Private Machine Learning on Human Activity Recognition with Federate Learning

ROAD TO EXPO 2020

Session 2.3 – Privacy Preserving Techniques

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On behalf of the team from the Input Privacy Preserving Project, as part of the High-Level Group for Modernization of Official Statistics, supported by UNECE.

Introduction

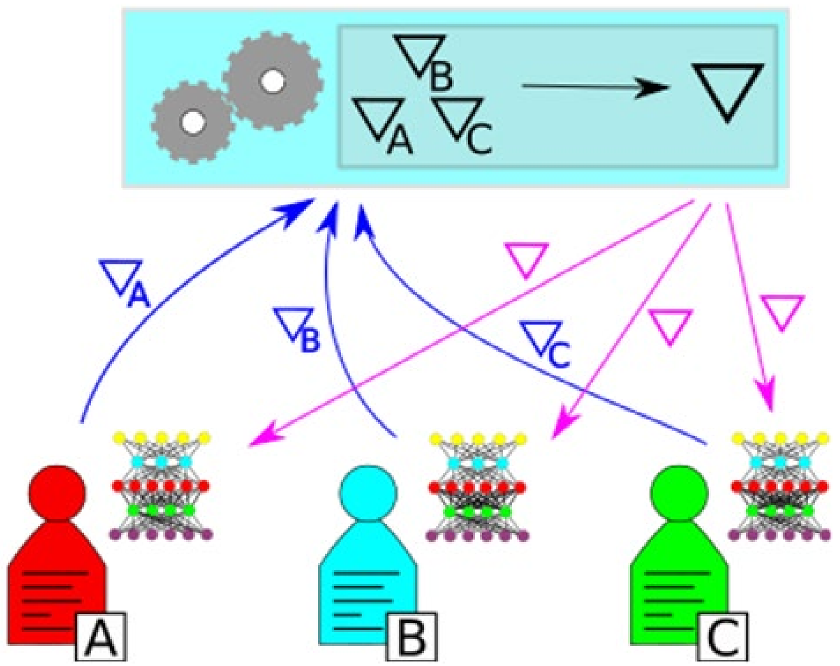
- **Pilot's goal:**
  - Build a simulated environment to validate the concept of multi-party privacy preserving Machine Learning (PPML) for both training and inference.
- **Project's scope:**
  - Investigate best practices and open source tools for distributed and collaborative ML among multiple organisations in a low trust environment whilst mutually benefitting from the outcomes (the final model) or allowing safe 3rd party access.
- **Environment:**
  - Simulated multi-organisational set-up with several National Statistical Offices gathering data from individuals (sensor data) to predict their activities (also related to time use and well-being surveys in Official Statistics).

Introduction

- **Architecture:**
  - Distributed and containerized PPML architecture utilising Federated Learning to train a neural network model and enable inference while protecting security, privacy and confidentiality of the isolated data sources.
- **Data:**
  - Moderately sensitive - collected by wearable/smart devices using accelerometers, e.g. smart/sports watches. Open data used in the pilot.
- **Method:**
  - A typical ML classification task (i.e. to recognize and predict human activities from accelerometer data)

