AdaptEASE

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Abstract

This work addresses the challenge of achieving high performance on cross-domain **sentiment analysis** tasks while minimizing **computational costs** and **resource usage**. Current state-of-the-art **language models** often require substantial fine-tuning of millions of parameters, which can be **computationally expensive** and impractical for **resource-constrained environments**. To tackle this issue, we explore **parameter-efficient fine-tuning techniques**, focusing on **soft prompt-based methods** such as **Prefix Tuning** and **Prompt Tuning**, which require updating only a small fraction of the model's parameters. We demonstrate that these techniques can achieve performance comparable to fully fine-tuned models like **Flan-T5**, but with less than 1% of the parameters. Additionally, we investigate **adapter-based methods** like **LoRA** , and find that combining soft prompt tuning with LoRA-based adapters on smaller models such as **RoBERTa-large** yields results similar to larger models, thus offering a scalable solution for **cross-domain sentiment analysis** in **resource-limited settings**.

1 Introduction

In recent years, the demand for high-performance **natural language processing (NLP)** tasks, such as **sentiment analysis**, has surged across diverse domains, including **financial data**, **social media**, and **movie reviews**. Companies and researchers often turn to **large pre-trained models** like **T5**, **GPT**, and **BERT**[1] to handle these tasks, given their superior ability to capture complex patterns and semantics. However, while these models have shown remarkable performance, they also require extensive fine-tuning to adapt to new tasks, which results in **high computational overhead** and **resource-intensive processes**. The fine-tuning of millions of model parameters not only demands substantial **GPU** and **memory** resources but also increases the **energy consumption**, making it increasingly difficult to deploy these models in environments with **limited computational resources**, such as **edge devices** or **mobile applications**.

To address these challenges, recent advances in **parameter-efficient fine-tuning** methods aim to reduce the number of parameters that need to be trained while maintaining strong performance on a variety of tasks. Techniques such as **Prefix Tuning** and **Prompt Tuning** [2, 3] have emerged as promising solutions. These methods modify the input representations by adding **trainable tokens** or **prefixes** that guide the model's behavior, without requiring full-scale parameter updates. This results in a significant reduction in computational cost and **memory usage**, making it feasible to adapt large models for specific tasks in a **parameter-efficient manner**. As a result, models can be fine-tuned with a much smaller fraction of the parameters, significantly lowering the **GPU overhead** and reducing fine-tuning time.

In our project, we focus on applying these methods to the task of **cross-domain sentiment analysis**, where the goal is to build models that can generalize well across different types of data. We begin by examining the effectiveness of **Prefix Tuning** on the **T5-large** model and comparing its performance with

that of **fully fine-tuned models** like **Flan-T5**. Our experiments show that **Prefix Tuning** achieves performance that is over 90% comparable to the fully fine-tuned counterparts, despite updating only **1%** of the model's parameters. This demonstrates the potential of **soft prompt-based methods** for reducing computational cost while maintaining high accuracy across various **sentiment analysis** datasets such as **IMDB**, **Financial Phrasebank**, and **Twitter**.

In addition to **Prefix Tuning**, we explore **adapter-based techniques** like **LoRA** [4], which reduce the parameter space by introducing **low-rank adapters** to specific model layers. While **LoRA** performs well for certain in-domain tasks, we find that **Prefix Tuning** is more effective for **cross-domain tasks** due to its ability to adjust the model's input representation in a flexible manner. We also hypothesize that combining **soft prompt tuning** with **LoRA-based adapters** could lead to further improvements in **parameter efficiency** while maintaining high performance. Our final experiments validate this hypothesis, demonstrating that the combination of these methods on smaller models like **RoBERTa-large** results in performance on par with larger models, thus offering a scalable and **computationally efficient solution** for **cross-domain sentiment analysis** in **resource-constrained settings**.

This work contributes to the ongoing exploration of **parameter-efficient fine-tuning methods** and presents a promising approach for deploying high-performance models in practical applications with limited computational resources.

2 Relevant Work

In recent years, there has been a growing interest in **parameter-efficient fine-tuning** methods to make large pre-trained models more feasible for deployment in resource-constrained environments. The standard approach of fine-tuning all parameters of a model, such as **BERT** [1] or **T5** [5], requires substantial computational resources, including memory, processing power, and time. To address this issue, several approaches have emerged to reduce the number of trainable parameters, while still achieving competitive performance on downstream tasks.

