Enhanced Federated Learning with funcX

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Abstract

Federated Learning is a distributed machine learning approach that allows for machine learning algorithms to be trained across multiple decentralized computing resources. A set of models are trained independently, with unique training data, and are deployed on remote resources. These models are then aggregated to produce a single model for inference. Federated learning is primarily used in scenarios in which independent datasets are protected and thus cannot be shared or in edge computing environments in which it is infeasible (cost, size, time) to transfer training data (e.g., images) to a central resource for training. We explore the difference in model performance when varying number of participating devices, number of epochs per device, number of epochs per training interaction, and number of samples per device.

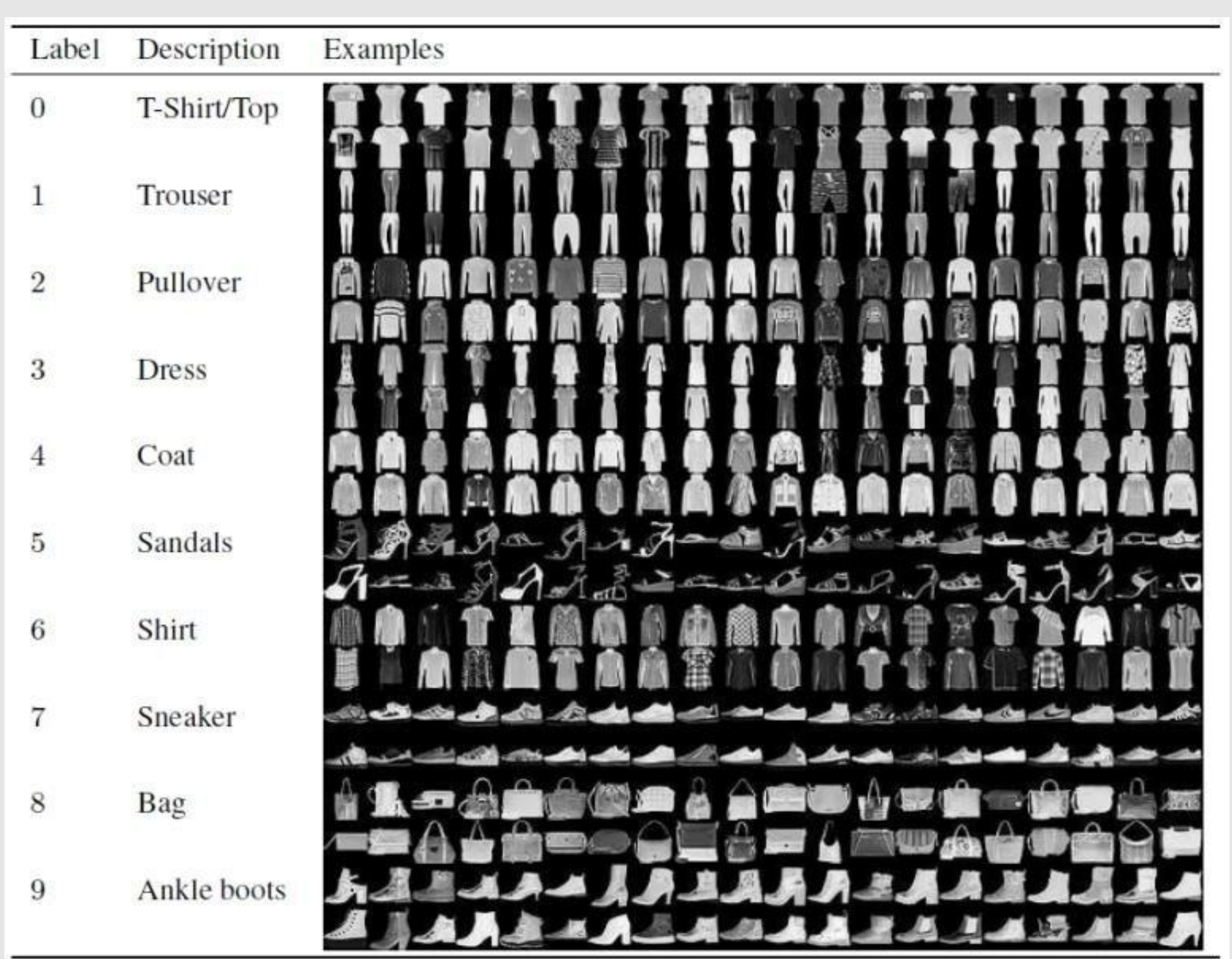
Background

We used an application called FLoX, which implements federated learning algorithms over funcX. funcX is a federated serverless framework that enables fire-and-forget function execution. FLoX performs FL using Tensorflow.

