Anarchic Federated Learning

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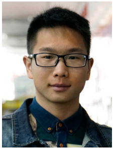
Joint Work



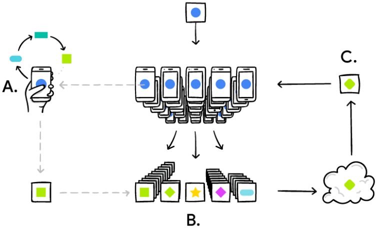
Haibo Yang
OSU

Xin Zhang
ISU/Meta

Prashant Khanduri
OSU/UMN

Jia (Kevin) Liu
OSU

From Distributed Learning to Federated Learning

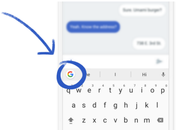


Distributed Learning
Parallelism

→

Federated Learning
Parallelism + Data Privacy + ...

Applications of Federated Learning



Google Gboard

Apple QuickType

Apple “Hey Siri”

- Google: Use FL in Gboard mobile keyboard, featured in Pixel phones, and Android Messages
- Apple: Use FL in QuickType keyboard next word prediction and vocal classifier for “Hey Siri”
- doc.ai uses FL for medical research, Snips uses FL for hotword detection, etc.

Federated Learning vs. Distributed Learning

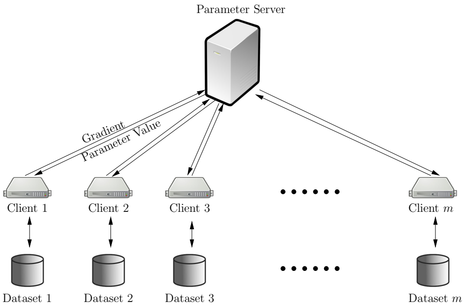
Distributed Learning	Cross-Device FL	Cross-Silo FL
IID dataset	Non-IID dataset	Non-IID dataset
Fast wired communication	Slow wireless communication	Fast communication
Centrally orchestrated	Flexible participation	Centrally orchestrated
Small scale (1 - 1000)	Large scale ($10^6 - 10^{10}$)	Small scale (2 - 100)
Few worker failures	Highly unreliable	Few worker failures
...	...	...

Data Heterogeneity

System Heterogeneity

[1] Kairouz, Peter, et al. "Advances and open problems in federated learning," Foundations and Trends in Machine Learning, 2021.

Sever-Centric Federated Learning



$$\min_{\mathbf{x}\in\mathbb{R}^d} f(\mathbf{x}) \triangleq \min_{\mathbf{x}\in\mathbb{R}^d} \sum_{i\in[M]} \alpha_i f_i(\mathbf{x}, D_i)$$

f_i : Non-convex loss function

α_i : Data proportion

D_i : Local data $\sim P_i$

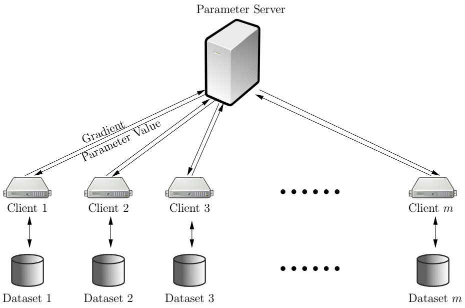
Selection:
- server select m workers to participate

Computation:
- worker makes local updates (K)

Aggregation:
- server aggregates results and updates model

[2] McMahan, H. B., Moore, E., Ramage, and D., Hampson, S., et al., "Communication-efficient learning of deep networks from decentralized data," Proc. AISTATS 2017.

Sever-Centric Federated Learning



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Server-centric "FedAvg" algorithm (selection-computation-aggregation):
Linear speedup for convergence: $\mathcal{O}(1/\sqrt{mKT})$

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Limitations of Server-Centric Federated Learning

Server-centric FL (Selection-Computation-Aggregation):