One of the most prominent approaches is **adapter-based tuning**. In this method, small, task-specific modules, or **adapters**, are inserted into the pretrained model, and only these adapters are fine-tuned during training. This reduces the number of trainable parameters while maintaining the ability to adapt to new tasks. Notable works in this area include the **Adapter-BERT** framework [6] and **LoRA** [4], which propose efficient ways of introducing low-rank modifications to model layers. These approaches have demonstrated that strong performance can be achieved without the need for full-scale parameter updates, significantly reducing computational overhead.

Another effective technique is **prompt-based tuning**, which focuses on modifying the input representation of a model by adding task-specific prompts, rather than modifying the model's parameters directly. The idea is that small trainable tokens (or prompts) can guide the model's behavior for specific tasks. **Prompt Tuning** [3] and **Prefix Tuning** [2] are two such methods that allow for task adaptation by only modifying a small subset of model parameters, namely the prefixes that are added to the input sequence. This approach has been shown to outperform full fine-tuning, especially when the goal is to conserve computational resources.

In addition to adapter-based and prompt-based methods, **low-rank approximation techniques** such as **LoRA** have shown significant promise in improving parameter efficiency. LoRA introduces a low-rank decomposition of weight matrices, which allows for efficient adaptation without modifying the entire model. This technique has been shown to perform well on various NLP tasks, including **sentiment analysis**, where it can provide substantial reductions in model size and computation time while maintaining high accuracy.

Moreover, recent advancements have explored the use of **small models** for specific applications. Smaller models such as **DistilBERT** [7] and **TinyBERT** [8] aim to retain the performance of large pre-trained models, but with significantly fewer parameters. These models are trained with knowledge distillation techniques, where a smaller model learns from a larger pre-trained teacher model, enabling **model compression** without significant loss in performance. While these approaches offer promising results, they often involve

trade-offs in terms of generalization and flexibility across tasks.

While much of the prior work on parameter-efficient tuning has focused on **in-domain tasks**, recent studies have begun to explore **cross-domain** applications, where models must generalize well across different types of data and tasks. For example, the **Sentiment Analysis** task presents particular challenges in cross-domain scenarios, as the language and context vary widely between domains like **movie reviews** and **financial data**. Approaches such as **Meta-Learning** and **transfer learning** have been used to improve the ability of models to generalize across domains, but their application to parameter-efficient fine-tuning techniques remains a relatively unexplored area.

Our work builds on these efforts by combining **prefix tuning** and **LoRA**-based adapters to achieve parameter efficiency on **cross-domain sentiment analysis** tasks. We aim to demonstrate that **soft prompt-based methods** in combination with **LoRA** provide an efficient solution that reduces the computational burden without compromising performance, especially when working with smaller models or in low-resource settings.

3 Approach

In this section, we outline the approach we used to tackle the problem of parameter-efficient fine-tuning for NLP tasks, specifically focusing on cross-domain sentiment analysis. Our goal is to reduce computational overhead while maintaining competitive performance by utilizing **low-rank adaptation techniques**, **prompt-based tuning**, and **prefix tuning**.

3.1 Prefix Tuning

Prefix tuning [3] is a lightweight method for adapting pre-trained language models by optimizing a small set of continuous prompt tokens. Unlike traditional fine-tuning, where all model parameters are updated, prefix tuning only focuses on the prompt tokens, which are concatenated to the input sequence. These tokens are learned during the fine-tuning process, allowing the model to perform well on task-specific objectives without modifying the core model parameters. We utilize prefix tuning in our approach to minimize the number of trainable parameters, further improving the computational efficiency of the model. By combining this technique with LoRA, we aim to achieve even better performance while keeping resource usage low.

