# **FL under intermittent and** correlated client availability









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#### Clients $k = 1, \ldots, K$









# Dataset $D_k = \{\xi_{kl}\}_{l=1}^{n_k}$







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#### Global model $oldsymbol{w} \in \mathbb{R}^d$







Clients  $k = 1, \ldots, K$ 





# Solve the optimization problem $\min_{\boldsymbol{w}} F(\boldsymbol{w}) = \sum_{k=1}^{K} \alpha_k F_k(\boldsymbol{w})$

where

$$F_k(\boldsymbol{w}) = rac{1}{n_k} \sum_{l=1}^{n_k} \ell(\boldsymbol{w}, \xi_{kl})$$











#### Solve the optimization problem

$$\min_{\boldsymbol{w}} F(\boldsymbol{w}) = \sum_{k=1}^{K} \alpha_k F_k(\boldsymbol{w})$$

$$\uparrow \boldsymbol{\alpha} : \text{importance}$$

where

$$F_k(\boldsymbol{w}) = \frac{1}{n_k} \sum_{l=1}^{n_k} \ell(\boldsymbol{w}, \xi_{kl})$$



#### weights



















 $A_t$ : set of active clients at time t for  $t \in \{0, ..., T - 1\}$  do:

(1)









































(4) 
$$w_{t+1,0} = w_{t,0} + \sum_{k \in A_t} q_k (w_{t,E}^k - q_k)$$
  
 $q$ : aggregation weights















### Intermittent and Correlated Client Availability

#### • Intermittent:

clients are not always active

• Correlated:

the activity of a client is correlated over time the activity is correlated across clients



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#### **Intermittent:**

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**Correlated:** 

the activity of a client is correlated over time the activity is correlated across clients

# Contributions

Understanding the effects on FL training

2. Client sampling and aggregation strategies



#### Main assumption

- $A_t$ : set of active clients at time t
- Clients' activities follow a discrete-time Markov chain  $(A_t)_{t\geq 0}$ with transition matrix P and stationary distribution  $\pi$



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 $k \in [K]$ 



#### Contributions

#### 1. Understanding the effects on FL training

#### 2. Client sampling and aggregation strategies



### The effect of Intermittent Availability

Under intermittent availability  $\pi$ , FedAvg converges to a biased objective  $F_B(w)$ 

$$F_B(\boldsymbol{w}) := \sum_{k=1}^{K} p_k F_k(\boldsymbol{w}), \ p_k = rac{\pi_k}{\langle \pi, p \rangle}$$
 $p: ext{biased importance}$ 

 $\frac{\langle \boldsymbol{q}_k}{\langle \boldsymbol{q}_k \rangle} \neq F(\boldsymbol{w}) := \sum_{k=1}^K \alpha_k F_k(\boldsymbol{w})$  $\alpha$  : true importance





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Unbiased aggregation strategy:  $\boldsymbol{q} \propto \frac{\alpha}{-}$  $\pi$ 

 $rac{k}{k} rac{q_k}{\langle q \rangle} 
eq F(w) := \sum_{k=1}^K \alpha_k F_k(w)$  $\alpha$  : true importance





#### The effect of Correlated Availability

# $\mathbb{E}[F_B(\bar{\boldsymbol{w}}_{T,0}) - F_B^*] \leq \mathcal{O}\left(\frac{1}{\sqrt{T}} \cdot \frac{1}{\ln(1/\lambda(\boldsymbol{P}))}\right)$

where T is the total communication rounds and  $\lambda(P)$  quantifies the correlation



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#### where T is the total communication rounds and $\lambda(P)$ quantifies the correlation

Correlation slows down the convergence



#### The effect of Intermittent + Correlated Availability



where  $p_k = \frac{\pi_k q_k}{\langle \boldsymbol{\pi}, \boldsymbol{q} \rangle}$ ,  $d_{TV}(\boldsymbol{\alpha}, \boldsymbol{p}) = \frac{1}{2} \sum_{k=1}^{\kappa} |\alpha_k - p_k|$ , and  $\Gamma = \max_{k \in [\kappa]} \{F_k(\boldsymbol{w}_B^*) - F_k^*\}$ 