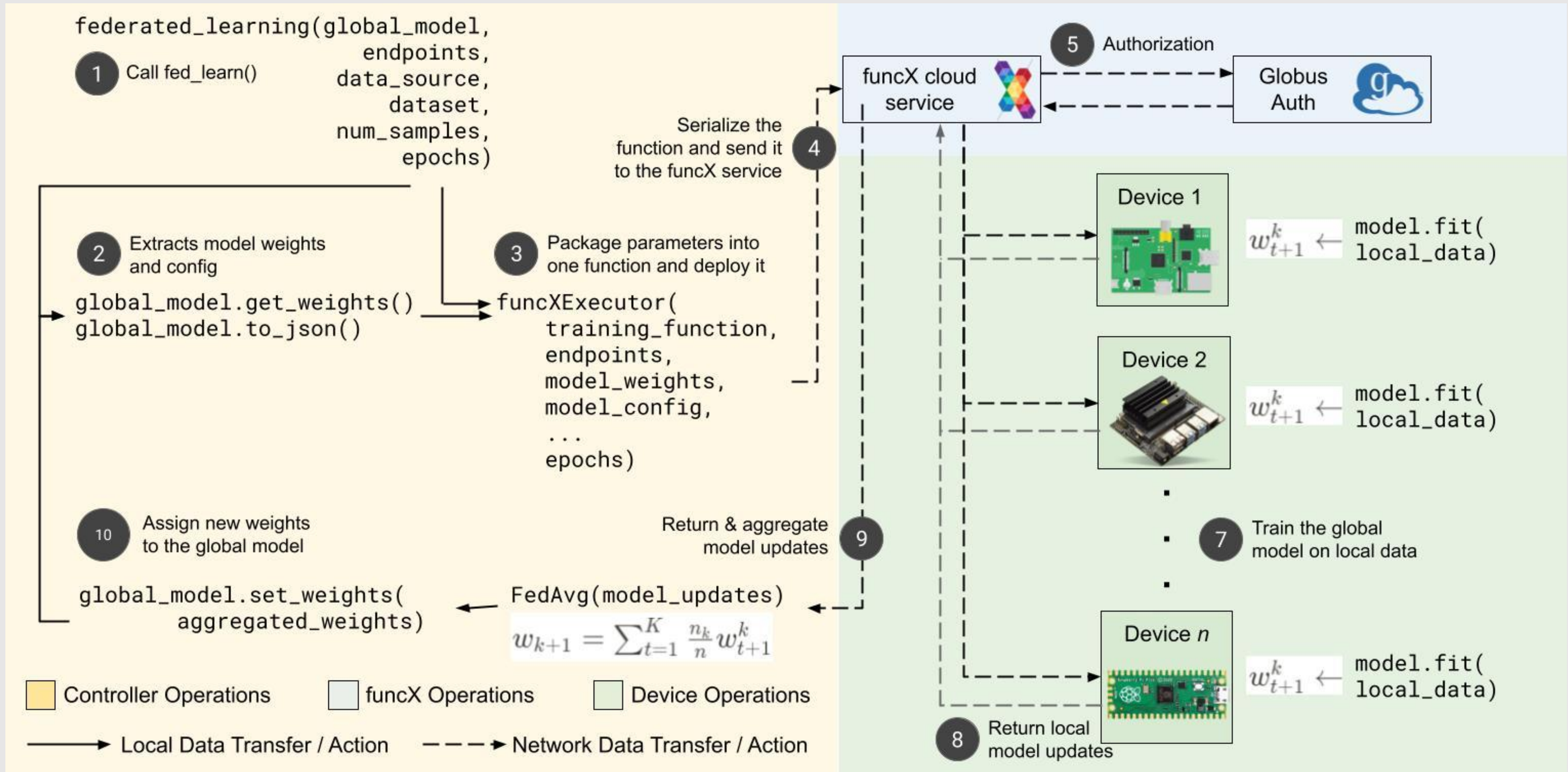
Dataset

Why fashion-mnist?

