Abstract

Recently, fine-tuning language models pre-trained on large text corpora have provided huge improvements on vision-and-language (V&L) tasks as well as on pure language tasks. However, fine-tuning the entire parameter set of pre-trained models becomes impractical since the model size is growing rapidly. Hence, in this paper, we introduce adapter-based parameter-efficient transfer learning techniques to V&L models such as VL-BART and VL-T5. We evaluate our methods in a unified multi-task setup on four diverse V&L tasks: VQAv2, GQA, NLVR², and MSCOCO image captioning. With careful training and thorough experiments, we benchmark three popular adapter-based methods (Adapter, Hyperformer, Compacter) against the standard full fine-tuning and the recently proposed prompt-tuning approach. We also enhance the efficiency and performance of adapters by sharing their weights to attain knowledge across tasks. Our results demonstrate that training the adapter with the weight-sharing technique (4.4% of total parameters) can match the performance of fine-tuning the entire model. Lastly, we present a comprehensive analysis including the combination of adapter and task-specific prompts and the impact of V&L pre-training on adapters.

1. Introduction

Following the success in the language domain [4, 8, 24, 27, 35, 36], large-scale pre-training of vision-and-language (V&L) models has become a standard framework to tackle V&L tasks [6, 7, 18, 29, 41, 43]. In such frameworks, V&L models, which are usually the combination of the vision encoders and language models, are first pre-trained on large-scale unlabeled data, then fine-tuned for downstream V&L tasks. However, given that such models’ size grows very rapidly nowadays, either pre-training or fine-tuning of the V&L model can still contribute to an unignorable, large memory and storage cost. For instance, if we use GPT-3 [4] with 175B parameters as a V&L model backbone, we would need 700 GB of memory to store its entire parameters. To address this problem, recently, several parameter-efficient training methods have been proposed [12, 16, 17, 20, 25, 30, 46]. Among them, the adapter [16] and its variants [20, 30] are widely used in the NLP domain and applied to different architectures. An adapter is a small module added to intermediate layers of the model (which is illustrated in Figure 2), and it allows only fine-tuning its small set of parameters but to still achieve the same level of performance as full fine-tuning (i.e., updating all parameters). Despite adapters having achieved success in text classification [16, 20, 30] and image-text alignment [2], to the best of our knowledge, no work has utilized this efficient method for the more challenging downstream V&L problems, such as visual question answering and image captioning. Besides the applications side, as mentioned above,
V&L models also usually cost more memory because they are the combination of the models of two sources. Hence, these observations motivate us to investigate the application of adapter-based parameter-efficient training techniques to V&L tasks.

We first motivate that fine-tuning (i.e., not freezing) the language model is crucial to achieving competitive performance on diverse downstream V&L tasks, and hence we focus on how to achieve this much more efficiently via different adapter methods and knowledge sharing across tasks. We analyze these parameter-efficient training techniques on a unified multi-task learning setup, and we benchmark different adapter [16, 20, 30] and prompt-based methods [23]. For our V&L model, following Cho et al. [7], we adopt encoder-decoder language models (BART [24] and T5 [36]) that tackle multiple V&L tasks as text generation to avoid designing task-specific architectures. We use CLIP [33], a pretrained image-text alignment model, as our visual encoder (ResNet [14] from CLIP) for the ease of doing V&L pre-training. To inform the model about which task it is going to perform, we follow [7, 36] to add task-specific (text) prompts to the front of the input sentence (e.g., “vqa: [Q]” for VQA). We then insert adapter modules, such as Adapter [16], Hyperformer [20] and Compact [30], to the model to perform parameter-efficient training. Hyperformer and Compact are the recently proposed state-of-the-art approaches: Hyperformer improves the efficiency of adapters by generating their weights via a hyper-network, while Compact reduces the parameters by utilizing Kronecker products and low-rank parameterization for the adapters’ weights. We also compare the adapter-based approaches against prompt-tuning [23], which adds trainable prompts to the input. We show the high-level concept of our work in Figure 1. Practically, the adapter training includes trainable weights of adapter modules, layer normalization layers, and the visual projection layer (see Section 3.1 and Figure 2 for more details). Since we tackle multiple tasks simultaneously, we also explore taking advantage of sharing information across tasks in adapters and prompts. In this work, we propose a simple approach to also enable adapters to learn both global and local information beyond a single task. Specifically, we make some of the trainable parameters to be shareable to learn cross-task information while reserving the rest of them for task-specific information. With this technique, the number of trainable parameters can be even further reduced.

We conduct our experiments and analysis on four diverse V&L tasks: VQA v2 [10], GQA [19], NLVR2 [42], and MSCOCO captioning [5]. Overall, with proper training and tuning, the performance of the three adapter-based approaches closes the gap between which of full fine-tuning. In our experiments, Compact doesn’t stand out in terms of efficiency since we remove the low-rank approximation for trading performance. Hyperformer is more efficient than adapters, but we eventually show our adapter training with the weight-sharing technique can achieve the same performance as full fine-tuning while only updating 4.4% of the full parameter set. Next, we ablate the design of either fine-tuning or freezing the CLIP, and results show that the latter one has the best trade-off between performance and parameter efficiency. We also present a detailed analysis for understanding the contribution of each trainable component in adapters, as well as the different parameter-sharing mechanisms. We find that using one set of adapter modules across all the tasks attains the best results and accuracy-efficiency trade-off, showing the possibility of pursuing efficiency with simplicity (Fig. 4). Since most of the experiments are based on the pre-trained weights accompanied with the models (e.g., CLIP pre-trained weights for ResNet and BART pre-trained weights), we lastly demonstrate that the results of training adapters on top of V&L pre-trained weights can match or even exceed which of the full fine-tuning counterpart. We also report the results of comprehensive hyper-parameter search in the Appendix B, hoping them be useful for the related research about parameter-efficient training.

