Communication-Efficient Federated Learning via Optimal Client Sampling

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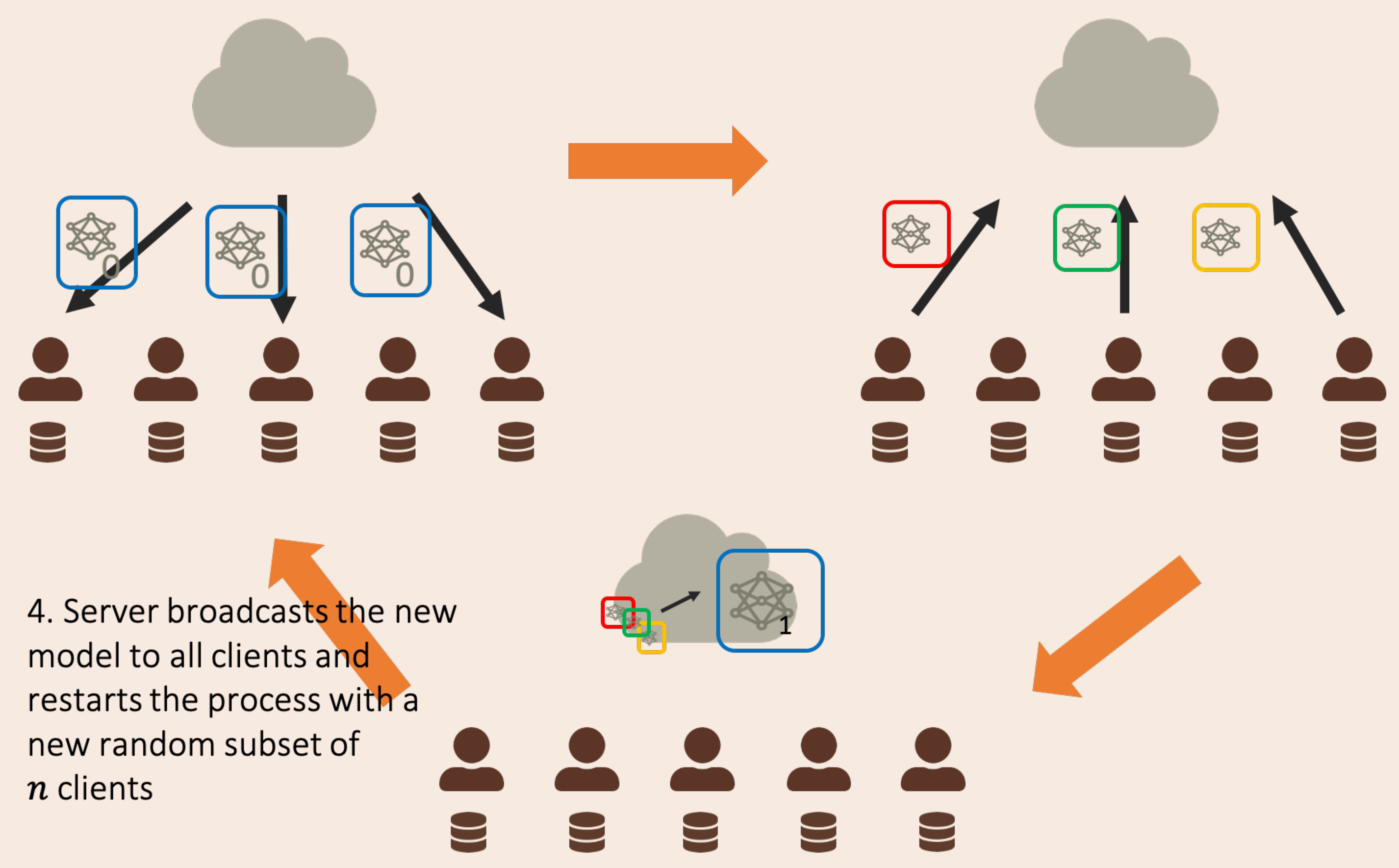
Federated Learning

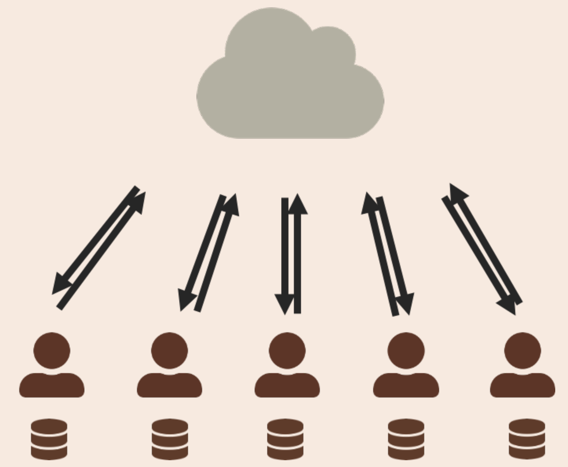
Federated learning provides a private and efficient way of learning machine learning models when the data is distributed across many clients[1]



