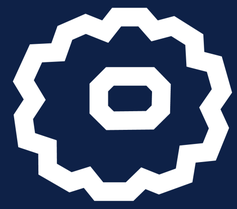

Federating Large Language Models from Scratch

On the opportunities and challenges of the federated pre-training of large language models

Lorenzo Sani, 7th October 2024 @ Alan Turing Institute - “*Robots in Disguise*: Fundamental AI Reading Group”

Federated Learning

Privacy and more...

"***Federated learning*** *is a machine learning setting where multiple entities (clients) collaborate in solving a machine learning problem, under the coordination of a central server or service provider. Each client's raw data is stored locally and not exchanged or transferred; instead, focused updates intended for immediate aggregation are used to achieve the learning objective."*

Algorithm 1 `FederatedAveraging`. The K clients are indexed by k; B is the local minibatch size, E is the number of local epochs, and η is the learning rate.

Server executes:

initialize w_0

for each round $t = 1, 2, \dots$ **do**

$m \leftarrow \max(C \cdot K, 1)$

$S_t \leftarrow$ (random set of m clients)

for each client $k \in S_t$ **in parallel do**

$w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$

$m_t \leftarrow \sum_{k \in S_t} n_k$

$w_{t+1} \leftarrow \sum_{k \in S_t} \frac{n_k}{m_t} w_{t+1}^k$ *// Erratum*[4]

ClientUpdate(k, w): *// Run on client k*

$\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)

for each local epoch i from 1 to E **do**

for batch $b \in \mathcal{B}$ **do**

$w \leftarrow w - \eta \nabla \ell(w; b)$

return w to server

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[1] Communication-Efficient Learning of Deep Networks from Decentralized Data. (McMahan, H.B., et al., '17)
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- Protecting the privacy
  - clients and/or server
- Leaking privacy from clients' updates
- Pseudo-gradient vs model updates
- Hyperparameters and trade-offs

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From Distributed to Federated

The LLM pre-training example

Algorithm 1 Distributed Data Parallel (DDP) Training Algorithm

Require: N: Number of devices (workers), f_θ: Model with parameters θ
Require: T: Number of epochs
Require: $\mathcal{D}$: Dataset partitioned across devices $\mathcal{D}_i$ where $i \in \{1, 2, \ldots, N\}$
Require: `RingAllReduce`: All-reduce operation to aggregate across devices on a ring
Require: `Opt`: Optimizer for updating θ with gradients

Initialize:
    Randomly initialize model parameters θ_0 on each device
for $t = 1$ to T **do**

    Step 1: Parallel Local Training
    for each device $i \in \{1, 2, \ldots, N\}$ **in parallel do**
        Compute local mini-batch loss $\mathcal{L}_i(\theta_{t-1}, \mathcal{D}_i)$
        Compute local gradients $\nabla_{\theta_{t-1}} \mathcal{L}_i(\theta_{t-1})$

    Step 2: Distributed `RingAllReduce` Gradient Aggregation
    $\nabla_{\theta_{t-1}} \mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \nabla_{\theta_{t-1}} \mathcal{L}_i$
    Each device now possesses the global gradient $\nabla_{\theta_{t-1}} \mathcal{L}$

    Step 3: Parallel Model Update
    for each device $i \in \{1, 2, \ldots, N\}$ **in parallel do**
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Output: Trained model parameters θ_T

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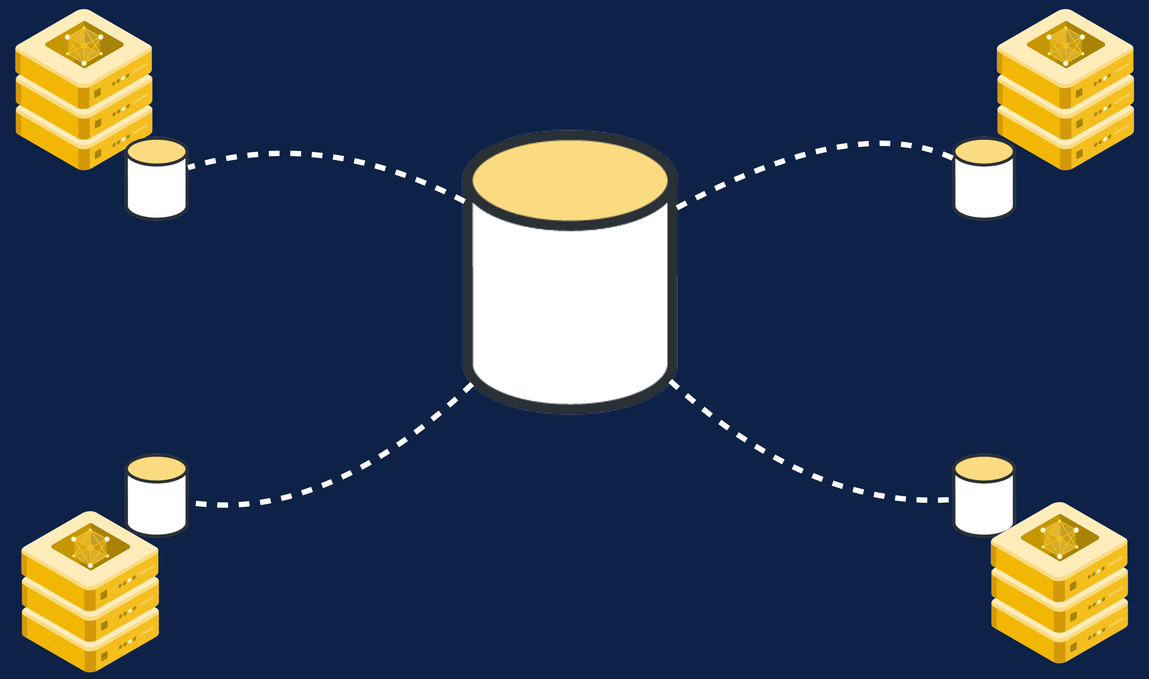