The main contributions of our work are: (1) the first work benchmarking different types of parameter-efficient training techniques (Adapter, Hyperformer and Compact) for diverse, challenging downstream V&L tasks; (2) empirical demonstration of the adapters reaching the performance of full fine-tuning while updating only 4.4% of the parameters; (3) comprehensive analysis on the design of freezing CLIP, impact of different architectural components, weight-sharing techniques, task-specific prompts, and vision-language pretraining.

2. Related Work

Our research is built upon previous works about language models, V&L models, and parameter-efficient training. In this section, we introduce previous literature and discuss their similarities and difference with this work.

Language Model Pre-training. The workflow of pre-training and fine-tuning has become a popular paradigm for solving many downstream tasks in the NLP field. Several papers accordingly propose new architectures and objectives to model language, such as ELMo [32], BERT [8], RoBERTa [28], GPT series [4,34,35], and encoder-decoder versions such as BART [24] and T5 [36]. Comprehensive studies [36] have shown the effectiveness of the encoder-decoder model compared to other architectures. Hence, we choose BART and T5 as our text generative model.

V&L Pre-training. To tackle V&L tasks, most existing approaches combine respective models specialized for either pure language or pure vision tasks as a V&L model.
ViLBERT [29], UNITER [6] and LXMERT [43] use the faster R-CNN [39] object detector to extract the bottom-up [1] features from the image, and provide them with text features to a cross-modality transformer to solve visual question answering and image-text alignment tasks. Cho et al. [7] adopt encoder-decoder language models [24, 36] to generalize V&L tasks to text generation with a task-agnostic architecture, which combines R-CNN and T5 (or BART). In practice, the R-CNN is usually frozen in most of the V&L models because the end-to-end training of the R-CNN and language models is unstable. This prevents the R-CNN, which is trained to solve object detection, adapting its weights to V&L tasks. PixelBERT [18] replaces R-CNN to plain ResNet [14], and demonstrates the advantage to include the vision model into training. Inspired by the success of pre-training with web-scale unlabeled data in the NLP field, Radford et al. [33] propose CLIP to show the success can be transferred to the V&L field. With the pre-training on 400 million image-text pairs, CLIP has a rich cross-modal representation and can solve a wide range of tasks without additional supervision. CLIP-ViL [41] takes advantage of using the cross-modal CLIP (ResNet or ViT [9]), and it also explores enhancing the performance by end-to-end training the visual model with Transformers.

Although language models are tuned for downstream tasks in prior works, some recent research [44, 45] attempts to freeze large language models (e.g., GPT-3) to achieve zero-shot learning for V&L tasks. This line of research focuses on how to map images to the inputs that the language model can make use of. Frozen [44] achieves this by jointly training an NF-ResNet-50 [3] and frozen GPT-3 with the Conceptual Captioning dataset [40]. Instead of aligning images to text features, Yang et al. [45] directly utilize a pre-trained image captioner to transform images to texts, which is a useful resource for a language model, and they demonstrate the effectiveness of this framework on visual question answering tasks. Our V&L model is the combination of CLIP and BART (or T5). We conduct thorough ablations to test the performance of four different training scenarios: all possible pairs of training or freezing the CLIP and BART. The results in Section 5.2 show that fine-tuning (i.e., not freezing) the language model is crucial to achieving competitive performance on diverse downstream V&L tasks, which is why we focus on how to achieve this much more efficiently via different adapter methods and knowledge sharing across tasks. Our results also show that training the BART model only has the best trade-off between performance and parameter efficiency, hence even though the architecture is end-to-end trainable, we decide to freeze the CLIP to fulfill our goal of parameter-efficient training.

Parameter-Efficient Training. As recent models grow in size rapidly, updating them in parameter-efficient ways becomes crucial. Recently, three types of methods have been proposed: (1) only training on newly added trainable parameters (added either to the input or model) [16, 20, 23, 25, 30]; (2) sparsely updating small number of parameters of the model [12, 46] (3) low-rank parameterization of the changing of the weights [17]. There is also some recent research that combines the three types of approaches to propose a unified parameter-efficient training framework [13, 31]. Among these approaches, adapters, which belong to the first category, are widely used and are adapted to computer vision [37, 38] and natural language processing [16, 20, 30]. While adapters add additional parameters into models, prompt-based approaches instead add trainable parameters into the inputs [11, 23, 25], and experiments have shown their value in language tasks. Some concurrent works also extend the parameter-efficient techniques to CLIP models [2, 48, 49]. However, they mainly tackle image-text alignment problems, while in this paper we target more challenging downstream V&L tasks, such as visual question answering, visual reasoning, and image captioning. The typical usage of adapters is training them independently on different tasks. This training manner prevents these adapters from learning the shared information across tasks. In this paper, we find that making these convenient plug-and-play adapters shareable improves the performance of low resource dataset and make the overall trainable parameters smaller.

3. Methods

Our main contribution is to exploit adapter-based methods to efficiently fine-tune generative models in the multi-task setting. We explore several state-of-the-art variations of adapters (Adapter, Hyperformer, Compacter) on 4 V&L tasks and show that the vanilla adapters are the best among them. We further demonstrate that sharing adapters across tasks can boost the performance to match full fine-tuning results and further improve the parameter efficiency.

