Federated Learning For Multi-Center Breast Cancer Classification in the Real World

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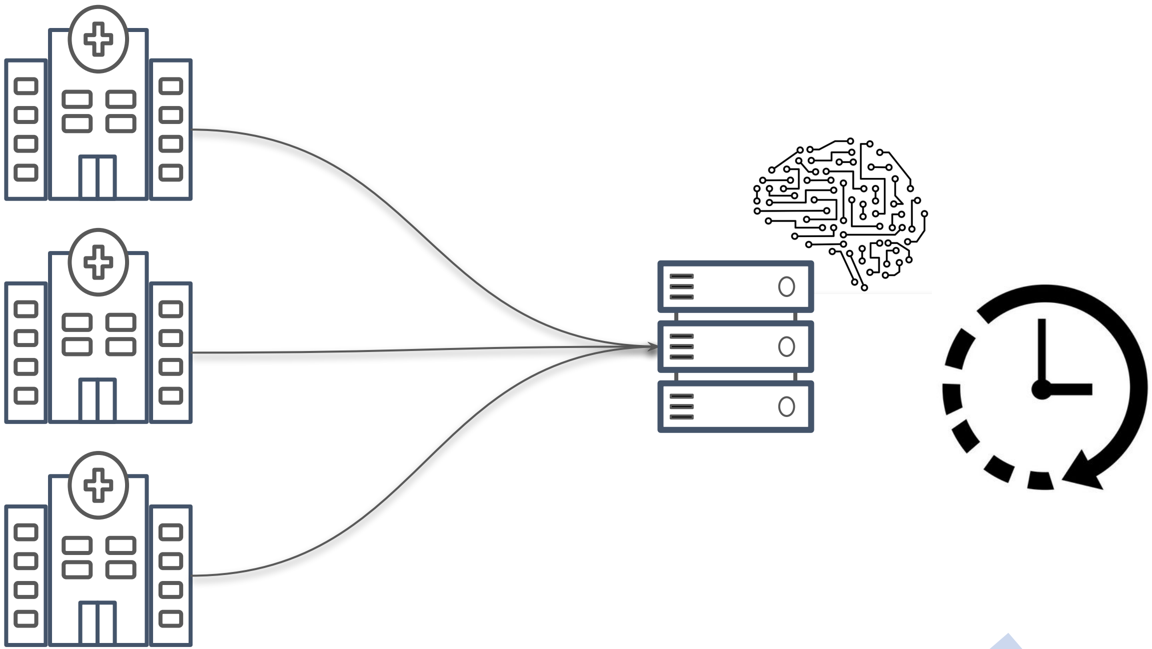
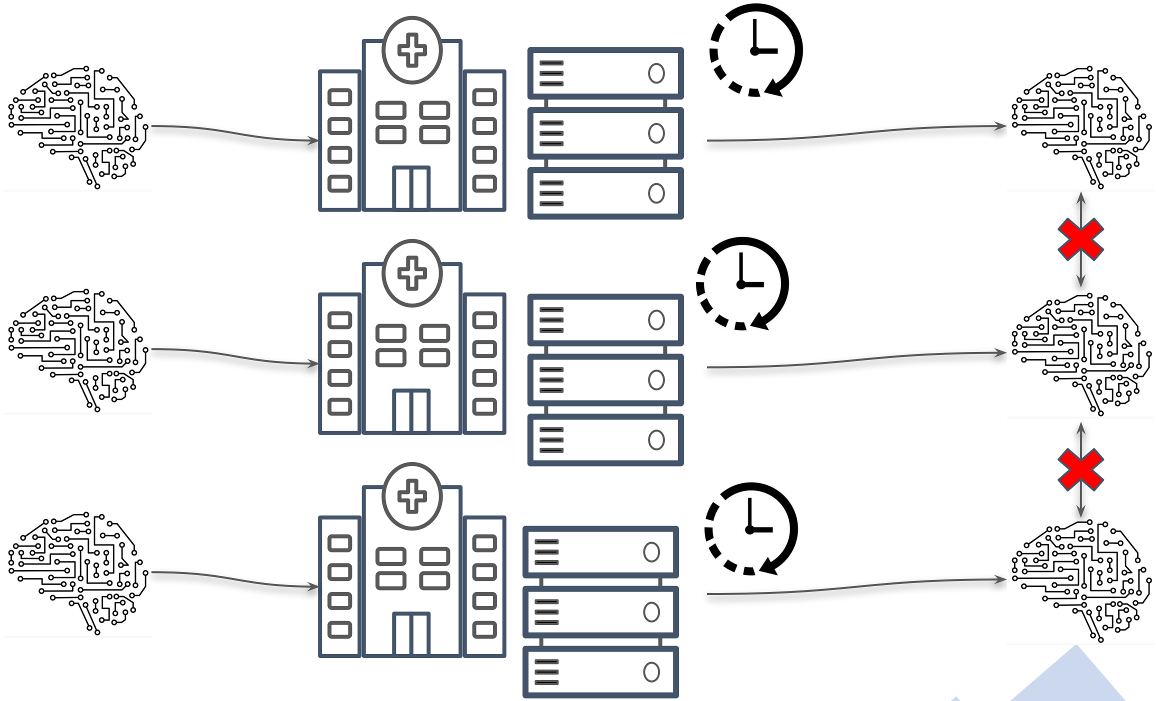
Collaborative Data Sharing (CDS)



