SaCS
Scalable computing systems laboratory

EPFL

Decentralized Learning made Practical

Martijn de Vos
martijn.devos@epfl.ch

In collaboration with Anne-Marie Kermarrec, Rishi Sharma, Akash Dhasade, Johan Pouwelse and Erick Lavoie.

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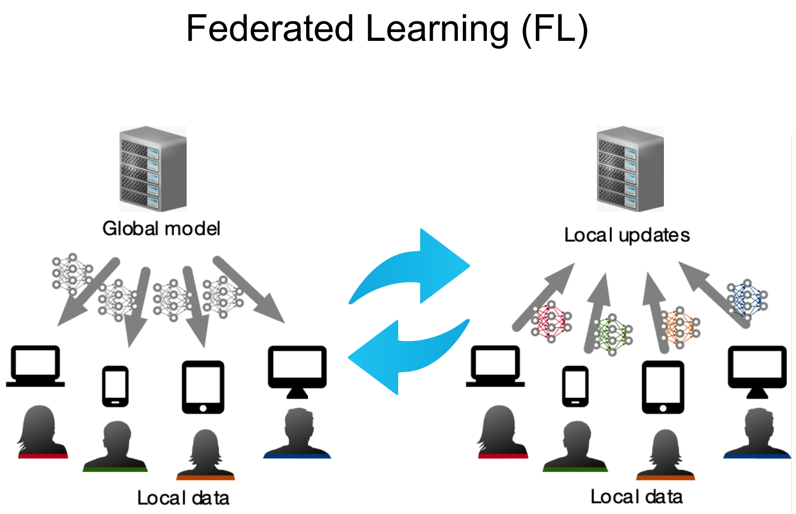
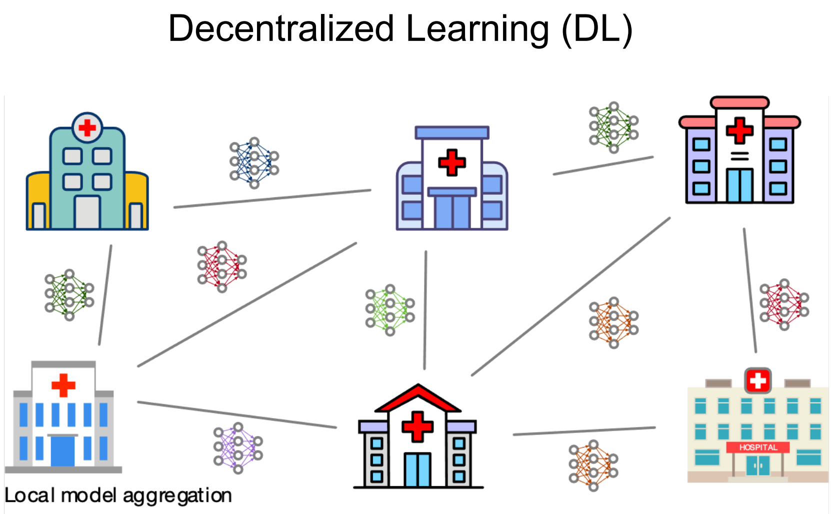
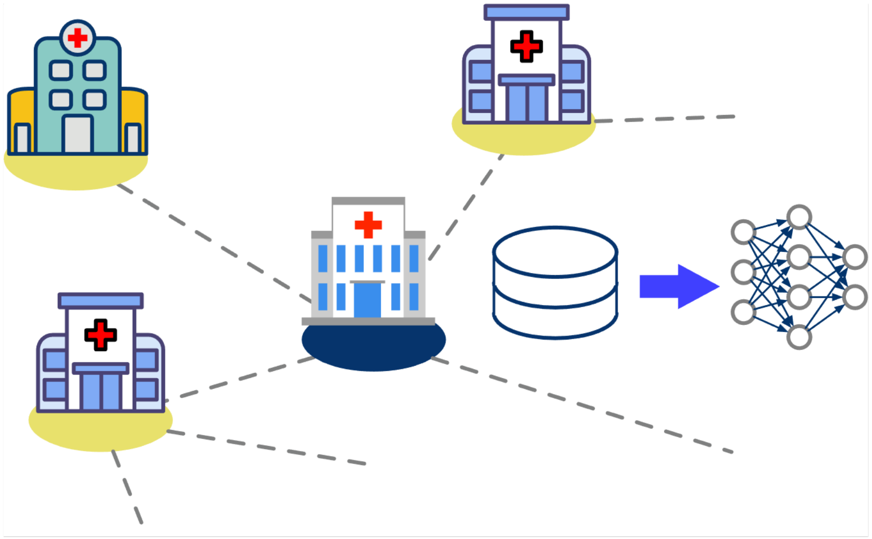
Distributed Learning with Decentralized Data





Data stay where it is generated. Learning happens by model exchange.