3.1. Unified Framework for V&L Tasks

We illustrate our V&L model in Figure 2(a). We follow [7] to unify V&L tasks to a text generation problem. Our V&L model is a combination of CLIP and BART (T5), and therefore, we name our base architecture CLIP-BART (CLIP-T5). To be more specific, assuming we have a pair of an image \( x^L \) and a sentence \( x^S \) (e.g. the question in VQA) as the input for our model, then our goal is to maximize the agreement between the model’s output and the text label of \( M \) tokens \( y = (y_1, y_2, ..., y_M) \) (e.g. the ground truth answer in VQA). As for architectures, we use an encoder-decoder language model (parameterized by \( \theta^L \)) as our main generative model. We connect a CLIP (parameterized by \( \theta^V \)) and a visual projection layer (parameterized by \( \theta^{V\rightarrow L} \); it projects the visual representation to the correct dimension for language model) to the model for extracting the visual
representation from input images and feed the concatenation of visual representation and sentence representation to the encoder-decoder model. The multi-head attention layers inside the encoder learn the cross-modality representations and the decoder utilizes them to generate the targeted text by maximizing its likelihood. Note that the sentence representation is the output of an embedding layer, and positional embeddings are added to both visual and sentence representation. For simplicity, we omit the notations for embedding embeddings are added to both visual and sentence representation is the output of an embedding layer, and positional embeddings are added to both visual and sentence representation. For simplicity, we omit the notations for embedding embeddings are added to both visual and sentence representation.

Our goal is to minimize the cross entropy (CE) loss:

\[
L(l(x^l, x^s, y; \theta^L, \theta^V, \theta^{V \rightarrow L})) = \sum_{(x^l, x^s, y) \in D} l(x^l, x^s, y; \theta^L, \theta^V, \theta^{V \rightarrow L})
\]

Our trainable parameters are the union of \(\theta^L, \theta^V,\) and \(\theta^{V \rightarrow L}\). As deep learning models grow rapidly in recent times, updating and storing the whole parameters of either visual or language models can be inefficient. Thus, this motivates us to introduce adapter-based approaches into V&L models for parameter-efficient tuning.

### 3.2. Adapters for V&L Models

**Adapters.** Figure 2(b) left. Adapters [16] are sub-networks with small parameters that are inserted after every attention and feed-forward layer in a model. With adapters, models learn downstream tasks by only updating the small number of parameters in adapters. Adapters consist of a pair of downsampling and upsampling layers, and a residual connection from input to output is also added. To be more specific, we denote the input feeding to the adapter as \(x \in \mathbb{R}^{d_i}\), and the weight matrices for downsampling and upsampling layers to be \(\theta^D \in \mathbb{R}^{d \times d_i}\) and \(\theta^U \in \mathbb{R}^{d \times d}_i\), where \(d_i\) and \(d\) are the input and hidden dimension respectively. The mechanism of adapters is defined as:

\[
h = f_{\theta^v}(\sigma(f_{\theta^D}(x))) + x
\]

where \(\sigma(\cdot)\) is an activation function, and we use GELU [15] in this paper. With adapters, the parameter complexity (i.e.,
the number of added parameters) is $O(d_d d)$, and it usually is $2 \sim 3\%$ of the whole model’s parameters. Note that all the layer normalization layers are also updated to adapt to the data distribution of downstream data.

**Hyperformers.** Figure 2(b) top-right. The typical usage of adapters is that separately training one adapter for one task. In that fashion, adapter modules are independent across tasks, preventing the possibility of reducing the required parameters by sharing the weights for similar tasks. Hence, in order to make the adapter module even more efficient, we extend the Hyperformer [20] to a V&L architecture. More specifically, we maintain a hyper-network that is shared over tasks to generate the adapters’ weights conditioned on the task and the index of the layer. Suppose we have $N_T$ tasks at hands, the number of layers of the model is $N_L$, and we can use $t_1, t_2, ..., t_{N_T} \in \mathbb{R}^{d_t}$ and $l_1, l_2, ..., l_{N_L} \in \mathbb{R}^{d_l}$ to represent their $d_t$ dimensional embeddings. Hyperformer is composed of a two-layer task projector network $\theta^T \in \mathbb{R}^{d_t \times 2 \times d_p}$ and the hyper-network $\theta^H \in \mathbb{R}^{d_r \times (2 \times d_t \times d_l)}$, which aims to generate the weights for the upsampling and downsampling layer in adapters based on the projected embedding. Without loss of generality, to generate the adapter’s weights in the $i$th layer for $j$th task, the generation process is:

$$[\theta^D, \theta^U] = f_{\theta_H}(f_{\theta_T}([t_j, l_i]))$$

where $[\cdot]$ is concatenation. We demonstrate the concept of Hyperformer in a high-level way at the right of Figure 2. Note that to save memory with Hyperformer, we need the number of trainable parameters of Hyperformer is smaller than that of adapters, namely, $|\theta^H| + |\theta^T| < N_T N_L (|\theta^U| + |\theta^D|)$. In general, we have $|\theta^T| \ll |\theta^H|$, so we can further induce the proper range of $d_p$, which is $d_p < N_T N_L$.