Data is pooled in one server where training occurs.

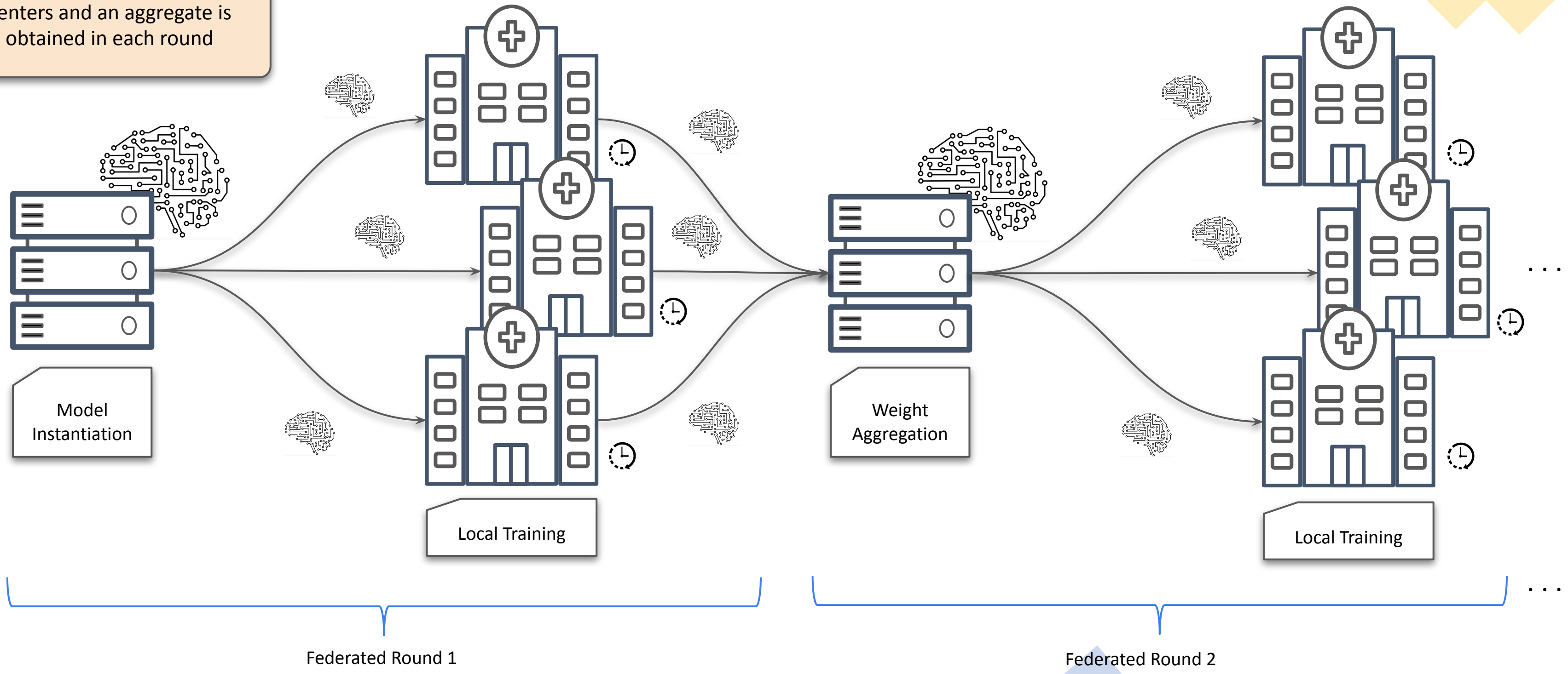
What really happens



Models are trained on single center data. Their generalization is questionable.

