize deviations from the original feature representation. Typically, it is easier to specify meaningful explicit priors on outputs (e.g., L2 for pixels) than on the latent representations, which can be difficult if not impossible to interpret. As long as the decoder $D : \mathbb{Y} \rightarrow \mathbb{A}$ is differentiable, any distance measure on the outputs can be pulled back through the decoder and into the latent space. This induced distance $d_D$ on the latent representations is called the pullback metric in differential geometry, and in deep learning it is called the perceptual loss [11]. This may be a useful method for knowledge transfer when (i) the previous task is relevant to the new task and (ii) there is limited training data. A recent successful application of this approach would be the auxiliary losses in GPT [19], though we did not find it effective.

Perceptual regularization is often used to dampen catastrophic forgetting. For example, Elastic Weight Consolidation uses a diagonalized second-order Taylor expansion of the expectation of the pullback metric. Learning Without Forgetting uses a decoder-based approach that can be interpreted as jointly updating both the base network and the pullback metric. We show that such regularization does not fully address the problem of catastrophic forgetting (Section 4.2.1). Side-tuning avoids catastrophic forgetting by design (as the base network is never updated).

3.4. Side-Tuning for Incremental Learning

We often care about the performance not only on the current target task but also on the previously learned tasks. This is the case for incremental learning, where we want an agent that can learn a sequence of tasks $T_1, ..., T_m$ and is capable of reasonable performance across the entire set at the end of training. In this paradigm, catastrophic forgetting (diminished performance on $\{T_1, ..., T_{m-1}\}$ due to learning $T_m$) becomes a major issue.

In our experiments, we dedicate one new side network to each task, depicted in Figure 3. For task $T_t$, our loss function is

$$L(x_t, y_t) = \|D_t(\alpha_t B(x_t) + (1 - \alpha_t) S_t(x_t)) - y_t\|
$$

where $t$ is the task number and $D_t$ is some readout of the side-tuning representation. This simple approach follows the training curve in Figure 4 with no possible catastrophic forgetting. Furthermore, since side-tuning is independent of task order, training does not slow down as training progresses (as $m$ increases, see Section 4.2.2). We observe that this approach provides a strong baseline for incremental learning, outperforming existing approaches in the literature while using fewer parameters on more tasks (in Section 4.2).

![Figure 4. Theoretical learning curve of side-tuning.](image)

Side-tuning naturally handles other continuous learning scenarios besides incremental learning. A related problem is that of continuous adaptation, where the agent needs to perform well (e.g., minimizing regret) on a stream of tasks with undefined boundaries and where there might very little data per task and no task repeats. As we show in Section 4.2, inflexibility becomes a serious problem for constraint-based methods and task-specific performance declines after learning more than a handful of tasks. Moreover, continuous adaptation requires an online method as task boundaries must be detected and data cannot be replayed (e.g., to generate constraints for EWC).

Side-tuning could be applied to continuous adaptation by keeping a small working memory of cheap side networks that constantly adapt the base network to the input task. These side networks are small, easy to train, and when one
4. Experiments

In the first section we show that side-tuning compares favorably to existing incremental learning approaches on both iCIFAR and the more challenging Taskonomy dataset. We then extend to multiple domains (computer vision, RL, imitation learning, NLP) in the simplified (transfer learning) scenario for $m = 2$ tasks. Finally, we interpret side-tuning in a series of analysis experiments.

4.1. Baselines

We provide comparisons of side-tuning against the following methods:

**Scratch:** The network is initialized with appropriate random weights and trained using minibatch SGD with Adam [12].

**Feature extraction (features):** The pretrained base network is used as-is and is not updated during training.

**Fine-tuning:** An umbrella term that encompasses a variety of techniques, we consider a more narrow definition where pretrained weights are used as initialization and then training proceeds as in scratch.

**Elastic Weight Consolidation (EWC).** A constraint-based substitutive approach from [13]. We use the formulation from [29] which scales better, giving an advantage to EWC since otherwise we could use a larger side-tune network and maintain parameter parity.

**Parameter Superposition (PSP):** A parameter-masking substitutive approach from [3] which attempts to make tasks independent from one another by mapping the weights to approximately orthogonal spaces. This approach is unable to transfer across tasks.

