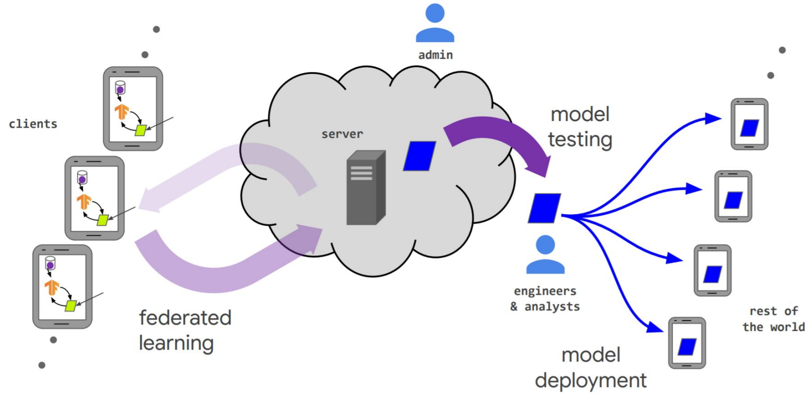
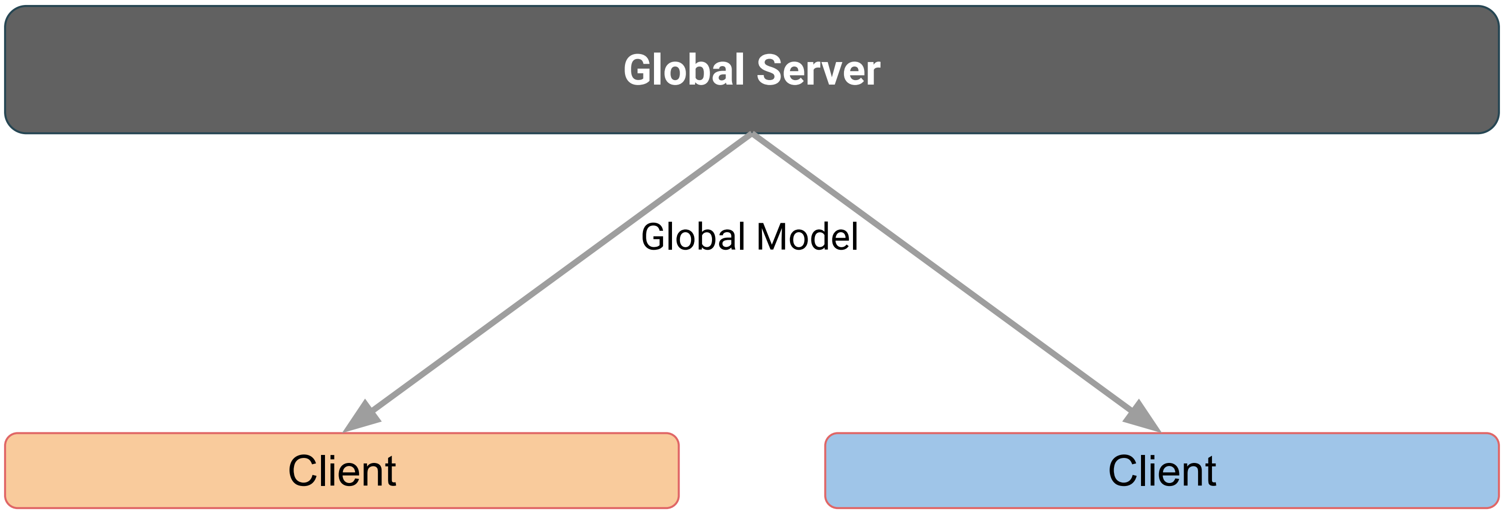
Optimizing Federated Learning Hyper-Parameters in Flower

What is Federated Learning?



- Federated Learning is a form of distributed Machine Learning working over large numbers of resource constrained devices.
- It attempts to reduce communication costs by alternating local training with global aggregation of model parameters without ever directly sharing client data.

