LOSSLESS ADAPTATION OF PRETRAINED VISION MODELS FOR ROBOTIC MANIPULATION

Anonymous authors
Paper under double-blind review

ABSTRACT

Recent works have shown that large models pretrained on common visual learning tasks can provide useful representations for a wide range of specialized perception problems, as well as a variety of robotic manipulation tasks. While prior work on robotic manipulation has predominantly used frozen pretrained features, we demonstrate that in robotics, unlike in other domains, this approach can fail to reach optimal performance, and that fine-tuning of the full model can lead to significantly better results. Unfortunately, fine-tuning disrupts the pretrained visual representation, and causes representational drift towards the fine-tuned task thus leading to a loss of the versatility of the original model. We introduce a method for *lossless adaptation* to address this shortcoming of classical fine-tuning. We demonstrate that appropriate placement of our *parameter efficient adapters* can significantly reduce the performance gap between frozen pretrained representations and full end-to-end fine-tuning without changes to the original representation and thus preserving original capabilities of the pretrained model. We perform a comprehensive investigation across three major model architectures (ViTs, NFNets, and ResNets), supervised (ImageNet-1K classification) and self-supervised pretrained weights (CLIP, BYOL, Visual MAE) in three manipulation task domains and 35 individual tasks, and demonstrate that our claims are strongly validated in various settings.

1 INTRODUCTION

Pretrained general-purpose vision models, often also referred to as vision foundation models (Yuan et al., 2021), have developed a growing set of perceptual capabilities in recent years. Large-scale vision-language models such as CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021)) are examples of these highly capable general-purpose vision models which have enabled many applications for image generation/editing (Ramesh et al., 2022; Saharia et al.) and image-based dialog (Alayrac et al., 2022). Existing self-supervised pretrained visual models, such as SimCLR (Chen et al., 2020), BYOL (Grill et al., 2020) or Visual MAE (He et al., 2022), have also been shown to provide strong initializations for a wide range of visual downstream tasks, and can thus also be considered general-purpose vision models. Even pretrained imagenet classification models can be included in this category considering their effectiveness on downstream tasks. How can we unlock the power of these models for increasingly novel and challenging control applications?

In principle the solution is simple: add an output head for each control task and fine-tune the entire architecture. However, fine-tuning degrades performance on the original task(s) the model was trained for, and therefore requires maintaining copies of the model for all tasks we wish to concurrently support. This strategy quickly becomes infeasible as we move towards more general and multi-task agents.

In this paper our target is to achieve *lossless adaptation*, which we define as adapting the original pretrained model for the new task or series of tasks, while maintaining the original capabilities of the model. To solve the *lossless adaptation* problem we inject additional parameters, i.e. adapters, to several specific locations throughout pretrained architecture. We demonstrate that, with a reasonably small cost ($\sim 1\%$ of the original model size) of additional parameters scattered throughout the model, we can bridge the performance gap between frozen pretrained features and full end-to-end fine-tuning. Our approach offers close to the performance of full fine-tuning while maintaining all the original capabilities of a pretrained model (the original model definition can co-exist with the

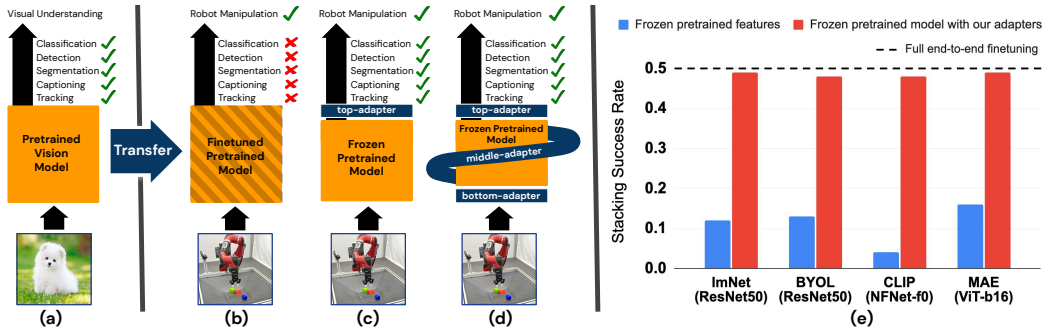

Figure 1: **Parameter efficient lossless adaptation**. Existing works adapt preretrained general purpose visual models (a) through full end-to-end fine-tuning as shown in (b), which looses the original capabilities of the model; or adapting frozen pretrained models through top-adapters as shown in (c), which often fails to achieve optimal control performance. However, by introducing additional mid-level and bottom-level adaptation as in (d), we still maintain the existing perceptual capabilities while approaching the full fine-tuning performance as empirically shown in (e) over many network architectures and pretraining methods.