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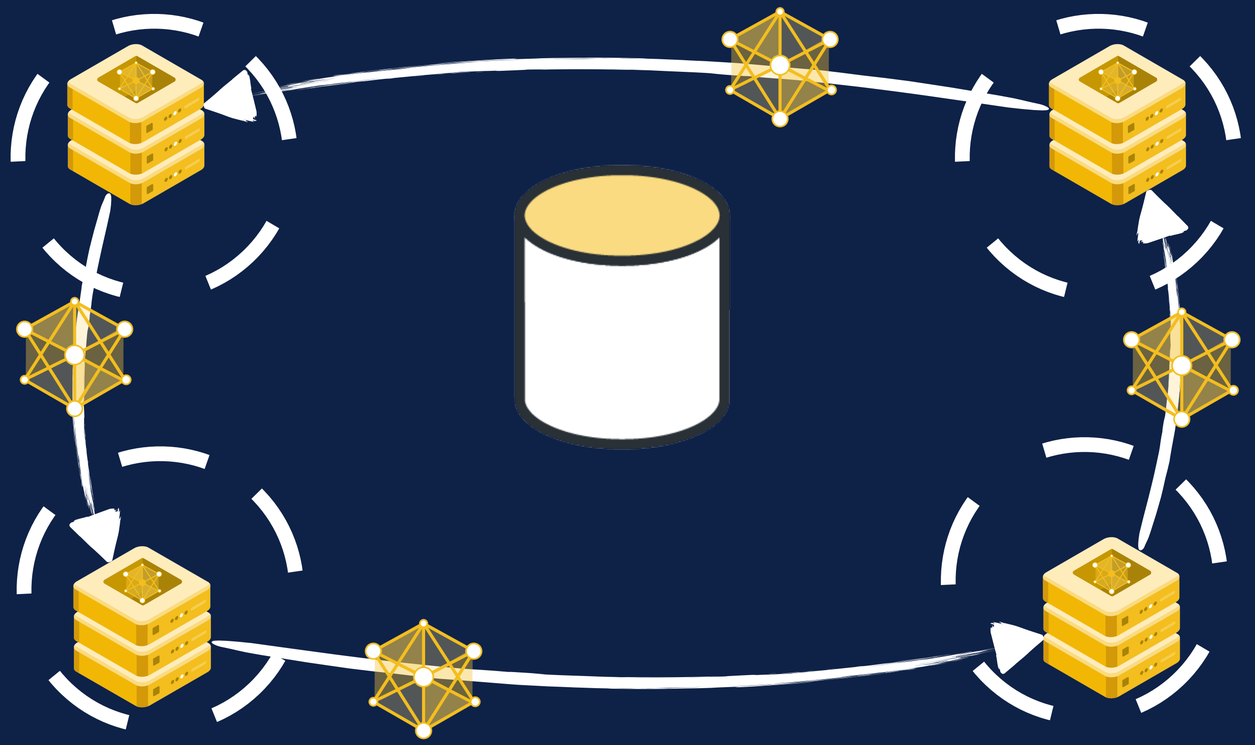

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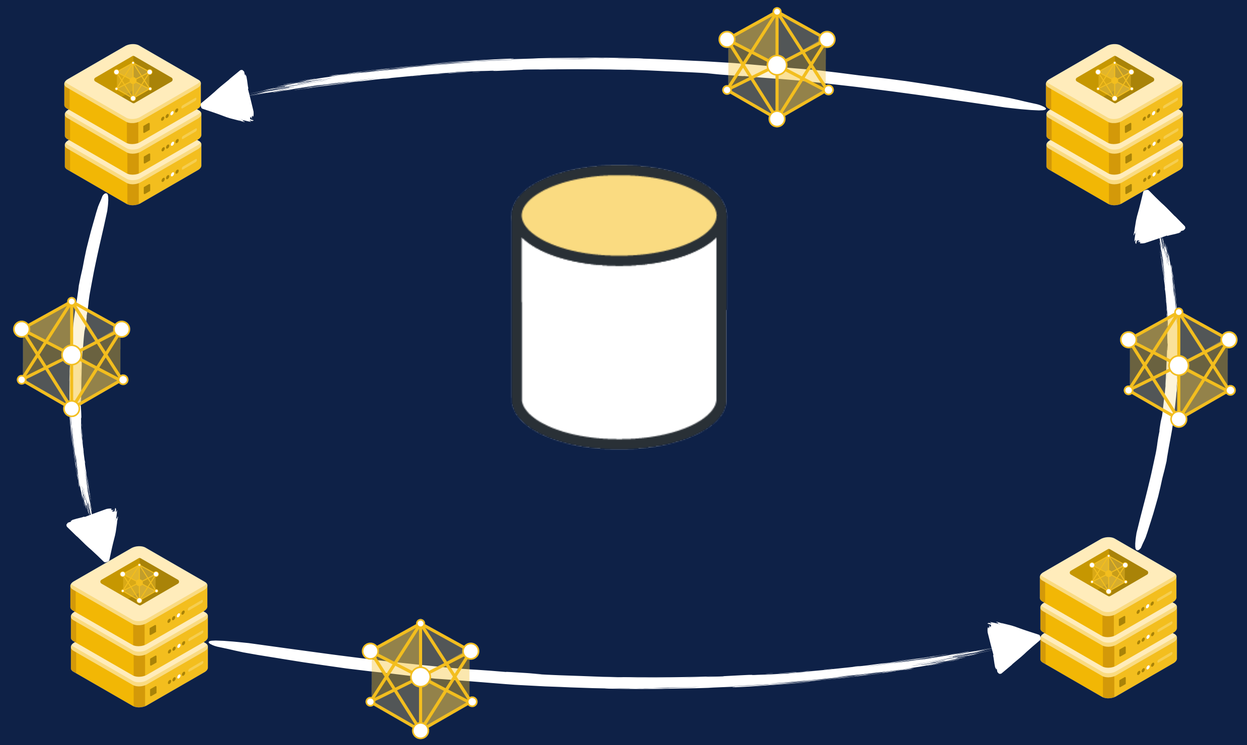