**Progressive Neural Network (PNN):** An additive approach from [27] which utilizes many lateral connections between the base and side networks. This requires the base model to be a neural network and the

of the networks begins performing poorly (e.g. signaling a distribution shift) that network can simply be discarded. This is an online approach, and online adaptation with small cheap networks has found recent success in (e.g. [17]).
Figure 6. Incremental Learning on Taskonomy and iCIFAR. The above curves show loss and error on incremental learning experiments for three tasks on Taskonomy (left) and iCIFAR (right) datasets. The fact that side-tuning losses are flat after training (as we go right) shows that it does not forget previously learned tasks. Similarly, the performance remains consistent even on later tasks (as we go down), showing that side-tuning does not become rigid. Substitutive methods clearly forget (e.g. PSP) and/or become rigid (e.g. EWC). In Taskonomy, PNN and Independent are hidden under Sidetune. In iCIFAR, Sidetune (A) merges base and side information with a multilayer perceptron (adapter).

4.2. Incremental Learning

On both the Taskonomy [31] and incremental CIFAR (iCIFAR, [24]) datasets, side-tuning performs competitively against existing incremental learning approaches while using fewer parameters\(^1\). Moreover, side-tuning outperforms other approaches on the more challenging Taskonomy dataset.

Taskonomy includes labels for multiple computer vision tasks including 2D (e.g. edge detection), 3D (e.g. surface normal estimation), and semantic (e.g. object classification) tasks. We first selected the twelve tasks that make predictions from a single RGB image, and then created an incremental learning setup by selecting a random order in which to learn these tasks (starting with curvature). The images are 256x256 and we use a ResNet-50 for the base network and a 5-layer convolutional network for the side-tuning side network. The number of learnable network parameters used across all tasks is 24.6M for EWC and PSP, and 11.0M for side-tuning\(^2\).

iCIFAR. First, we pretrain the base network (ResNet-44) on CIFAR-10. Then the 10 subsequent tasks are formed by partitioning CIFAR-100 classes into 10 disjoint sets of 10-classes each. We train on each subtask for 20k steps before moving to the next one. Our state-of-the-art substitutive baselines (EWC and PSP) update the base network for each task (683K parameters), while side-tuning updates a four layer convolutional network per task (259K parameters after 10 tasks).

4.2.1 Catastrophic Forgetting

As expected, there is no catastrophic forgetting in side-tuning and other additive methods. Figure 6 shows that the error for side-tuning does not increase after training (blue shaded region), while it increases sharply for the substitutive methods on both Taskonomy and iCIFAR.

The difference is meaningful, and Figure 5 shows sample predictions from side-tuning and EWC for a few tasks during and after training. As is evident from the bottom rows, EWC exhibits catastrophic forgetting on all tasks (worse image quality as we move right). In contrast, side-tuning (top) shows no forgetting and the final predictions are significantly closer to the ground-truth (boxed red).

\(^1\)Full experimental details (e.g. learning rate and architecture) provided in the supplementary.

\(^2\)All numbers not counting readout parameters, which are common between all methods.
4.2.2 Rigidity

Side-tuning learns later tasks as easily as the first, while constraint-based methods such as EWC stagnate. The predictions for later tasks such as surface normals (seen in Figure 5) are significantly better using side-tuning—even immediately after training and before any forgetting can occur.

![Figure 7. Rigidity on Taskonomy and iCIFAR. Side-tuning always learns new tasks easily; EWC becomes increasingly unable to learn new tasks as training progresses. The same trend holds on iCIFAR (right), and the average rigidity is zero for side-tuning (and almost zero for PSP). The trend switches for PNN, which is not rigid on iCIFAR but is for Taskonomy.](image)

Figure 7 quantifies this slowdown. We measure rigidity as the log-ratio of the actual loss of the $i$th task over the loss when that task is instead trained first in the sequence. As expected, side-tuning experiences effectively zero slowdown on both datasets. For EWC, the increasing constraints make learning new tasks increasingly difficult—and the log-ratio increases with the number of tasks (Taskonomy, left). It is too rigid (log-ratio > 0) even in iCIFAR. While PNN learns iCIFAR tasks faster (evident by a negative ratio value), it also becomes rigid on the Taskonomy dataset.