new task head, reusing the vast majority of parameters). We show that as the manipulation tasks get harder through complex multi-object interaction and increased level of variation in the randomized initial configurations, the pretrained visual features can't cope with the increased complexity but our parameter efficient adapters can. Overall our contributions include:

- We show that frozen pretrained representations are insufficient to reach optimal manipulation task performance especially for complex manipulation tasks.
- We propose the use of adapters with strong evidence that our adapters can largely close the performance gap between frozen pretrained representations and full end-to-end fine-tuning while adding only a small amount of ($\approx 1\%$ of the original model) adapter parameters.
- Comprehensive evaluation of our parameter efficient adapters across 3 different manipulation suites (35 individual tasks), 3 major model architectures (ViTs, NFNets, and ResNets) with supervised (imagenet classification) and self-supervised pretrained weights (CLIP, BYOL, Visual MAE).
- Experiments demonstrating that adapters also bridge the performance gap in sim2real transfer. Thus, enabling fixed large pretrained visual models to be directly used for real world manipulation tasks.

2 Related Works

The general problem of representation learning for control can be broadly divided into two distinct categories – works that use *in-domain* task data to learn task relevant representations for the underlying task, and on the other hand are more recent works that use *out-of-domain* visual data to learn generally useful representations for control.

In Domain Representation Learning for Control: Within the first broad category the majority of works learn representations that reflect certain invariances that are presumed to be relevant for the downstream task(s) of interest. Prior works show that useful representations can be learned via data augmentations (Kostrikov et al., 2020; Laskin et al., 2020b), temporal contrastive learning (Laskin et al., 2020a), information bottlenecks (Pacelli & Majumdar, 2020), goal relabeling (Zhou et al., 2021), or via real world priors (Jonschkowski et al., 2017; Jonschkowski & Brock, 2014).

Out of Domain Representation Learning for Control: An alternative set of works have emphasized the use of in-the-wild visual datasets for representation learning (Parisi et al., 2022; Shridhar et al., 2022; Khandelwal et al., 2022). They have shown that features learned by large visual models pretrained on common visual learning tasks such as image classification, image inpainting, and contrastive learning can be surprisingly effective for downstream control tasks. Many of these works utilize the large scale pretrained CLIP model (Gadre et al., 2022; Khandelwal et al., 2022; Shridhar et al., 2022), while other works also show the effectiveness of features trained on ImageNet (Shah & Kumar, 2021; Parisi et al., 2022), or using temporal data from Ego4D (Nair et al., 2022). Our work is similar in spirit to these works, i.e., we focus on models trained on large scale out-of-domain data.

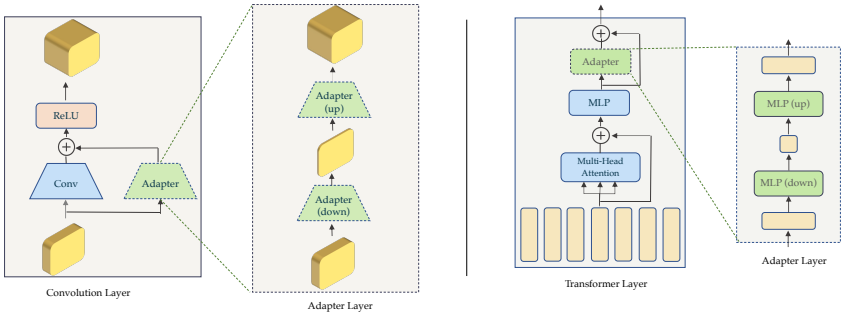

Figure 2: Adapter layers used for convolution based (Left) and transformer based (Right) architectures. For both scenarios we use a bottleneck design.

However, in contrast to prior work which solely shows the effectiveness of the extracted off-the-shelf representations, we aim to adapt those representations for better downstream performance.

Transfer Learning: Adapting a given large model for different downstream tasks has been widely studied in the literature (Rebuffi et al., 2017; Castrejon et al., 2016; Carion et al., 2020; Li et al., 2022; Li & Liang, 2021; Jia et al., 2022). Within the vision community Rebuffi et al. (2017); Li et al. (2022) introduced adapter modules which allowed a single visual representation learned from a given domain to be adapted to multiple different domains. On the other hand, (Castrejon et al., 2016) show how domain agnostic representations can be learned for widely different input modalities ranging from natural images, clip-art to spatial texts. Similar techniques have also been explored in the language community. For instance, Houlsby et al. (2019) adapt the BERT transformer model for different tasks, while Li & Liang (2021) show that optimizing small amount of task-specific vectors (prefixes) can often match the full fine-tuning performance Liu et al. (2021). Another aspect of transfer learning is continual or lifelong learning wherein learning involves a sequence of tasks (Aljundi et al., 2017; Rannen et al., 2017; Rusu et al., 2016; Shin et al., 2017; Schwarz et al., 2018; Yoon et al., 2017), but wherein the original model is distilled for new tasks and thus not necessarily perfectly preserved. Our work is similar to the former set works in that we keep the large pretrained model *frozen* and aim to improve upon its features using light-weight adaptation to extract the final representation for control.

