# Quantifying the Impact of Label Noise on Federated Learning

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## Problem

- **Label noise** has been identified in many widely used datasets. The cause of label noise could be human error.
- **Federated Learning** (FL) is a distributed machine learning paradigm where clients collaboratively train a model using their local (human-generated) datasets.

How does label noise affect FL generalization?

## Observation

Label noise linearly degrades FL performance by reducing the test accuracy of the global model.

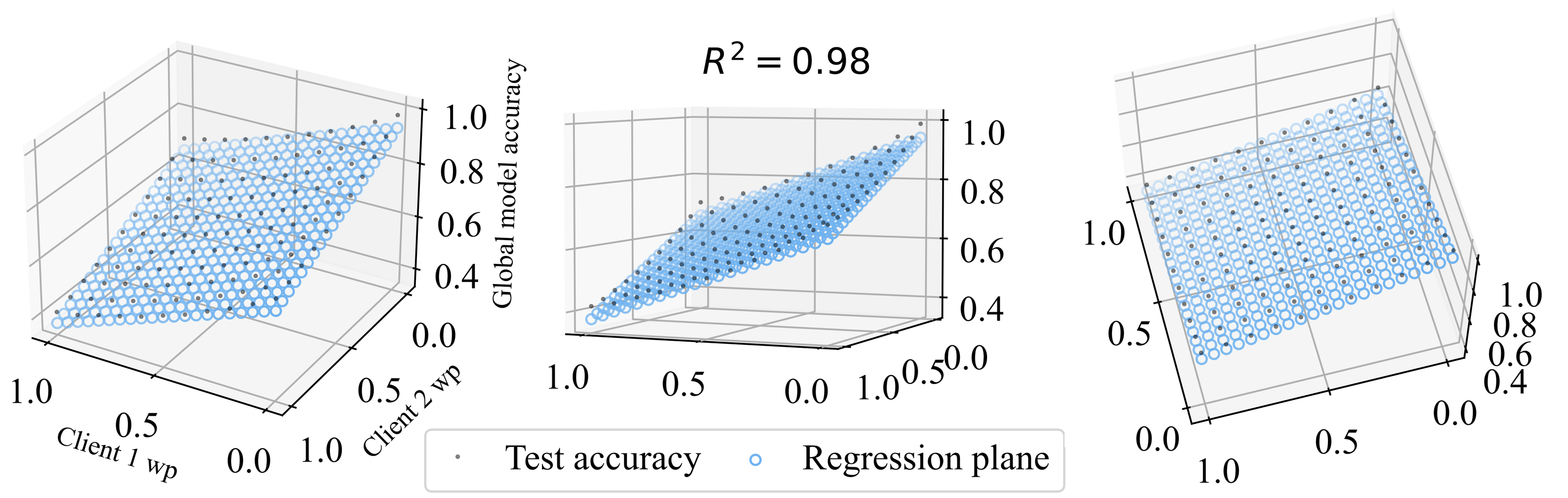
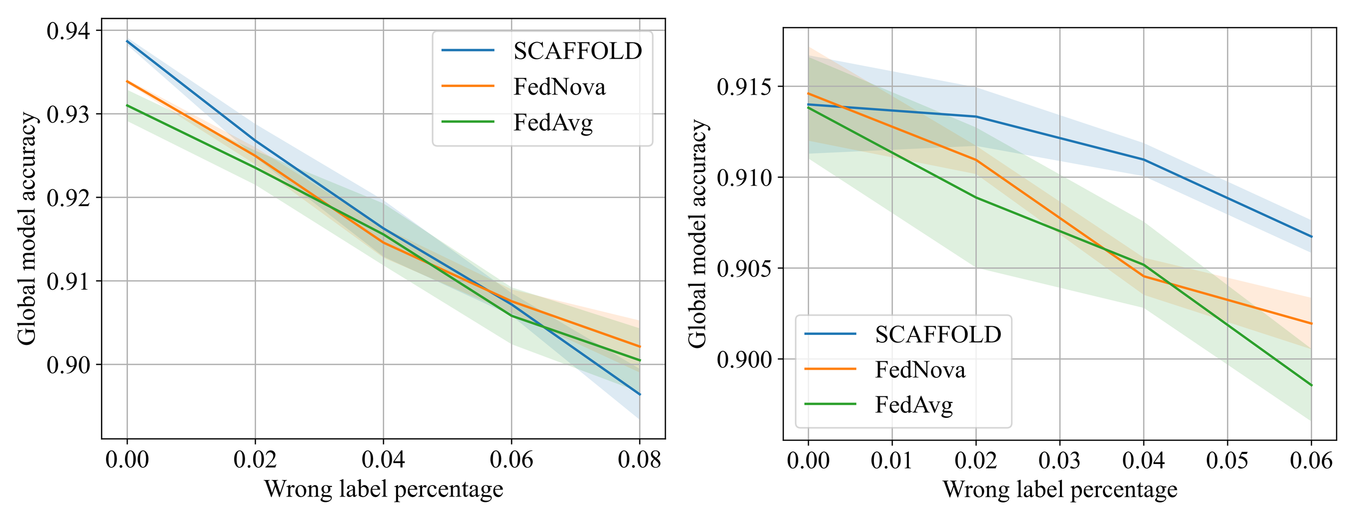