Communication challenge

Federated Learning requires massive communication
- Millions of clients
- Thousands of iterations
- Models ~ 1-20 MB

Most of current communication reduction strategies focus on compressing the model [2-7] using a variety of strategies:
- Reducing network architecture
- Quantization
- Sparsification
- Low rank matrices



Research Goal

Reduce communication by reducing the amount of clients communicating with the server. Only the clients whose updates are deemed informative communicate their updates.
- Clients train locally
- Clients assess how informative their update is and decide to communicate or not.

Methods

We model the progression of each user's vector of weights during SGD as a stochastic process.

OU process definition: An Ornstein-Uhlenbeck processes is a stationary Gauss-Markov processes that, over time, tends to drift towards a mean value. Formally, let W_t be a standard Wiener process, then an OU process is defined by

$$d\theta_t = \lambda(\mu - \theta_t) + \sigma W_t$$

SGD as an OU process: Consider the loss function $\mathcal{L}(\theta; X) = \sum_{i=1}^{N} \ell_i(\theta)$ where X is a dataset with N samples. In SGD, $\mathcal{L}$ is minimized by evaluating an approximation of the gradient on a mini-batch $\mathcal{S} \subseteq X$,

$$\theta_{t+1} \leftarrow \theta_t - \eta \frac{1}{|\mathcal{S}|} \sum_{i \in \mathcal{S}} g_i(\theta)$$

Under some mild assumptions,

$$\Delta\theta = \theta_{t+1} - \theta_t \approx \eta g(\theta) - \sqrt{\frac{\eta}{N}} B\, \mathcal{N}(0, \eta I)$$

where BB^T approximates the covariance of gradients. Essentially, this is a discretization of an OU process.

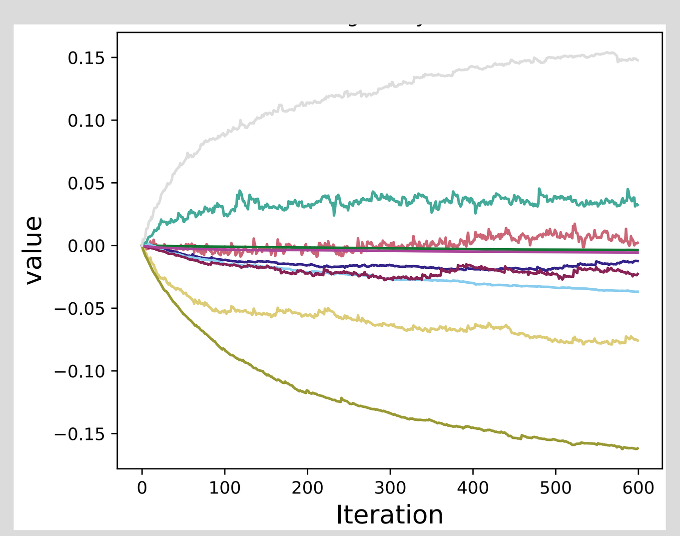


Figure 1. Weight updates can be interpreted as a realization of an OU process.

Optimal sampling: The following thresholding strategy outperforms deterministic sampling; the threshold is derived from a frequency constraint [8],

$$|\theta_t - E[\theta_t|\theta_0]| > \gamma$$

Two different strategies for selecting the threshold:

- **Fixed Threshold (FT):** Fix a threshold γ for the entire duration of the iterative process.
- **Adaptive Threshold (AT):** Compute threshold γ_t based on the previous updates' statistics.

Benchmark the proposed strategies vs. two baselines:

- Full communication
- Randomly dropping clients to match the communication rate of the best approach (FT or AT).

Experiments

We test our methods in two settings:

1. A classification task on EMNIST. To this end, we train and use a convolutional neural network.
2. A realistic language modeling task using the Stackoverflow dataset. For this, we train a recurrent neural network on a next word prediction task.

At each round, 50 clients are uniformly selected to update the model. Each client locally trains for $E = 20$ epochs on EMNIST and $E = 1$ epochs for Stackoverflow, using SGD. We train each model for 100 rounds.