From Distributed to Federated

The LLM pre-training example

Algorithm 2 Cross-silo Federated Learning (FL) Algorithm

Require: N: Number of clients, f_θ: Model with parameters θ
Require: T: Number of federated rounds, K: Number of local steps
Require: $\{\mathcal{D}_i\}$: Federated dataset, i.e., a set of private $\mathcal{D}_i$, $i \in \{1, \ldots, N\}$
Require: `ClientOpt`: local client optimizer
Require: `ServerOpt`: server optimizer

Initialize:
  Randomly initialize global model parameters θ_0 on the server
for $t = 1$ to T **do**

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  for each client $i \in \{1, 2, \ldots, N\}$ **in parallel do**
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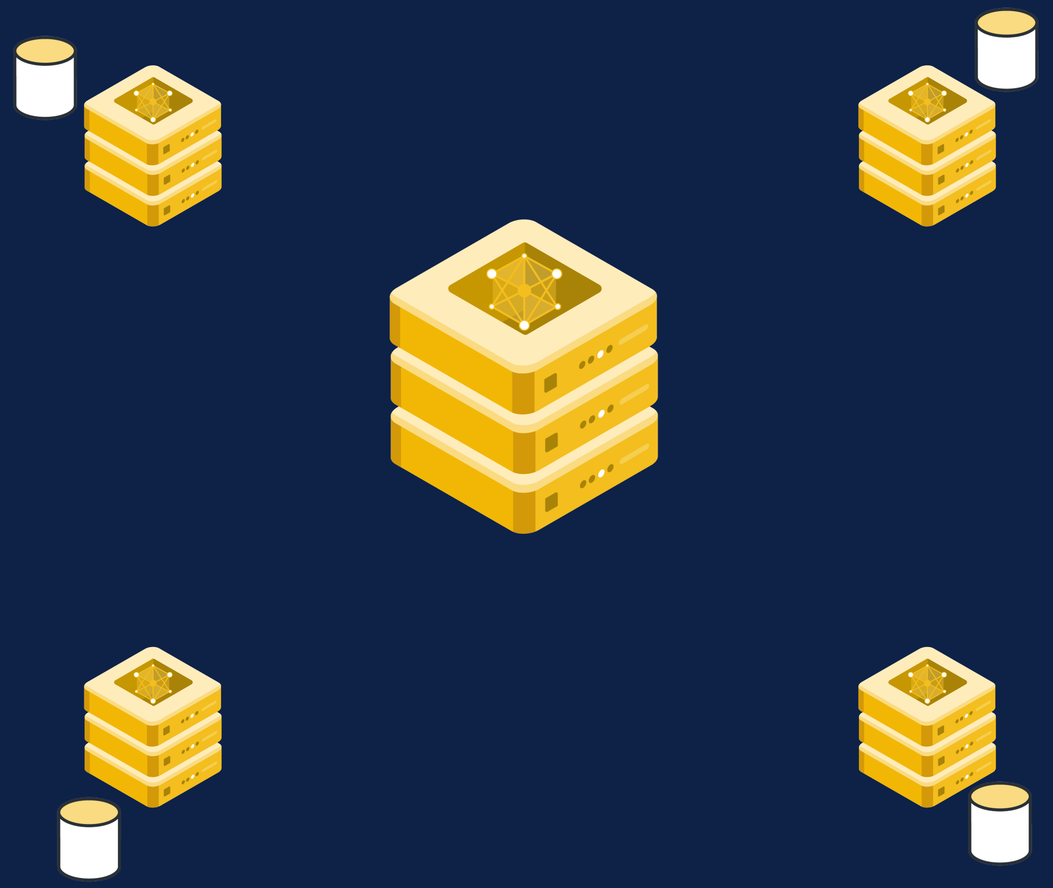

