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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 and speed forecasting using solar EUV images

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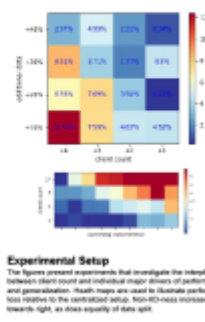
Abstract
Distributed training is the future of on-board computation in space as it offers scalability, resilience, and flexibility that can not be matched by a centralized setup. In the communication space it trades-in the cost of a full-dataset aggregation for that of an intermittent exchange of training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

Introduction
On-board computation is relevant to current missions necessary for the future ones as it offers resiliency and the ability to greatly reduce the communication costs associated with sending large amounts of data back to the Earth. Extreme solar winds, can impact communication, disrupt data and operations. Consequently, accurately forecasting the solar wind speed on-board is an important priority ground for near distributed training.

Search Objectives
This study distributes the training of the 2022 Svoboda, Brown et al. solar wind speed model across 2 to 12 clients, nodes, or spacecraft, on data by OMNIWeb and the Solar Dynamics Observatory (SDO). The resulting dataset includes 1000 images for forecasting. Non-day lag from a single 211 Å image are presented.

Benchmark Performance
Central and the federated distributed training achieve their best of performance, as in our experiments they follow the same and training same patterns as centralized setup and achieve similar performance when Squared Errors equal to 0.000. However, they differ markedly in their communication.

3. The basic distributed setup requires the communication of all clients at each training step. In our setup this is 100MB worth of data 1000 times per epoch, or about 100 MB per epoch. This comes very unfavourably with the 1000 size of the full dataset. Federated Learning, on the other hand, communication and training, work with communicating a comparable 100MB per epoch across per epoch. Given per 10 epochs to other speed loss.



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