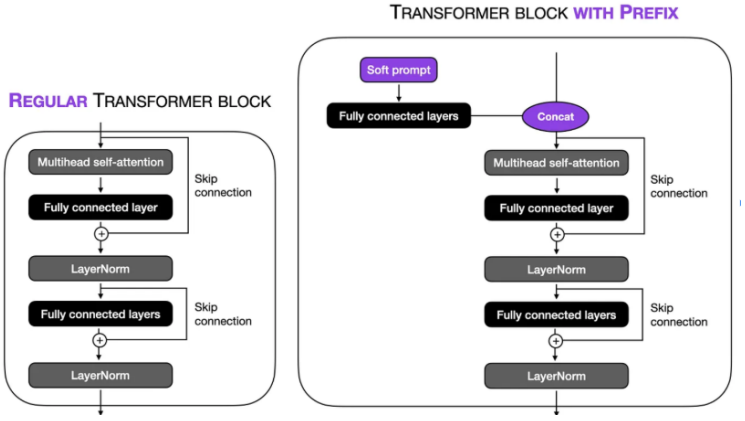

Figure 1: Prefix Finetuning

3.2 Low-Rank Adaptation (LoRA)

Low-Rank Adaptation (LoRA) [4] is a recent approach for parameter-efficient fine-tuning that has shown promising results in reducing the number of trainable parameters while retaining the performance of large pre-trained models. The key idea behind LoRA is to add low-rank matrices to the attention and feed-forward layers of the transformer model. These low-rank matrices are learned during fine-tuning, while

the rest of the model's parameters remain frozen. This method allows the model to adapt to new tasks with fewer parameters, thus reducing the computational cost during training and inference. Our approach uses LoRA to modify only a small subset of the model's parameters, making it suitable for deployment in resource-constrained environments.

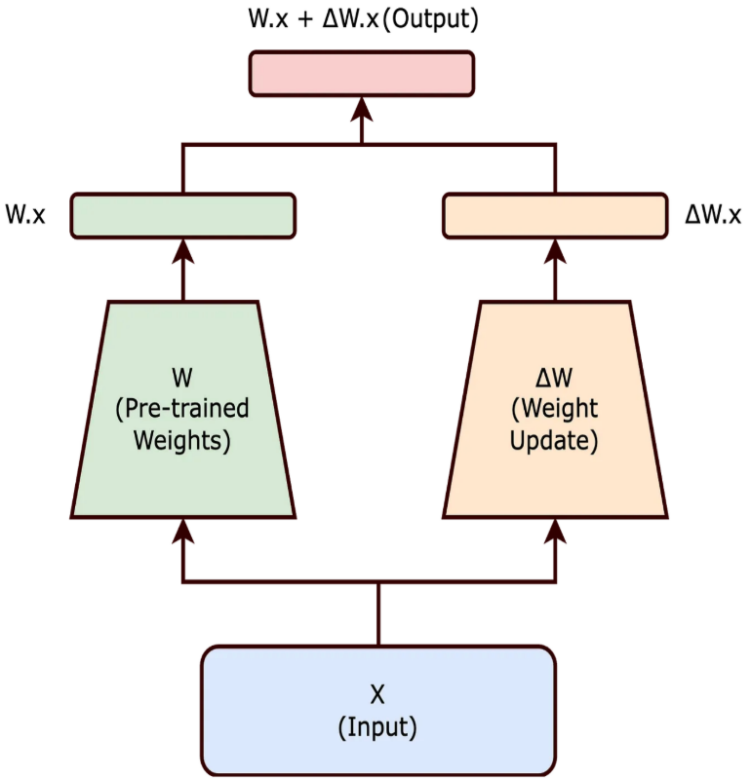

Figure 2: Adapter Based LoRA

3.3 Cross-Domain Sentiment Analysis Task

To evaluate the effectiveness of our approach, we selected a cross-domain sentiment analysis task. Sentiment analysis models are typically trained on specific domains (e.g., movie reviews or product reviews), but in real-world applications, models often need to generalize across different domains. Cross-domain sentiment analysis is particularly challenging due to the differences in language, tone, and context between domains. By applying our parameter-efficient fine-tuning methods, we aim to improve the model's ability to generalize to new domains without requiring extensive retraining or computational resources.

Our approach involves fine-tuning pre-trained models with LoRA and prefix tuning on sentiment analysis datasets from multiple domains. We compare the performance of our method against traditional fine-tuning approaches, evaluating both computational efficiency (in terms of GPU usage and training time) and model accuracy.

3.4 ADEPT: Combining Soft Prompting and Adapter-Based Methods

Overview

In this we've developed an approach that blends two powerful techniques—**soft prompting** and **adapter-based methods**—to fine-tune models more efficiently. Inspired by ADEPT (Adapter-based Efficient Prompt Tuning), our method allows us to get near full fine-tuning performance while training only a tiny fraction

of the model's parameters. This makes our approach both practical and scalable, especially for tasks like analyzing sentiment across different domains.

