We show that in decentralized federated learning, even if you lose an agent, you can still converge to a well-performing model

Project website

Adaptive Fill-in: How to Mitigate the Loss of an Agent in Decentralized Federated Learning

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Introduction

Motivation

- **Privacy:** Data can't be shared directly (e.g., hospitals, regulations)
- **Solution:** Use distributed learning to share models, not data
- **Objective:** Converge to a well-performing model on all agents

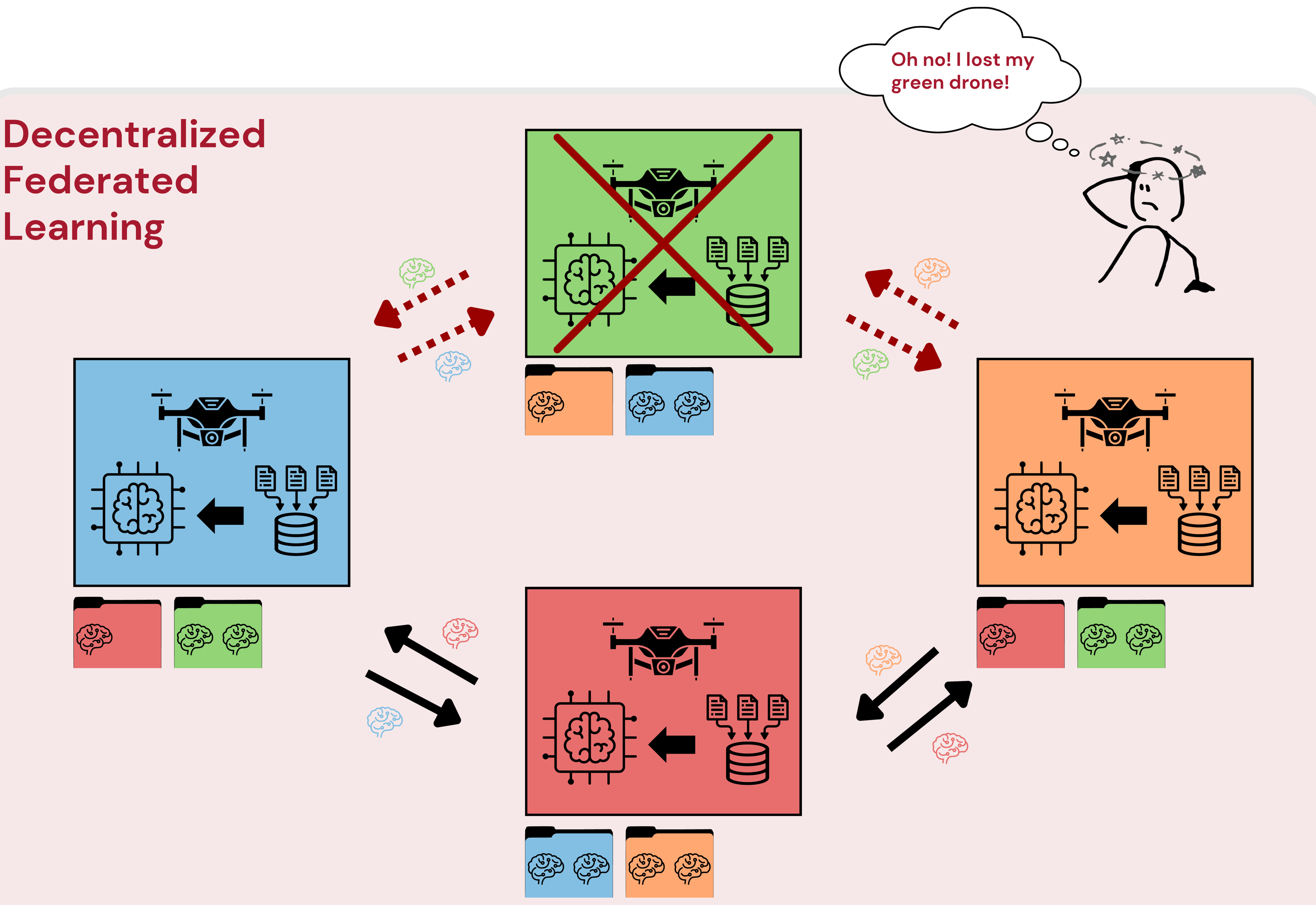
Problem Setting

- **Data distribution:** Each agent has access to some unique data
- **Collaboration:** Agents share latest models with their neighbors
- **Regularization:** Agents consider neighbors' models in their loss
- **Challenge:** One agent may be permanently lost during training

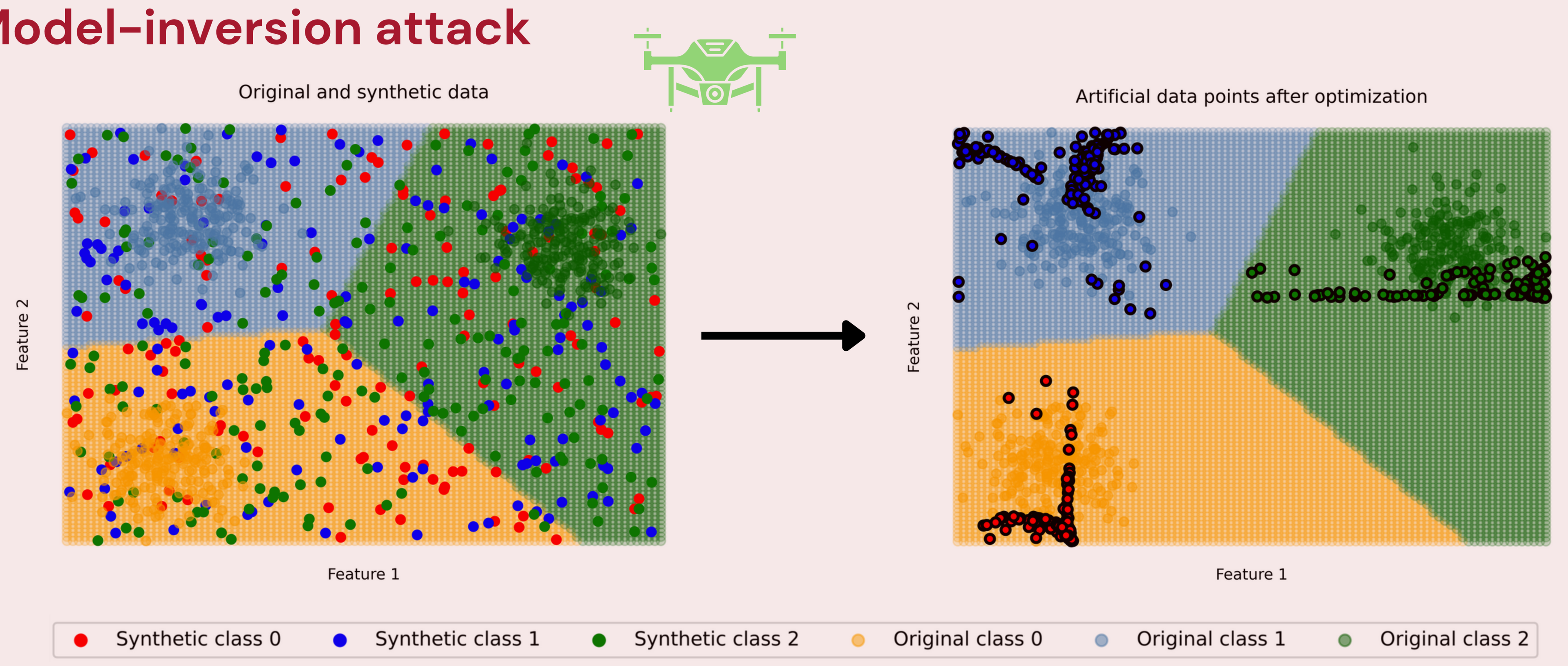
Idea

- Use the destroyed agent's model to create its virtual copy
- Approximate training data distribution via model-inversion attack
- Deploy new virtual agent with created synthetic dataset