3 Approach

Our main aim is to use fixed pretrained visual models but adapt their representations for improved downstream control task performance. To achieve this we use parameter efficient adapter modules that can be inserted in appropriate locations throughout the deep network. These non-pretrained adapter modules are the only set of parameters that are updated during downstream policy learning.

A common approach to use fixed pretrained visual models is to attach a learned policy head (i.e. top-adapter) and train for the downstream control task (Nair et al., 2022; Parisi et al., 2022). However such an approach cannot adjust the low-level perception and mid-level abstraction for the downstream control task. By contrast, other works have shown that adapting the initial layers (i.e. bottom-adapter) can be important for transferring across large domain-shifts (i.e. sim2real (Jeong et al., 2020), images to line-drawings (Aytar et al., 2017)). One can also inject mid-level adapters as demonstrated in many non-control settings (Rebuffi et al., 2017; Houlsby et al., 2019). We build our method on top of these insightful works and investigate lossless adaptation through parameter efficient adapters in bottom, middle and top parts of the pretrained network in a control setting.

3.1 Adapter Modules

Adapter modules are light-weight neural modules that can be inserted at different layers of a pretrained deep neural network. Prior works have explored adapter modules for transfer learning, wherein adapter modules are inserted at each layer of a pretrained deep network and only these adapters are updated at the fine-tuning stage (Houlsby et al., 2019). Overall, adapter modules have two important properties, 1) they are *lightweight*, i.e., they have fewer parameters compared to the original network, and 2) they keep the *initialization* provided by the pretrained deep network. Below, we provide a short discussion on how adapter modules achieve these properties.

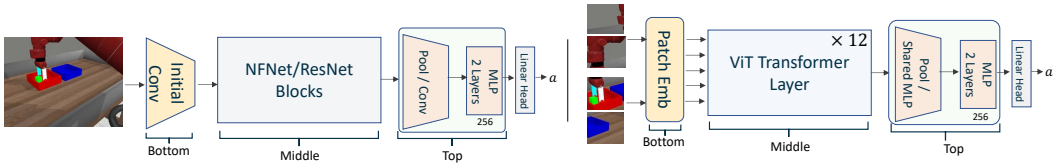

Figure 3: Different locations where we insert adapter modules for both convolution (Left) and transformer (Right) based architectures.

Prior works often limit the number of parameters in the adapter modules by either using 1×1 convolutions (Rebuffi et al., 2017) or via bottleneck architectures for transformers (Houlsby et al., 2019). In our formulation, we use a bottleneck architecture for both convolution- and attention-based architectures, as well as utilizing 1×1 convolutions for the former. Specifically, for a given input $x \in \mathbb{R}^{n \times f}$ where n is the number of samples, f is the input feature dimensionality, adapter outputs are parameterized as a combination of down- (d) and up-projection (u) weights: $x' \leftarrow W_A^u \left(h\left(W_A^d x\right)\right)$, where h is some non-linearity, $W_A^d \in \mathbb{R}^{f \times f'}$ and $W_A^u \in \mathbb{R}^{f' \times f}$ are the adapter (A) weights, f' is the bottleneck feature size. Since $f' << f$, the adapter modules utilize a very small number of parameters in comparison to the original pretrained network. Importantly, we use the above formulation for both convolutional and transformer based architectures – for convolutional architectures we downproject across the channel (feature) dimension, while for transformer based architectures we downproject along the feature dimension for each patch. Figure 2 visualizes the adapters used in our work.

To fully utilize the initialization provided by the pretrained weights, we initialize the adapter modules with weights close to 0 and add skip connections when inserting the adapter modules into the pretrained network. This ensures that adapter modules have no effect at initialization and thus the pretrained network's initialization remains intact. Overall, for a input x, the output for a pretrained model's layer with an adapter is $x' \leftarrow g_{\text{pretrain}}(x) + g_{\text{adapter}}(x)$. Finally, we note that the adapter modules can also be added serially, i.e., directly after the output of a pretrained layer, in which case g_{pretrain} can be viewed as an identity function. Finally, similar to previous works (De Vries et al., 2017; Perez et al., 2018; Houlsby et al., 2019) we also add offsets to the normalization parameters used in different architectures (e.g. layernorm (Ba et al., 2016) for vision transformers). However, as we show in Section 5, our results also hold for architectures that do not utilize any normalization techniques such as the normalizer free networks (Brock et al., 2021).