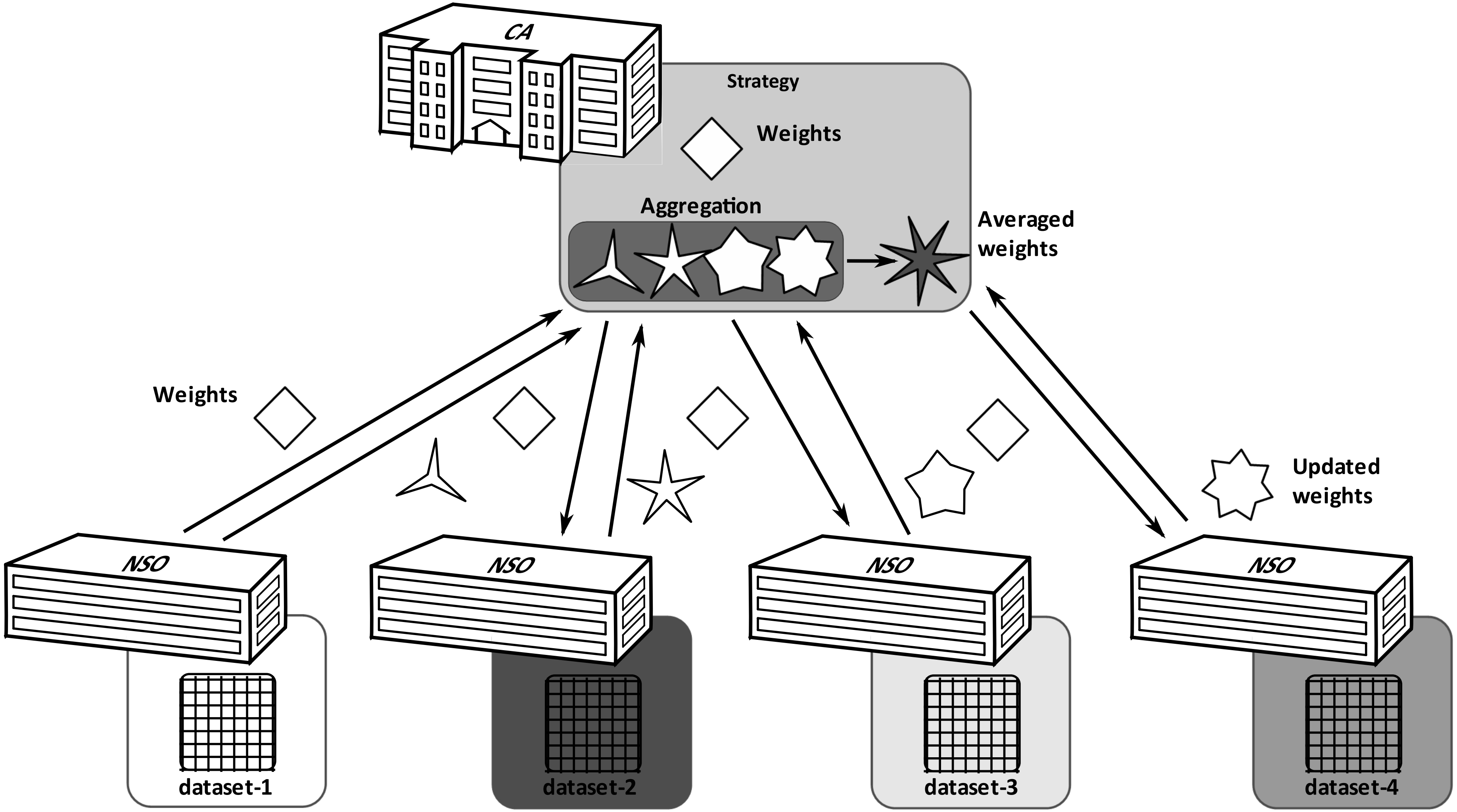
Federated Learning (FL)

- In FL, each party (i.e. data source) holds a neural network that would like to train.
- After each round of the training, the parties send their weights (or parameters) to a central authority.
- Central authority aggregates the weights and send instructions to parties to update their local models.
- This process is repeated several times. Note that only the accumulated weights are shared among parties.
- The final model can be used locally by parties for inference on new data.
- FL protects the privacy of the input data by ensuring that the data never leaves the clients’ devices.



https://www.statcan.gc.ca/eng/data-science/network/privacy-preserving

Simulated Environment (Scenario 1)



A client (NSO) wants to start FL with a server (CA)