Tight worker-server coupling: 1) straggler, 2) energy waste, 3) bias/fairness …

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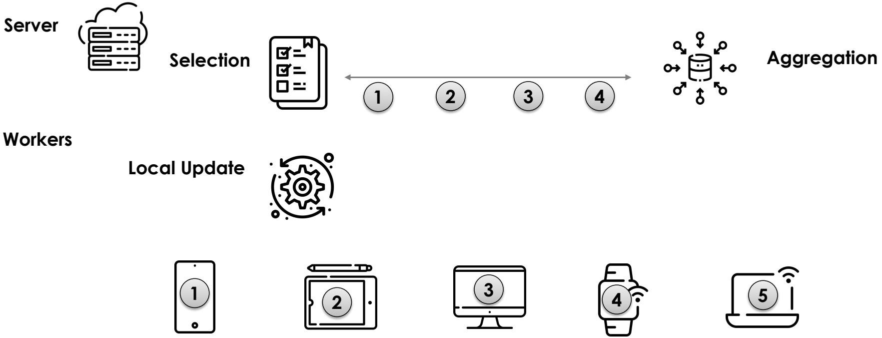

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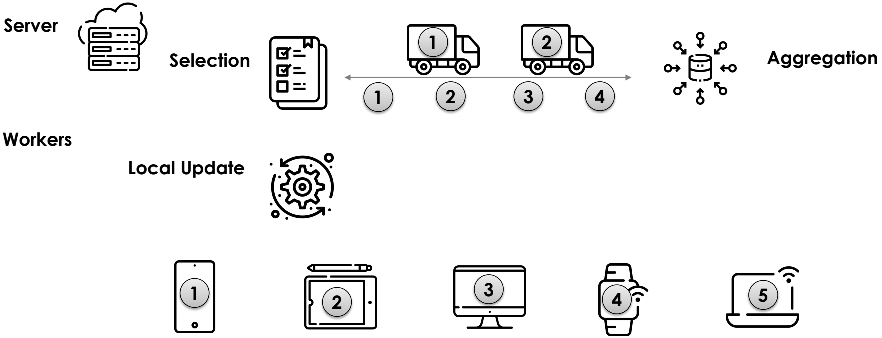

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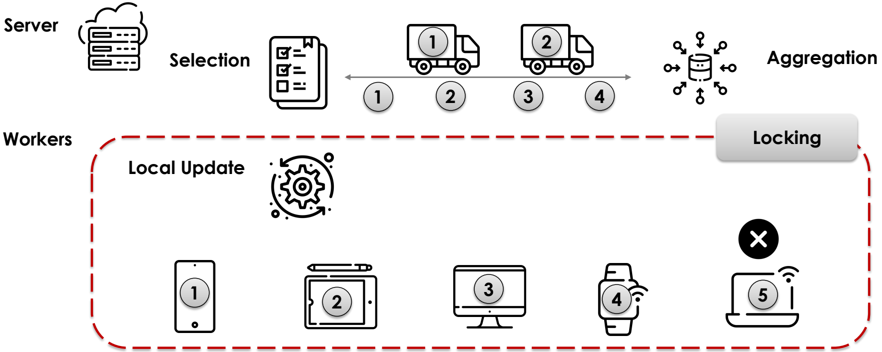

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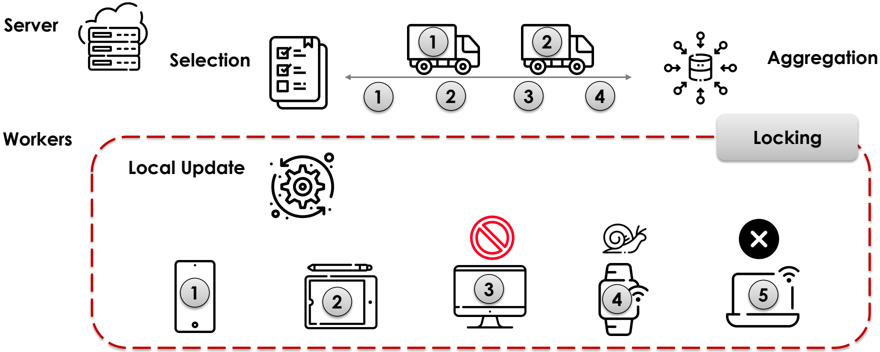