4.2.3 Final Performance

Overall, side-tuning significantly outperforms the substitutive methods while using fewer than half the number of trainable parameters, and is comparable with PNN while remaining remarkably simpler. When the other methods use smaller networks, their performance decreases further. On iCIFAR, vanilla side-tuning achieves a strong average rank (2.30 of 5, see Table 2) and, just by using the same combining operator (MLP) as PNN, is able to match the performance (see Figure 6 right). On Taskonomy, side-tuning achieves the best average rank (1.13 of 5, while the next best is 1.88 by PNN, see Table 2).

This is a direct result of the fact (shown above) that side-tuning does not suffer from catastrophic forgetting or rigidity. It is not due to the fact that the sidetuning structure is specially designed for these types of image tasks; it is not (we show in Sec. 4.3 that it performs well on other domains). In fact, the much larger networks used in EWC and PSP should achieve better performance on any single task. For example, EWC produces sharper images early on in training, before it has had a chance to accumulate too many constraints (e.g., reshading in Figure 5). But this factor was outweighed by side-tuning’s immunity from the effects of catastrophic forgetting and creeping rigidity.

![Table 2. Average rank on Taskonomy and iCIFAR. While being remarkably simpler, side-tuning generally achieved a better average rank than other approaches. The difference increases on the more challenging Taskonomy dataset, where side-tuning significantly outperformed all tested alternatives.](image)

4.3. Universality of the Experimental Trends

In order to address the possibility that side-tuning is somehow domain- or task-specific, we provide results showing that it is well-behaved in other settings. As the concern with additive learning is mainly that it is too inflexible to learn new tasks, we compare with fine-tuning (which outperforms other lifelong learning tasks when forgetting is not an issue). For extremely limited amounts of data, feature extraction can outperform fine-tuning. We show that side-tuning generally performs as well as features or fine-tuning—whichever is better.

Transfer learning in Taskonomy. We trained networks to perform one of three target tasks (object classification, surface normal estimation, and curvature estimation) on the Taskonomy dataset [31] and varied the size of the training set $N \in \{100, 4 \times 10^6\}$. In each scenario, the base network was trained (from scratch) to predict one of the non-target tasks. The side network was a copy of the original base network. We experimented with a version of fine-tuning that updated both the base and side networks; the results were similar to standard fine-tuning.

We deferred remaining experimental details (learning rate, full architecture, etc.) to the supplementary materials. See provided code for full details.
new task just as well as fine-tuning, outperforming features and scratch (Table 3b).

**Imitation Learning for Navigation in Habitat.** We trained an agent to navigate to a target coordinate in the Habitat environment. The agent is provided with both RGB input image and also an occupancy map of previous locations. The map does not contain any information about the environment—just previous locations. In this section we use Behavior Cloning to train an agent to imitate experts following the shortest path on 49k trajectories in 72 buildings. The agents are evaluated in 14 held-out validation buildings. Depending on what the base network was trained on, the source task might be useful (Curvature) or harmful (Denoising) for imitating the expert and this determines whether features or learning from scratch performs best. Table 3c shows that regardless of the which approach worked best, side-tuning consistently matched or beat it.

**Reinforcement Learning for Navigation in Habitat.** Using a different learning algorithm (PPO) and using direct interaction instead of expert trajectories, we observe identical trends. We trained agents directly in Habitat (74 buildings). Table 3d shows performance in 14 held-out buildings after 10M frames of training. Side-tuning performs comparably to the max of competing approaches.

### 4.4. Learning Mechanics in Side-Tuning

**Task relevance predicts alpha α.** In our experiments, we treat α as a learnable parameter (initialized to 0.5) and find that the relative values of α are predictive of empirical performance. In imitation learning (Table 3c), curvature (α = 0.557) outperformed denoising (α = 0.252). In Taskonomy, the α values from training on just 100 images predicted the actual transfer performance to normals in [31], (e.g. curvature (α = 0.56) outperformed object classification (α = 0.50)). For small datasets, usually α ≈ 0.5 and the relative order, rather than the actual value is important.