3.2 Visual Adapters for Control

Prior works often utilize adapter modules for a broadly similar set of tasks in a given domain. For instance, text classification tasks (Houlsby et al., 2019), neural machine translation tasks (Pham et al., 2020), or few-shot visual classification tasks (Li et al., 2022). Additionally, the pretrained model used in these tasks (e.g. BERT Devlin et al. (2018) or ImageNet pretraining) is strongly correlated with the downstream tasks. By contrast, in our work the visual pretraining task (e.g. image-inpainting, image classification) is vastly different than the downstream robotic manipulation tasks. Additionally, there exist significant domain gap between in-the-wild visual pretraining data and robotic manipulation data (often simulated images and table-top settings). Based on these differences we next discuss how and where to efficiently insert adapter modules to improve upon "off-the-shelf" representations produced by the fixed pretrained network.

While we can add adapter modules through all layers of the pretrained network, such a choice is highly parameter inefficient and can be highly redundant especially for large networks with many layers. We coarsely categorize the network layers based on their functional forms as *bottom*, *middle* and *top* sections as visualized in Figure 3. Importantly, as we show empirically, using trainable adapter parameters at each of these network sections is important for improved task performance. Now we provide intuitive reasoning on why injecting adapters in each section is important.

The *bottom* layer directly uses the raw images as input. In scenarios where there is a mismatch between the downstream task's image observations and the pretrained bottom layer feature statistics, the downstream task performance can be sub-optimal. Such scenarios are common for downstream manipulation tasks, since there exists a significant domain gap between the data distribution of

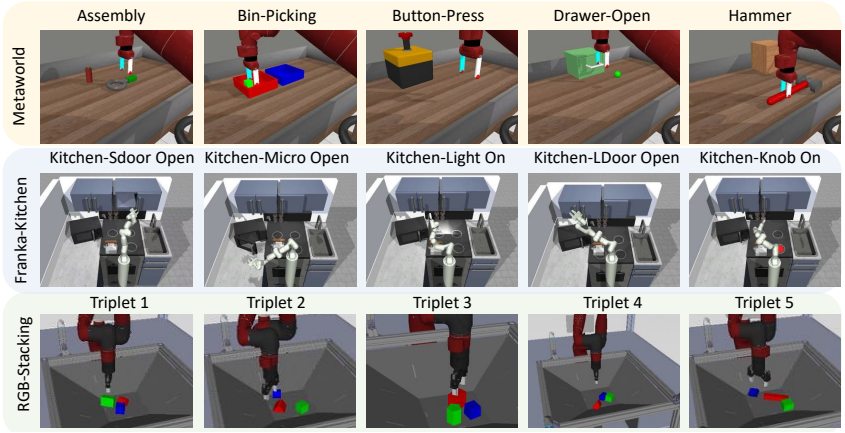

Figure 4: Different environments we evaluate our approach on. For Metaworld and Kitchen suites we frollow the setup from (Nair et al., 2022) including the same set of demonstrations. For RGB-Stacking suite we use Skill Mastery setting (Lee et al., 2021).

pretrained vision models (often in-the-wild data) and standard table-top settings with much closer and non-canonical camera views.

The *middle* category, which contains most of the fixed pretrained network ($\approx 90\%$) weights, is used to extract the appropriate input abstraction. However, these network weights are trained on visual learning tasks which often focus on semantic understanding (e.g. image classification) instead of spatial and causal understanding which are important for control. Nevertheless, earlier layers of the network are known to capture useful invariances (Zeiler & Fergus, 2014; Parisi et al., 2022). Hence, *sparsely* inserting adapter layers through the pretrained network can allow us to better adapt "off-the-shelf" representations for downstream manipulation tasks. Finally, we note that the output of the middle category is a set of spatial features for conv-nets and patch features for ViTs.

The *top* category uses the spatial representation from the middle category as input and outputs the robot action. This high dimensional spatial representation (size $\approx 20K$) is converted into a smaller representation (size $\approx 2K$) either via average/max pooling or by down-projecting using 1×1 convolutions or a small shared MLP. Finally, this smaller representation can be used to directly output the action using a linear policy head. While a linear head is sufficient in settings where there is strong task alignment (Chen et al., 2020), given the large difference in the pretraining and downstream tasks, additional top layer adaptation helps further improve performance. We note that most prior works that use fixed pretrained features (Pari et al., 2021; Nair et al., 2022) also utilize such top layer adaptation. We discuss implementation details for specific architectures in Section 4.2.