Federated Learning At A Glance



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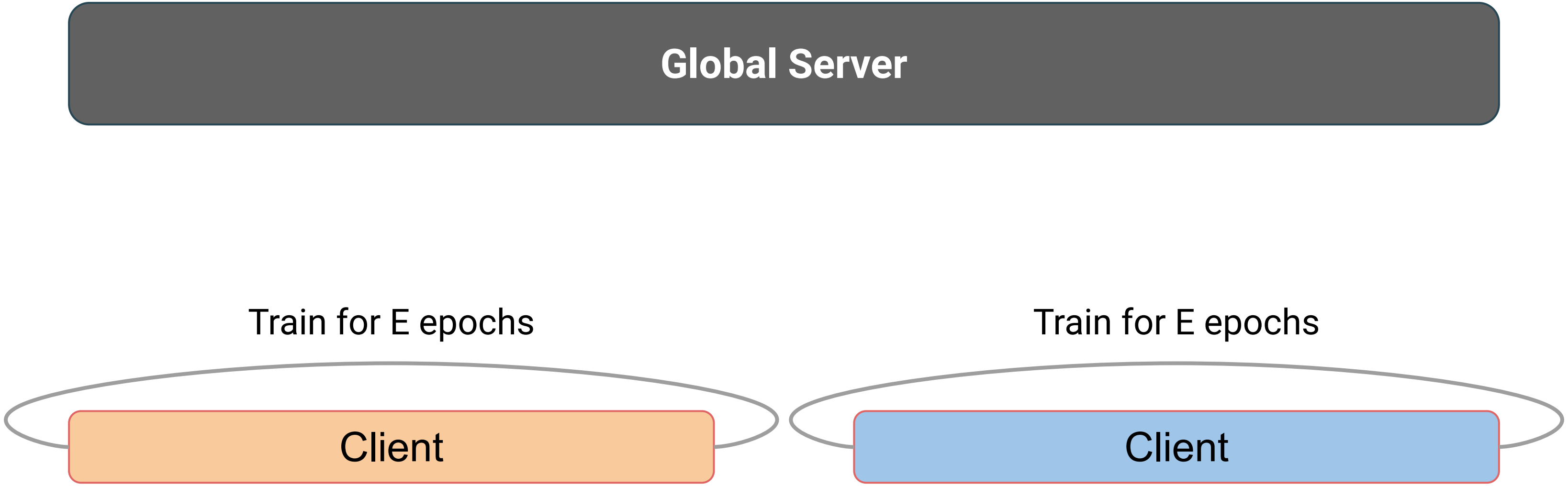

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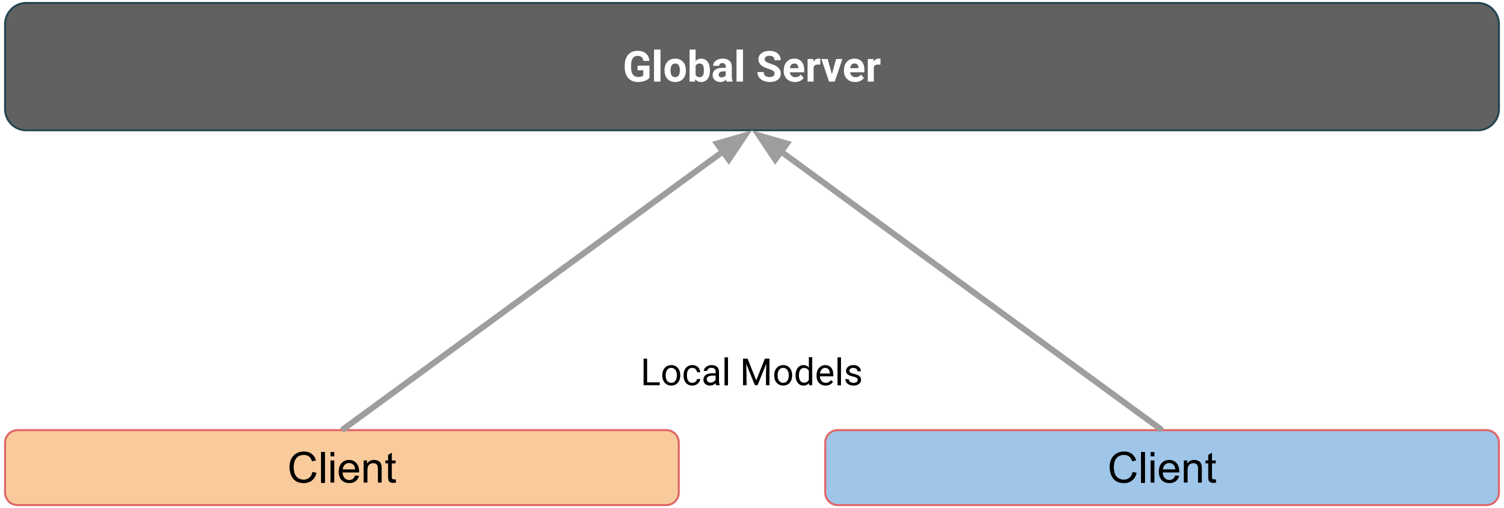