**Compacters.** Figure 2(b) bottom-right. Although adapters have attained great success on parameter-efficient training, they still have redundant parameters and usually underperform full fine-tuning. Compacter hence is introduced by [30] to solve the issues with the matrix decomposition and parameter sharing, and eventually, Compacter has been shown to have a better trade-off between performance and efficiency compared to adapters. In the following, we demonstrate the mechanism of Compacter with the weights of the downsampling layer. First, Compacter introduces \textbf{parameterized hypercomplex multiplication layers (PHM layers)} [47], whose parameters are the decomposition of the $\theta^D \in \mathbb{R}^{d_d \times d}$ to the sum of $k$ Kronecker products:

$$\theta^D = \sum_{i=1}^{k} A_i \otimes B_i$$

where $A_i \in \mathbb{R}^{k \times k}$, $B_i \in \mathbb{R}^{d_d \times \frac{d}{k}}$. The parameter complexity of the PHM layer is $O\left(\frac{d_d d}{k}\right)$, reducing the cost by at most $\frac{1}{k}$. To further improve the efficiency of PHM layers, Compacter shares the parameters of a smaller matrix $A_i$ across all layers, and decomposes the bigger matrix $B_i$ even more with low-rank parameterization. Specifically, the matrix $B_i$ is approximated to be a low-rank matrix, which is the product of two low-rank matrices, $u_i \in \mathbb{R}^{\frac{d_d}{r}}$ and $v_i \in \mathbb{R}^{r \times \frac{d}{r}}$, where $r$ is the matrix’s rank. This results in the \textbf{low-rank parameterized hypercomplex multiplication layer (LPHM)}:

$$\theta^D = \sum_{i=1}^{k} A_i \otimes B_i = \sum_{i=1}^{k} A_i \otimes (u_i v_i)$$

Empirically, $r = 1$ is sufficient to achieve competitive performance, deriving the complexity of the LPHM layer to be $O\left(\frac{d_d d}{r^2}\right)$. Nevertheless, we find sharing matrix and low-rank decomposition in LPHM layers both severely hurt the performance of V&L tasks, so we remove them and use the PHM layers instead.

**Shared-Weight Adapters.** Figure 3. Inspired by Hyperformer, we explore sharing information across $N_T$ tasks in vanilla adapters with the weight-sharing technique. We denote $\Theta = \{\Theta^D, \Theta^U\}$, is the collection of all inserted adapter modules’ weights in the model, and $\Theta^D$ ($\Theta^U$) is the subset that only includes downsampling (upsampling) layers in adapters. As we have mentioned earlier, adapters are trained independently, so we have unique $\{\Theta^D_i, \Theta^U_i\}$ for the $i$th task. To enable the adapter to learn cross-task information, we make part of the weights of the adapter to be shareable. For instance, we can make $\Theta^D_i$ equal to $\Theta^D_j$ ($i \neq j$), and the rest of parameters ($\Theta^U_j$) can still learn the task-specific information for the $i$th task. Note that we also consider the extreme case that using one set of adapters for
all tasks ($\Theta_i = \Theta_j$). The different weight-sharing mechanisms are illustrated in Figure 3.

**Where to Add Adapters?** Recall that our goal is to apply adapters into V&L models to efficiently update their parameters. Since our architecture is composed of visual and language models, it’s expected to inject adapter layers into both of them. However, we observe that even fully fine-tuning the whole model doesn’t bring much improvement compared to solely updating the language one (results are displayed in Section 5.2). Since freezing the CLIP has the best trade-off between performance and parameter efficiency, we eventually don’t add adapter layers into it.

**Multi-task Adapter Variants.** We consider several approaches to use adapters. Since we are in a multi-task setting, the first two straightforward methods are training adapters and Compacter per task, and we call Multiple Adapters and Multiple Compacters (illustrated in Figure 3(a)). To enable the adapters to learn information across tasks, we utilize weight-sharing techniques mentioned in Section 3.2 to form Shared-weight Adapters, illustrated in Figure 3(c). Notably, we can form the two types of Shared-weight Adapters by sharing either upsampling layers or downsampling layers. However, we use Shared-weight Adapters to represent the adapters with sharing upsampling layers since they have almost no differences in terms of accuracy and efficiency. We also consider the extreme case to train multiple tasks with one set of adapter layers, and this brings Single Adapter and Single Compacter (refer to Figure 3(b) for details). Lastly, we have Hyperformer which essentially shares information from multiple tasks. Note that we also update $\theta^{V,T\rightarrow L}$ (1.14% of parameters) and all layer normalization (0.04% of parameters) in the language model. We freeze the output layer, whose weights are tied with word embeddings, because it occupies about 30% of the language model’s parameters, and updating it doesn’t come with a performance boost.

4. Experimental Setup

**Datasets.** We evaluate our models on four V&L datasets: VQA v2 [10] and GQA [19] for visual question answering, NLVR$^2$ [42] for visual reasoning, and MSCOCO [5] for image captioning. We follow VL-T5 [7] to use Karpathy split [21] to split COCO images to 113,287 / 5,000 / 5,000 for train/validation/test (used in VQA and COCO captioning). Next, we introduce the detail and statistics of the datasets. VQA v2 balances the answer distribution for the yes/no questions to force the model to put more attention to images. The Karpathy split [21] splits the VQA dataset into 605,102 / 26,729 / 26,280 image and question pairs for train / validation / test set. GQA is a diverse dataset with the characteristics of real-world reasoning, scene understanding, and compositional question answering. The data is split into three sets: train, val, and test-dev, and they have 943,000, 132,062, and 12,578 questions, respectively. The task of NLVR$^2$ is to determine the correctness of a natural language description based on a pair of images, and the three splits: train, val, and test-P split consist of 86,373, 6,982, and 6,967 sentences, respectively. For COCO captioning, our modes learn to generate a textual description given input images. MSCOCO contains 5 reference captions per image. Therefore, following the Karpathy split [21], we have 566,747 captions for the training set.

