| Model & Method | # Trainable Parameters | E2E NLG Challenge | | | | |
|---|---|---|---|---|---|---|
| | | BLEU | NIST | MET | ROUGE-L | CIDEr |
| GPT-2 M (FT)* | 354.92M | 68.2 | 8.62 | 46.2 | 71.0 | 2.47 |
| GPT-2 M ($\text{Adapter}^{\text{L}}$)* | 0.37M | 66.3 | 8.41 | 45.0 | 69.8 | 2.40 |
| GPT-2 M ($\text{Adapter}^{\text{L}}$)* | 11.09M | 68.9 | 8.71 | 46.1 | 71.3 | 2.47 |
| GPT-2 M ($\text{Adapter}^{\text{H}}$) | 11.09M | $67.3_{\pm.6}$ | $8.50_{\pm.07}$ | $46.0_{\pm.2}$ | $70.7_{\pm.2}$ | $2.44_{\pm.01}$ |
| GPT-2 M ($\text{FT}^{\text{Top2}}$)* | 25.19M | 68.1 | 8.59 | 46.0 | 70.8 | 2.41 |
| GPT-2 M (PreLayer)* | 0.35M | 69.7 | 8.81 | 46.1 | 71.4 | 2.49 |
| GPT-2 M (LoRA) | 0.35M | $\mathbf{70.4}_{\pm.1}$ | $\mathbf{8.85}_{\pm.02}$ | $\mathbf{46.8}_{\pm.2}$ | $\mathbf{71.8}_{\pm.1}$ | $\mathbf{2.53}_{\pm.02}$ |
| GPT-2 L (FT)* | 774.03M | 68.5 | 8.78 | 46.0 | 69.9 | 2.45 |
| GPT-2 L ($\text{Adapter}^{\text{L}}$) | 0.88M | $69.1_{\pm.1}$ | $8.68_{\pm.03}$ | $46.3_{\pm.0}$ | $71.4_{\pm.2}$ | $\mathbf{2.49}_{\pm.0}$ |
| GPT-2 L ($\text{Adapter}^{\text{L}}$) | 23.00M | $68.9_{\pm.3}$ | $8.70_{\pm.04}$ | $46.1_{\pm.1}$ | $71.3_{\pm.2}$ | $2.45_{\pm.02}$ |
| GPT-2 L (PreLayer)* | 0.77M | 70.3 | 8.85 | 46.2 | 71.7 | 2.47 |
| GPT-2 L (LoRA) | 0.77M | $\mathbf{70.4}_{\pm.1}$ | $\mathbf{8.89}_{\pm.02}$ | $\mathbf{46.8}_{\pm.2}$ | $\mathbf{72.0}_{\pm.2}$ | $2.47_{\pm.02}$ |

Table 3: GPT-2 medium (M) and large (L) with different adaptation methods on the E2E NLG Challenge. For all metrics, higher is better. LoRA outperforms several baselines with comparable or fewer trainable parameters. Confidence intervals are shown for experiments we ran. * indicates numbers published in prior works.

### 5.2 RoBERTa base/large

RoBERTa (Liu et al., 2019) optimized the pre-training recipe originally proposed in BERT (Devlin et al., 2019a) and boosted the latter's task performance without introducing many more trainable parameters. While RoBERTa has been overtaken by much larger models on NLP leaderboards such as the GLUE benchmark (Wang et al., 2019) in recent years, it remains a competitive and popular pre-trained model for its size among practitioners. We take the pre-trained RoBERTa base (125M) and RoBERTa large (355M) from the HuggingFace Transformers library (Wolf et al., 2020) and evaluate the performance of different efficient adaptation approaches on tasks from the GLUE benchmark. We also replicate Houlsby et al. (2019) and Pfeiffer et al. (2021) according to their setup. To ensure a fair comparison, we make two crucial changes to how we evaluate LoRA when comparing with adapters. First, we use the same batch size for all tasks and use a sequence length of 128 to match the adapter baselines. Second, we initialize the model to the pre-trained model for MRPC, RTE, and STS-B, not a model already adapted to MNLI like the fine-tuning baseline. Runs following this more restricted setup from Houlsby et al. (2019) are labeled with †. The result is presented in Table 2 (Top Three Sections). See Section D.1 for details on the hyperparameters used.

### 5.3 DeBERTa XXL

DeBERTa (He et al., 2021) is a more recent variant of BERT that is trained on a much larger scale and performs very competitively on benchmarks such as GLUE (Wang et al., 2019) and SuperGLUE (Wang et al., 2020). We evaluate if LoRA can still match the performance of a fully fine-tuned DeBERTa XXL (1.5B) on GLUE. The result is presented in Table 2 (Bottom Section). See Section D.2 for details on the hyperparameters used.