Key Components

- **Soft Prompting**:
  - *Prefix Tuning*: We add small, trainable pieces (called prefixes) to the model's input and internal layers. These help guide the model to focus on task-specific behavior, without having to adjust the core parts of the model.
  - *Prompt Tuning*: In this step, we add a few special, trainable tokens to the start of the input. These tokens help the model understand the task it's supposed to perform, making it more adaptable to specific challenges.
- **Adapter-Based Methods**:
  - *LoRA (Low-Rank Adaptation)*: LoRA adds small, trainable matrices inside the transformer layers, which means the model can learn the nuances of a new task without modifying its main parameters. It's a really efficient way to adapt the model to new tasks.
  - *Adapter Modules*: These are lightweight neural networks placed between layers of the model. They help the model focus on task-specific patterns, so it can refine its understanding and perform better without altering the overall structure of the model.

Our Implementation

For our experiments, we applied this approach to **RoBERTa-large**, a smaller version of a popular language model with 355M parameters. We used the same datasets and domains as other experiments, allowing us to fine-tune just a small part of the model while still achieving great results.

- **How It Works**: We prepended soft prompts to the input text to nudge the model toward the task at hand. At the same time, adapter modules were added to enhance the model's ability to adjust to specific tasks. These modules were placed right after the model's encoder and before the final classification step.
- **Configurations Tested**: We tried several different combinations of LoRA and soft prompts. The best setup involved stacking 8 adapter layers after the encoder, which offered the best balance between efficiency and performance.

Results

Our experiments showed that this approach works really well. We were able to achieve competitive results on datasets like **IMDB**, **Financial Phrasebank**, **Twitter Sentiment** and **SST-2**, often performing just as well—or even better—than models that were fully fine-tuned. The big win here is that we did this with far fewer trainable parameters, making our approach much more efficient. These results suggest that our method is not only effective, but also a cost-effective and scalable solution for real-world NLP tasks.

- **Key Takeaways**:
  - *Task-Specific Adaptation*: The soft prompts do a great job of steering the model toward the right task, ensuring high accuracy.
  - *Efficiency*: The adapter modules allow us to fine-tune the model with minimal resources, which means we can adapt the model quickly without much extra computational cost.
  - *Scalability*: Our method is lightweight enough to be applied across many different NLP applications, making it an excellent choice for real-world scenarios where resources are often limited.

