Winter 2021 CSC 2228 Project Progress Update

Title:

Improving performance of federated learning on heterogeneous data through various client update schemes

Team Members:

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Link to project webpage: https://tim-tianyu.github.io/CSC2228-webpage/

Project Goals:

- Non IID unequal data distribution is the setting that is most likely to be found in the wild when applying federated learning, and thus we focus our primary goal on improving the accuracy of ML models that work on these types of data distribution (eg. non IID unequal data partition).
- Adaptive federated optimization" finds that it is particularly important to optimize the client optimizer learning rate in federated learning. We take this as an inspiration to improve the performance of ML models on non IID unequal data distribution with three methods that explore and refine ways to improve client optimizers:
    - (a) Implementing and experimenting with different local client optimizers that have not been tried yet on non IID unequal data.
    - (b) Implementing and experimenting with learning rate schedulers on non IID unequal data.
    - (c) Designing a new local client optimizer which helps achieve higher model accuracies.

Work Completed:

- New additions to previous framework [4]:
    - Modified the CNN model for the FMNIST dataset to improve accuracy.
    - Added functionality to create non IID unequal data distribution for the CIFAR10 dataset.
    - Added new local client optimizers (e.g. ASGD, RMSProp, Adadelta, Adagrad) and the corresponding learning rate schedulers.
    - Ran experiments on performance of the 6 local client optimizers on both unequal and equal non IID data distributions on the MNIST dataset with the CNN model.
- Distilled project direction on how to improve accuracy further
    - 1) Dynamically adjust the learning rate using schedulers.
    - 2) [Reach Goal]: Implement a new client optimizer with the aim of improving performance.

Work Pending:

- Run experiments on other combinations of datasets and models (e.g. CNN + FMNIST, CNN + CIFAR10, MLP + MNIST, MLP + FMNIST, MLP + CIFAR10), and record and compare the accuracies in terms of the different local optimizers.
- Research different learning rate schedulers to determine which to implement.
- Research how to design and implement a new client optimizer to improve accuracy based on identifying strengths / weaknesses of other optimizers through running experiments.
- Implement the learning rate schedulers.
- Implement the new client optimizer.
- Run experiments to evaluate whether using learning rate schedulers improves accuracy.
- Run experiments to evaluate whether the new client optimizer improves accuracy.
- Presentation and Final report.

Timeline:

Date	Goal
Week 5-7: Mar 2nd - Mar 16th	• Run experiments with multiple combinations of datasets and models, research different learning rate schedulers, research how to implement a new local client optimizer. • Make the paper outline.
Week 7-8: Mar 17th - Mar 31th	• Implement the learning rate schedulers, run experiments to evaluate whether using learning rate schedulers benefits accuracy. • Prepare the presentation. • Write the paper.
Week 9: Apr 1st - Apr 7th	• Do practice presentation dry run. • Polish the paper.
Week 10: Apr 7th - April 16th	• Submit the final report.

References:

[1] Reddi, S., Charles, Z., Zaheer, M., Garrett, Z., Rush, K., Konečný, J., ... & McMahan, H. B. (2020). Adaptive federated optimization. arXiv preprint arXiv:2003.00295..

[2] Felbab, V., Kiss, P., & Horváth, T. (2019, September). Optimization in Federated Learning. In ITAT (pp. 58-65).
[3] Ek, S., Portet, F., Lalanda, P., & Vega, G. (2020, September). Evaluation of federated learning aggregation algorithms: application to human activity recognition. In Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers (pp. 638-643).
[4] McMahan, H., Moore, E., Ramage, D., Hampson, S., & Arcas, B.A. (2017). Communication-Efficient Learning of Deep Networks from Decentralized Data. *AISTATS.*