Training Adapters for Control: We use behaviour cloning to learn task policies from a set of demonstrations. Overall, our network uses the input observations to predicts actions. We optimize the adapter parameters by minimizing euclidean loss between the predicted and expert actions.

4 Experimental Setup

We evaluate our use of adapters for large pretrained visual models across three different environment suites each with increasing task complexity and across three different network architectures. We elaborate on each of these further below.

4.1 Manipulation Tasks

In this work, we consider Metaworld (Yu et al., 2020), Franka-Kitchen (Gupta et al., 2019), and RGB-Stacking task suites (Lee et al., 2021). Figure 4 visualizes the tasks considered from each of these task suites. Both Metaworld and Kitchen have been used in previous works (Nair et al., 2022) to evaluate fixed "off-the-shelf" pretrained visual representations. Hence, we use the same set of environments and demonstrations provided by (Nair et al., 2022) for both of these task suites. Overall, we use 5 different environments from the Metaworld and Kitchen task suites. For each environment we use 3 different camera configurations as provided by Nair et al. (2022). Additionally, similar to

	Metaworld	Franka-Kitchen	RGB Stacking
Fixed Pretrained Feat. - ImNet (R3M) (Nair et al., 2022)	0.66	0.30	-
Fixed Pretrained Feat. - MoCo-345 (R3M) (Parisi et al., 2022)	0.64	0.38	-
Fixed Pretrained Feat. - R3M (R3M) (Nair et al., 2022)	0.78	0.56	0.30
Fixed Pretrained Feat- (Ours - ImNet)	0.62	0.48	0.28
Full Finetune (Ours)	0.98	0.72	0.70
Fixed Pretrained Feat. - (Ours ImNet - mean succ)	0.44	0.34	0.14
Full Finetune (Ours - mean succ)	0.91	0.57	0.49

Table 1: Success rate comparison using fixed pretrained features (using pretrained large vision models) with methods that update the pretrained visual features on the downstream manipulation task.

previous work we use 25 demonstrations for each environment and train a separate policy for each environment and camera configuration.

While both Metaworld and Kitchen suites consider many tasks, each task often has a very narrow state-space distribution. For instance, Kitchen tasks use fixed object positions while MetaWorld tasks have limited position variance only. Hence, we also evaluate our approach on a much more challenging RGB-stacking suite (Lee et al., 2021) (Figure 4 bottom). The RGB-stacking tasks involve three objects colored Red, Green, and Blue and the goal is to stack the red object on top of blue object. These tasks use randomize object positions and orientations in a basket and thus result in a large initial state-space distribution. Further, since these tasks consider a diverse range of shapes, stacking requires precise control and cannot be achieved simply by dropping one object onto the other. To obtain demonstrations for these tasks, we initially train an RL policy and collect 100,000 demonstrations from it. We use the *Skill Mastery* setting from (Lee et al., 2021) for evaluation.

4.2 Network Architectures

We evaluate the effectiveness of adapters for manipulation tasks in the context of three different network architectures. Specifically, we use normalization free networks (NFNet) (Brock et al., 2021), residual networks (ResNet) (He et al., 2016) and vision transformers (ViT) (Dosovitskiy et al., 2020). Among the different architectures within each category we use *NFNet-f0*, *ResNet-50* and *ViT-B/16*. In addition to imagenet pretraining across all three architectures, we also evaluate using ALIGN (Jia et al., 2021) for NFNet, BYOL for ResNet (Grill et al., 2020) and masked auto-encoder (MAE) for ViT (He et al., 2022).

Adapter Parameterizations: As noted previously in Sub-Section 3.2 we use *bottom*, *middle* and *top* adapters. We discuss the specific parameterizations for each of these adapter types. Table 4 provides an overall adapter parameter count. We provide detailed parameterization in Appendix A.1.

Bottom: For NFNet and ResNet architectures we use the initial convolution, while for ViT we use the initial patch embedding as the only bottom set of layers. We add 1 adapter for this bottom layer.

Middle: For middle adapters we use 4 and 6 adapters for the convnet and transformer based architectures respectively. For the convnet based architectures we add each adapter to the first convolution in each block group except the last group, where we add it at the end. While for the transformer based architectures we apply them at layers $\{0, 1, 5, 6, 10, 11\}$.

Top: We project spatial features from the middle layer onto a lower dimensional space. Finally, to further process these features we *optionally* add 2 MLPs each with 256 parameters, we refer to these as top layer adapters.