Federated Learning (FL)

A model is distributed across centers and an aggregate is obtained in each round



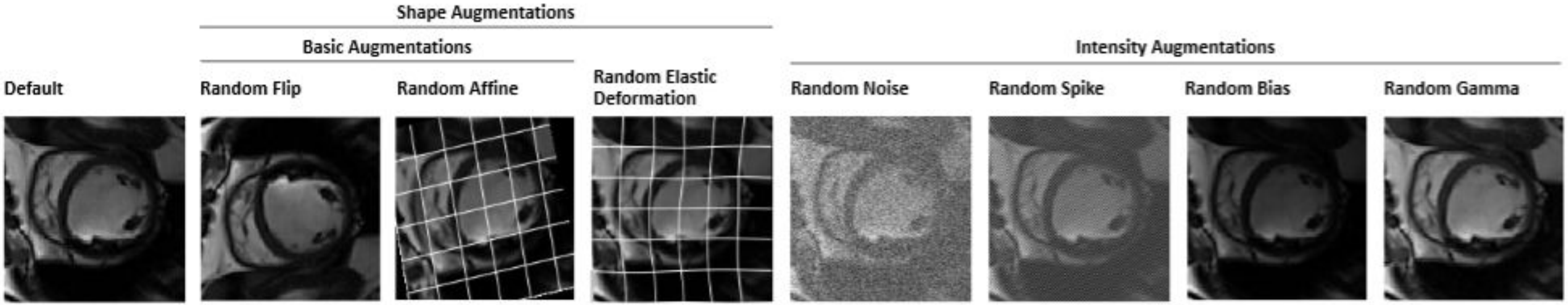
A **Simulation** Study in Cardiovascular Disease

https://arxiv.org/abs/2107.03901

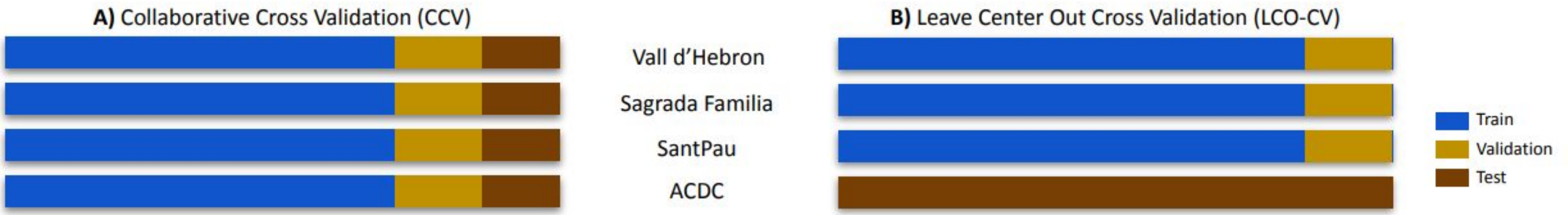
Linardos, Akis, et al. "Federated Learning for Multi-Center Imaging Diagnostics: A Study in Cardiovascular Disease." *arXiv preprint arXiv:2107.03901* (2021).

Cardiac MRI Multi-center Data

Center	Vendor	Spatial Resolution (mm)	Slice Thickness (mm^2)	NOR	HCM	Total
Vall d'Hebron	Philips	1.1516-1.2362	10.0	21	25	46
Sagrada Familia	Siemens	0.9765-1.6200	8.0-10.0	33	37	70
SantPau	Canon	0.7955-1.8228	10.0	14	10	24
ACDC	Siemens	1.3400-1.6800	5.0-10.0	20	20	40
Total				88	92	180