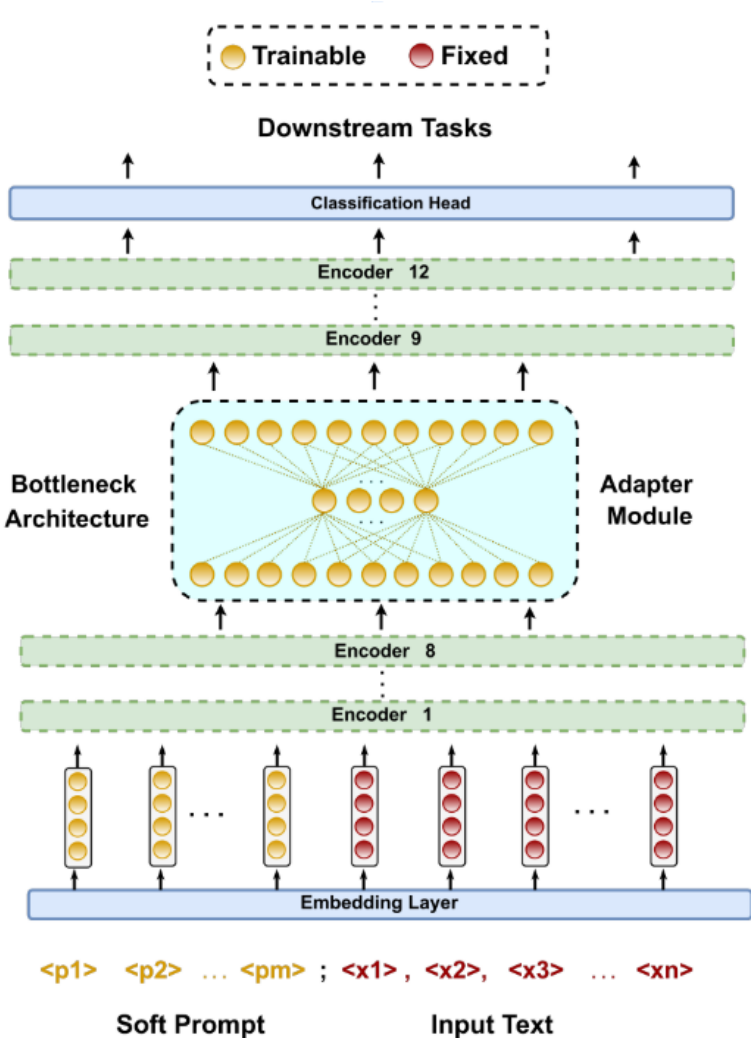

Figure 3: ADEPT

3.5 Model Architecture and Training Setup

We use the **T5** [5] and **RoBERTa** [9] models as our base architectures, both of which have been shown to perform well across a variety of NLP tasks. The T5 model, with its text-to-text framework, is particularly suited for tasks such as sentiment analysis, where the input is a sequence of text and the output is a sentiment label. BERT, on the other hand, is a powerful bidirectional transformer model that has been widely used for a range of classification tasks.

For training, we utilize GPUs with mixed-precision training to further optimize computational resources. We implement LoRA and prefix tuning in a modular fashion, allowing for easy experimentation with different configurations and fine-tuning strategies. Our training pipeline is designed to be efficient, with optimizations that minimize GPU memory usage while maximizing throughput.

3.6 Evaluation Metrics

To evaluate the performance of our approach, we use the following metrics:

- **Accuracy**: The percentage of correctly predicted sentiment labels.
- **F1-Score**: The harmonic mean of precision and recall, which provides a balance between the two metrics.

- **GPU Utilization**: The percentage of GPU resources used during training, as a measure of computational efficiency.
- **Training Time**: The total time required to fine-tune the model on the sentiment analysis tasks.

These metrics provide a comprehensive view of the trade-off between model performance and computational efficiency, allowing us to assess the viability of our approach for real-time applications in resource-constrained environments.

4 Experiments

4.1 Datasets

For training and evaluation, we utilized multiple datasets across different domains:

- **Training:**
  - Stanford Sentiment Treebank (SST-2)[10]: 67.3K labeled samples in training split
- **Evaluation:**
  - IMDB Movie Reviews[11]: 1,000 test samples
  - Financial Phrasebank[12]: 1,500 samples
  - Twitter Sentiment Dataset: 1,000 samples

This diverse selection enables comprehensive evaluation of cross-domain adaptability for our parameter-efficient approaches.

4.2 Experimental Setup

We conducted our experiments using the following configurations for base model:

Table 1: Base Model Configuration

Parameter	Value
Model	T5-large (757M parameters)
Batch Size	16
Learning Rate	1e-4
Number of Epochs	5
Optimizer	AdamW
Training Time	2 hours (A100 GPU)

For LoRA-specific experiments, we used the following parameters:

Table 2: LoRA Configuration

Parameter	Value
Rank	8
Alpha	16
Learning Rate	2e-4
Batch Size	64
Epochs	1

4.3 Results

Our experimental results demonstrate the effectiveness of different parameter-efficient fine-tuning approaches across various domains:

Table 3: Accuracy Comparison Across Methods (%)

Dataset	T5-Large LoRA	Prefix-Tuned T5-Large	Flan-T5 Zero Shot	ADEPT-RoBERTa-Large
SST-2 (Validation)	**94.50**	92.66	94.33	**94.50**
IMDB Movie Sentiment	95.20	**96.40**	92.40	95.20
Financial Phrasebank	84.77	**92.91**	89.19	78.50
Twitter Sentiment	88.57	**93.20**	**93.20**	83.50