Results and Discussion

Table 2: Results for convMNIST and Stackoverflow

	Accuracy		**Accuracy rate** (acc/byte)		**Overall comm.**(GB)		**Communication used**(%)	
Dataset	EMNIST	Stack	EMNIST	Stack	EMNIST	Stack	EMNIST	Stack
Baseline	**97.5%**	**13.07 %**	**29.3**	1.61	**33.27**	81.0	**100%**	100 %
FT	95.4%	**13.63 %**	**150**	2.34	**6.3**	58.3	**19%**	71.96 %
AT	**97.4%**	13.04 %	34.9	**2.99**	27.9	**43.6**	83%	**54 %**
Random	94.2 %	9.67 %	148.9	2.22	**6.3**	**43.6**	**19%**	**54 %**

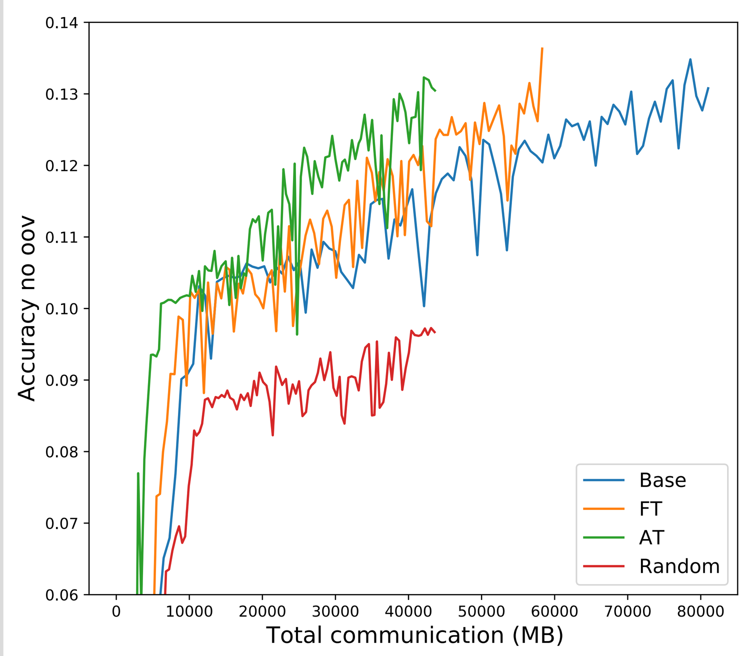


Figure 2. Accuracy rate per amount of communication on Stackoverflow.

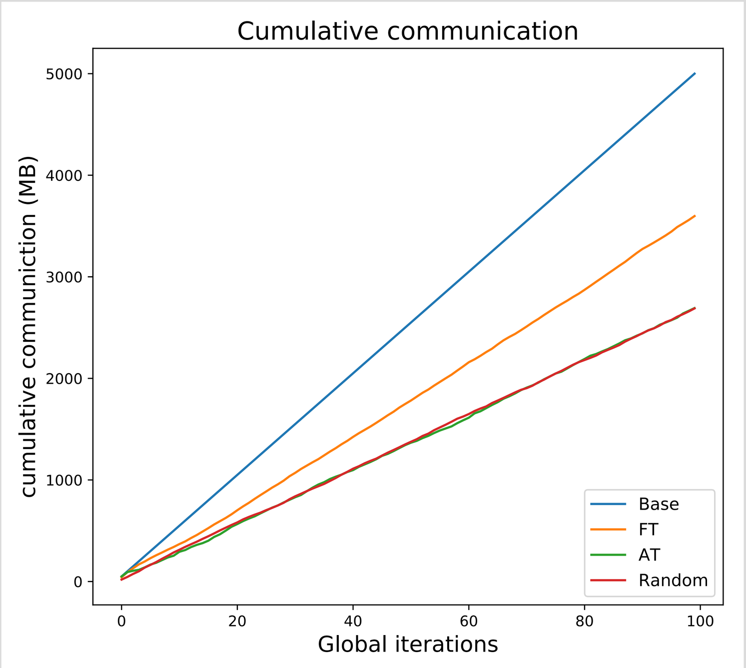


Figure 3.Overall communication on Stackoverflow.

- Randomly dropping clients reduces communication but deteriorates performance significantly.
- Thresholding techniques reduce communication while achieving better performance than random selection.
- The accuracy rate per amount of communication is higher for thresholding strategies than for either random selection or full communication.
- For both datasets, at least one thresholding strategy achieves the same performance as the full communication baseline while considerably reducing communication.
- Our approaches can be combined with compression strategies to lower the communication rates even further.

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