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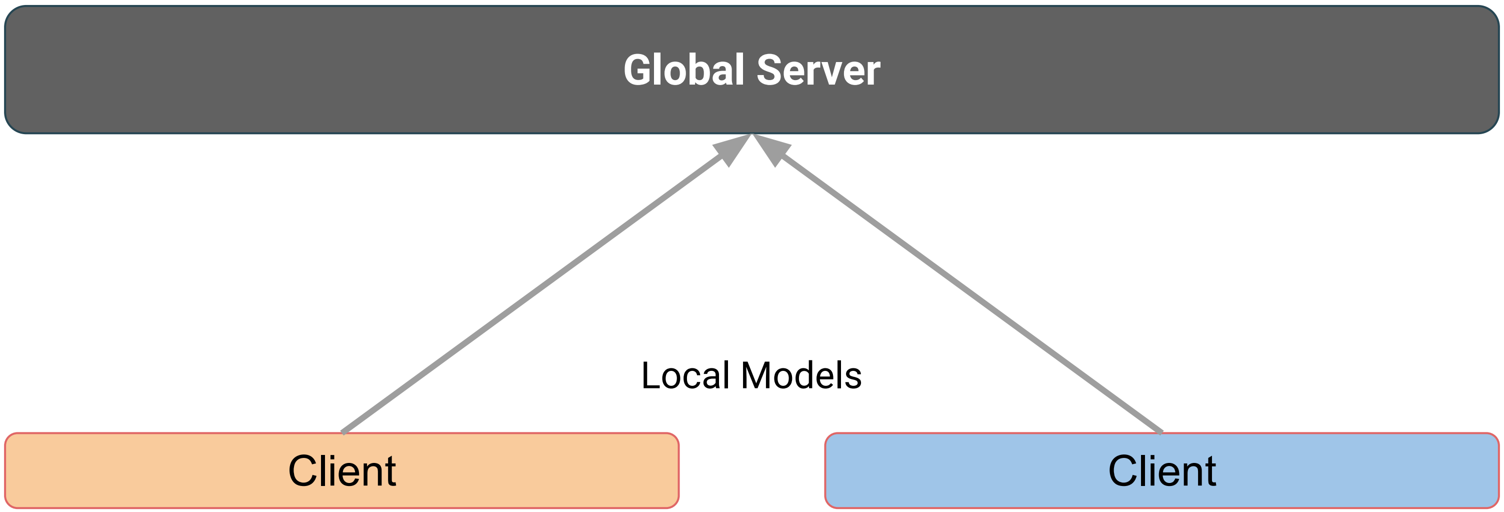