**Benefits for intermediate amounts of data.** We showed in the previous section that side-tuning performs like the best of {features, fine-tuning, scratch} in domains with abundant or scant data.

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Table 3. **Side-tuning comparisons in other domains.** Sidetuning matched the adaptability of fine-tuning on large datasets, while performing as well or better than the best competing method in each domain: (a) In Taskonomy, performing either Normal Estimation or Object Classification using a base trained for Curvatures and either 100 or 4M images for transfer. Results using Obj.Cls. base are similar and provided in the supplementary materials. (b) In SQuAD v2 question-answering, using BERT instead of a convolutional architecture. (c) In Habitat, learning to navigate by imitating expert navigation policies, using inputs based on either Curvature or Denoising. Finetuning does not perform as well in this domain. (d) Using RL (PPO) and direct interaction instead of supervised learning for navigation.

| Method       | Transfer Learning in Taskonomy | QA on SQuAD | Navigation (IL) | Navigation (RL) |
|--------------|--------------------------------|-------------|-----------------|-----------------|
|              | From Curvature (100/4M ims.)   | Match (%)   | Nat. Rew. (%)   | Nat. Rew. (%)   |
|              | Normals (MSE ↓)                | Exact F1     | Curvature       | Curvature       |
| Fine-tune    | 0.200 / 0.094                  | 79.0 / 82.7  | 10.5 / 9.2      | 10.7 / 10.0     |
| Features     | 0.204 / 0.117                  | 49.4 / 49.5  | 11.2 / 8.2      | 11.9 / 8.3      |
| Scratch      | 0.323 / 0.095                  | 0.98 / 4.65  | 9.4 / 9.4       | 7.5 / 7.5       |
| Side-tune    | 0.199 / 0.095                  | 79.6 / 82.7  | 11.1 / 9.5      | 11.8 / 10.4     |

Figure 8. **Side-tuning performs favorably against alternatives on intermediate amounts of data.**

In order to test whether side-tuning could profitably synthesize the features with intermediate amounts of data, we evaluated each approach’s ability to learn to navigate using 49, 490, 4900, or 49k expert trajectories and pretrained denoising features. Side-tuning was always the best-performing approach and, on intermediate amounts of data (e.g. 49k trajectories), outperformed the other techniques (side-tune 9.3, fine-tune: 7.5, features: 6.7, scratch: 6.6), Figure 8.

**Network size.** Does network size matter? We find (i) If the target problem benefits from a large network (e.g. classification tasks), then performance is sensitive to side network size but not size of the base. (ii) The base network can usually be distilled to a smaller network and sidetuning will still offer advantages over alternatives. In the supplementary material we provide supporting experiments from Taskonomy using both high- and low-data settings (curvature → {obj. class, normals}, obj. class → normals), and in Habitat (RL using {curvature, denoise} → navigation).

**Not Boosting.** Since the side network learns a residual on top of the base network, we ask: what benefits we could glean by extending side-tuning to do boosting? Although network boosting this does improve performance on iCIFAR (Figure 9 Left), if catastrophic forgetting is not a concern then the parameters would’ve been better used in a deeper network rather than many shallow networks.
More than just stable updates. In RL, fine-tuning often fails to improve performance. One common rationalization is that the early updates in RL are ‘high variance’. The usual solution is to first train using fixed features and then unfreeze the weights at some point in training (via a hyperparameter to be set). We found that this stage-wise approach performs as well (but no better than) keeping the features fixed—and side-tuning performed as well as both while being simpler than stage-wise (Fig. 9 Right). We tested the ‘high-variance update’ theory by fine-tuning with both gradient clipping and an optimizer designed to prevent such high-variance updates by adaptively warming up the learning rate (RAdam, [15]). This provided no benefits over vanilla fine-tuning, suggesting that the benefits of side-tuning are not solely due to gradient stabilization early in training.

Initialization. A good side network initialization can yield a minor boost in performance. We found that initializing from the base network slightly outperforms a low-energy initialization, which slightly outperforms Xavier initialization. However, we found that these differences were not statistically significant across tasks ($H_0 :$ pretrained = xavier; $p = 0.07$, Wilcoxon signed-rank test). We suspect that initialization might be more important on harder problems. We test this by repeating the analysis without the simple texture-based tasks (2D keypoint + edge detection and autoencoding) and find the difference in initialization is now significant ($p = 0.01$).