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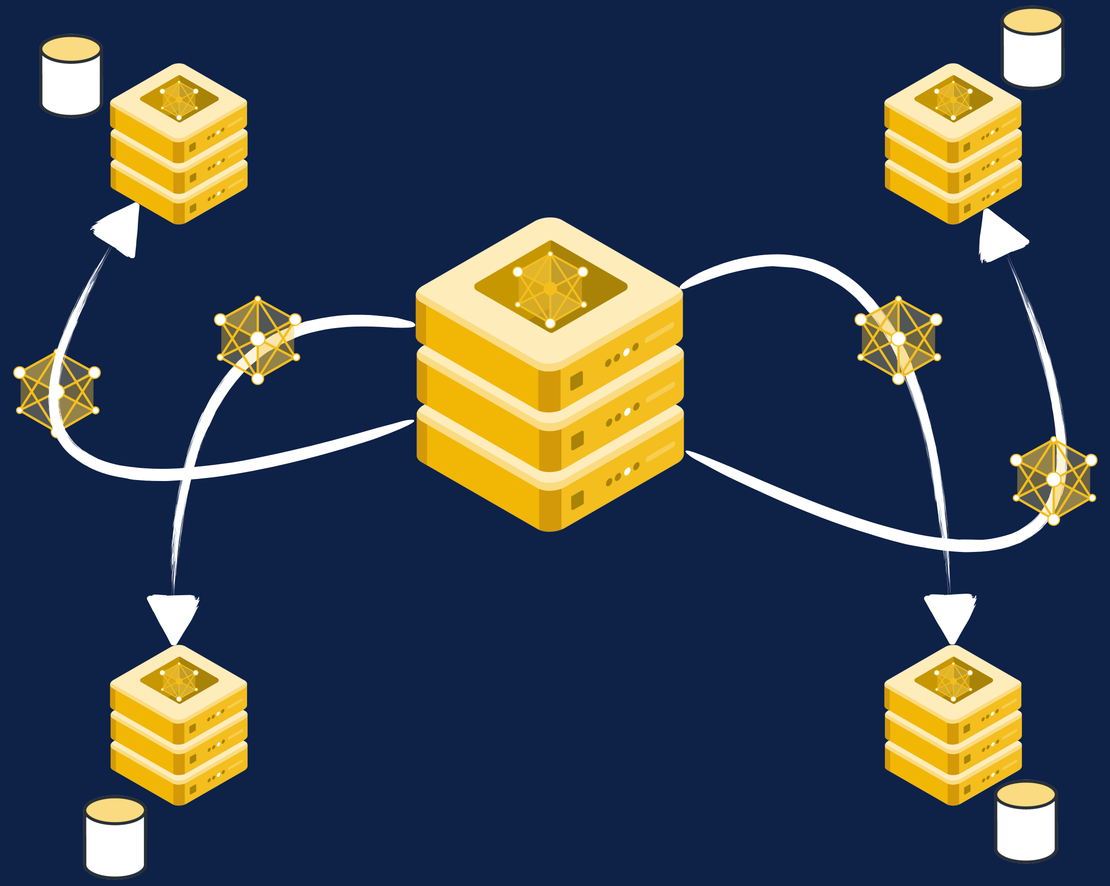

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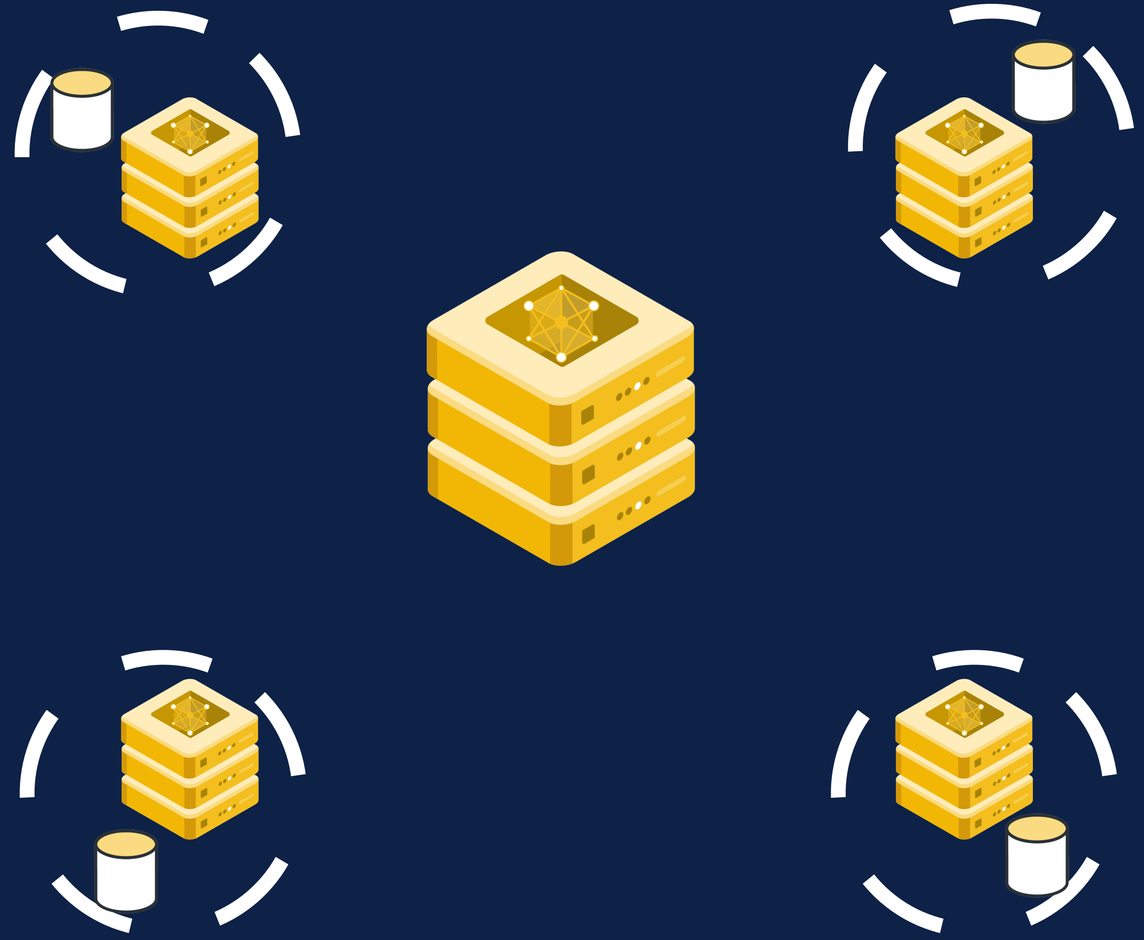