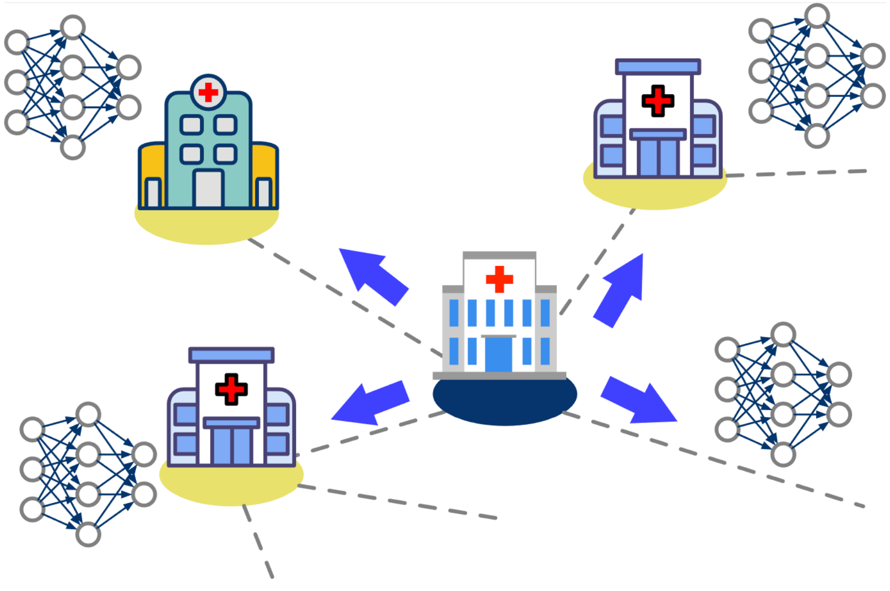
Decentralized Learning



Train

Share

Decentralized Learning



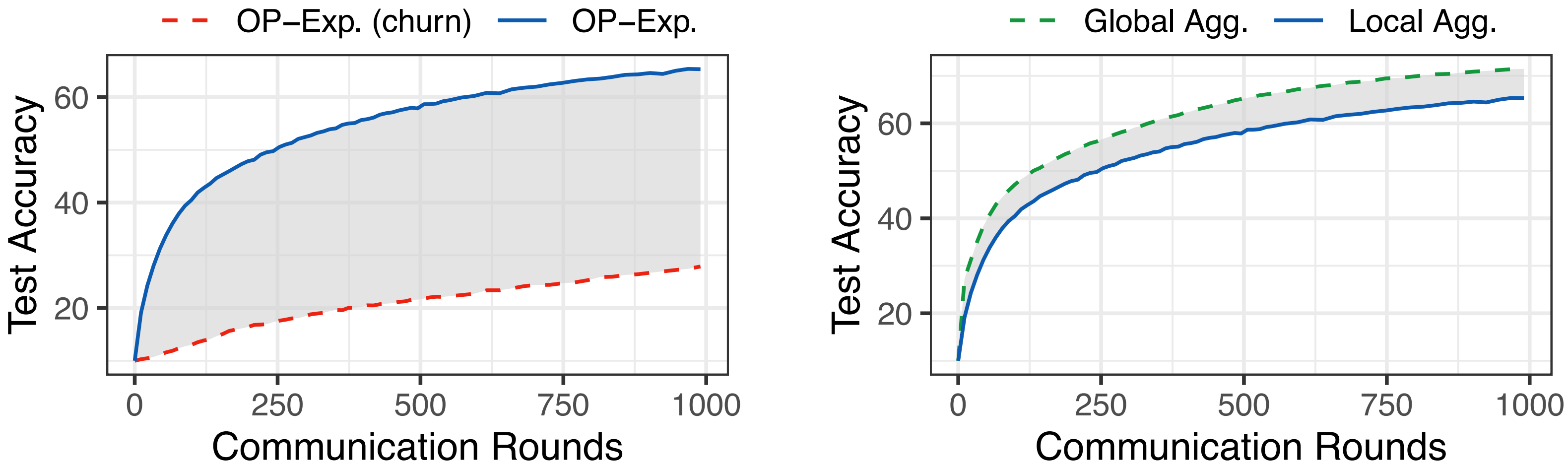
Receive

⇩

Aggregate

Improving Decentralized Learning

1. **Churn** impacts convergence
2. **Global aggregation** improves convergence
3. Not all nodes need to work each round (theory in [1])



[1] Liu, Ziwei, et al. "Decentralized stochastic optimization with client sampling." *OPT 2022: Optimization for Machine Learning (NeurIPS 2022 Workshop)*. 2022.