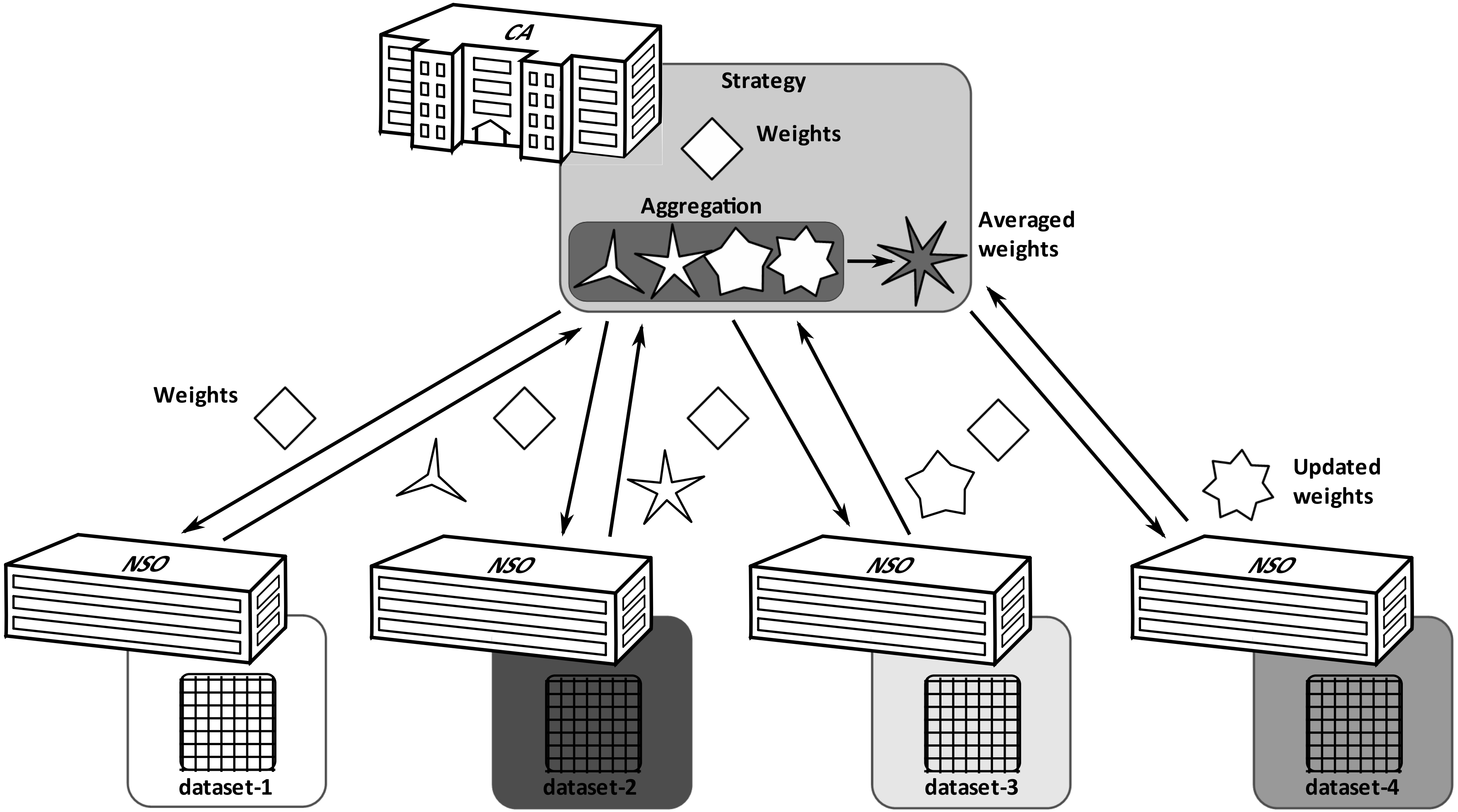
1- The server sets the FL strategy and the client sends the initial weights.
Client data stays on his side

2- Another client with different data joins and receives the initial weights from the server

3- Each client trains its own model with local data and sends the updated weights back to the server

4- The server averages the models following the selected strategy

Simulated Environment (Scenario 2)



A Central Authority (server) wants to start a FL training with 4 clients (NSO).