### 5.4 GPT-2 medium/large

Having shown that LoRA can be a competitive alternative to full fine-tuning on NLU, we hope to answer if LoRA still prevails on NLG models, such as GPT-2 medium and large (Radford et al., b). We keep our setup as close as possible to Li & Liang (2021) for a direct comparison. Due to space constraint, we only present our result on E2E NLG Challenge (Table 3) in this section. See Section F.1 for results on WebNLG (Gardent et al., 2017) and DART (Nan et al., 2020). We include a list of the hyperparameters used in Section D.3.

| Model&Method | # Trainable Parameters | WikiSQL Acc. (%) | MNLI-m Acc. (%) | SAMSum R1/R2/RL |
|---|---|---|---|---|
| GPT-3 (FT) | 175,255.8M | **73.8** | 89.5 | 52.0/28.0/44.5 |
| GPT-3 (BitFit) | 14.2M | 71.3 | 91.0 | 51.3/27.4/43.5 |
| GPT-3 (PreEmbed) | 3.2M | 63.1 | 88.6 | 48.3/24.2/40.5 |
| GPT-3 (PreLayer) | 20.2M | 70.1 | 89.5 | 50.8/27.3/43.5 |
| GPT-3 ($\text{Adapter}^{\text{H}}$) | 7.1M | 71.9 | 89.8 | 53.0/28.9/44.8 |
| GPT-3 ($\text{Adapter}^{\text{H}}$) | 40.1M | 73.2 | **91.5** | 53.2/29.0/45.1 |
| GPT-3 (LoRA) | 4.7M | 73.4 | **91.7** | **53.8/29.8/45.9** |
| GPT-3 (LoRA) | 37.7M | **74.0** | **91.6** | 53.4/29.2/45.1 |

Table 4: Performance of different adaptation methods on GPT-3 175B. We report the logical form validation accuracy on WikiSQL, validation accuracy on MultiNLI-matched, and Rouge-1/2/L on SAMSum. LoRA performs better than prior approaches, including full fine-tuning. The results on WikiSQL have a fluctuation around $\pm 0.5\%$, MNLI-m around $\pm 0.1\%$, and SAMSum around $\pm 0.2/\pm 0.2/\pm 0.1$ for the three metrics.

### 5.5 Scaling up to GPT-3 175B

As a final stress test for LoRA, we scale up to GPT-3 with 175 billion parameters. Due to the high training cost, we only report the typical standard deviation for a given task over random seeds, as opposed to providing one for every entry. See Section D.4 for details on the hyperparameters used.

As shown in Table 4, LoRA matches or exceeds the fine-tuning baseline on all three datasets. Note that not all methods benefit monotonically from having more trainable parameters, as shown in Figure 2. We observe a significant performance drop when we use more than 256 special tokens for prefix-embedding tuning or more than 32 special tokens for prefix-layer tuning. This corroborates similar observations in Li & Liang (2021). While a thorough investigation into this phenomenon is out-of-scope for this work, we suspect that having more special tokens causes the input distribution to shift further away from the pre-training data distribution. Separately, we investigate the performance of different adaptation approaches in the low-data regime in Section F.3.

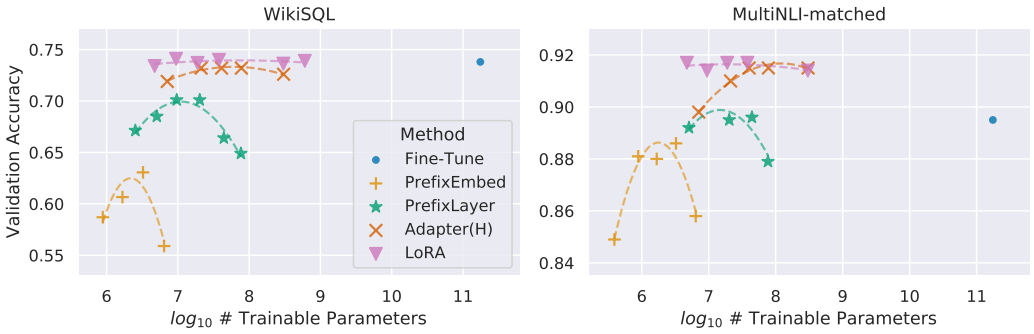


Figure 2: GPT-3 175B validation accuracy vs. number of trainable parameters of several adaptation methods on WikiSQL and MNLI-matched. LoRA exhibits better scalability and task performance. See Section F.2 for more details on the plotted data points.