#### The effect of Intermittent + Correlated Availability

$$\epsilon(\boldsymbol{q}) \coloneqq F(\boldsymbol{w}_{T,0}) - F^* \leq \underbrace{\mathcal{O}\left(F_B(\boldsymbol{w}_{T,0}) - F_B^*\right)}_{\coloneqq = \epsilon_{\text{opt}}(\boldsymbol{q})} + \underbrace{\mathcal{O}\left(d_{TV}^2(\alpha, \boldsymbol{p})\Gamma\right)}_{\coloneqq = \epsilon_{\text{bias}}(\boldsymbol{q})}$$
  
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• The convergence of the true objective F(w) depends on q

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$$\sum_{k=1}^{\kappa} |\alpha_k - p_k|, \text{ and } \Gamma = \max_{k \in [\kappa]} \{F_k(\boldsymbol{w}_B^*) - F_k^*\}$$

• The convergence of the true objective F(w) depends on q• Propose a client aggregation strategy that minimizes  $\epsilon(\boldsymbol{q})$ 



#### Contributions

#### 1. Understanding the effects on FL training

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q

- minimize  $\epsilon_{opt}(\boldsymbol{q}) + \epsilon_{bias}(\boldsymbol{q})$
- subject to  $\boldsymbol{q} \geq 0, \|\boldsymbol{q}\|_1 = Q$



q

• The solution of this optimization problem suggests:

#### Guidelines

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q

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#### Guidelines

A. Some clients can be excluded from training, i.e., receive  $q_k^* = 0$ 

- minimize  $\epsilon_{opt}(\boldsymbol{q}) + \epsilon_{bias}(\boldsymbol{q})$
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The solution of this optimization problem suggests:

#### Guidelines

A. Some clients can be excluded from training, i.e., receive  $q_k^* = 0$ 

B. Exclude clients with low availability  $\pi_k$  and large correlation  $\lambda(P_k)$ 

- minimize  $\epsilon_{opt}(\boldsymbol{q}) + \epsilon_{bias}(\boldsymbol{q})$
- subject to  $\boldsymbol{q} \geq 0$ ,  $\|\boldsymbol{q}\|_1 = Q$



The solution of this optimization problem suggests:

#### Guidelines

- A. Some clients can be excluded from training, i.e., receive  $q_k^* = 0$
- B. Exclude clients with low availability  $\pi_k$  and large correlation  $\lambda(P_k)$
- C. Assign aggregations  $q_k = \alpha_k / \pi_k$  to the included clients

- minimize  $\epsilon_{opt}(\boldsymbol{q}) + \epsilon_{bias}(\boldsymbol{q})$
- subject to  $\boldsymbol{q} \geq 0$ ,  $\|\boldsymbol{q}\|_1 = Q$



(1) The server











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• Estimate  $\hat{\pi}^{(t)}, \hat{\lambda}^{(t)}$ 











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- Initialize  $\boldsymbol{q}^{(t)} = rac{lpha}{\hat{\pi}^{(t)}}$





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- Estimate  $\hat{\pi}^{(t)}, \hat{\lambda}^{(t)}$
- Initialize  $oldsymbol{q}^{(t)} = rac{lpha}{\hat{\pi}^{(t)}}$
- Compute  $\hat{\epsilon}^{(t)}(\boldsymbol{q})$





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- (2) For k in [K], starting from the"Less Available, Correlated" clients:
  - Try  $q_k = 0$
  - Compute  $\hat{\epsilon}^{\text{new}}$
  - If  $\hat{\epsilon}^{\text{old}} \hat{\epsilon}^{\text{new}} \ge 0$ :

Exclude client k





(3) Only the clients  $\{k \in A_t; q_k^{(t)} > 0\}$  train





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#### **Experimental setting**

• Population of K=24 clients, divided in:





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#### **Experimental results**

We compare CA-Fed with the Unbiased baseline



#### CA-Fed excludes clients from training without performance drop



### Conclusions

- Introducing a correlation process in the modeling of FL population
- First convergence analysis under intermittent and correlated client availability
- Adaptively excluding less available and correlated clients can be effective
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## Thank you for your attention!