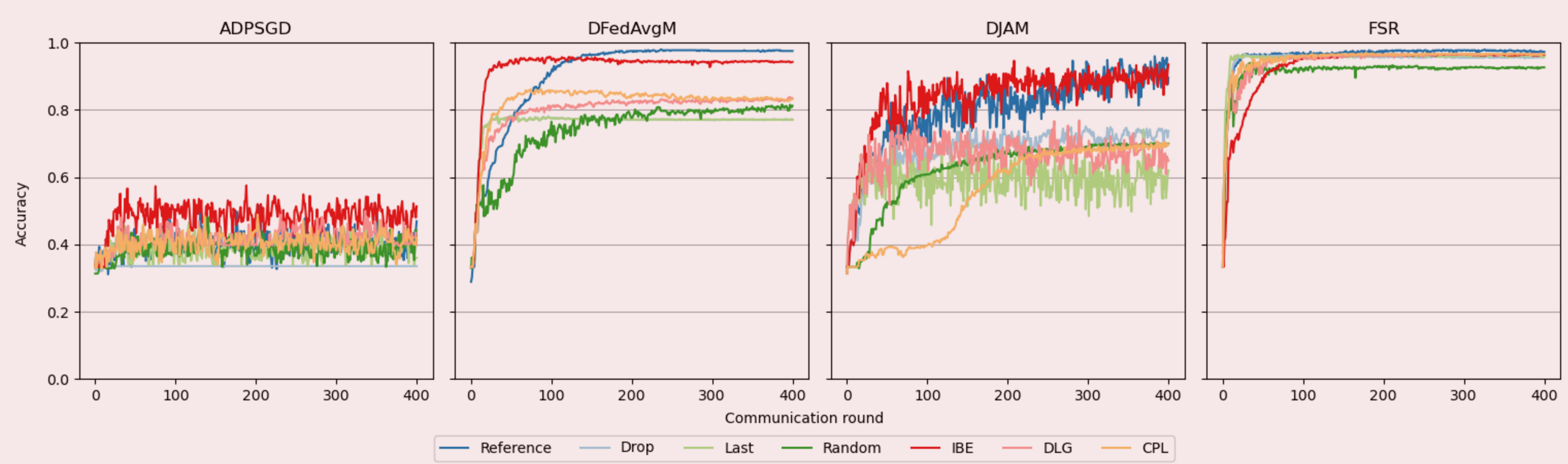
Decentralized Federated Learning



Model-inversion attack



Convergence



Method

- Every agent optimizes the same loss function via GD

$$\theta^{t+1} := \theta^t - \eta \nabla_{\theta^t} L(\theta^t; X, Y)$$

- After each communication round, agents train their model on local data until it (approx) converges to a local stationary point

$$\nabla_\theta \mathcal{L}_d(\theta, X, Y) - \epsilon = 0$$

- Create synthetic data points with random labels

$$X_{\mathtt{synth}} \sim \mathtt{Uniform}[0,1] \quad Y_{\mathtt{synth}} \sim \mathtt{Uniform}\{0,1,\ldots,C\}$$

- Optimize synthetic data points until the gradient of the loss function w.r.t. parameters is again zero using:

$$X^{t+1}_{\mathtt{synth}} := X^t_{\mathtt{synth}} - \eta \nabla_{X^t_{\mathtt{synth}}} L(\theta; X^t_{\mathtt{synth}}, Y_{\mathtt{synth}})$$

- Use the new synthetic dataset to train the model of the neighbor and proceed with the distributed optimization process