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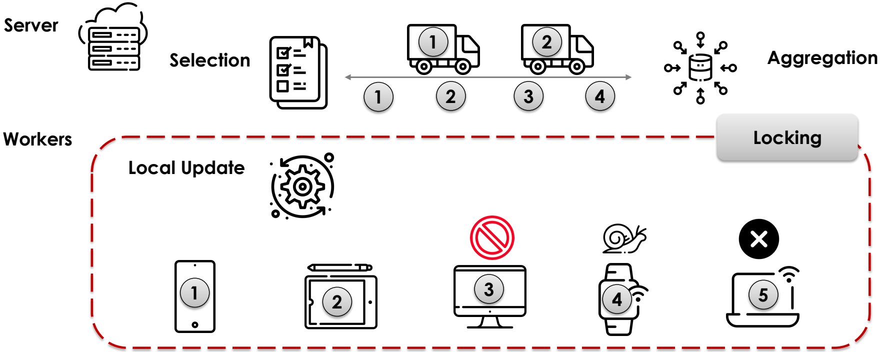

Our Solution: Anarchic Federated Learning

General Framework of AFL

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At the Server (Concurrently with Workers):

1. (Concurrent Thread) Collect local updates returned from the workers.
2. (Concurrent Thread) Aggregate the workers' results and update global model following some server-side optimization process.

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2. (Concurrent Thread) Aggregate the workers' results and update global model following some server-side optimization process.

At Each Worker (Concurrently with Server):

1. Once decided to participate in the training, pull the global model with current timestamp.
2. Perform (multiple) local update steps following some worker-side optimization process.
3. Return the result and the associated pulling timestamp to the server, with extra processing if so desired.

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The answers to all these questions are affirmative under AFL!

Fundamental Convergence Error Lower Bound

Theorem 1 (Convergence Error Lower Bound)

- *L-Lipschitz smoothness:* $\|\nabla f_i(\mathbf{x}) - \nabla f_i(\mathbf{y})\| \leq L\|\mathbf{x} - \mathbf{y}\|$
- *Unbiased stochastic gradients:* $\mathbb{E}[\nabla f_i(\mathbf{x}_i, \xi_k^i)] = \nabla f_i(\mathbf{x}_k)$
- *Bounded dissimilarity for non-i.i.d. data across workers:* $\mathbb{E}[\|\nabla f_i(\mathbf{x}_i, \xi_k^i) - \nabla f_i(\mathbf{x}_k)\|^2] \leq \sigma_L^2$ *and* $\mathbb{E}[\|\nabla f_i(\mathbf{x}_k) - \nabla f(\mathbf{x}_k)\|^2] \leq \sigma_G^2$

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- *Then, under general worker information arrival processes, there exists a loss function (and its stochastic gradient estimator) such that the output* $\tilde{\mathbf{x}}$ *of any state-less AFL algorithm satisfies:*

$$\mathbb{E}[\|\nabla f(\tilde{\mathbf{x}})\|^2] = \Omega(\sigma_G^2).$$

Anarchic FedAvg for Cross-Device (AFA-CD)

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At the Server (Concurrently with Workers):

1. In t-th round, collect m local updates $\{\mathbf{G}_i(\mathbf{x}_{t-\tau_{t,i}}), i \in \mathcal{M}_t\}$ from workers to form set $\mathcal{M}_t$, where $\tau_{t,i}$ is the random delay of worker i, $i \in \mathcal{M}_t$.
2. Aggregate and update: $\mathbf{G}_t = \frac{1}{m}\sum_{i\in\mathcal{M}_t}\mathbf{G}_i(\mathbf{x}_{t-\tau_{t,i}}), \quad \mathbf{x}_{t+1} = \mathbf{x}_t - \eta\mathbf{G}_t.$

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At Each Worker (Concurrently with Server):

1. Once decided to participate in the training, retrieve the parameter $\mathbf{x}_\mu$ from the server and its timestamp, set local model: $\mathbf{x}^i_{\mu,0} = \mathbf{x}_\mu$.
2. Choose a local step number $K_{t,i}$ (can be time-varying & device-dependent). Let $\mathbf{x}^i_{\mu,k+1} = \mathbf{x}^i_{\mu,k} - \eta_L \mathbf{g}^i_{\mu,k}$, where $\mathbf{g}^i_{\mu,k} = \nabla f_i(\mathbf{x}^i_{\mu,k}, \xi^i_{\mu,k})$, $k = 0, \ldots, K_{t,i} - 1$.
3. Sum & scale stochastic gradients: $\mathbf{G}_i(\mathbf{x}_\mu) = \frac{1}{K_{t,i}} \sum_{j=0}^{K_{t,i}-1} \mathbf{g}^i_{\mu,j}$. Return $\mathbf{G}_i(\mathbf{x}_\mu)$.