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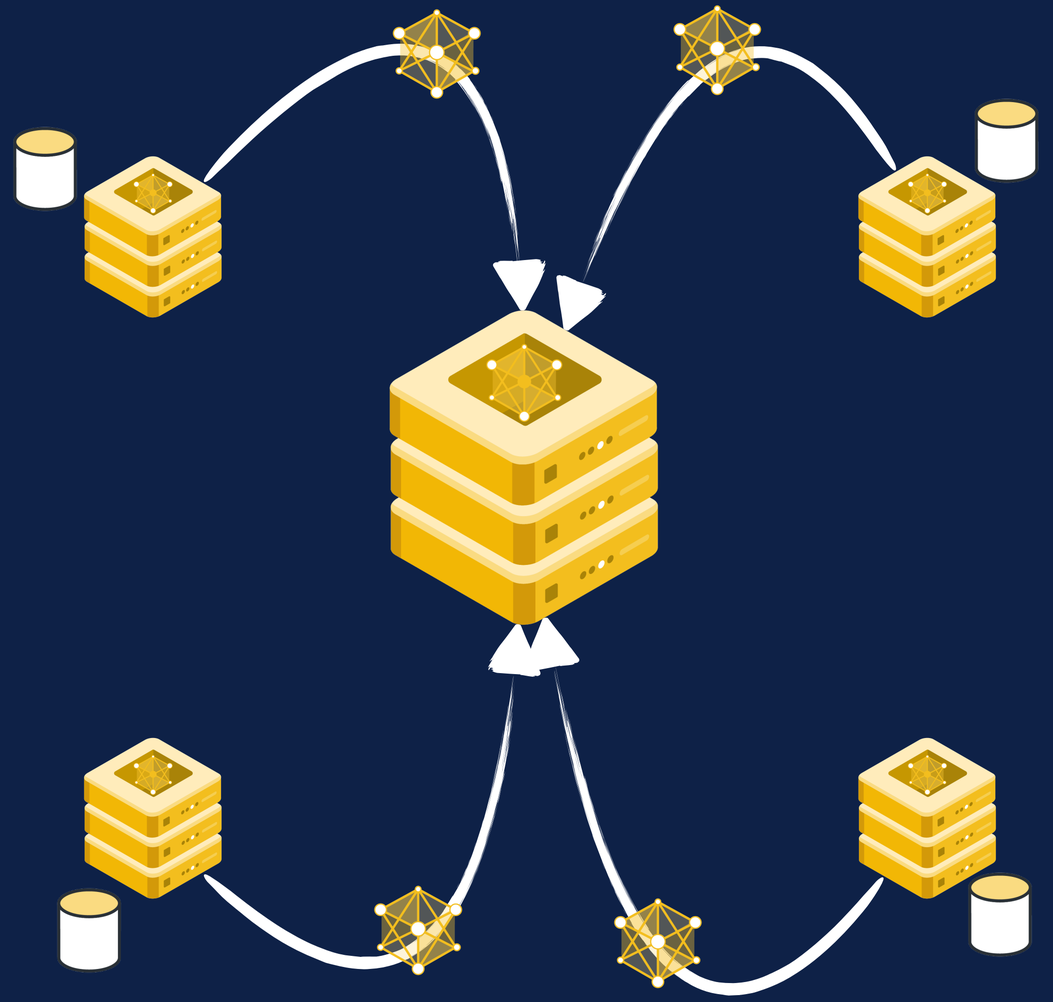
Output: Trained model parameters θ_T



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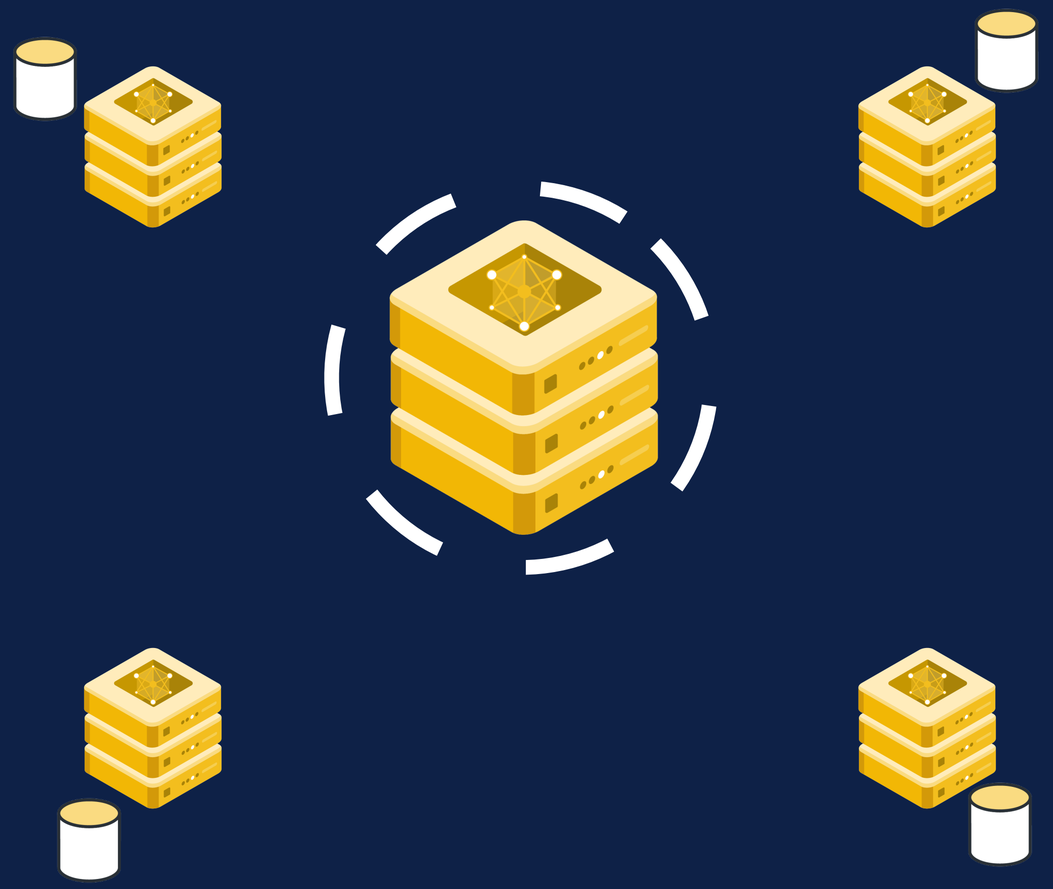

