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Distributed training is the future of on-board computation in space as it offers scalability, resilience, and flexibility that can not be matched by a centralized setup. In the communication space it trades-in the cost of a full-dataset aggregation for that of an intermittent exchange of training messages. This work first explores the resource cost landscape of centralized training and a number of distributed variants. Federated learning, we observe, greatly lowers the communication cost of message passing relative to its distributed peers. It is, therefore, chosen for closer examination in the second part of this work. When used on the state of the art transformer model for solar wind speed prediction (Svoboda, Brown et al., 2022) and the Extreme UV images taken by the Solar Dynamics Observatory (OmniWeb, 2023) it retains the performance of the centralized model under both IID and non-IID conditions, while offering significant communication savings. Our extensive battery of experiments shows that the observed results are robust to a wide array of changes in the client count and the degree of data distribution heterogeneity. Furthermore, our results give materially significant recommendations relevant to the design of future missions as they identify a substantial trade-off between the benefits of adding new data, and the cost of adding more clients.

Federated Distributed Learning Benchmark Wind speed forecasting using solar EUV images

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Abstract
 Related training is the future of on-board computation in space as it offers scalability, resilience, and flexibility that can not be matched by a centralized setup. In the communication space it trades-in the cost of a full-dataset aggregation for that of an intermittent exchange of training messages.

Centralized computation is relevant to current missions necessary for the future ones as it offers the resilience to quickly reduce the communication costs associated with the data distribution heterogeneity.

Extreme solar winds can impair communication, disrupt data and mission. Consequently, accurately forecasting the solar wind speed is an important growing ground for smart distributed training.

Research Objectives

1. Study distributed training of the 2022 (Lionne, Brown et al.) solar wind speed model across 3 to 17 clients, nodes, or spacetiffs, as well as the communication cost and the generalization error.

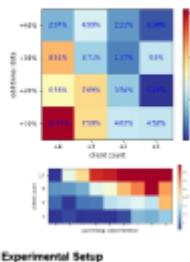
2. The resulting dataset occupies 200GB. Results for forecasting four-day lag from a single 211-A image are presented.

Benchmark Performance

both the centralized and the federated distributed training achieve the same error as a spacetiff, as in our experiments we use the same test and training sets. The centralized setup and the federated setup achieve indistinguishable Mean Squared Errors equal to 0.099.

3. However, the federated setup requires the communication of all clients at each training step, in which this is 104MB worth of data. This is a significant problem for the spacetiff setup (which costs) very unfavorably with the 355GB size of the full dataset.

4. Federated Learning can, in the end, conservative and in some cases, work better than the centralized approach. 500MB worth of data per 10 epochs is often used here.



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