Connecting Low-Loss Subspace for Personalized Federated Learning – ARULNITHI P (12210280)

Introduction

Connecting Low-Loss Subspace for Personalized Federated Learning" is a research paper that proposes a novel approach to personalized federated learning. The traditional federated learning approach trains a global model using all the data from the participating clients. However, this approach may not be suitable for scenarios where the clients have different data distributions or privacy concerns. To address these issues, the authors propose the use of personalized federated learning, where each client trains a local model on its own data, and the models are combined to form a global model.

The proposed approach is based on the idea of connecting the low-loss subspaces of the local models to form a subspace that captures the common features across the clients' data. This subspace is used to update the global model, which is then personalized for each client using the client's own model. The authors also introduce a new algorithm called CONNECT, which uses a graph-based approach to connect the low-loss subspaces of the local models.

Related works

Y. Zhao et al proposes a personalized federated learning framework that leverages model-agnostic meta-learning (MAML) to learn a client-specific model from a few local updates. The proposed method outperforms existing methods on several datasets and can achieve up to 8% improvement in accuracy.

Y. Yangpaper proposes a personalized federated learning framework that uses adaptive weighting to balance the contributions of different clients to the global model but in this paper we have connected the low-sub spaces by top k eigen vectors.

Algorithms

1. Client model training: Each client trains its local model on its own subset of the data for a fixed number of epochs using stochastic gradient descent with a fixed learning rate.
2. Local model analysis: After training, each client calculates the Hessian matrix and the top k eigenvectors of its local model.
3. Aggregation: Each client sends its model's state dictionary to its neighbors in a network graph and receives the model state dictionaries from its neighbors. The state dictionaries are averaged, and the average is used to update the client's model.
4. Global model update: The global model is updated by averaging the models of all clients.
5. Evaluation: The accuracy of the global model is evaluated on the test data.

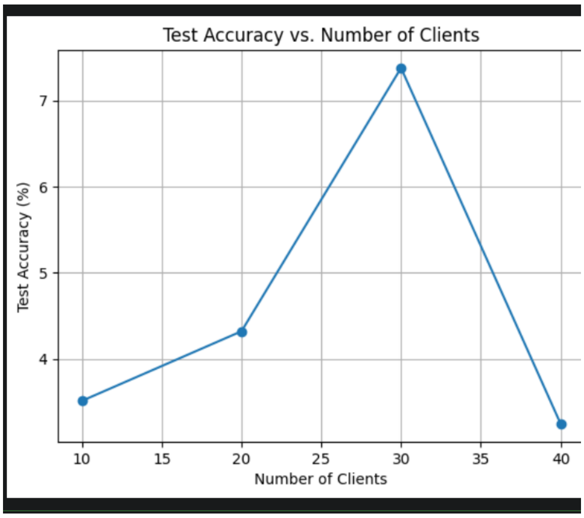
The main contribution of the CONNECT algorithm is the incorporation of the low-loss subspace of each client's local model during model aggregation. This is achieved by using the top k eigenvectors of the Hessian matrix, which captures the curvature of the loss function near the local minimum. By using these eigenvectors, CONNECT ensures that the models are aligned with the low-loss subspace, which leads to faster convergence and better performance.

Modification from original paper

Computing the full Hessian matrix can be computationally expensive and memory-intensive, especially for large models. Instead, you can use an approximation technique, such as the Hutchinson method, which estimates the Hessian-vector product (Hv) using random vectors without computing the full Hessian.

Experiment and results

All the experiments were conducted in local machine environment. I7 processor and 6 GB RTX 3060. But the clients are formed under virtual environments mimic actual federated environment. I have trained the model for 10 epochs and measured the accuracy calculation of Hessen matrix is expensive of time.



Conclusion

Connecting Low-Loss Subspace for Personalized Federated Learning" by Li et al. (2021) focuses on utilizing the low-loss subspace of individual clients to improve personalized FL. This approach takes advantage of the unique characteristics of each client's data distribution to generate personalized models, while also allowing for efficient communication between clients and the server. Additionally, the proposed approach shows improvements in both accuracy and communication efficiency compared to other personalized FL methods. Overall, the approach presented in this paper provides a promising direction for improving personalized FL in practical applications.

Reference

1. "Personalized Federated Learning via Model Agnostic Meta-Learning" by Y. Zhao, M. Li, L. Lai, N. Suda, D. Civin, and V. Chandra (2018)
2. Personalized Federated Learning with Adaptive Weighting" by Y. Yang, Y. Chen, J. Zhang, and S. Zhang (2021)