Figure 1. Linear regression on the global model accuracy under label noise. Two clients trained the global model with FedAvg.




(a) 4-client (b) 15-client

Figure 2. Test accuracy of global model by different FL algorithms under different label error rates.

## Theoretic analysis

### Formulation

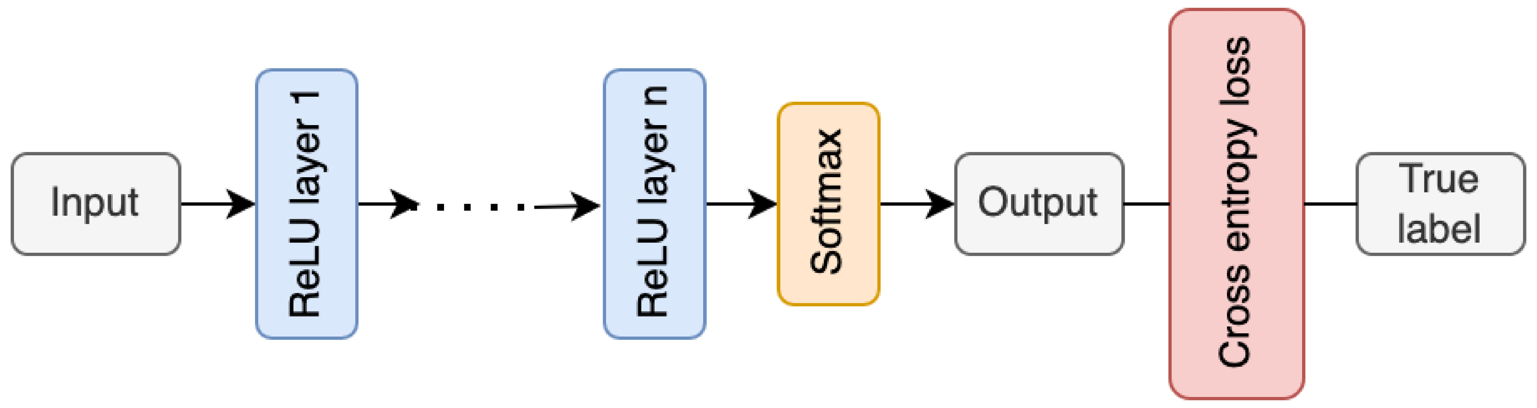



Figure 3. We consider a classification task and ReLU networks.