The Design of Plexus

High-level algorithm

1. Each round, a unique subset of online nodes, or a **sample**, train the model.
2. These nodes send their trained model to an **aggregator.**
3. The aggregator aggregates models and sends the model to the next sample.

Resembles Federated Learning, but without server.

Three Technical Challenges (TCs)

TC1: How can nodes derive samples?

TC2: How can Plexus avoid selecting offline nodes during sampling?

TC3: How can Plexus ensure system progression when nodes go offline during training or aggregation?

TC1: How can nodes derive samples?

- Important that different nodes derive the same sample.
- Each peer stores all peer IDs in a **local view**.
- Each peer samples peer for the next round using its population view.
- Aggregator selected like this as well, based on bandwidth.

TC1: How can nodes derive samples?

Algorithm 1 Sampling by node i where k denotes the round number and s is the requested sample size.

Require: Ping timeout Δt_p

procedure $\textsc{Sample}(k, s)$
    /* $\textsc{Actives}()$ are the online nodes in local views */
    $H \leftarrow \textsc{sort}([\textsc{hash}(j + k)$ **for** j **in** $\textsc{Actives}()])$
    $C \leftarrow [j$ **for** h_j **in** $H]$ ▷ Candidate identifiers
    return the first s in C that answer a ping within Δt_p

TC2: How can Plexus avoid selecting offline nodes during sampling?

- Nodes send a join or leave message to other random nodes.
- Nodes keep track of the membership status of other nodes in their local view.

- Local views are gossiped and merged between nodes.

ID	Seq. no.	Status
3b9f8	2	LEAVE
u7nk3	3	JOIN
a2o8g	2	JOIN

Local view of node a

+

ID	Seq. no.	Status
3b9f8	2	LEAVE
u7nk3	4	LEAVE
a2o8g	1	LEAVE

Local view of node b

ID	Seq. no.	Status
3b9f8	2	LEAVE
u7nk3	4	LEAVE
a2o8g	2	JOIN

After merge

TC3: How can Plexus ensure system progression when nodes go offline during training or aggregation?

<u>Participant failure</u>

- Aggregator proceeds when
  - Received $f < s$ trained models
  - After some aggregation timeout

<u>Aggregator failure</u>

- Aggregator sends ACK message to previous participants when finished.
- Participants await ACK message
  - Retry with another aggregator after some timeout.

Experiment Setup (1/2)

- Implemented Plexus in Python 3 using PyTorch.
- Evaluation on the DAS6 compute cluster.

- Metrics:
  1. Time-to-accuracy
  2. Communication-to-accuracy
  3. Training-resources-to-accuracy

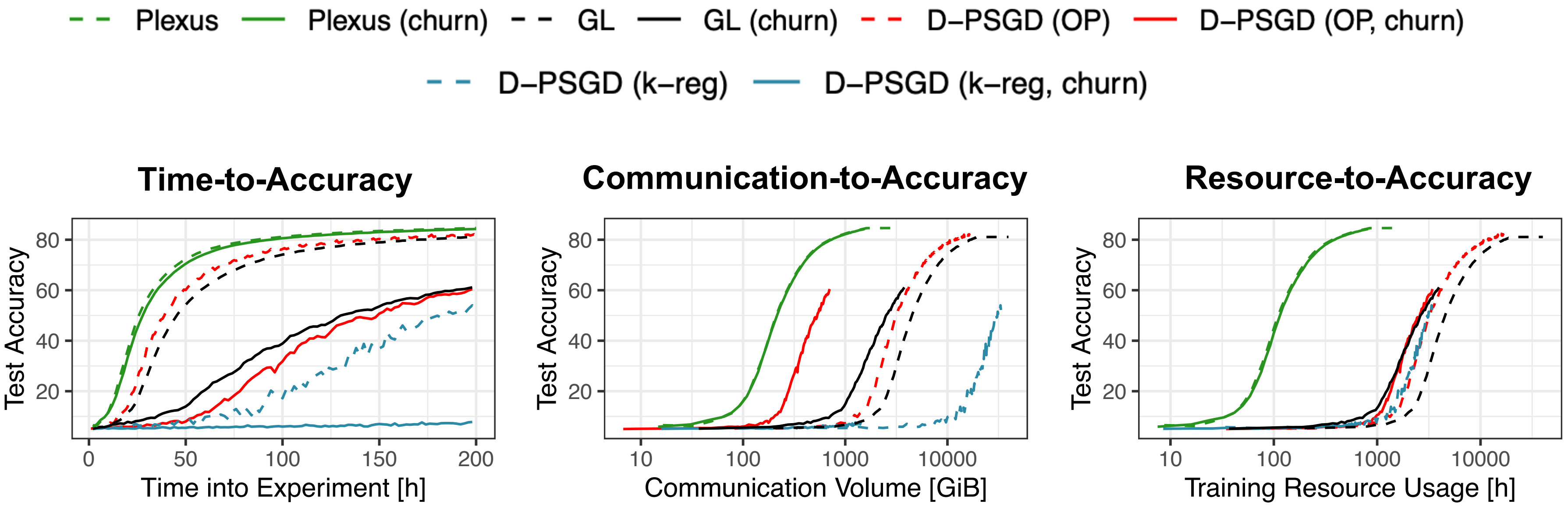
Experiment Setup (2/2)