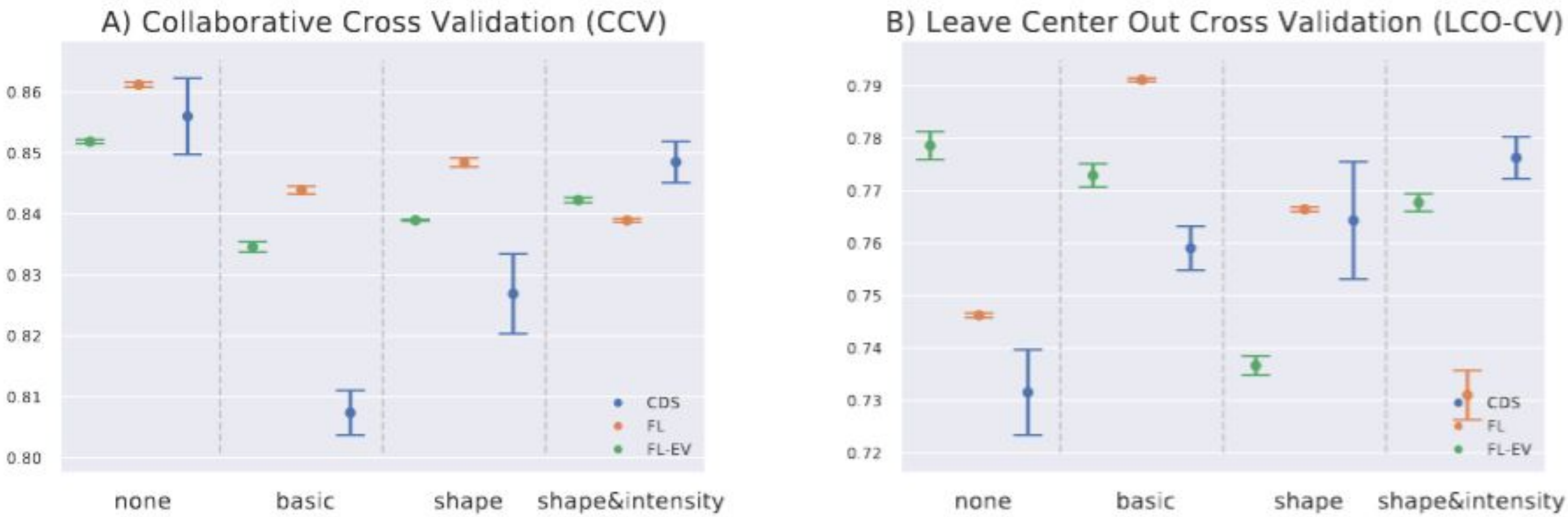


Principled Evaluation



LCO-CV gives us an estimate of *out-of-site* generalization performance, by testing iteratively on an unseen-center fold

Results: 5 seeds per configuration



FL-EV is an alternate aggregation technique we tried: contrast to the original **FL** algorithm, in this case each center gets an *Equal Vote*

FL outperforms **CDS** in many cases.

FL and **FL-EV** are more robust across different seeds, while **CDS** exhibits significant error bars.

Now onto the real challenge: Actual Deployment.

Federated Learning
For Multi-Center Breast Cancer Classification in the Real World

Our process: One Step at A Time

- Phase 1: Set up a federated network across collaborators. Tackle classification.
    - Test technical innovations in the real world (already found to work well in FeTS Challenge which was a simulation)
    - Labels: (**Normal / Benign Tumor / Malignant Tumor**)
- Phase 2: Improve classification, tackle other use cases. Required annotations on previously gathered data:
    - Bounding boxes around lesions

What technical innovations?

