Winter 2021 CSC 2228 Project Proposal

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

Team Members:
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Project website: https://tim-tianyu.github.io/CSC2228-webpage/

Motivation:

Federated Learning (FL) offers the benefits of machine learning without compromising the privacy of the users. However, the implementation of federated learning introduces new challenges for convergence and optimizing the accuracy of ML models due to the nature and distribution of training data used in federated learning. Namely, there are three attributes of data in federated learning that greatly impede the optimization process: Massively Distributed Data, Non-IID Data and Unbalanced Data [2]. Nevertheless, progress has been made to improve federated learning by exploring different server aggregation algorithms [1]. One finding from this study showed that model accuracy improvement was more sensitive to the enhancement of the client update schemes than the refinement of the server aggregation methods. As such, our CSC 2228 course project will use this finding as an inspiration to explore how to improve federated learning on unbalanced Non-IID data by upgrading existing client update schemes. While “Optimization in Federated Learning”[2] has explored the behaviors of existing client update algorithms in model accuracy via reimplementation, this work focuses solely on Non-IID data. In reality, Unbalanced Non-IID data presents significant challenges for realizing competitive model accuracy above as well as converging in an efficient manner, which is beyond the challenges presented by Non-IID data alone. To our knowledge, our project will be the first to improve federated learning on Unbalanced Non-IID data via implementing advanced client update schemes.

Project Goals:

- Baseline Goals
  - Simulate a federated learning setting where local data is unbalanced and Non-IID distributed across remote clients.
  - Improve and implement different client update schemes and evaluate them on the simulated unbalanced and Non-IID settings.

- Reimplement the state-of-the-art algorithms and introduce them as the comparison groups.
- Compare the proposed methods with comparison groups in different scenarios and draw final conclusions.

- Reach Goals
  - *Note: Some or all of these goals will be attempted if baseline goals are met.*
    - Moderate Reach Goal: Investigate ways to improve model performance for unbalanced Non-IID data by fine-tuning client update hyper-parameters (e.g., learning rate, momentum, etc.)
    - Advanced Reach Goal: Investigate ways to improve performance of federated learning for unbalanced Non-IID data distribution further by possibly proposing a novel client update optimization method or an advanced server aggregation approach.

Timeline:

Date	Goal
Week 1: Feb 2nd - Feb 9th	Setting up environment and ensuring existing code for us to build upon works.
Week 2: Feb 9th - Feb 16th	Simulate federated learning clients with Non-IID data and unbalanced data.
Week 2-3: Feb 9th - Feb 23rd	Research different client update schemes to improve and implement them.
Week 3: Feb 16th - Feb 23rd	Evaluate the performance of our schemes on heterogeneous settings and make comparisons with the SOFAs. Start writing the progress report.
Week 4: Feb 23rd - Mar 2nd	Fine-tune hyper parameters of client update schemes to improve performance. Begin outline for the final paper.
Week 5-7: Mar 2nd - Mar 16th	Experiments running Get feedback from TA on paper outline

	Writing Paper
Week 7-8: Mar 17th - Mar 31st	Prepare presentation Get feedback from TA on presentation outline Polish paper
Week 9: Apr 1st - Apr 7th	Polish presentation Do practice presentation dry run
Week 10: Apr 7th - April 16th	Submit 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).