Evaluation: To evaluate our approach we use multiple (40) rollouts using the policy learned via BC and use the mean success rate of the final policy as our metric. When providing task suite metric we average the mean success rate across all environments and camera configurations. We also note that some previous works evaluate the BC policy at fixed training step intervals and use the maximum over the mean success rates at each interval as the metric. However, using max as a statistic is not robust and is easily influenced by outliers. While comparing with previous works we use the max statistic, however for all other results we use the mean. Detailed hyper-parameters and training setup is provided in Appendix A.

	Metaworld			Franka-Kitchen			RGB Stacking		
	Pretrain Feat.	Adapters	Full FT.	Pretrain Feat.	Adapters	Full FT.	Pretrain Feat.	Adapters	Full FT.
NFNet	0.44	0.82	0.94	0.12	0.39	0.42	0.14	0.45	0.47
ResNet	0.39	0.80	0.88	0.12	0.24	0.25	0.14	0.48	0.49
ViT	0.19	0.78	0.84	0.15	0.26	0.25	0.18	0.49	0.48

Table 2: Mean success rate comparisons between using *fixed* pretrained features, adapters and full fine-tuning across all three different environments with three different architecture choices.

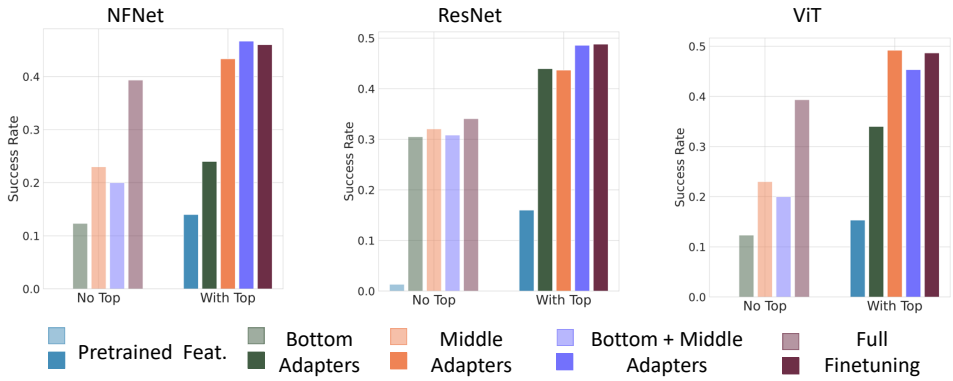

Figure 5: Ablation results on the RGB-Stacking environment for 3 different network architectures.

5 Results

With our experiments we aim to show the following: 1) Using fixed pretrained representations often leads to sub-optimal task performance as compared to directly adapting the representation for the downstream task, especially for more challenging manipulation tasks. 2) Inserting small adapter modules into a fixed pretrained network (i.e. lossless adaptation) is sufficient to achieve optimal manipulation task performance across a wide range of tasks and network architectures. 3) Adapter modules are parameter efficient as well as robust to different initializations of the fixed large pretrained vision model (e.g. via different visual pretraining strategies). We look at each of these points in the following subsections.

5.1 Fixed Pretrained Features vs Adapter Representations

Fixed Off-the-Shelf Representations: In the first part of our experiments we show that while fixed off-the-shelf representations (without any adaptation) are useful, they can be highly sub-optimal for the given downstream task. To show this we compare the fixed representations extracted using pretrained weights (Pretrained Feat.) obtained via supervised imagenet pretraining and compare them with full fine-tuning (Full FT). Table 1 compares these across all task suites. For a fixed comparison with previous works Table 1 reports results for the ResNet-50 model, since previous works only evaluate the ResNet architecture. As seen in Table 1, fixed off the shelf-representations are comparatively much worse across all environment suites. For Metaworld, Kitchen and RGB-Stacking suites the *relative* change in performance is around $\approx 20\%, 30\%$ and 100% respectively. Also, for the RGB-stacking suite the mean performance is much lower 14%, which shows that fixed pretrained representations become significantly less effective for challenging manipulation tasks.

Lossless Adaptation of pretrained Visual Features: We now show that our proposed adapters can match full-fine-tuning performance for downstream manipulation tasks without losing any existing information. Table 2 compare full fine-tuning (Full FT.) approaches with our adapters (Adapters) as well as fixed pretrained representations (Pretrained Feat.) We note that for these and future results we report metrics using the more robust mean statistic. Additionally, for task suites with limited state-space distributions, *i.e.*, Metaworld and Franka-Kitchen, we avoid using any proprioceptive information (see Appendix B for results with proprioceptive). This allows us to robustly verify the visual representation and avoids any proprioceptive information leakage which can allow to solve the task even without using the visual features.