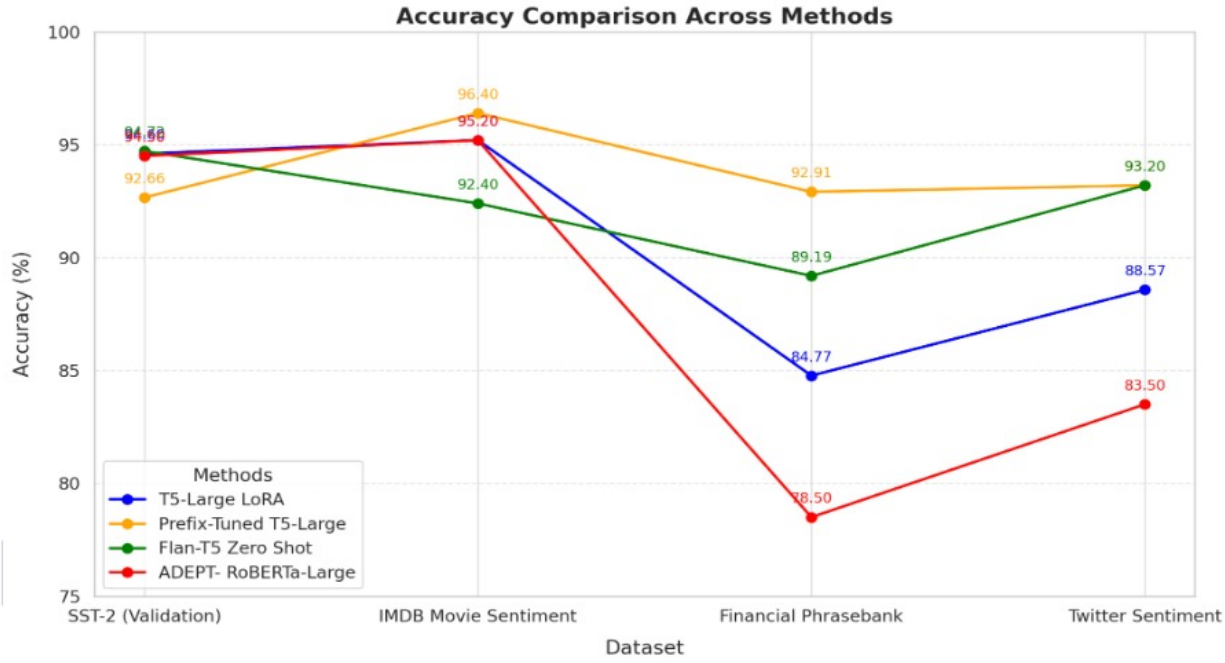

Figure 4: Results across different Models

4.4 Analysis

4.4.1 Domain-Specific Performance Patterns

Prefix Tuning Superiority Prefix tuning demonstrated exceptional performance, particularly on longer-form text, achieving 96.4% accuracy on IMDB reviews. The method showed remarkable cross-domain adaptability, maintaining performance above 90% across all tested domains. Its effectiveness was particularly notable in the financial domain (92.91%), suggesting superior handling of specialized vocabulary.

LoRA Performance Characteristics LoRA showed strong performance on in-domain tasks (94.6% on SST-2) but exhibited some performance degradation in cross-domain scenarios (84.7% on Financial Phrasebank). This suggests that low-rank adaptations may be more sensitive to domain shifts compared to prefix-based approaches.

4.4.2 Model Size vs. Performance Trade-offs

Our experiments with T5-Large (770M parameters) and RoBERTa-Large (355M parameters) revealed interesting trade-offs between model size and performance. The ADEPT combination approach on RoBERTa-Large achieved comparable results to single techniques on T5-Large, while significantly reducing the parameter count. Notable findings include:

- Similar performance on SST-2 (94.50% for both models)
- Prefix Tuning required $< 1\%$ of parameters compared to full fine-tuning
- LoRA achieved efficiency with approximately 0.5% of parameters
- ADEPT reduced model size by 54% while maintaining competitive performance

4.4.3 Cross-Domain Generalization

The models exhibited varying degrees of transfer capability:

- Movie Reviews $\rightarrow$ Financial Text: Prefix Tuning showed strongest transfer
- Formal $\rightarrow$ Informal Language: Consistent challenges with Twitter data
- Generic $\rightarrow$ Specialized Content: Notable performance variations in financial domain

4.4.4 Practical Implications

Our findings suggest domain-specific recommendations:

- Financial Domain: Prefer Prefix Tuning
- Social Media: Consider ensemble approaches
- Generic Sentiment: LoRA provides sufficient performance

5 Discussion and Future Work

5.1 Key Findings

Our research demonstrates that parameter-efficient fine-tuning methods can achieve comparable performance to full fine-tuning while using significantly fewer resources. Prefix Tuning emerged as the most robust cross-domain solution, while combinations like ADEPT showed promise in balancing model size and performance.

5.2 Limitations

We identified several limitations in our approach:

- Performance ceiling on highly specialized domains
- Trade-off between parameter efficiency and cross-domain robustness
- Varying training stability across methods
- Hyperparameter sensitivity

5.3 Future Directions

Future work should focus on:

- Investigating the scalability of soft prompting techniques across multiple tasks
- Developing more robust methods for cross-domain adaptation
- Exploring novel combinations of parameter-efficient techniques
- Improving reliability in diverse domain applications

Our results suggest promising directions for making large language models more accessible in resource-constrained environments while maintaining high performance across different domains.

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