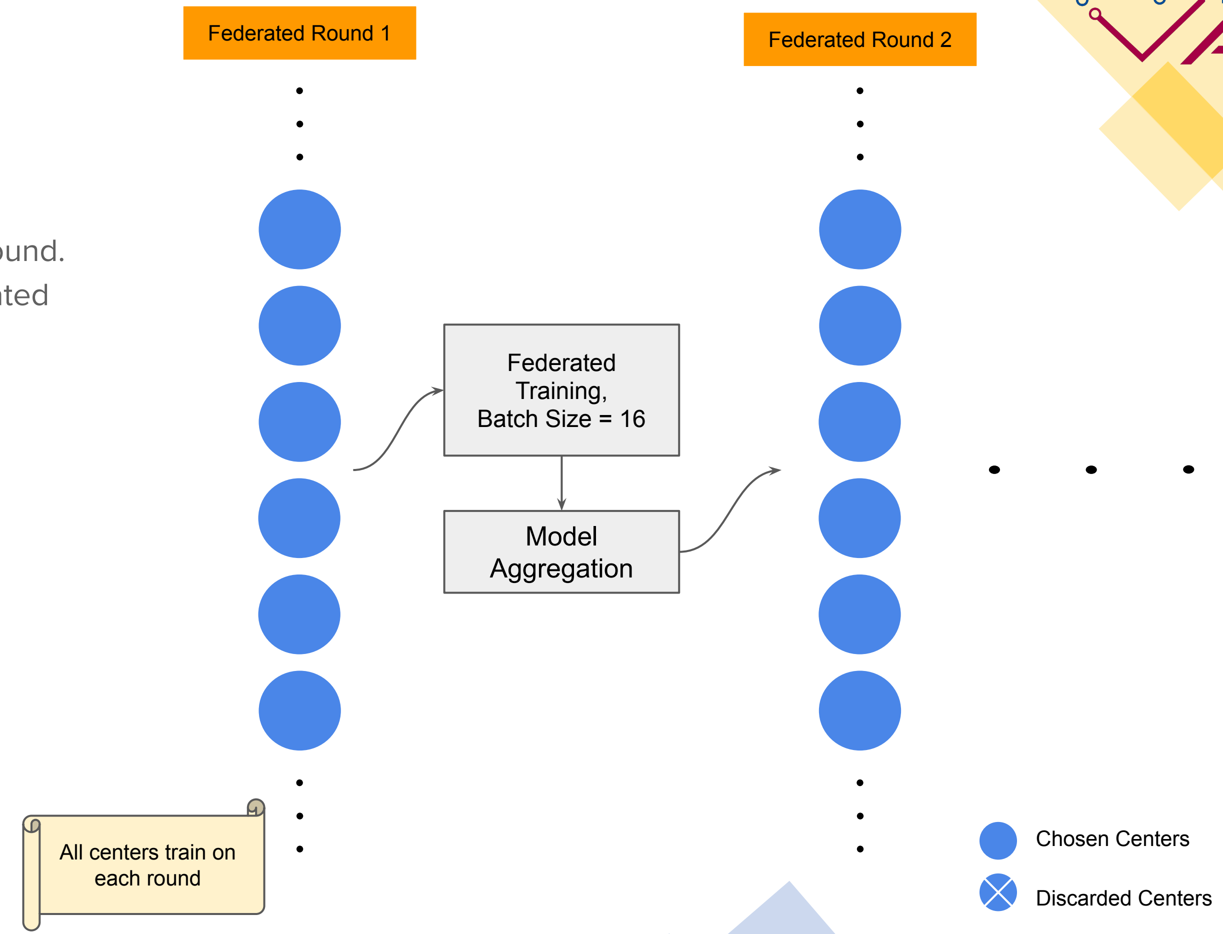
We proposed *Center Dropout* in the first Federated Challenge at MICCAI and scored ***1st*** on one of the leaderboards.

Since this was a simulation, we will now have the chance to test it in a real world setting.

Rank	Team Name	Institution	Lead Author
1	BCN-AIM	University of Barcelona	Akis Linardos
2	HT-TUAS	Turku University of Applied Sciences	Irfan Khan
3	Shoulders	Chinese University of Hong Kong	Quande Liu