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DDP

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Initialize:
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Cross-silo FL

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    Step 2: Parallel Local Training
    for each client $i \in \{1, 2, \ldots, N\}$ **in parallel do**
        $\omega_{i,0} \leftarrow \theta_{t-1}$
        for each local iteration $k \in \{1, 2, \ldots, K\}$ **do**
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            Compute local gradients $\nabla_{\omega_{i,k-1}} \mathcal{L}_i(\omega_{i,k-1})$
            $\omega_{i,k} \leftarrow \texttt{ClientOpt}(\omega_{i,k-1}, \nabla_{\omega_{i,k-1}} \mathcal{L}_i(\omega_{i,k-1}))$
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From Distributed to Federated

DDP

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Cross-silo FL

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Can FL be useful to LLMs?

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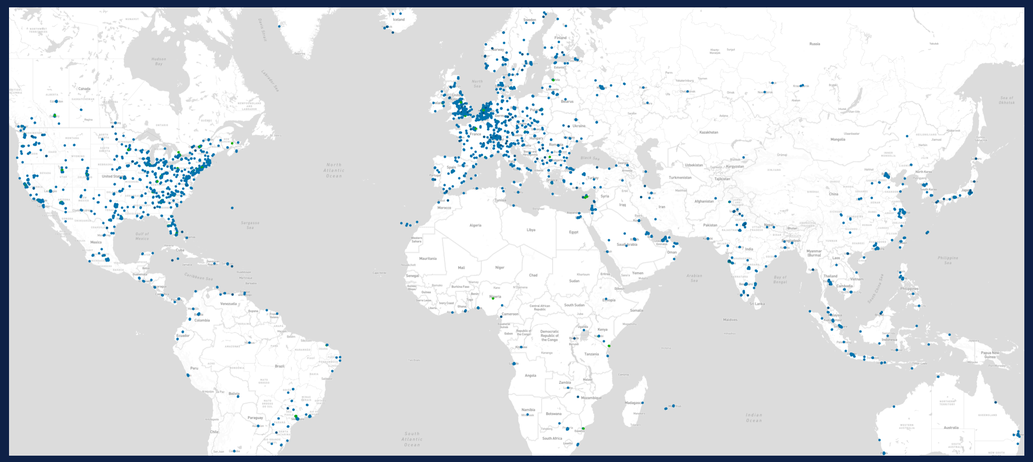

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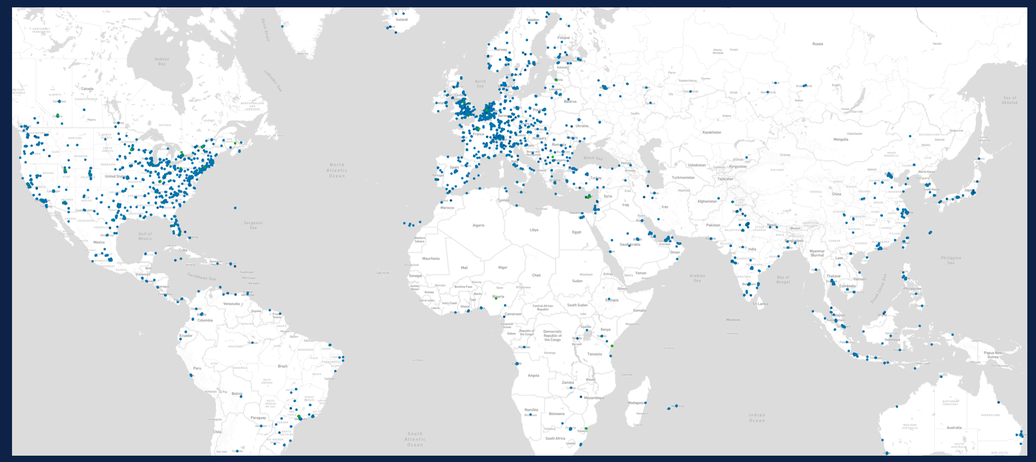

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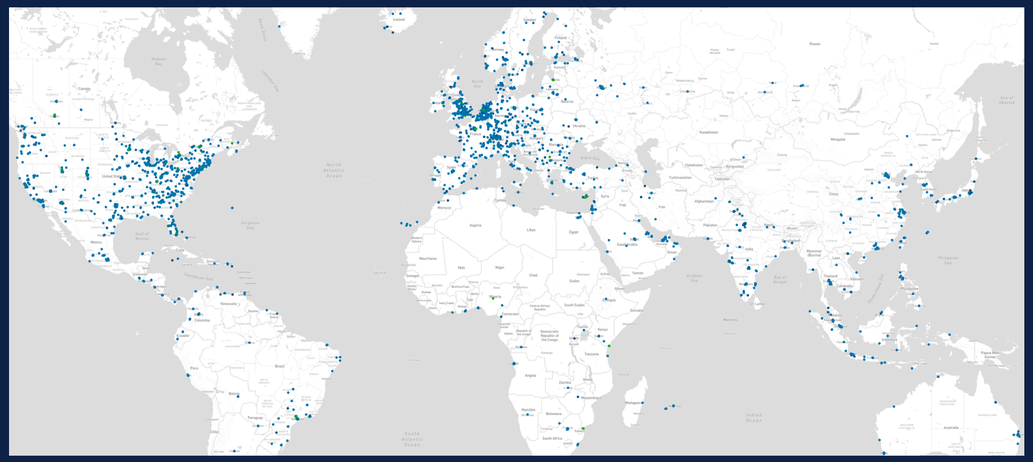