**Architecture Details.** We follow [7] to combine vision encoder and an encoder-decoder language model to deal with the unified text generation problems. We use ResNet101 as our vision encoder, and initialize it with CLIP [33] pretrained weights. Input images are resized to $224 \times 224$ for the memory efficiency. We extract the $7 \times 7$ grid features produced by the last convolutional layer, and apply adaptive max-pooling over the features for downsampling then to $6 \times 6$ for a fair comparison to [7]. In addition, we choose BART$_{base}$ [24] as our main encoder-decoder language model, but we also extend the studies to T5$_{base}$ [36]. We use CLIP-BART and CLIP-T5 for representing these two V&L architectures.

**Training and Evaluation.** We perform an extensive hyperparameter search for our models. See Appendix B for details. We use AdamW to train the model unless we additionally specify and apply a linear decay scheduler. We train the models for 20 epochs for each task, and we warm up the learning rate from 0 to peak learning rate in the first 2 epochs. The batch size is set to 500 for CLIP-BART and 250 for CLIP-T5, and the total training time is about 20 hours and 40 hours for CLIP-BART and CLIP-T5 with one A6000 GPU (48G memory), respectively. We select the last checkpoint for evaluation and report the evaluation score of the four tasks as well as the average score in our experiments. The percentage of updated parameters is also reported as the metric for approaches’ efficiency, and we don’t take visual encoder into computation since it’s frozen.

5. Results and Analysis

5.1. Multi-Task Parameter-Efficient Fine-Tuning

Next, we move to our main experiments about applying parameter-efficient training techniques for V&L models. We note that the techniques are only used for the language model as we mentioned in Section 3.2. Besides the adapter-based methods and full fine-tuning, we also consider prompt-tuning [23], which concatenates trainable parameters to the inputs while keeping the model unmodified. In this case, we also have two variants, Single Prompt-Tuning and Multiple Prompt-Tuning, where the former one uses the same prompt for multiple tasks while the latter one has one prompt for each task respectively. The prompts...
Table 1. The multi-task evaluation results on VQA, GQA, NLI2, and COCO Caption between full fine-tuning, adapter-based approaches, prompt-tuning, and VL-BART. We bold the highest scores separately for approaches which are with or without parameter-efficient training techniques. Note that we don’t use V&L pre-training for every model.

| Method       | Updated Params (%) | VQA Karpathy test Acc. (%) | GQA test-dev Acc. (%) | NLVR2 test-P Acc. (%) | COCO Cap. Karpathy test CIDEr Avg. |
|--------------|--------------------|----------------------------|-----------------------|-----------------------|-----------------------------------|
| VL-BART [7]  | 100.00             | 67.8                       | 57.3                  | 72.3                  | 109.4 76.7                        |
| CLIP-BART    |                    |                            |                       |                       |                                   |
| + Full fine-tuning | 100.00             | 67.6                       | 56.7                  | 73.0                  | 112.9 77.6                        |
| + Multiple Adapters | 12.22             | 65.4                       | 54.0                  | 69.8                  | 114.3 75.9                        |
| + Shared-weight Adapters | 8.36           | 65.2                       | 53.4                  | 71.2                  | 113.7 75.9                        |
| + Single Adapter | 4.36            | 65.9                       | 54.5                  | 74.2                  | 114.9 77.4                        |
| + Hyperformer | 5.79              | 65.1                       | 53.4                  | 72.3                  | 114.6 76.4                        |
| + Multiple Compacters | 7.02         | 64.6                       | 53.4                  | 69.1                  | 116.0 75.8                        |
| + Single Compacter | 2.67            | 64.2                       | 53.3                  | 71.7                  | 114.1 75.8                        |
| + Multiple Prompts | 4.53            | 43.8                       | 38.1                  | 51.1                  | 104.6 59.4                        |
| + Single Prompt | 2.00             | 44.0                       | 36.3                  | 51.8                  | 103.9 59.0                        |

Figure 4. The comparison of three adapter-based approaches over the different percentages of updated parameters. We adjust the hidden dimension $d$ to attain the model with different sizes.

Adapters perform on par with Multiple Adapters with fewer parameters, and the Single Adapter’s performance is as competitive as which of the full fine-tuning (77.4 vs. 77.6). The performance boost of Share-weight Adapters and Single Adapter mainly comes from a smaller dataset, NLI2, and this demonstrates that information sharing benefits the low resource tasks. We next turn to the results of Hyperformer and Compacter. The Hyperformer shares the information across tasks in the hyper-network and thus resulting in that it’s more parameter-efficient than the Multiple Adapters (12.22% vs. 5.79%). However, Single Adapter still outperforms Hyperformer in terms of its parameter-efficiency (4.36% vs. 5.79%) and effectiveness (77.4 vs. 76.4). The optimization of hyper-network is harder and it might be one of the reasons to produce this outcome. Compared to Adapter, Compacter doesn’t stand out in our experiments. We hypothesize the reason causing the outcomes is: our BART model is pre-trained on pure language tasks, and we would like to adapt the model to perform on V&L tasks. Nevertheless, the assumption of Kronecker products might be too restrictive, so that Compacter fails to overcome the huge discrepancy between tasks. To have a complete comparison between three adapter-based approaches, in Figure 4, we show their performance over the different percentages of updated parameters. We observe that Single Adapter, despite its simple architecture, achieves the best accuracy-efficiency trade-off. Lastly, we transfer the best
setting of the Single Adapter to CLIP-T5 and show the results in Table 2. Note that we use a larger hidden dimension for adapters in this case, and the percentage of updated parameters is 7.98%. The results conclude that the Single Adapter still attains a promising accuracy-efficiency trade-off in T5. We leave the results of adding other approaches into T5 in the Appendix B.2.