Merge methods. Section 2 and 3.1 described different ways to merge the base and side networks. Table 4 evaluates a few of these approaches on the Taskonomy dataset. Element-wise product and addition via alpha-blending are two of the simplest approaches and have little overhead in terms of compute and parameter count. [27] uses $B(x) \odot S(x) \triangleq F_{\theta}(B(x)) + S(x)$ where $F_{\theta}$ is an a Multi-Layer Perceptron (MLP). FiLM [18] similarly adds additional compute by defining $B(x) \oplus S(x) \triangleq \gamma_{\theta}(B(x)) \odot S(x) + \beta_{\theta}(B(x))$ where $\gamma_{\theta}$ and $\beta_{\theta}$ is an MLP with two heads. Table 4 shows that addition, MLP, and FiLM are roughly comparable, though the MLP-based methods achieve marginally better average rank on the Taskonomy dataset. Nonetheless, we chose to use the simplest feature-wise transformation (alpha-blending) since it adds no parameters and achieves similar performance.

Ablating Base and Side Elements. Side-tuning uses two streams of information - one from the base model and one from the side model. Are both streams necessary? Figure 5 shows that on the Taskonomy experiment performance improves when using both models.

5. Conclusion

We have introduced the side-tuning framework, a simple yet effective approach for additive learning. Since it does not suffer from catastrophic forgetting or rigidity, it is naturally suited to incremental learning. The theoretical advantages are reflected in empirical results, and side-tuning outperforms existing approaches in challenging contexts and with state-of-the-art neural networks. We further demonstrated that the approach is effective in multiple domains and with various network types. Overall, we found side-tuning to perform on-par-with or better-than many current lifelong-learning approaches, while being significantly simpler.

6. Limitations

The naive approach to incremental learning used in this paper made a number of design decisions. These decisions could be analyzed and subsequently relaxed. In particular:

Flexible parameterizations for side networks: Our incremental learning experiments used the same side network architecture for all subtasks. A method for automatically adapting the networks to the subtask at hand could make more efficient use of the computation and supervision.

Better forward transfer: Our experiments used only a single
base and single side network. Leveraging the already previously trained side networks could yield better performance on later tasks. Learning when to deploy side networks: Like most incremental learning setups, we assume that the tasks are presented in a sequence and that task identities are known. Using several active side networks in tandem would provide a natural way to detecting distribution shift. Using side-tuning to measure task relevance: We noted that α tracked task relevance, but a more rigorous treatment of the interaction between the base network, side network, and final performance could yield insight into how tasks relate to one another.