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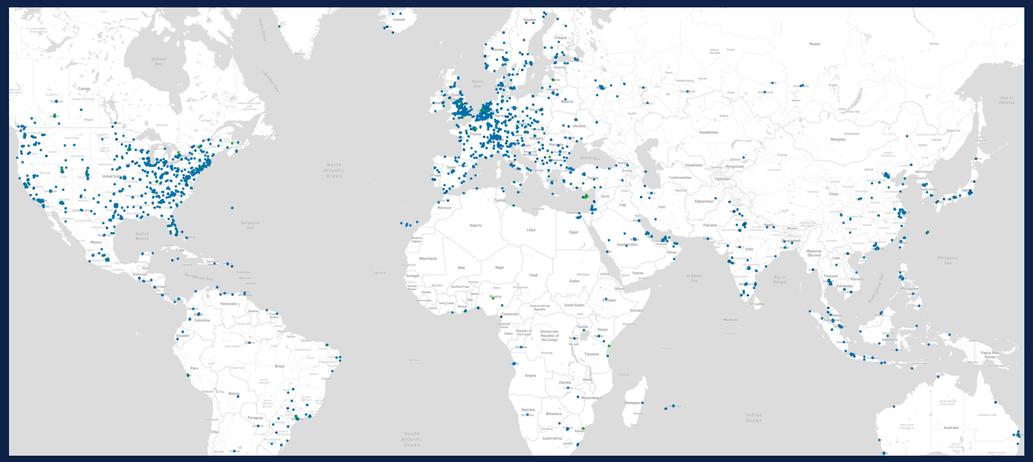

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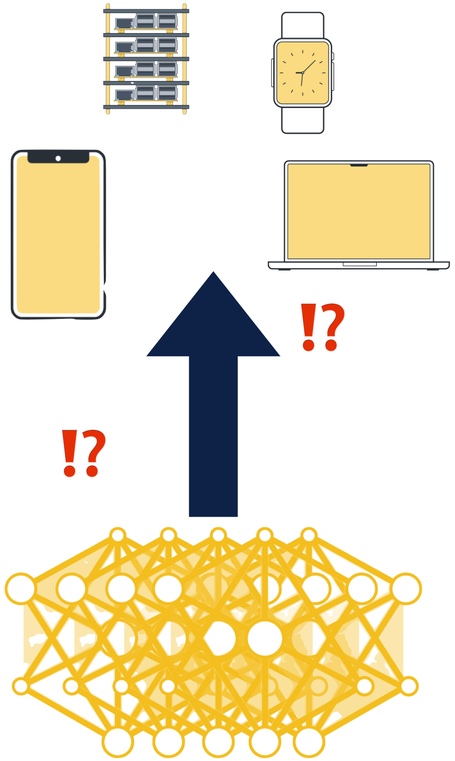

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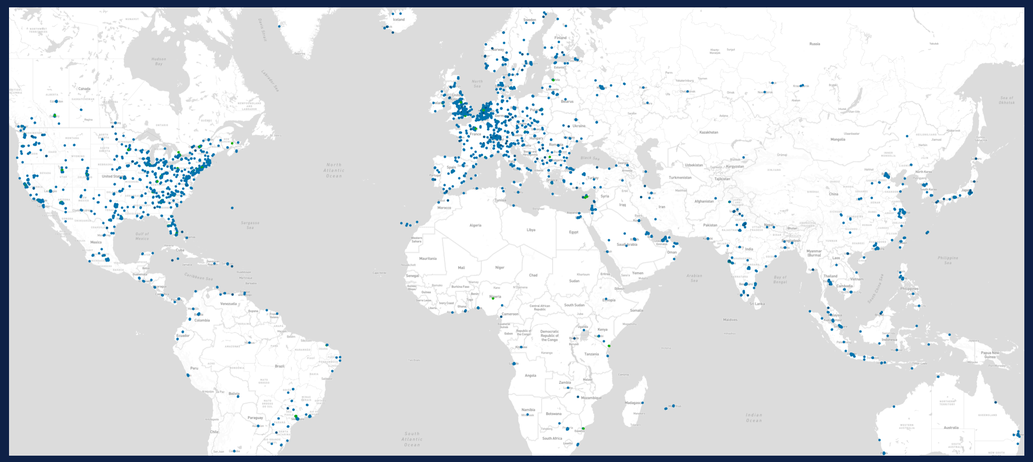

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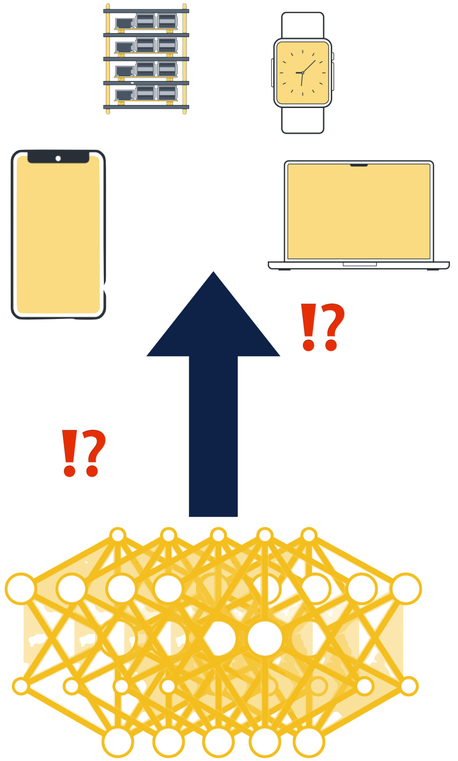