### Method

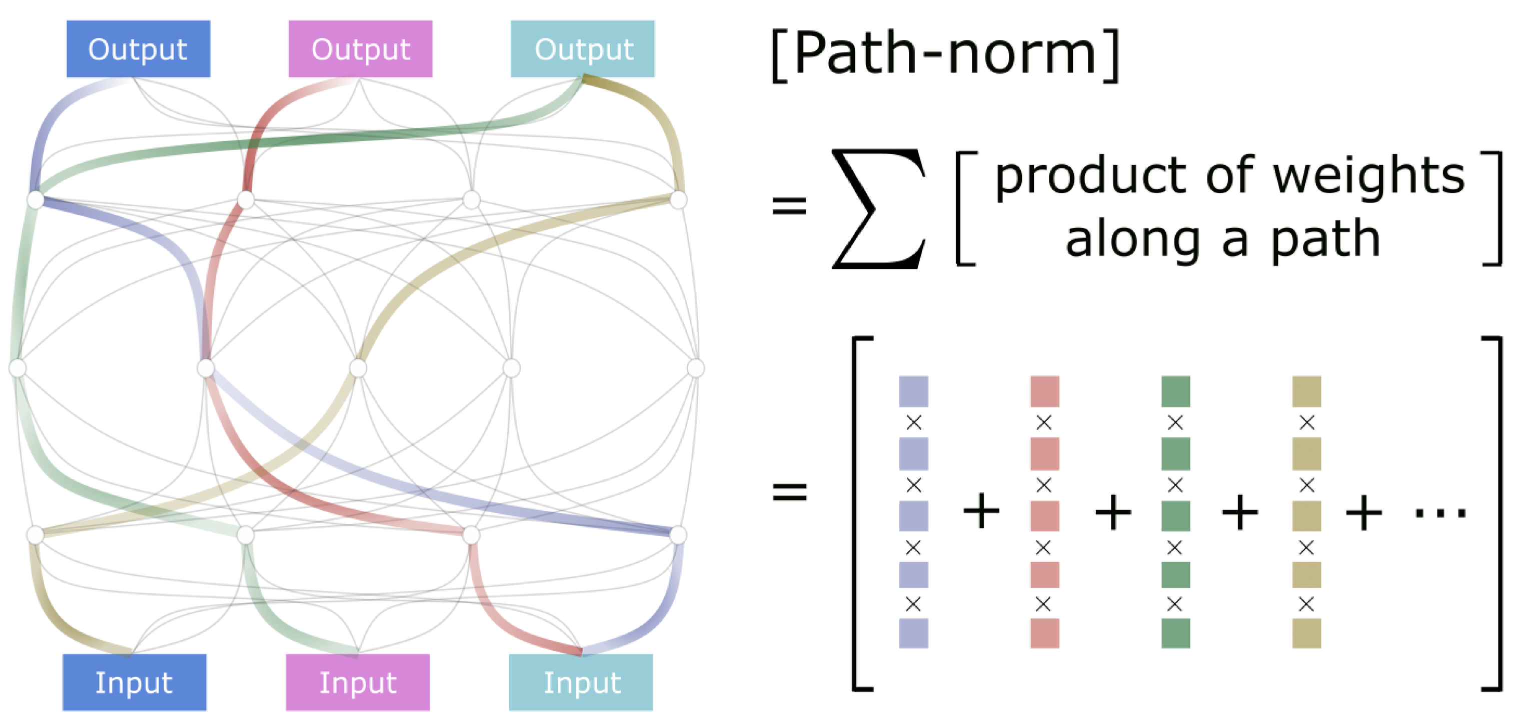



Figure 4. This paper uses ReLU network and path-norm proxy for a case study of the generalization error.

Consider an FL process with a $L$-layer neural network $f : \mathbb{R}^{d_x} \times \mathcal{W} \to \mathbb{R}^{d_y}$ as its global model. Then its **path-norm** increases at most polynomially,

$$\|f(\cdot;\theta(t))\|_{\text{pnp}} = \mathcal{O}(t^{L+1}E^{(L+1)/2})$$

where $t \le R$ denotes the number of communication rounds and $E$ denotes the local training time.

If we consider a generic decentralized algorithm, we have

$$\|f(\cdot;\theta(t))\|_{\text{pnp}} = \mathcal{O}(e^{C't(L+1)}E^{(L+1)/2})$$

where $C'$ is a constant independent of $t, L, E$.

Consider **any distributed/decentralized learning algorithm** with a neural network with an arbitrary structure for a classification task of $C$ classes under label noise and cross-entropy loss, then

$$G(W) \le \Omega \cdot \mathbb{E}_X\left[\sum_{i=1}^{C}\sum_{k=1}^{N}\frac{n_k}{n}\left|\Pr_{\mu}(Y=i|X) - \Pr_{\pi_k}(Y=i|X)\right|\right]$$

If we use a ReLU network as our model in the FL task, then $\Omega = \|f(\cdot;\theta(t))\|_{\text{pnp}}$.

## Contributions

- The **first quantitative study** that analyzes the impact of label noise on FL.
- An analysis on path-norm growth under distributed/decentralized setting.
- A linear upper bound on the generalization error of the global model under label noise, which is **consistent with the empirical results**.

## Discussion

- **Improving theoretical bounds:** We prove a linear upper bound for the generalization error, and the bound is consistent with numerical results. However, the upper bound can be loose. One can provide a lower bound or improve the upper bound by making more restrictive assumptions.
- **More comprehensive experiments:** Our experiments use a small number of clients, which applies to cross-silo FL. In future research, we plan to study the impact of label noise with a larger number of clients (e.g., as in cross-device FL).

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