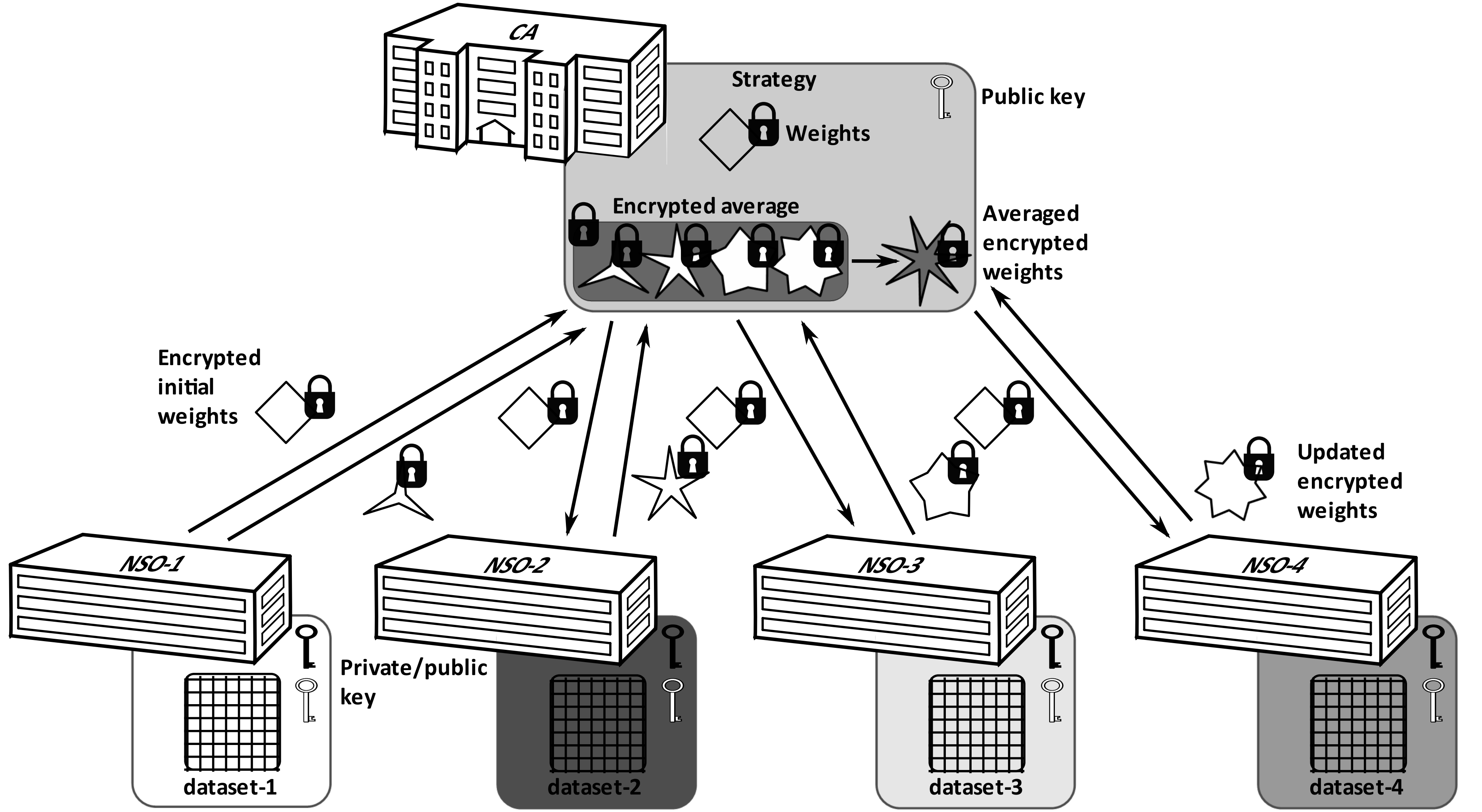
1- The server sets the FL strategy and clients connect to the server.
Client data stays on its side.

2- CA sends the model configuration and weights.

3- Each client trains its own model with local data and sends updated weights back to the server.

4- The server aggregates the models following the selected strategy.

Simulated Environment (Scenario 3)



NSO-1 starts a FL training with the CA as the aggregator. NSOs share a common set of private and public keys.

1- NSO-1 sends the encrypted weights to CA. CA only has access to the public key. NSO-1 data stays on his side.

2- CA sends the encrypted weights to other clients.

3- Each client train its model and sends encrypted weights back to the server.

4- The server averages the encrypted weights following the selected strategy.

5- CA sends the encrypted averaged weights back to each NSO.

Simulated Environment (Data & Model)

- Human activity recognition using smart devices' accelerometer and gyroscope data*, after pre-processing.
- The goal is to classify the data into 6 classes: *WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING.*
- The data was split into four subsets, one for each NSO (i.e. STATCAN, ONS, ISTAT and CBS), in the experiments.
- A neural network (Multi-Layer Perceptron with linear layers and ReLU activations) is used for the purpose of classification.

