Paper Title : When Federated Learning Meets Pre-trained Language Models' Parameter-Efficient Tuning Methods

Paper link : https://arxiv.org/abs/2212.10025

1. Summary

1.1 Motivation

The study's main goal is to solve the difficulties associated with optimizing pre-trained language models (PLMs) for tasks that come later in federated learning (FL) environments. The goal is to provide parameter-efficient tuning techniques that minimize communication overhead and maintain privacy, enabling massive PLMs to be tailored to local customers.

1.2 Contribution

FedPETuning, a technique that successfully lowers communication costs and customizes PLMs for local clients in Florida, is one way that the study makes a contribution. It also sheds light on how various FL circumstances, local training epochs, and heterogeneous data affect PLM performance.

1.3 Methodology

In order to assess FedPETuning's performance in FL, a comprehensive set of experiments encompassing resource-constrained analysis, privacy assaults, and performance comparisons are conducted. A thorough ablation analysis of FedPETuning with respect to various FL situations, local training epochs, and heterogeneous data is also included in the paper.

1.4 Conclusion

According to the study's findings, FedPETuning techniques work well at cutting communication overhead while maintaining performance that is equivalent in FL situations. It also emphasizes how crucial it is to take local training epochs and data heterogeneity into account when fine-tuning.

2 Limitations

2.1 First Limitation

The community must develop FL-friendly PETuning techniques in order to handle the growing size of contemporary pre-trained models, which is another constraint. The paper recognises that more research and comparisons with PETuning in FL are required.

2.2 Second Limitation

The absence of FedPETuning validation on large-scale models—which are becoming more and more common in the area of pre-trained language models—is one of the study's limitations. One problem is the computing resources needed to implement such large-scale models in FL environments.

3 Synthesis

The concepts expounded in this study bear noteworthy implications for prospective uses in the creation of parameter-efficient tuning techniques that are FL-friendly for extensive pre-trained language models. Future directions include tackling the computing difficulties related to deploying large-scale models in FL

contexts and investigating PETuning techniques to support the growing size of contemporary pre-trained models.