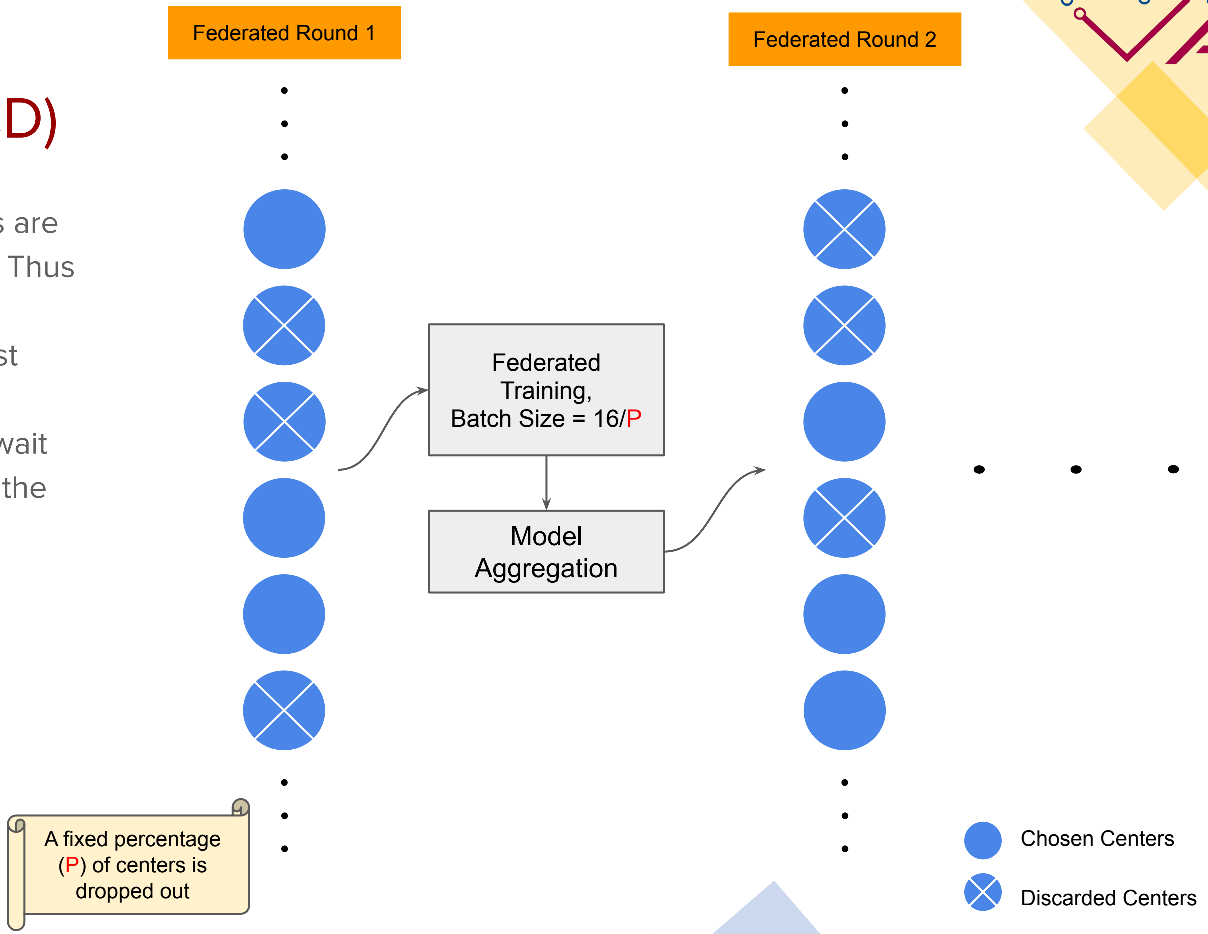
Vanilla FL

- All centers train in each round.
- Local models are aggregated



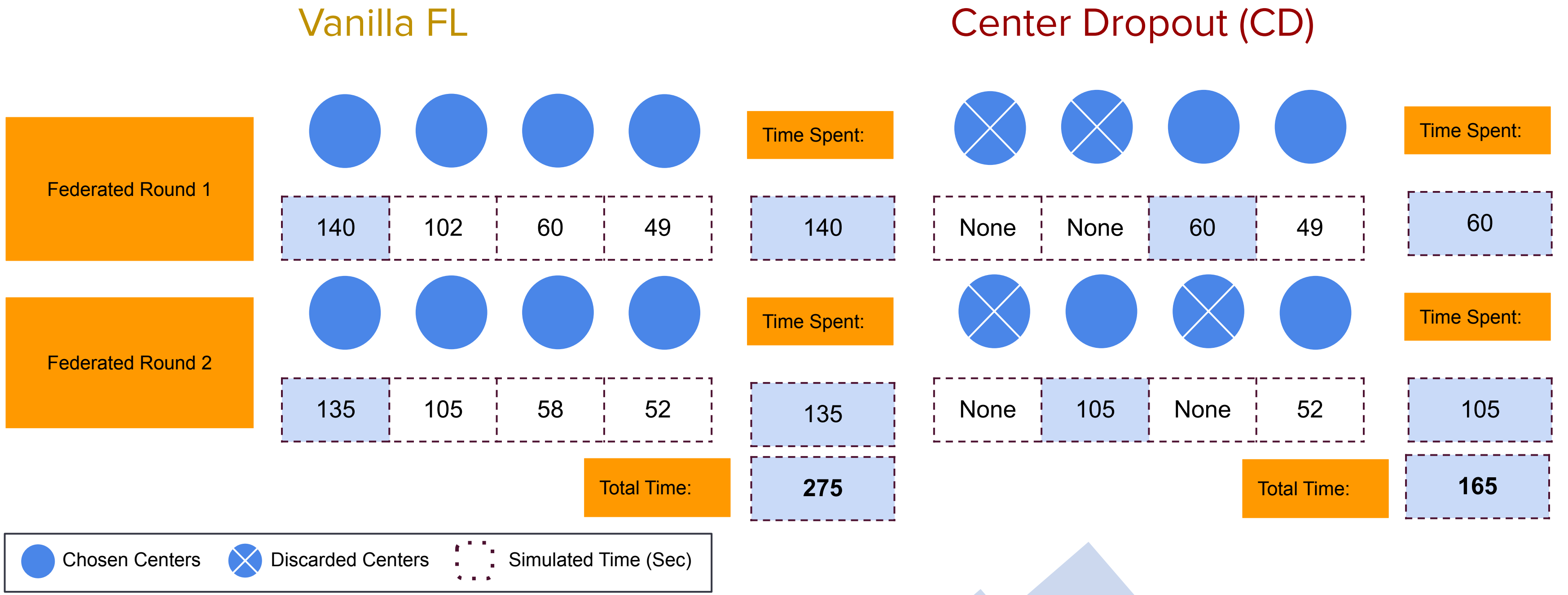
Center Dropout (CD)