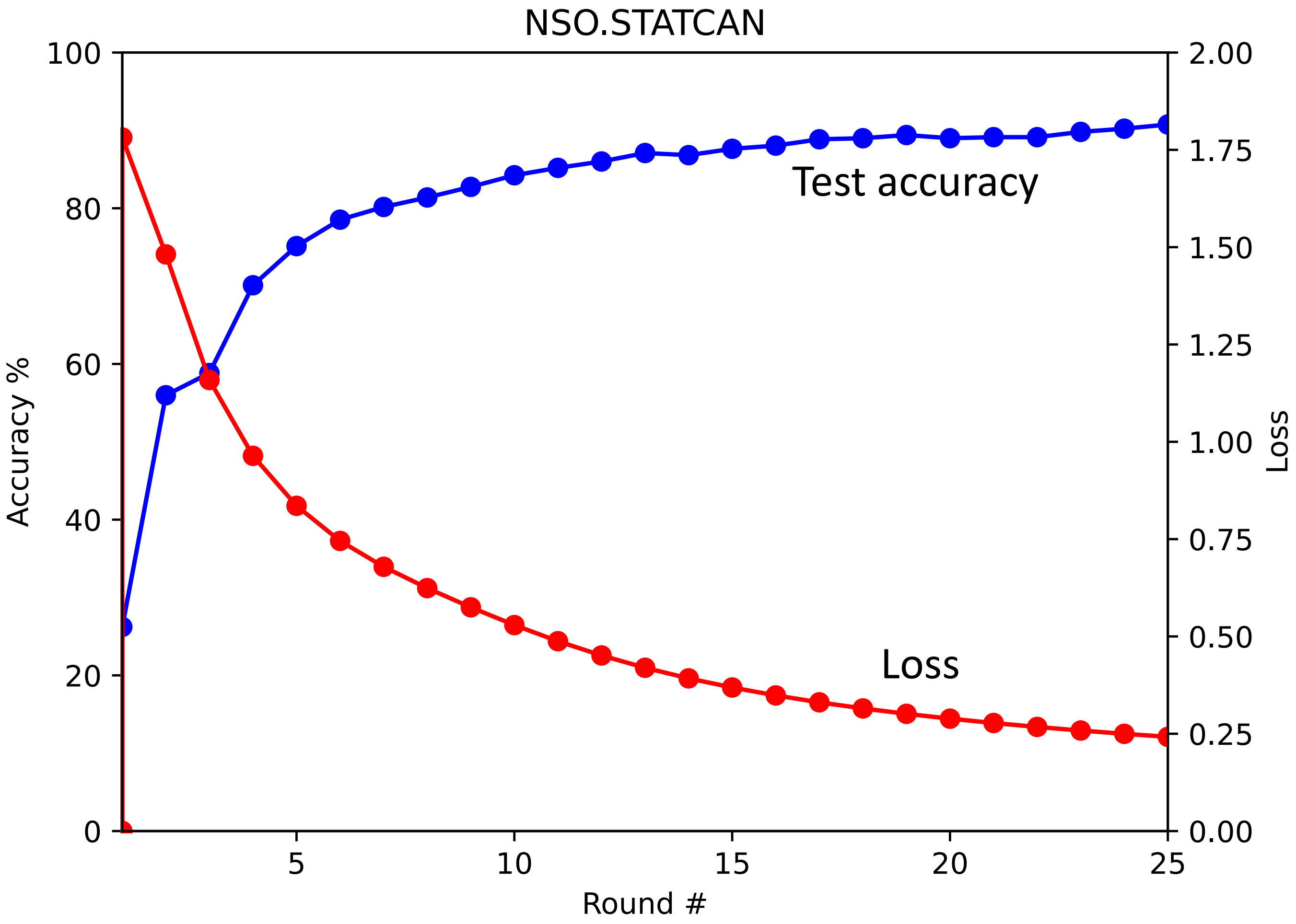
* D. Anguita, A. Ghio, L. Oneto, X. Parra and J. L. Reyes-Ortiz. A Public Domain Dataset for Human Activity Recognition Using Smartphones. 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium 24-26 April 2013.

Simulated Environment (Architecture)