Fashion-mnist is an open-source dataset, with 10 classes and 60000 samples for training and 10000 samples for testing. It is a simple introductory dataset for machine learning with images.



Methodology



FLoX Architecture

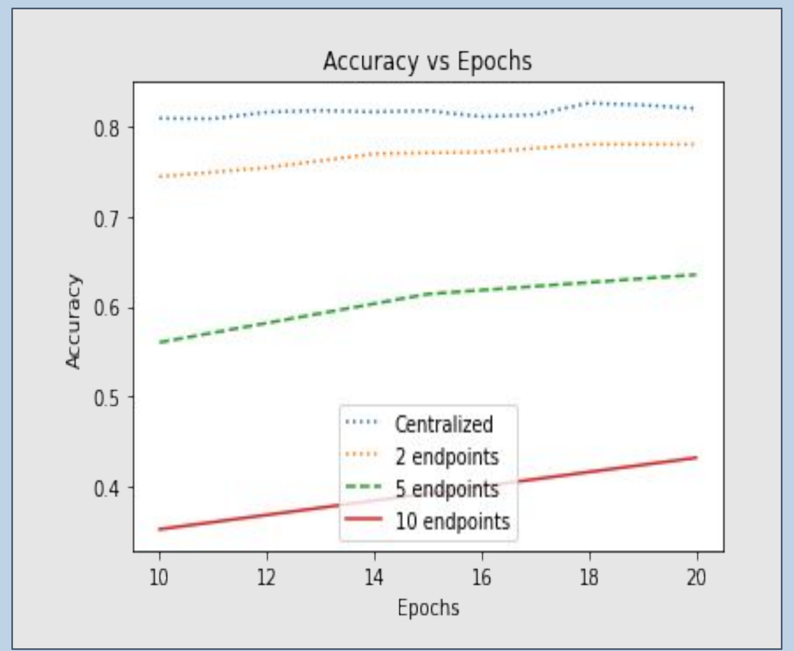
The federated learning process proceeds as follows:

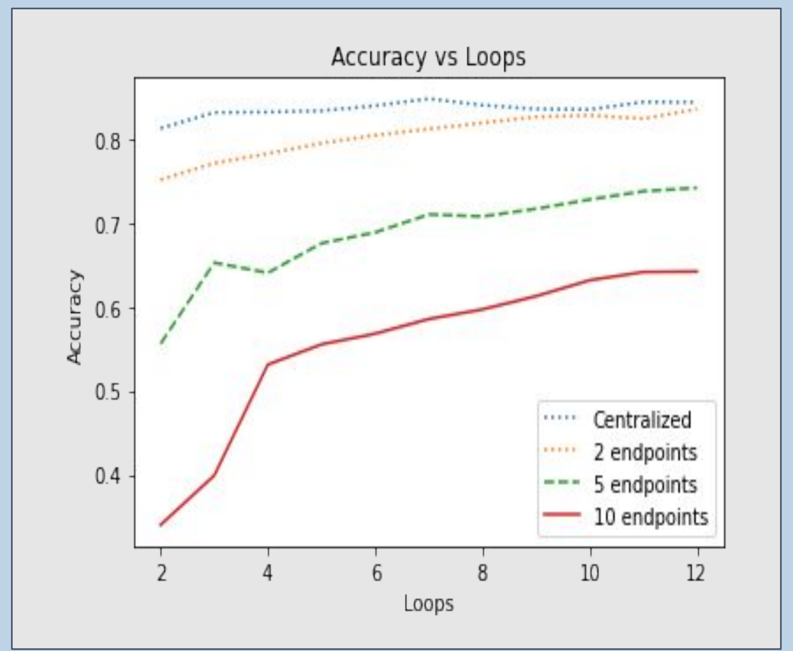
- Sample data is evenly distributed among endpoints
- A unique model is trained at each endpoint using available data
- The weights of the models are aggregated