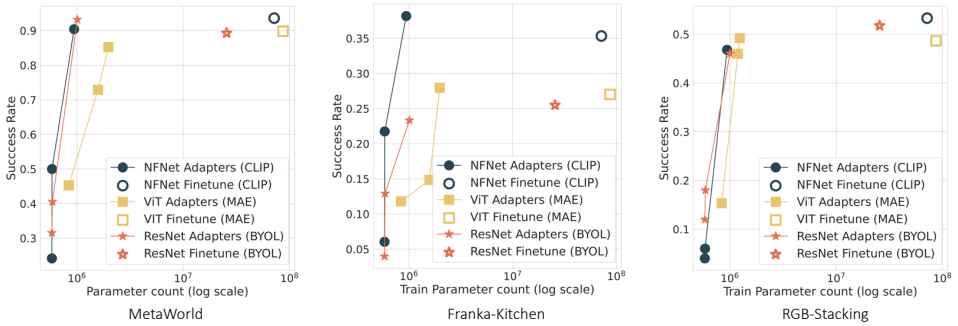

Figure 6: Results with different pretraining initializations (for 3 different models) all 3 environments – NFNet with CLIP, ResNet with BYOL and ViT with MAE. *Bottom Left:* points plots performance of fixed pretrained features with top adapters. *Top Right:* points plot full fine-tuning performance (with top adapters). *Solid Lines:* indicate adapter performance with adapters first added to bottom and then middle layers.

Table 2 shows the results for each task suite and network architecture combination. For the adapter results we report results with bottom, middle and top adapters. As before, for a fair comparison we use top adapters for all other approaches. As seen in the above table, our parameter efficient adapters can closely match full fine-tuning performance across all environment suites and architectures. Most noticeably, for both Franka-Kitchen and RGB-Stacking tasks, our use of adapters is able to exactly match (average difference in performance $< 2\%$) the performance derived from full fine-tuning (Full FT). While there exists a slightly larger gap for the metaworld environments – average performance difference $\approx 6\%$. However, compared with directly utilizing the fixed pretrained features, we see a huge performance increase of around 30% averaged over all tasks and architectures. In addition to the average results, Table 2 also shows that there exists a performance increase across all architectures. Our results clearly show that the features derived from visual pretraining are quite useful and inserting few additional adapters allows us to achieve close to optimal performance without sacrificing any of the previously learned abilities of the pretrained vision models.

5.2 Effects of Adapter Locations & Different Pretrained Representations

We investigate the effect of inserting adapters in each of the different network layers (see Subsection 3.2). Figure 5 shows results for inserting adapters in each network layer for RGB stacking suite (due to space limitations Appendix B.2 has results/discussion for all suites). We split each network plot above into two parts – 1) without using top layer adapters (i.e. directly using a linear policy head), and 2) using a top layer adapter (i.e. using 2 additional MLPs before the linear policy head).

From Figure 5 we see that *without* top layer adapters (greyed out left plots) the performance for all methods decreases – more so for fixed pretrained features. As seen above, top adapters can have significant impact, e.g., not using top layer adapters almost *halves* the control performance across all different architectures. Figure 5 also shows that bottom adapters alone can give a significant performance boost (almost $2\times$ than Pretrained Feat. with top adapters). Since bottom adapters for conv-net architectures have very few parameters (a few thousand see Table-4), this performance increase is not merely a function of more parameters and thus shows the need for better adaptation of pretrained visual features. Overall, best performance is often achieved when using all top, middle and bottom adapters together. Please see Appendix B.2 for more results.

Adapters with Different Pretrained Representations: We now show that our proposed adapters give similar benefits with pretrained weights obtained from vastly different pretraining (pretext) tasks. For NFNet we use CLIP pretraining (Radford et al., 2021), for ResNet we use BYOL (Grill et al., 2020) and for ViT we use masked auto-encoder (MAE) (He et al., 2022). Figure 6 plots the result for each of these architectures across all three task suites. The X-axes shows the number of train parameters (see Table 4). The *bottom left* points in each of the above plots indicate the performance of fixed pretrained features. While *top right* points show full fine-tuning's performance. On the other hand, the solid lines indicate the performance improvements on inserting bottom and middle adapters (top adapters are used for all approaches). As seen in Figure 6, for all tasks and pretrained weights adapters are able to closely match the performance of full fine-tuning approach, while only registering a very marginal increase in the number of trainable parameters.