Prompt-tuning vs. Adapters. In general, prompt-tuning doesn’t perform well in our experiments. The reason might be similar to Compacter’s: because the pre-trained tasks and downstream tasks are dissimilar, the model cannot adapt to the distribution of new datasets with few parameters. Also, prompt-based approaches don’t update the layer normalization layers for adapting distribution. The results might be better for the prefix-tuning [25] (add prompts to hidden states as well) approach, but we leave this in future work.

5.2. Training or Freezing Visual Encoder

Because the use of CLIP enables the whole model to be end-to-end trainable with stability [41], we conduct ablations to test the performance of four different training scenarios: all possible pairs of training (full fine-tuning) or freezing the CLIP and BART. Every combination is trained and evaluated on VQA. We apply the training tricks used in [18, 41] and report the results in Table 3. The results show that there is only 1% improvement with adding the CLIP into training. Given this outcome, the advantage of adding adapters into CLIP over keeping it frozen is limited. Therefore, we have determined to freeze the CLIP consistently to save memory, and this also ideally fits our purpose to train models efficiently. We also report the result of our version of “Frozen” [4] [44], where we freeze BART and only fine-tune CLIP. However, the accuracy of 39.4 (in Table 3) is far from which of updating BART, suggesting that fine-tuning language model is still necessary.

5.3. Ablations and Analysis

In the following paragraphs, we sequentially present our ablation studies and analysis on (1) the contribution of different modules, (2) adapters with task-specific prompts. (3)

Table 3. The VQA results of all possible pairs of full fine-tuning or freezing the CLIP and BART. Note that we only train the visual projection layer ($\theta_V \rightarrow L$) in “frozen CLIP + frozen BART”.

|                  | fine-tuning CLIP | frozen CLIP |
|------------------|-----------------|-------------|
| fine-tuning BART | 65.6            | 39.4        |
| frozen BART      | 64.7            | 39.1        |

Table 4. Ablation on adding components while adapter training.

| Method                  | VQA | GQA | NLVR$^2$ | COCO Cap. | Avg. |
|------------------------|-----|-----|----------|-----------|------|
| $\theta_V \rightarrow L$ only | 32.2 | 25.6 | 52.1     | 78.5      | 47.1 |
| $\theta_V \rightarrow L$ + Layer Norm | 49.5 | 40.1 | 52.4     | 109.6     | 62.9 |
| Single Adapter         | 65.9 | 54.5 | 74.2     | 114.9     | 77.4 |

Table 5. Ablation results of adding task-specific prompts.

| Method                  | VQA | GQA | NLVR$^2$ | COCO Cap. | Avg. |
|------------------------|-----|-----|----------|-----------|------|
| CLIP-BART w/o prompt   | 66.7 | 56.5 | 73.2     | 112.4     | 77.2 |
| CLIP-BART w/ prompt    | 67.6 | 56.7 | 73.0     | 112.9     | 77.6 |
| CLIP-BART + Single Adapter w/o prompt | 65.1 | 53.9 | 72.7     | 115.6     | 76.8 |
| CLIP-BART + Single Adapter w/ prompt | 65.9 | 54.5 | 74.2     | 114.9     | 77.4 |

effect of V&L pre-training on adapters.

Contribution of Modules ($\theta_V \rightarrow L$, Layer Norm). Recall that our adapter training not only includes the adapters’ modules but layer normalization layers and the visual projection layer $\theta_V \rightarrow L$. To have a better understanding of the contribution to the accuracy of adapters, we conduct the ablation studies to gradually add trainable modules and compare their results in Table 4. We observe that only updating $\theta_V \rightarrow L$ produces insufficient results, suggesting the need to update the language model partially. We do find a considerable improvement with updating layer normalization layers, but the accuracy is still behind that of the full fine-tuning greatly, and this result also displays the effectiveness of adapters. We note that this finding deviates from the conclusion in [2], where updating layer normalization layer is comparable or even better than training adapters inside CLIP for the image classification task.

Adapters with Task-specific Prompts. We experiment to remove task-specific prompts before the input sequence, namely, from “[task]: [input]” to “[input]”, where [task] is vqa, gqa, nlvr or caption. The ablation is only for the approaches using one set of parameters for multi-tasking, such as full fine-tuning and Single Adapter. We exclude Hyperformer in this experiment since we follow the original implementation to remove all prompts and use task embedding as the condition. The results of whether using task-specific prompts are displayed in Table 5. We find that using prompts can improve performance, and improvement likely comes from resolving the confusion between tasks. However, the model still performs well without prompts. We hypothesize the data distribution between tasks is large enough for the model to understand to treat them differently, so the added prompts might become redundant. For example, there is no text input in MSCOCO while there are two input images in NLVR$^2$. Hence, the model could distinguish tasks via these kinds of data properties.
Furthermore, we have presented the three popular and the effect of V&L pre-training to adapters. We thus also explore if the adapter training can take advantage of V&L pre-trained weights. We follow [41] to pre-train on COCO [26] and VG [22] images with multi-modal language modeling, visual question answering, and image-text matching. We exclude the referring tasks (grounded captioning and visual grounding) because they need bounding box information, which can not be obtained using CLIP. The training details are left in the appendix. Table 6 shows the fine-tuning results with V&L pre-training. In this case, the Single Adapter even is more competitive than full fine-tuning with only a few parameters being trained, suggesting that the adapters work well in different kinds of pre-trained weights.

6. Discussion and Conclusion

We conduct comprehensive studies on evaluating three adapter-based approaches on four challenging V&L tasks. We employ a unified format and architecture to solve the tasks in a multi-tasking setup. With a thorough hyper-parameter search, we benchmark the performance of those methods and find the Single Adapter, which is a shared-weight vanilla adapter, attains the best results in terms of accuracy, efficiency, and simplicity. We also perform the ablation studies about understanding the contribution of different trainable modules, adapters with task-specific prompts, and the effect of V&L pre-training to adapters.