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References
[1] Hakan Bilen and Andrea Vedaldi. Universal representations: The missing link between faces, text, planktons, and cat breeds. arXiv preprint arXiv:1701.07275, 2017. 2
[2] Arslan Chaudhry, Marc’Aurelio Ranzato, Marcus Rohrbach, and Mohamed Elhoseiny. Efficient lifelong learning with AGEM. CoRR, abs/1812.00420, 2018. 2
[3] Brian Cheung, Alex Terekhov, Yubei Chen, Pulkit Agrawal, and Bruno A. Olshausen. Superposition of many models into one. CoRR, abs/1902.05522, 2019. 2, 3, 5
[4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. CoRR, abs/1810.04805, 2018. 7
[5] Vincent Dumoulin, Ethan Perez, Nathan Schucher, Florian Strub, Harm de Vries, Aaron Courville, and Yoshua Bengio. Feature-wise transformations. Distill, 2018. https://distill.pub/2018/feature-wise-transformations. 2
[6] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. CoRR, abs/1703.03400, 2017. 2
[7] Stuart Geman, Elie Bienenstock, and René Doursat. Neural networks and the bias/variance dilemma. Neural computation, 4(1):1–58, 1992. 3
[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016. 2
[9] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015. 3
[10] Tobias Johannink, Shikhar Bahl, Ashvin Nair, Jianlan Luo, Avinash Kumar, Matthias Loskilly, Juan Aparicio Ojea, Eugen Solowjow, and Sergey Levine. Residual reinforcement learning for robot control. CoRR, abs/1812.03201, 2018. 2
[11] Justin Johnson, Alexandre Alahi, and Fei-Fei Li. Perceptual losses for real-time style transfer and super-resolution. CoRR, abs/1603.08155, 2016. 4
[12] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. International Conference on Learning Representations, 2015. 5
[13] James Kirkpatrick, Razvan Pascanu, Neil C. Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, Demis Hassabis, Claudia Clopath, Dharshan Kumaran, and Raia Hadsell. Overcoming catastrophic forgetting in neural networks. CoRR, abs/1612.00796, 2016. 2, 5
[14] Zhizhong Li and Derek Hoiem. Learning without forgetting. CoRR, abs/1606.09282, 2016. 2
[15] Liyuan Liu, Haoqing Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. On the variance of the adaptive learning rate and beyond. arXiv preprint arXiv:1908.03265, 2019. 9
[16] Arun Mallya and Svetlana Lazebnik. Piggyback: Adding multiple tasks to a single, fixed network by learning to mask. CoRR, abs/1801.06519, 2018. 2, 3
[17] Ravi Teja Mullapudi, Steven Chen, Keyi Zhang, Deva Ramanan, and Kayvon Fatahalian. Online model distillation for efficient video inference. CoRR, abs/1812.02699, 2018. 5
[18] Ethan Perez, Florian Strub, Harm De Vries, Vincent Dumoulin, and Aaron Courville. Film: Visual reasoning with a general conditioning layer. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018. 3, 9
[19] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. URL https://s3-us-west-2. amazonaws.com/openai-assets/researchcovers/languageunsupervised/language_understanding_paper.pdf, 2018. 4
[20] Aniruddh Raghu, Maithra Raghu, Samy Bengio, and Oriol Vinyals. Rapid Learning or Feature Reuse? Towards Understanding the Effectiveness of MAML. arXiv e-prints, page arXiv:1909.09157, Sep 2019. 2
[21] Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don’t know: Unanswerable questions for squad. CoRR, abs/1806.03822, 2018. 2, 7
[22] Ali Sharif Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. CNN features off-the-shelf: an astounding baseline for recognition. CoRR, abs/1403.6382, 2014. 2
[23] Sylvester-Alvise Rebuffi, Alexander Kolesnikov, and Christoph H. Lampert. icarl: Incremental classifier and representation learning. CoRR, abs/1611.07725, 2016. 2
[24] Sylvester-Alvise Rebuffi, Alexander Kolesnikov, and Christoph H. Lampert. icarl: Incremental classifier and representation learning. CoRR, abs/1611.07725, 2016. 6
[25] Sylvester-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. Efficient parametrization of multi-domain deep neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8119–8127, 2018. 2
[26] Amir Rosenfeld and John K Tsotsos. Incremental learning through deep adaptation. *IEEE transactions on pattern analysis and machine intelligence*, 2018. 2

[27] Andrei A. Rusu, Neil C. Rabinowitz, Guillaume Desjardins, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, and Raia Hadsell. Progressive neural networks. *CoRR*, abs/1606.04671, 2016. 1, 2, 5, 9

[28] Manolis Savva, Abhishek Kadian, Oleksandr Maksymets, Yili Zhao, Erik Wijmans, Bhavana Jain, Julian Straub, Jia Liu, Vladlen Koltun, Jitendra Malik, et al. Habitat: A platform for embodied ai research. *arXiv preprint arXiv:1904.01201*, 2019. 2

[29] Jonathan Schwarz, Jelena Luketina, Wojciech M Czarnecki, Agnieszka Grabska-Barwinska, Yee Whye Teh, Razvan Pascanu, and Raia Hadsell. Progress & compress: A scalable framework for continual learning. *arXiv preprint arXiv:1805.06370*, 2018. 2, 5

[30] Tom Silver, Kelsey R. Allen, Josh Tenenbaum, and Leslie Pack Kaelbling. Residual policy learning. *CoRR*, abs/1812.06298, 2018. 2

[31] Amir R. Zamir, Alexander Sax, William B. Shen, Leonidas J. Guibas, Jitendra Malik, and Silvio Savarese. Taskonomy: Disentangling task transfer learning. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2018. 2, 6, 7, 8