- Local models of subgroups are aggregated in each round. Thus the vote is not always overwhelmed by the largest center.
- Training does not have to wait for the slowest member of the consortium.



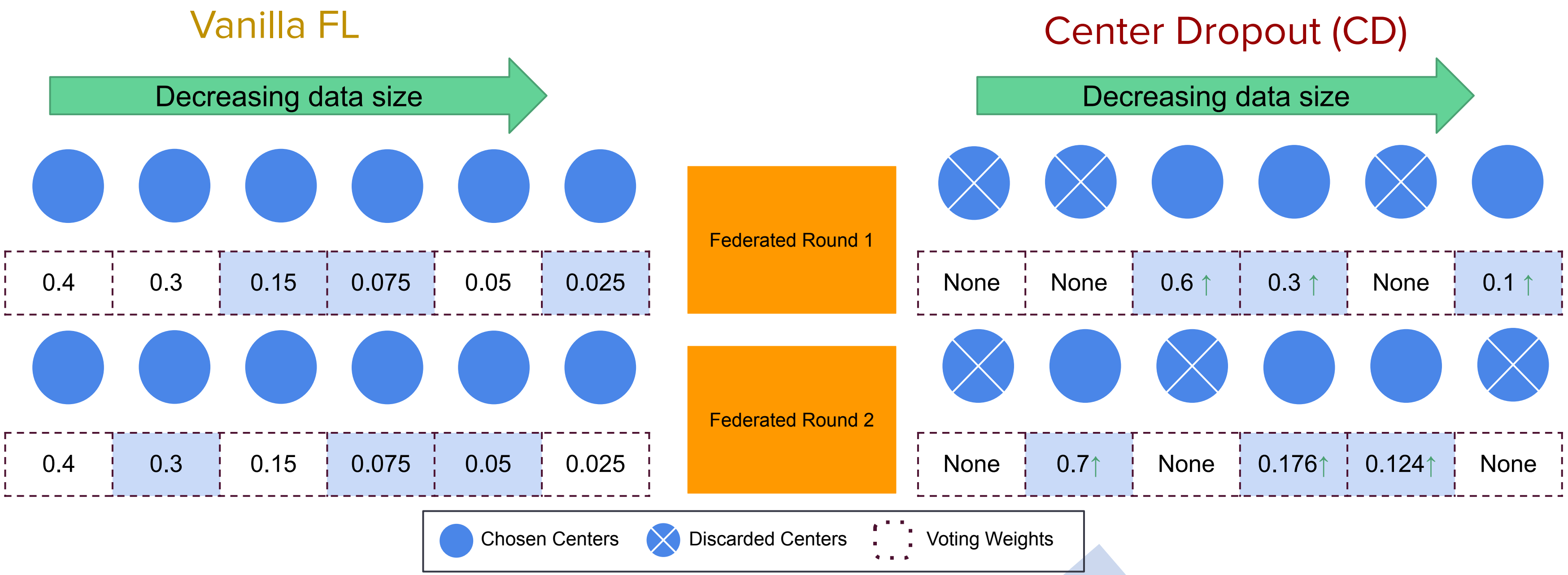
Intuitions: Speed

- In Vanilla FL, each round moves as slow as its slowest member. In CD the slowest member is different each round. We thus cut down on communication costs. By using a proportionally batch size, the same amount of training goes on with less communication.