## 6 Related Works

**Transformer Language Models.** Transformer (Vaswani et al., 2017) is a sequence-to-sequence architecture that makes heavy use of self-attention. Radford et al. (a) applied it to autoregressive language modeling by using a stack of Transformer decoders. Since then, Transformer-based language models have dominated NLP, achieving the state-of-the-art in many tasks. A new paradigm emerged with BERT (Devlin et al., 2019b) and GPT-2 (Radford et al., b) – both are large Transformer lan-

guage models trained on a large amount of text – where fine-tuning on task-specific data after pre-training on general domain data provides a significant performance gain compared to training on task-specific data directly. Training larger Transformers generally results in better performance and remains an active research direction. GPT-3 (Brown et al., 2020) is the largest single Transformer language model trained to-date with 175B parameters.

**Prompt Engineering and Fine-Tuning.** While GPT-3 175B can adapt its behavior with just a few additional training examples, the result depends heavily on the input prompt (Brown et al., 2020). This necessitates an empirical art of composing and formatting the prompt to maximize a model's performance on a desired task, which is known as prompt engineering or prompt hacking. Fine-tuning retrains a model pre-trained on general domains to a specific task Devlin et al. (2019b); Radford et al. (a). Variants of it include learning just a subset of the parameters Devlin et al. (2019b); Collobert & Weston (2008), yet practitioners often retrain all of them to maximize the downstream performance. However, the enormity of GPT-3 175B makes it challenging to perform fine-tuning in the usual way due to the large checkpoint it produces and the high hardware barrier to entry since it has the same memory footprint as pre-training.

**Parameter-Efficient Adaptation.** Many have proposed inserting *adapter* layers between existing layers in a neural network (Houlsby et al., 2019; Rebuffi et al., 2017; Lin et al., 2020). Our method uses a similar bottleneck structure to impose a low-rank constraint on the weight updates. The key functional difference is that our learned weights can be merged with the main weights during inference, thus not introducing any latency, which is not the case for the adapter layers (Section 3). A comtenporary extension of adapter is COMPACTER (Mahabadi et al., 2021), which essentially parametrizes the adapter layers using Kronecker products with some predetermined weight sharing scheme. Similarly, combining LoRA with other tensor product-based methods could potentially improve its parameter efficiency, which we leave to future work. More recently, many proposed optimizing the input word embeddings in lieu of fine-tuning, akin to a continuous and differentiable generalization of prompt engineering (Li & Liang, 2021; Lester et al., 2021; Hambardzumyan et al., 2020; Liu et al., 2021). We include comparisons with Li & Liang (2021) in our experiment section. However, this line of works can only scale up by using more special tokens in the prompt, which take up available sequence length for task tokens when positional embeddings are learned.

**Low-Rank Structures in Deep Learning.** Low-rank structure is very common in machine learning. A lot of machine learning problems have certain intrinsic low-rank structure (Li et al., 2016; Cai et al., 2010; Li et al., 2018b; Grasedyck et al., 2013). Moreover, it is known that for many deep learning tasks, especially those with a heavily over-parametrized neural network, the learned neural network will enjoy low-rank properties after training (Oymak et al., 2019). Some prior works even explicitly impose the low-rank constraint when training the original neural network (Sainath et al., 2013; Povey et al., 2018; Zhang et al., 2014; Jaderberg et al., 2014; Zhao et al., 2016; Khodak et al., 2021; Denil et al., 2014); however, to the best of our knowledge, none of these works considers low-rank update to a frozen model for *adaptation to downstream tasks*. In theory literature, it is known that neural networks outperform other classical learning methods, including the corresponding (finite-width) neural tangent kernels (Allen-Zhu et al., 2019; Li & Liang, 2018) when the underlying concept class has certain low-rank structure (Ghorbani et al., 2020; Allen-Zhu & Li, 2019; Allen-Zhu & Li, 2020a). Another theoretical result in Allen-Zhu & Li (2020b) suggests that low-rank adaptations can be useful for adversarial training. In sum, we believe that our proposed low-rank adaptation update is well-motivated by the literature.

## 7 UNDERSTANDING THE LOW-RANK UPDATES

Given the empirical advantage of LoRA, we hope to further explain the properties of the low-rank adaptation learned from downstream tasks. Note that the low-rank structure not only lowers the hardware barrier to entry which allows us to run multiple experiments in parallel, but also gives better interpretability of how the update weights are correlated with the pre-trained weights. We focus our study on GPT-3 175B, where we achieved the largest reduction of trainable parameters (up to 10,000$\times$) without adversely affecting task performances.

We perform a sequence of empirical studies to answer the following questions: 1) Given a parameter budget constraint, *which subset of weight matrices* in a pre-trained Transformer should we adapt