	Triplet 1	Triplet 2	Triplet 3	Triplet 4	Triplet 5	Average
NFNet - Pretrained Feat.	0	0	0	0	0	0.0
NFNet - Scratch	0.02	0.02	0.01	0.16	0.04	0.05
NFNet - Adapters	0.18	0.14	0.16	0.47	0.23	0.24
NFNet - Full FT.	0.22	0.36	0.15	0.76	0.26	0.35
NFNet - Pretrained Feat. (DR)	0.04	0.02	0.0	0.06	0.05	0.04
NFNet - Adapters. (DR)	0.38	0.40	0.38	0.88	0.64	0.53
NFNet - Full FT. (DR)	0.40	0.36	0.32	0.91	0.62	0.52
ViT - Adapters	0.04	0.08	0.04	0.24	0.12	0.10
ViT - Full FT.	0	0	0	0	0	0

Table 3: Sim2Real results for RGB-Stacking Task with and without using any visual domain randomized (DR) data for learning the manipulation task policy.

	Bottom	Middle	Top	Full
NFNet-f0	0.5K	0.4M	0.6M	71M
ResNet-50	6.9K	0.4M	0.6M	25M
ViT	0.74M	0.4M	0.9M	86M

Table 4: Number of parameters to be learned for different adapters as well as full fine-tuning.

Additionally, comparing MetaWorld results in Figure 6 (Left) and Table 2 we see that while there exists a minor gap between adapters and full-FT with imagenet-supervised weights $\approx 6\%$, this gap reduces significantly for self-supervised pretraining weights. Somewhat similar results on the benefits of MAE features for control were also observed in (Xiao et al., 2022). We further notice that CLIP pretrained weights (with only top adapters) for NFNet perform quite poorly on the RGB-stacking tasks $< 5\%$ (Figure 6 right). However, with our proposed adapters in all the layers the performance significantly improves $\approx 50\%$ and closely matches full-fine-tuning performance but with only a marginal increase in the number of train parameters.

5.3 Sim2Real Results

Finally, we investigate if large scale visual pretraining combined with our use of adapters can allow for *sim2real transfer*. Prior works that utilize fixed pretrained vision models for real robot tasks often only evaluate on tasks requiring simple motions (reach/grasp) and almost always train the policy on real robot data (Shridhar et al., 2022; Nair et al., 2022). By contrast, we show results for sim2real transfer, i.e, we use no extra real-world robot data. We use the more challenging RGB-stacking suite for evaluation. We evaluate sim2real transfer both *with* and *without* using any visual domain randomization data. We report results using 100 rollouts for each policy and object triplet.

Table 3 shows results for one conv- (NFNet) and transformer- (ViT) architecture. From the above results we see that ViT based policies perform much more poorly compared to NFNet policies. For instance, a fully fine-tuned ViT policy is completely unable to solve any task. We believe one reason for this is the high learning capacity of transformer based models which allows it to quickly learn on the given task and lose any prior information (Wortsman et al., 2022), thus making real world transfer challenging. However, using adapters instead of fine-tuning is able to achieve non-zero performance. While the average performance is poor 10%, it is able to achieve 24% success on the easier setting (triplet 4). Table 3 further shows that NFNet based policies perform much better than ViTs across different training settings. For full fine-tuning and adapter approaches NFNet policies can achieve 35% and 24% success rate, while training from scratch only achieves 5% and fixed pretrained features do not result in any successes. Finally, we also evaluate the NFNet policies using visual domain randomization data (DR rows). These policies show much superior performance $\approx 53\%$ for our adapters and full fine-tuning, and closely match the policy performance in simulation.

6 Conclusion

In this work we propose the lossless-adaptation problem, i.e., we aim to adapt representations from large-scale pretrained vision models for close to optimal manipulation task performance. We show that using fixed representations by solely using top-adapters (as is common) can fail to achieve optimal task performance especially for challenging manipulation tasks. To solve this we propose our parameter efficient adapters. We show that that inserting these adapters at appropriate network locations can achieve close to optimal downstream task performance (closely matching full fine-tuning performance). We show that our results hold across 3 different manipulation suites, 3 different network architectures and multiple different pretrained weights. Further, we show that adapters also allow for sim2real transfer, all while maintaining the pretrained network's original capabilities.

7 ETHICS STATEMENT

We have considered possible concerns regarding the ethics of this line of work, and to the best of our knowledge, can recognize no major reasons for concern. Our work uses pre-existing pre-training datasets that are publicly available, and that, to the best of our knowledge, are filtered to excise personally identifiable human data. This work does not delve into applications of models that might adversely affect or cause discrimination against groups. Our methodologies, as far as we can tell, would not be immediately translatable to harmful applications. The work has been screened internally (a technical and strategy check by non-author parties) for potential privacy and security issues.

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