Convergence Performance of AFA-CD

Theorem 2 (AFA-CD w/ General Worker Info Arrival Processes)

- *Bounded maximum delay:* $\exists\ \tau := \max_{t \in [T], i \in \mathcal{M}_t} \{\tau_{t,i}\} < \infty$
- *L-Lipschitz smoothness:* $\|\nabla f_i(\mathbf{x}) - \nabla f_i(\mathbf{y})\| \leq L\|\mathbf{x} - \mathbf{y}\|$
- *Unbiased stochastic gradients:* $\mathbb{E}[\nabla f_i(\mathbf{x}_i, \xi_k^i)] = \nabla f_i(\mathbf{x}_k)$
- *Bounded dissimilarity for non-i.i.d. data across workers:* $\mathbb{E}[\|\nabla f_i(\mathbf{x}_i, \xi_k^i) - \nabla f_i(\mathbf{x}_k)\|^2] \leq \sigma_L^2$ *and* $\mathbb{E}[\|\nabla f_i(\mathbf{x}_k) - \nabla f(\mathbf{x}_k)\|^2] \leq \sigma_G^2$

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- *Then output sequence $\{\mathbf{x}_t\}$ generated by AFA-CD with general worker information arrival processes satisfies:*

$$\frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\|\nabla f(\mathbf{x}_t)\|^2 \le \frac{4(f_0 - f_*)}{\eta\eta_L T} + 4\big(\alpha_L \sigma_L^2 + \alpha_G \sigma_G^2\big),$$

where the constants α_L and α_G are problem-dependent constants.

Convergence Performance of AFA-CD

Corollary 3 (Linear Speedup to an Error Ball)

With a constant local step K, let $\eta_L = \frac{1}{\sqrt{T}}$, and $\eta = \sqrt{mK}$, the convergence rate of AFA-CD with general worker information arrival processes is:

$$\mathcal{O}\left(\frac{1}{\sqrt{mKT}}\right) + \mathcal{O}\left(\frac{\tau^2}{T}\right) + \mathcal{O}\left(\frac{K^2}{T}\right) + \mathcal{O}(\sigma_G^2).$$

Anarchic Federated Averaging for Cross-Silo (AFA-CS)

At the Server (Concurrently w/ Workers):

1. In $t-$th round, collect m local updates.
2. Update worker i's information in memory using the returned local update $\mathbf{G}_i$.
3. Aggregate and update: $\mathbf{G}_t = \frac{1}{M}\sum_{i\in[M]}\mathbf{G}_i, \quad \mathbf{x}_{t+1} = \mathbf{x}_t - \eta\mathbf{G}_t.$

At Each Worker (Concurrently w/ Server): Same as AFA-CD.

Convergence Performance of AFA-CS

Theorem 4

- *Bounded maximum delay:* $\exists\ \tau := \max_{t\in[T], i\in\mathcal{M}_t}\{\tau_{t,i}\} < \infty$
- *L-Lipschitz smoothness:* $\|\nabla f_i(\mathbf{x}) - \nabla f_i(\mathbf{y})\| \leq L\|\mathbf{x}-\mathbf{y}\|$
- *Choose* η *and* η_L *as such that* $6\eta_L^2(2K_{t,i}^2 - 3K_{t,i} + 1)L^2 \leq 1, \forall t, i,$ $(\frac{\eta\eta_L(M-m^{'})^2L^2\tau^2}{M^2} + \frac{L}{2})\eta\eta_L \leq \frac{1}{4}$, *and* $\frac{30L^2\eta_L^2\tau}{M}(\sum_{i\in[M]} K_{t,i}^2) \leq \frac{1}{4}$.