Next, we discuss some limitations of this work. We have done thorough experiments on the four V&L tasks with our proposed CLIP-BART and CLIP-T5. However, the different architectures have their own best hyper-parameters, and the data distribution is varied across tasks, so our results and findings might not be able to generalize to some new tasks. Furthermore, we have presented the three popular and state-of-the-art adapter variants as benchmarks in this paper, but they cannot represent all the adapter-based approaches.

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| Method         | VQA | GQA | NLVR² | COCO Cap. | Avg. |
|----------------|-----|-----|-------|-----------|------|
| VL-BART [7]    | 69.1| 59.0| 73.3  | 111.5     | 78.2 |
| CLIP-BART      | 69.2| 57.5| 75.0  | 112.1     | 78.5 |
| + Full fine-tuning |    |     |       |           |      |
| + Single Adapter | 69.4| 58.1| 73.7  | 115.7     | 79.2 |

Table 6. The fine-tuning results of full fine-tuning and Single Adapter after pre-training on V&L tasks first.
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In this appendix, we first explain our prompt-tuning experiment setup with details (Appendix A). Then we show the experimental results of the complete hyper-parameter search for the adapter-based and prompt-based techniques (Appendix B).

A. Details for Prompt-tuning

Prompt-tuning [23] adds trainable parameters to the encoder’s inputs for adapting those parameters for new tasks without changing the model. Specifically, we assume the input indices for generating prompts are 1, 2, ..., $N_p$, where $N_p$ is the length of prompts. We next apply a three-layer neural network to transform the prompts embeddings to the correct dimension for the language model. The first layer is an embedding layer, parameterized by $\theta_E \in \mathbb{R}^{N_p \times d_e}$, and the rest of the two layers are parameterized by $\theta_D \in \mathbb{R}^{d_e \times d}$ and $\theta_U \in \mathbb{R}^{d \times d}$. Since the architecture of the prompt network is quite similar to the adapter module, we use the same notations as we used in adapters for simplicity. The mathematical form can be written as the following.

$$h = f_{\theta_E}(p)$$
$$h_p = f_{\theta_U}(\sigma(f_{\theta_D}(h)))$$

where $p \in 1, 2, ..., N_p$, $h_p$ being the prompt of index $p$, and we use Tanh as the activation function. Next, we can combine the prompt embeddings with vision and sentence embedding, feed-forward to the model, and train them with backpropagation. The trainable parameters consist of the input prompts embeddings and the parameters of the three-layer neural network. Note that unlike in adapter modules that $d$ is smaller than $d_e$ for saving memory, $d$ in the prompt module is sometimes greater than $d_e$ since it is the main hyper-parameter to increase the number of trainable parameters. The length of the prompt $N_p$ does not contribute much to the number of parameters since it only influences the embedding layer, which usually is a small layer. Thus, using longer prompts is a parameter-efficient method to train models. However, the memory usage would increase significantly with longer prompts due to the quadratic cost of attention layer on input lengths. For a fair comparison, we maximize $N_p$ to use the same amount of memory as being used in adapter-based approaches (around 40 GB).
Table 7. The multi-task evaluation results for CLIP-BART on VQA, GQA, NLVR² and COCO Caption between adapter-based approaches with different hyper-parameters. We bold the highest average accuracy separately for each approach, and we also bold the best configuration we used in the main paper. Note that we don’t use V&L pre-training for every model. * denotes the NLVR results might be improved if we use different learning rates.

### B. Hyper-parameter Search

We search over the learning rates among \{1 \times 10^{-4}, 3 \times 10^{-4}, 1 \times 10^{-3}\} for each hyper-parameter configuration. To reduce the cost of searching, we utilize a heuristic logic: we first search for the best learning rate for the one hyper-parameter configuration (randomly chosen) and then use the same learning rate for other configurations. We perform another learning rate search only if the results are diverge for some tasks (e.g. sometimes the results of NLVR² become very low at certain learning rates).

For the Adapter, the only hyper-parameter is hidden dimension \(d\). We also ablate two variants of Shared-weight Adapters: sharing upsampling or downsampling layers. We include the search about the projected hidden dimension \(d_e\) for the task projector network in the Hyperperformer. Regard-

### B.1. CLIP-BART Hyper-parameter Search

We show the results of the hyper-parameter search in Table 7. We bold the final configurations used in the main paper and we also list the configurations in Table 9. The exception is that we use the same hyper-parameters for the “Single” and “Multiple” approaches. For example, even though Multiple Prompts perform better when \(d_m = 100\), we still use \(d_m = 800\) for both Multiple Prompts and Single Prompt for consistency (J and K rows in Table 7).
Table 8. The multi-task evaluation results for CLIP-T5 on VQA, GQA, NLVR validated on T5 in [30].