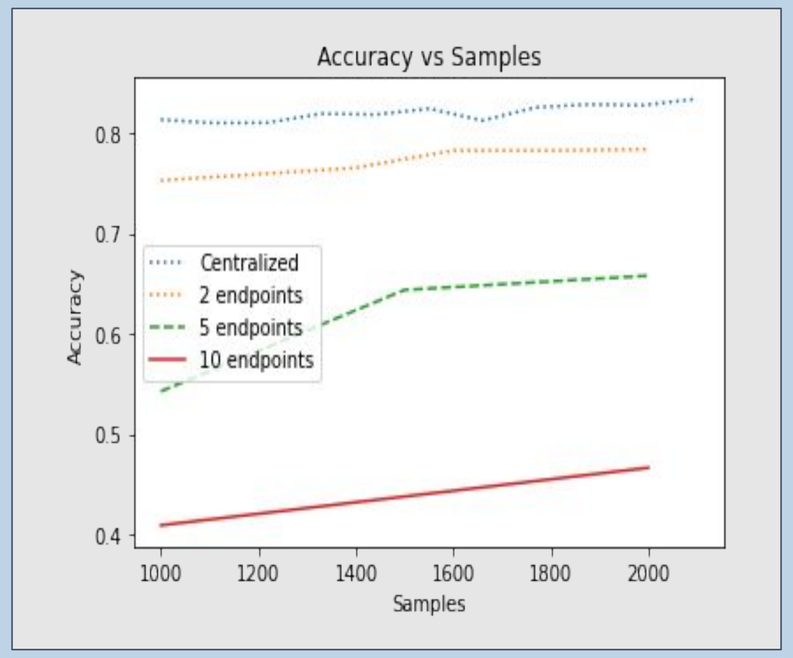
Experimental Approach

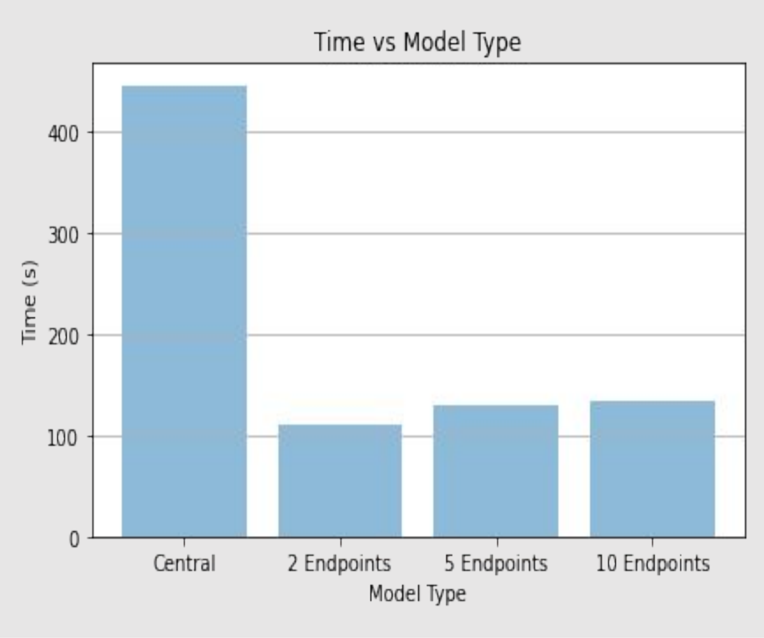
To investigate the tradeoffs presented by using a serverless federated learning framework, we identify several tunable "levers." Specifically, for number of endpoints, samples, epochs per training round, and total training rounds, we evaluate the speed and final accuracy of the global federated learning model. Additionally, we run each experiment multiple times to ensure accuracy of results. In evaluation below, we demonstrate the results of varying these tunables with respect to global model accuracy, loss, and convergence time. These experiments are compared against a centrally trained model that serves as our baseline.