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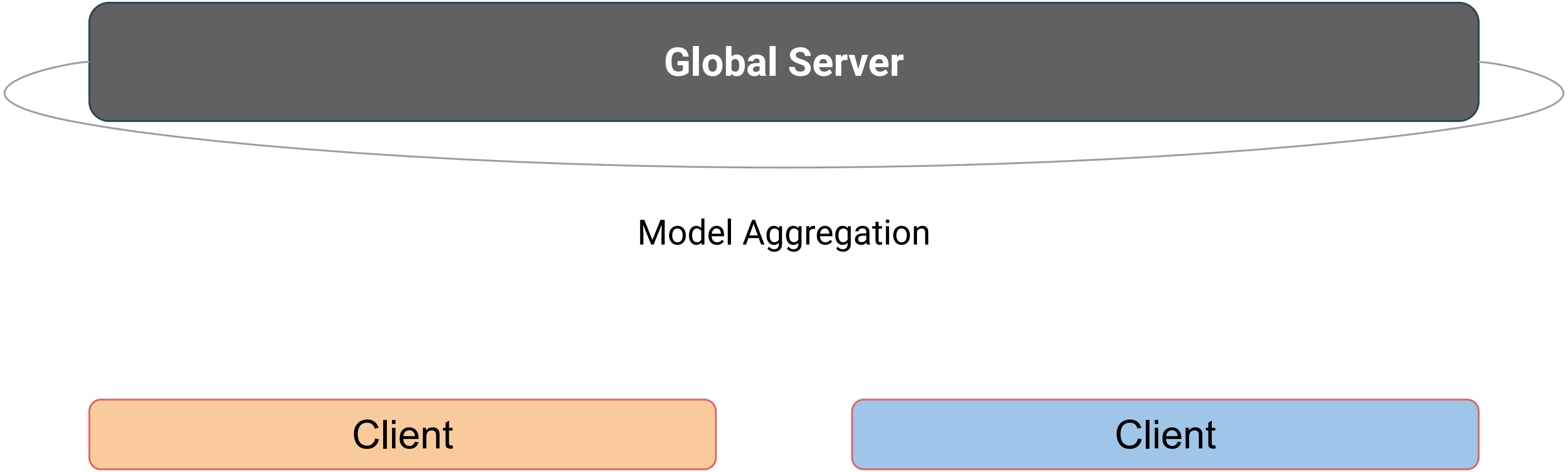
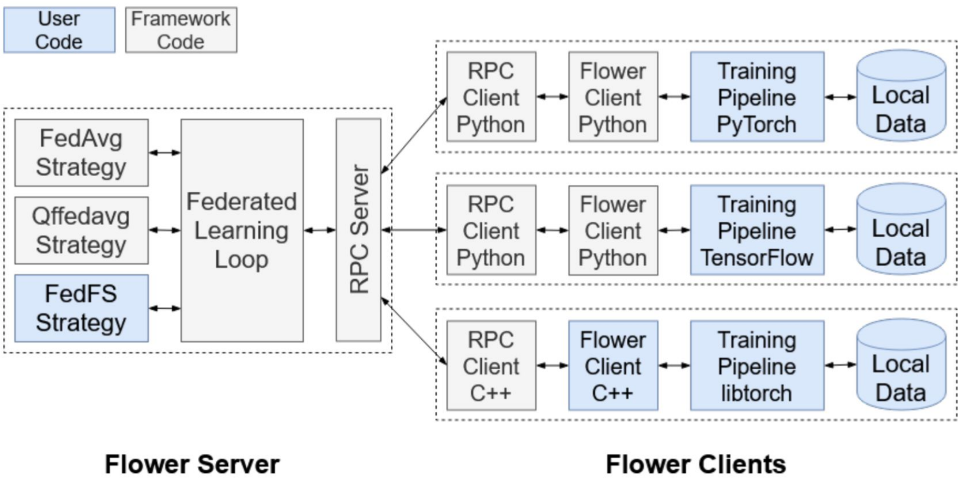


FLower



- Flower is a Federated Learning framework meant to allow full FL model development and deployment
- It offers a variety of aggregation algorithms and options for customization
- What sets it apart?