Convergence Performance of AFA-CS

Theorem 4

- *Bounded maximum delay:* $\exists\ \tau := \max_{t\in[T], i\in\mathcal{M}_t}\{\tau_{t,i}\} < \infty$
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- *Then, under same assumptions in Thm 2, output sequence $\{\mathbf{x}_t\}$ generated by AFA-CS under general worker information arrival processes satisfies:*

$$\frac{1}{T}\sum_{t=0}^{T-1}\|\nabla f(\mathbf{x}_t)\|^2 \leq \frac{4f(\mathbf{x}_0) - f(\mathbf{x}_T)}{\eta\eta_L T} + \alpha_L\sigma_L^2 + \alpha_G\sigma_G^2,$$

where the constants α_L and α_G are problem-dependent constants.

Convergence Performance of AFA-CS

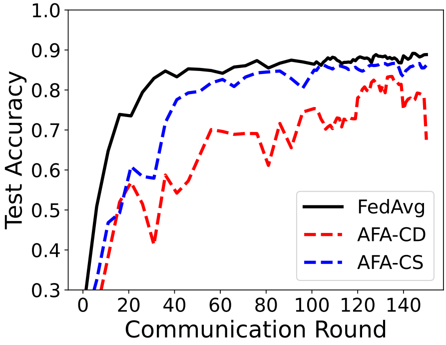
Corollary 5 (Linear Speedup)

Suppose a constant local step K, and let $\eta_L = \frac{1}{\sqrt{T}}$, and $\eta = \sqrt{MK}$, the convergence rate of the AFA-CS algorithm under general worker information arrival processes is:

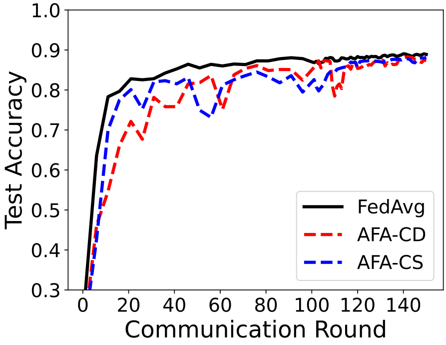
$$\mathcal{O}\left(\frac{1}{\sqrt{MKT}}\right) + \mathcal{O}\left(\frac{K^2}{MT}\right) + \mathcal{O}\left(\frac{\tau^2 (M - m')^2}{TM^2}\right).$$

Numerical Results

- Logistic regression test accuracy: 10-worker, non-i.i.d. MNIST dataset



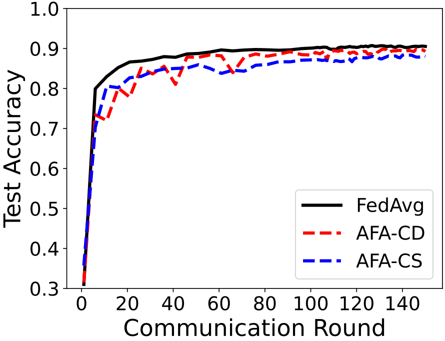
Non-i.i.d. index $p = 1$



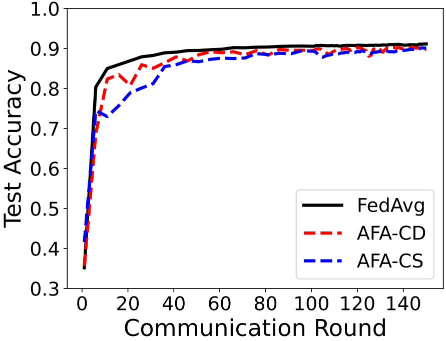
Non-i.i.d. index $p = 2$

Numerical Results

- Test accuarcy for logistic regression on non-i.i.d. MNIST dataset



Non-i.i.d. index $p = 5$



Non-i.i.d. index $p = 10$

Conclusion

- Proposed a new federated learning paradigm – Anarchic Federated Learning (AFL)
  - From server-centric to worker-spontaneous
  - Loose server-worker coupling
  - The workers can learn anytime in anyway they want

- Provided basic understandings on convergence conditions under AFL

- Showed that the highly desirable linear speedup effect remains achievable under AFL

Thank You!

Discussions: Poster Session 3, Thu 7/21 6 p.m. – 8 p.m. EDT, Hall E #711