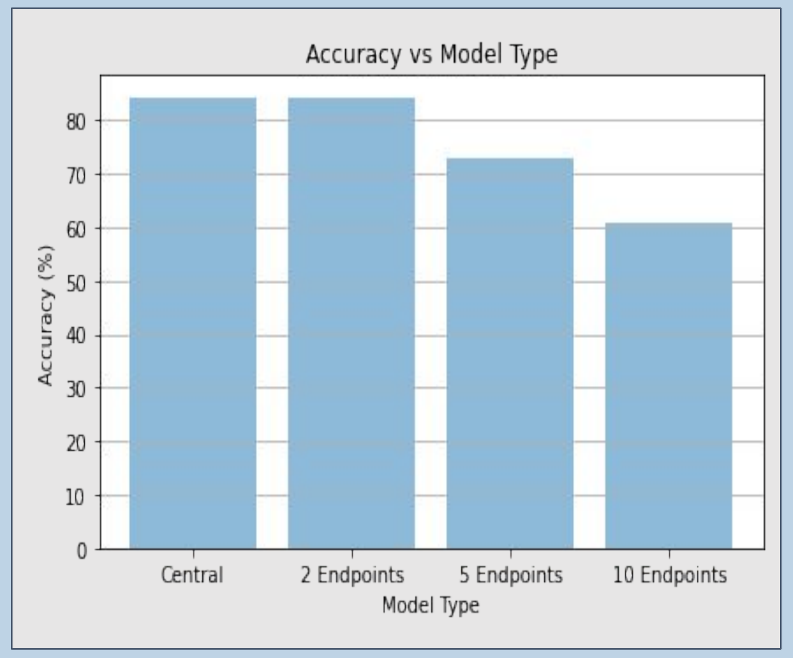
Evaluation

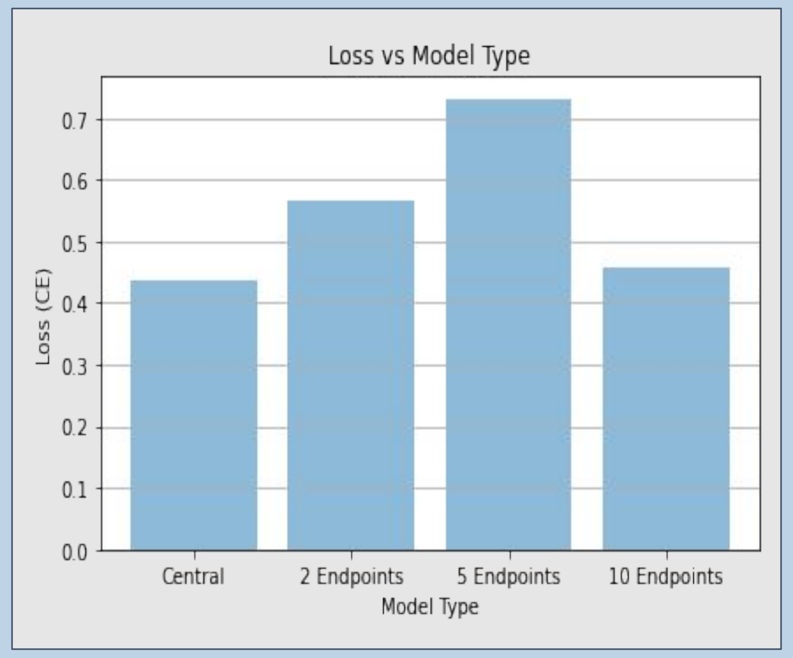












Conclusions

In the bar graphs, we see that the performance when adding endpoints in terms of accuracy shows a negative trend.

The time to train a model shows performance degradation as endpoints are added. Adding an extra endpoint, from one endpoint (a central model) to two endpoints showed a reduction by a factor of four in training time. This is likely due to resource contention as endpoints were deployed on a single computer.

When looking at model loss, it seems to increase from one to five endpoints, yet falls at ten endpoints.

In our plots, we see a consistent trend that our federated learning models consistently perform worse than a centralized model. However, a centralized model performs worse with respect to accuracy as the number of epochs, loops, and sample size, increase.

Our results show that a federated learning is indeed viable. Taking the model with 2 endpoints, for example, show that the accuracy does not differ significantly from a centralized learning model. As accuracy isn't seen to perform considerably worse, for the time that it takes to train such a model by four; this shows that federated learning is a valuable strategy.

Future Work

Our next steps include exploring performance on other datasets and models. We would also like to identify which numerical value (loops, epochs, and sample size) most significantly affects the accuracy.

The models with multiple endpoints improved accuracy at a faster rate than the centralized model. A possible research question is: if we were to optimize all federated learning models independently, how would the accuracies differ from one another. Perhaps, due to overfitting of a normal model (more samples per epoch), a federated model might perform better than a centralized model when the dataset is large.

References

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funcX: Federated Function as a Service

funcX: A Federated Function Serving Fabric for Science

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