- Four datasets:

DATASET	TASK	NODES	LEARNING PARAMETERS	MODEL	MODEL SIZE
CIFAR10 [31]	Image classification	1000	$\eta = 0.002$, momentum $= 0.9$	CNN (LeNet [20])	346 KB
CelebA [10]	Image classification	500	$\eta = 0.001$	CNN	124 KB
FEMNIST [10]	Image classification	355	$\eta = 0.004$	CNN	6.7 MB
MovieLens [18]	Recommendation	610	$\eta = 0.2$, embedding dim $= 20$	Matrix Factorization	827 KB

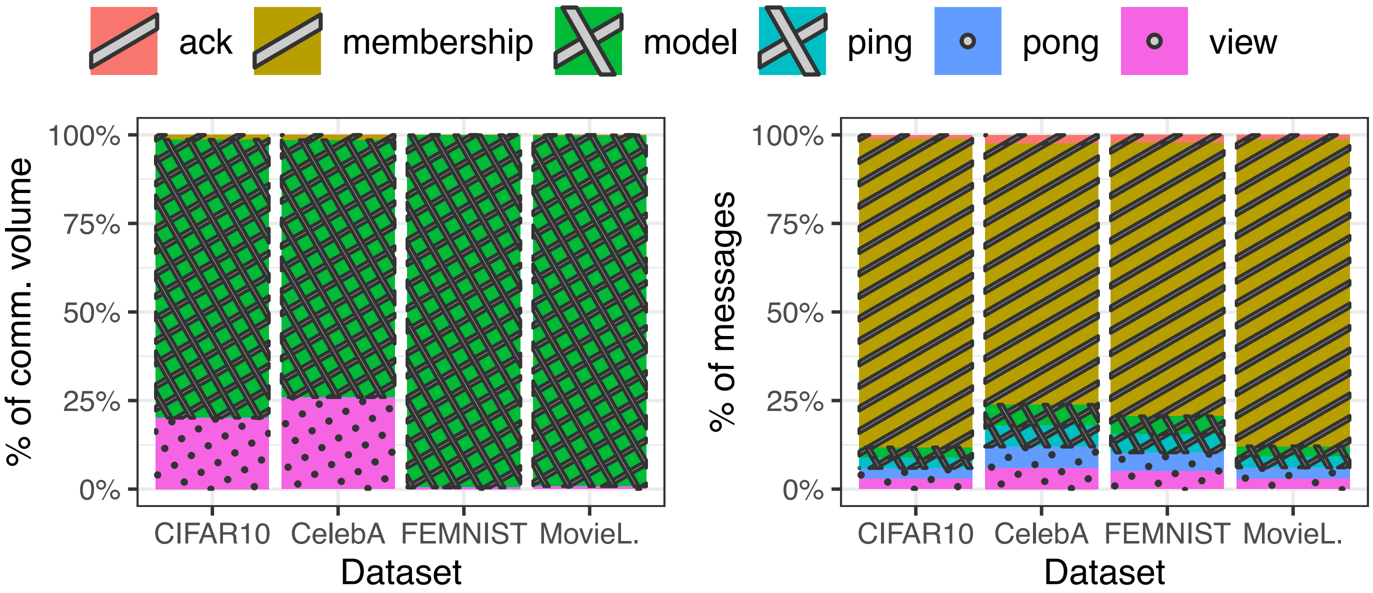
- Three baselines
  - D-PSGD (sparsely connected topology)
  - D-PSGD (k-regular topology)
  - Gossip Learning

Plexus Compared to DL Baselines (FEMNIST)



Plexus shows significant performance improvements over baselines!

Plexus Overhead



Conclusions

- Plexus is a practical and efficient DL system.
- Significant savings in time-to-accuracy (1.2-8.3x), communication-to-accuracy (2.4-15.3x) and resource-to-accuracy (6.4-370x).
- Future work: dealing with Byzantine nodes.

Thank you!

martijn.devos@epfl.ch