Intuitions: Fairness

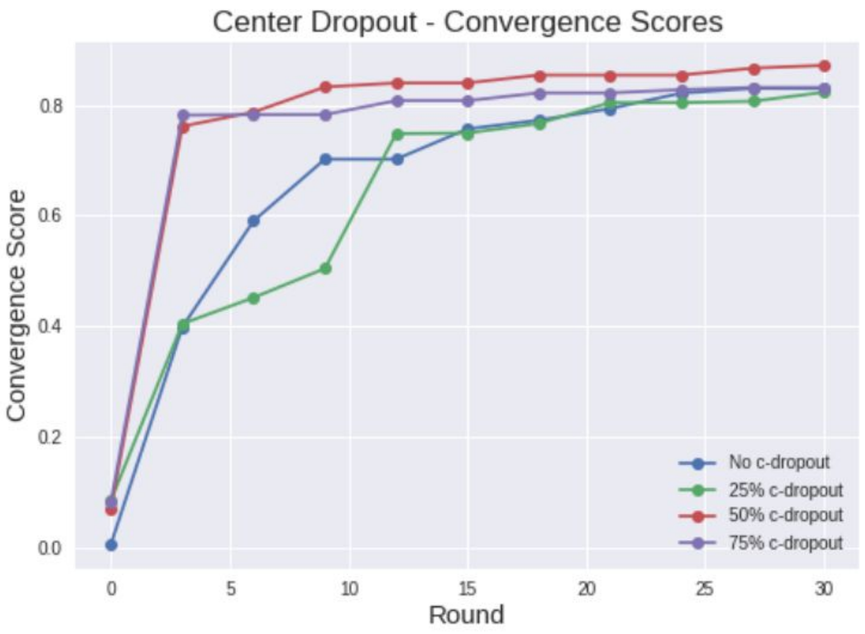
- In Vanilla FL, voting is the same in each round. In CD, smaller centers get the chance to have a higher vote, as they are not consistently overwhelmed.



Results: Better Performance, Faster Convergence

C. Dropout	Batch Size	Dice ET
None	16	0.6023
25%	21	0.58755
50%	32	**0.62857**
75%	64	0.62146

C. Dropout	Batch Size	Hausdorff95 ET
None	16	30.40639
25%	21	35.62406
50%	32	**25.439**
75%	64	33.87432



Plan Overview

Define Clinical Problem

Set up the Infrastructure

Test Connection and hardware with toy data

ETL Pipeline: Extract, Transform, Load

Data Harmonization

Deploy model, test with hospital data

Start Experiments

Analyze results

Bring the story together

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Can we leverage Topological Data Analysis in Federated Learning?

- No work on this currently
- Federated Learning allows training without ever seeing the data. In this set-up, the only privacy-respecting data analysis of individual points would require noise-inserting techniques. The denoising properties of Topological Data Analysis could help us study this noisy data.
- Perhaps TDA can also help us tackle domain shift between multiple centers?

Thank you for your attention!

More about me and my past work at:

linardos.github.io

Prior experience:

- We have completed a CMR study (available on arxiv) and are in the process of publishing at Scientific Reports
- Key findings from that study:
    - The Federated Algorithm is more robust than Collaborative Data sharing, even when the exact same data is used.
    - Different Cross-Validation splits provide different results. Leave Center Out is proposed as best alternative.
    -

Results

- 4 configurations of Center Dropout (CD) were tested with different percentages (P)
- 50% CD outperforms all alternatives by a significant margin, including baseline.
- Possible room to wiggle in the range 40-60% for further fine tuning

C. Dropout	Batch Size	Dice ET	Dice WT	Dice TC
None	16	0.6023	0.75637	0.60354
25%	21	0.58755	0.70387	0.60216
50%	32	**0.62857**	**0.78498**	0.6417
75%	64	0.62146	0.74899	**0.64332**
C. Dropout	**Batch Size**	**Hausdorff95 ET**	**Hausdorff95 WT**	**Hausdorff95 TC**
None	16	30.40639	34.34818	30.59265
25%	21	35.62406	44.66591	38.50768
50%	32	**25.439**	**24.74043**	**25.31731**
75%	64	33.87432	38.05616	39.45167