| Method                        | Updated Params (%) | VQA Karpathy test Acc. (%) | GQA test-dev Acc. (%) | NLVR\(^2\) test-P Acc. (%) | COCO Cap. Karpathy test Acc. (%) | Avg. |
|-------------------------------|-------------------|----------------------------|----------------------|-----------------------------|----------------------------------|------|
| (A) Full fine-tuning          | 1 × 10\(^{-4}\)   | 100.00                     | 67.3                 | 56.5                        | 75.4                             | 113.1 | 78.1 |
| (B) Multiple Adapters         |                   |                            |                      |                             |                                  |      |     |
| (B.1) · d = 192              | 1 × 10\(^{-3}\)   | 24.56                      | 66.0                 | 55.7                        | 51.8                             | 111.9 | 71.3 |
| (B.2) · d = 96               | 1 × 10\(^{-3}\)   | 14.29                      | 66.1                 | 55.7                        | 52.5                             | 112.8 | 71.8 |
| (C) Single Adapter            |                   |                            |                      |                             |                                  |      |     |
| (C.1) · d = 384              | 3 × 10\(^{-4}\)   | 14.25                      | 67.6                 | 55.9                        | 73.6                             | 111.8 | 77.2 |
| (C.2) · d = 192              | 3 × 10\(^{-4}\)   | 7.98                       | 67.6                 | 56.2                        | 73.9                             | 111.8 | 77.4 |
| (C.3) · d = 96               | 1 × 10\(^{-3}\)   | 4.49                       | 66.4                 | 55.5                        | 72.7                             | 111.5 | 76.5 |
| (C.4) · d = 48               | 1 × 10\(^{-3}\)   | 2.64                       | 65.7                 | 54.7                        | 70.9                             | 111.1 | 75.6 |
| (D) Hyperformer               |                   |                            |                      |                             |                                  |      |     |
| (D.1) · d = 192, \(d_p = 8\) | 1 × 10\(^{-3}\)   | 6.37                       | 65.5                 | 55.1                        | 71.5                             | 112.2 | 76.1 |
| (D.2) · d = 192, \(d_p = 4\) | 1 × 10\(^{-3}\)   | 3.99                       | 65.0                 | 53.9                        | 70.4                             | 111.7 | 75.2 |
| (E) Multiple Compacters (d = 192) |                 |                            |                      |                             |                                  |      |     |
| (E.1) · w/o sharing weights, w/o low-rank param., \(k = 2^*\) | 1 × 10\(^{-3}\)   | 14.30                      | 66.1                 | 55.0                        | 52.1                             | 112.9 | 71.5 |
| (E.2) · w/o sharing weights, w/o low-rank param., \(k = 4^*\) | 1 × 10\(^{-3}\)   | 8.06                       | 65.4                 | 55.0                        | 52.2                             | 113.2 | 71.5 |
| (E.3) · w/o sharing weights, w/o low-rank param., \(k = 8^*\) | 1 × 10\(^{-3}\)   | 4.66                       | 63.3                 | 52.9                        | 51.7                             | 110.4 | 69.6 |
| (F) Single Compacter (d = 192) |                 |                            |                      |                             |                                  |      |     |
| (F.1) · w/o sharing weights, w/o low-rank param., \(k = 2\) | 1 × 10\(^{-3}\)   | 4.49                       | 67.0                 | 56.6                        | 72.5                             | 112.7 | 77.2 |
| (F.2) · w/o sharing weights, w/o low-rank param., \(k = 4\) | 1 × 10\(^{-3}\)   | 2.65                       | 66.1                 | 55.2                        | 71.8                             | 111.7 | 76.2 |
| (F.3) · w/o sharing weights, w/o low-rank param., \(k = 8\) | 1 × 10\(^{-3}\)   | 1.72                       | 65.2                 | 54.1                        | 71.6                             | 111.5 | 75.6 |

* denotes the NLVR results might be improved if we use different learning rates.

Table 9. The best hyperparameter configurations for different parameter-efficient training approaches.

| Model       | Approach                     | Learning Rate | Batch size | Other hyper-parameters |
|-------------|------------------------------|---------------|------------|------------------------|
| CLIP-BART   | Full fine-tuning             | 1 × 10\(^{-4}\) | 500        |                        |
|             | Multiple Adapters            | 3 × 10\(^{-4}\) | 500        | \(d = 96\)             |
|             | Shared-weight Adapters       | 3 × 10\(^{-4}\) | 500        | sharing upsampling layers, \(d = 96\) |
|             | Single Adapter               | 1 × 10\(^{-3}\) | 500        | \(d = 96\)             |
|             | Hyperformer                  | 1 × 10\(^{-3}\) | 500        | \(d = 96, d_p = 8\)    |
|             | Multiple Compacters          | 1 × 10\(^{-3}\) | 500        | remove share weight and low-rank, \(d = 96, k = 2\) |
|             | Single Compacter             | 1 × 10\(^{-3}\) | 500        | remove share weight and low-rank, \(d = 96, k = 2\) |
|             | Multiple Prompts             | 1 × 10\(^{-3}\) | 500        | \(N_p = 40, d_m = 800\) |
|             | Single Prompt                | 1 × 10\(^{-3}\) | 500        | \(N_p = 40, d_m = 800\) |
| CLIP-T5     | Full fine-tuning             | 1 × 10\(^{-4}\) | 250        |                        |
|             | Multiple Adapters            | 1 × 10\(^{-3}\) | 250        | \(d = 192\)             |
|             | Single Adapter               | 3 × 10\(^{-4}\) | 250        | \(d = 192\)             |
|             | Hyperformer                  | 1 × 10\(^{-3}\) | 250        | \(d = 192, d_p = 8\)    |
|             | Multiple Compacters          | 1 × 10\(^{-3}\) | 250        | remove share weight and low-rank, \(d = 192, k = 2\) |
|             | Single Compacter             | 1 × 10\(^{-3}\) | 250        | remove share weight and low-rank, \(d = 192, k = 2\) |

B.2. CLIP-T5 Hyper-parameter Search

We display the results of the hyper-parameter search for CLIP-T5 in Table 8 and final configurations for each method in Table 9. We find that the Compacter (F.1 in Table 8) shows the different fashion in T5: it can perform similarly to the Single Adapter (C.2 in Table 8) using fewer parameters. This might because the Compacter is mainly validated on T5 in [30].