Gradient Leakage based attack methods

- Implicit Bias Exploitation (IBE)

$$\mathcal{L}_{IBE} = \mathcal{L}_d + \lambda \mathcal{L}_{prior}$$

- Deep Leakage Gradient (DLG) [5]

$$\mathcal{L}_{DLG} = \|\nabla W' - \nabla W\|^2 + \lambda \mathcal{L}_{prior}$$

- Client Private Leakage (CPL) [6]

$$\mathcal{L}_{CPL} = \|\nabla W' - \nabla W\|^2 + \lambda_1 \|f(x_{synth}) - \hat{y}\|^2 + \lambda_2 \mathcal{L}_{prior}$$

Prior term (optional)

$$\mathcal{L}_{prior} = \sum_{i=1}^{d} \mathrm{ReLU}(x-1) + \mathrm{ReLU}(-x)$$

Gradient from update history

$$\nabla W = \frac{\theta_t - \theta_{t-1}}{\eta}$$

Conclusions

- Active strategies with virtual agents lead to better results
- IBE on average is the best aid for agent loss
- DLG and CPL perform worse than IBE, but there is room for improvement in gradient estimation technique
- Further investigation into more complex datasets is needed (see additional results on the website)
- Theoretical analysis is crucial going forward

References

[1] Ovi et al. 2023 "A Comprehensive Study of Gradient Inversion Attacks in Federated Learning and Baseline Defense Strategies"
[2] Almeida et al. 2018 "Distributed Jacobi Asynchronous Method for Learning Personal Models"
[3] Tsun et al. 2021 "Decentralized Federated Averaging"
[4] Good 2024 "Trustworthy Learning using Uncertain Interpretation of Data"
[5] Zhu et al. 2019 "Deep Leakage from Gradients"
[6] Wei et al. 2020 " Framework for Evaluating Gradient Leakage Attacks in Federated Learning"

Results

Iris

	Reference	Drop	Last	Random	IBE	DLG	CPL
ADPSGD	0.47 ± 0.18	0.34 ± 0.05	0.36 ± 0.06	0.41 ± 0.16	0.51 ± 0.22	0.40 ± 0.16	0.42 ± 0.11
DFedAvgM	0.98 ± 0.02	0.77 ± 0.12	0.77 ± 0.12	0.81 ± 0.06	$\mathbf{0.94 \pm 0.02}$	0.83 ± 0.11	0.83 ± 0.10
DJAM	0.90 ± 0.09	0.74 ± 0.24	0.62 ± 0.13	0.70 ± 0.10	$\mathbf{0.94 \pm 0.03}$	0.65 ± 0.14	0.70 ± 0.08
FSR	0.97 ± 0.02	0.96 ± 0.03	0.96 ± 0.03	0.93 ± 0.01	0.96 ± 0.01	$\mathbf{0.97 \pm 0.03}$	0.97 ± 0.03

Wine

	Reference	Drop	Last	Random	IBE	DLG	CPL
ADPSGD	0.47 ± 0.13	0.43 ± 0.17	0.44 ± 0.14	0.50 ± 0.15	0.54 ± 0.20	0.50 ± 0.16	0.50 ± 0.16
DFedAvgM	0.98 ± 0.01	0.81 ± 0.15	0.81 ± 0.15	0.84 ± 0.05	0.93 ± 0.03	0.90 ± 0.07	0.91 ± 0.06
DJAM	0.79 ± 0.16	0.73 ± 0.27	0.47 ± 0.14	0.75 ± 0.19	0.80 ± 0.16	0.72 ± 0.16	0.77 ± 0.14
FSR	0.92 ± 0.03	0.91 ± 0.11	0.87 ± 0.11	0.86 ± 0.14	0.93 ± 0.04	0.80 ± 0.23	0.85 ± 0.17

Global accuracy on a test set after 300 rounds of peer-to-peer communications. Dense communication graph, best results out of 5-fold hyperparameters search on each method and patching strategy and three random seeds.

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