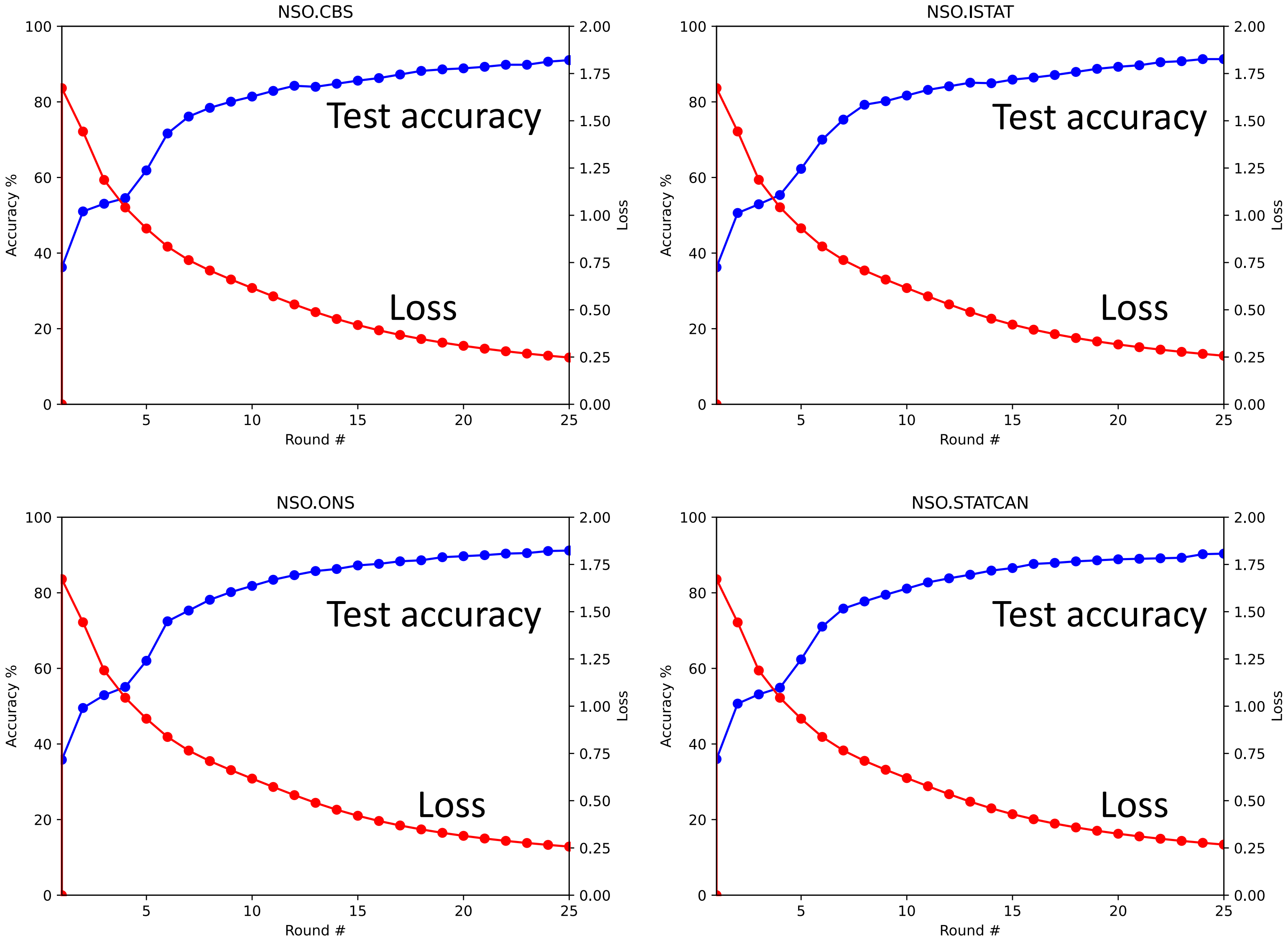
- A unified Federated Learning library called Flower* is used to simulate the environment.
- Only updated weights are transferred between the central authority and other NSOs during the training.
- Transferred weights are aggregated on server side after each round. The averaged weights are sent to clients (FedAvg). In the encrypted version, the average is computed on encrypted weights using the Paillier cryptosystem.
- This approach is very customizable: # training rounds, epochs, and network architecture can be changed.
- It is possible to use encryption at rest and in transit, using certificates with latest flower development for secure communication.

* https://flower.dev

Federated Averaged Weights Strategy Results



Encrypted Federated Learning



Conclusions and Results

- Collaborative privacy preserving ML with isolated lifestyle data (collected from sensors) is feasible.
- However, this experiment was conducted with a simplified scope and was performed in a simulation environment.
- We have built a community of Statistical Offices in the area of privacy enhancing technologies with link to open source community, industry and academia.
- There is a direct link to sustainability, when it comes to collaboration among NSOs, namely new ways of collaboration, driven by privacy requirements and technological constraints.

Challenges and Lessons Learned

- Open source software stack support for this particular scenarios.
- In reality, inconsistent data formats across multiple data holders.
- Unbalanced and outlier data points and lack of sufficient and good-quality data. Different aggregation strategies can be tested and used to mitigate this.
- Pre-processing steps to take into account different international labelling and standards in distributed ML for deployment.

Thank you/Merci.
Questions?

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