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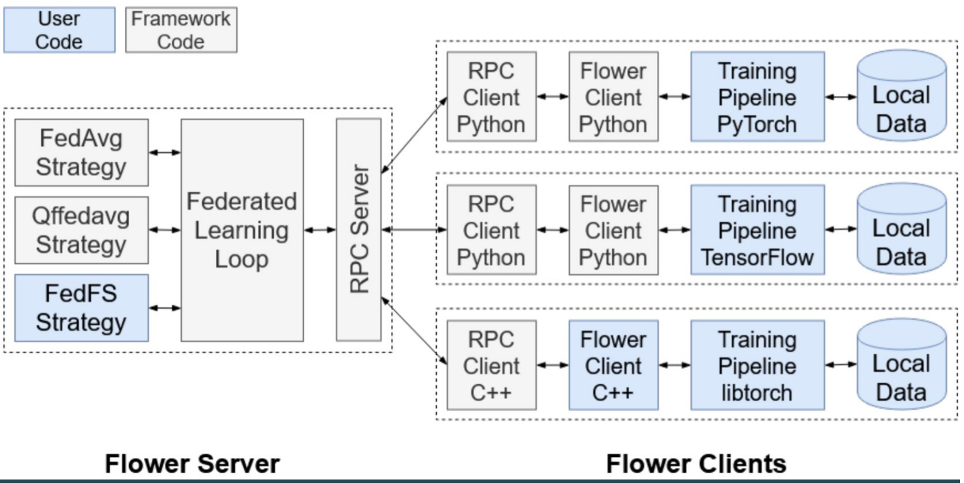

	TFF	PySyft	LEAF	Flower
Heterogeneous clients				√
Scalability	*	(√)**		√
Server-side definitions	√	√		
ML framework-agnostic		***		√
Language-agnostic				√
Baselines			√	√

planned * only Python-based instances ** limited to PyTorch and TF/Keras ***

Problems in Federated Learning

Expensive Communication | Systems Heterogeneity | Statistical Heterogeneity | Privacy Concerns

Data Heterogeneity:

- Unlike other ML settings, client data may be highly non-iid
- This can cause the entire global model to diverge
- Requires controlling the potential impact of a client model as well as the amount of training performed

System Heterogeneity:

- Device types may vary wildly in terms of specifications and internet connection
- Makes training unreliable

Global-Local Accuracy Trade-Off:

- Clients with unusual data and system characteristics end-up with a worse model than they could have trained on their own

Hyper-Parameter Optimization Component For Flower

Motivation:

- Handling data and system heterogeneity requires tuning both the aggregation algorithm and the clients
- Determining how much local computation should be done and with what parameters
- Flower currently lacks any means of optimizing parameters over the federated network

Method:

- Bayesian Optimization with BoTorch---subject to change---is the proposed optimization method, given that training and evaluating a federated network takes quite a long time.
- The component should be able to handle FL algorithms as black-boxes and allow the user to specify which parameters to optimize. Most classic FL aggregation algorithms are controlled by a few, less than 10, main parameters
- After construction, performance of the baseline models provided by flower will be evaluated after optimization

Algorithm 1 `FederatedAveraging`. The K clients are indexed by k; B is the local minibatch size, E is the number of local epochs, and η is the learning rate.

Server executes:
 initialize w_0
 for each round $t = 1, 2, \dots$ **do**
  $m \leftarrow \max(C \cdot K, 1)$
  $S_t \leftarrow$ (random set of m clients)
  for each client $k \in S_t$ **in parallel do**
   $w_{t+1}^k \leftarrow$ ClientUpdate(k, w_t)
  $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$

ClientUpdate(k, w)**:** *// Run on client k*
 $\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)
 for each local epoch i from 1 to E **do**
  for batch $b \in \mathcal{B}$ **do**
   $w \leftarrow w - \eta \nabla \ell(w; b)$
 return w to server

Justification and Impact

Justification:

- My MPhil dissertation focuses on **local adaptation** methods applied to Federated Learning, to be implemented in Flower
- Hyper-parameter optimization represents a parallel research direction which may help inform my work
- Most of the current Federated Learning work focuses on constructing increasingly complex aggregation algorithms, it is worth investigating if auto-tuning older algorithms is sufficient for them to compete on the baseline tasks

Impact:

- Flower is intended to be the primary FL framework in the vein of Tensorflow/Pytorch for general machine learning
- Constructing a new component for Flower, if accepted by the team, would represent a direct contribution to the FL community for both research and final-product development
- Hyper-parameter optimization has only began being explored in FL recently, one paper from 2019 and one from 2021, and providing more data for it would be directly useful

Questions?