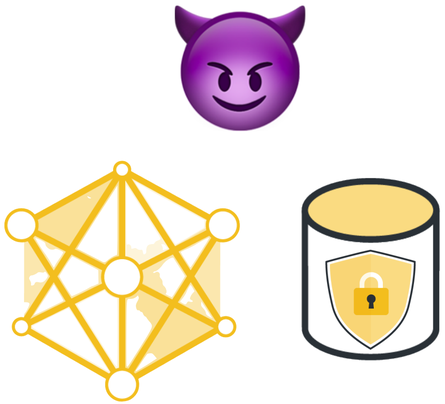

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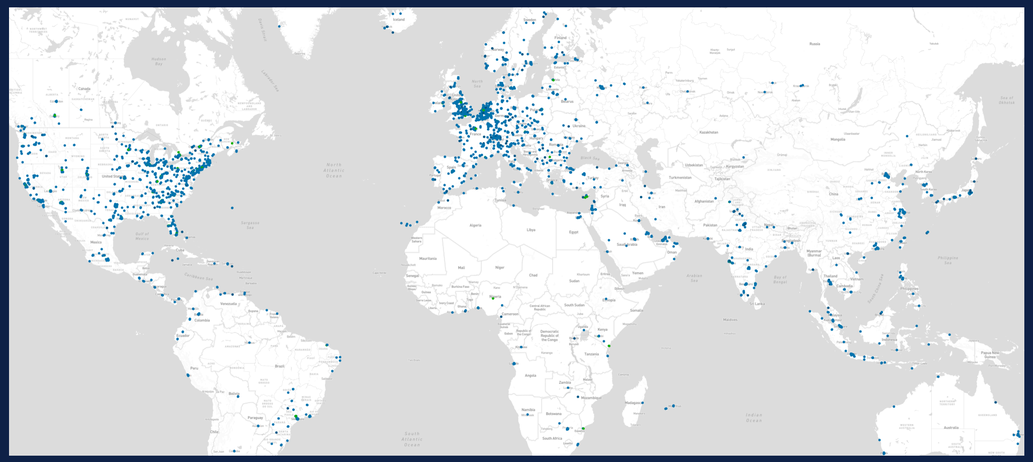

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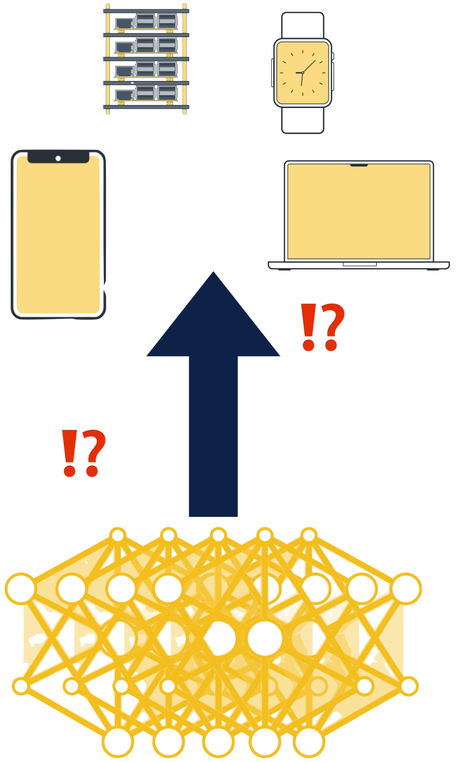

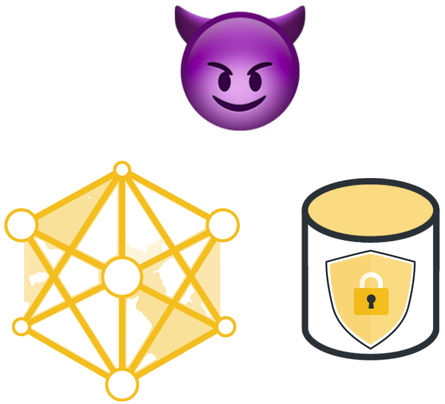

challenges and opportunities!

More motivations

Limitations of LLMs scaling laws [3,4] in context

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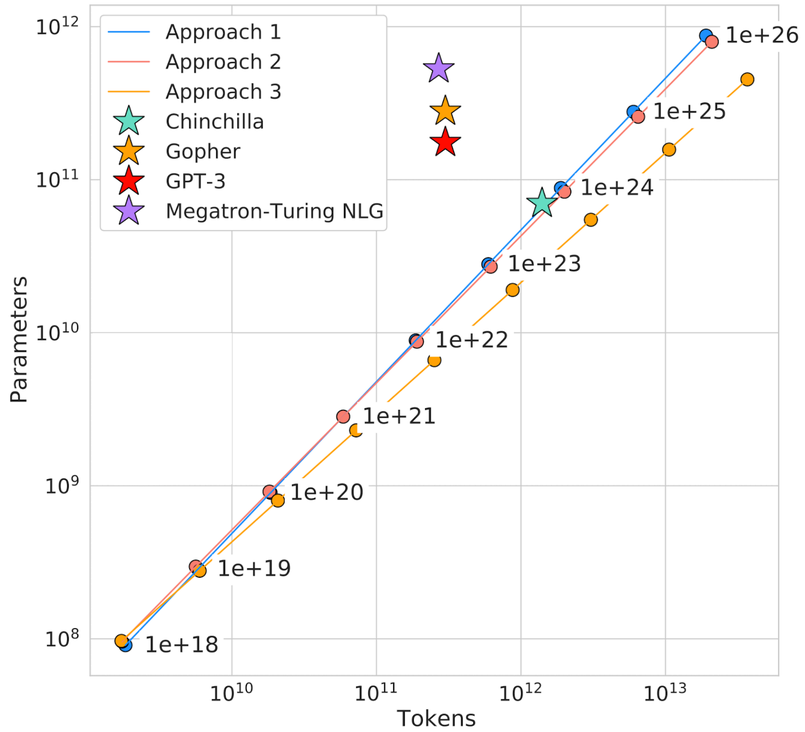

[3] Training Compute-Optimal Large Language Models (Hoffmann, J., et al., '22)

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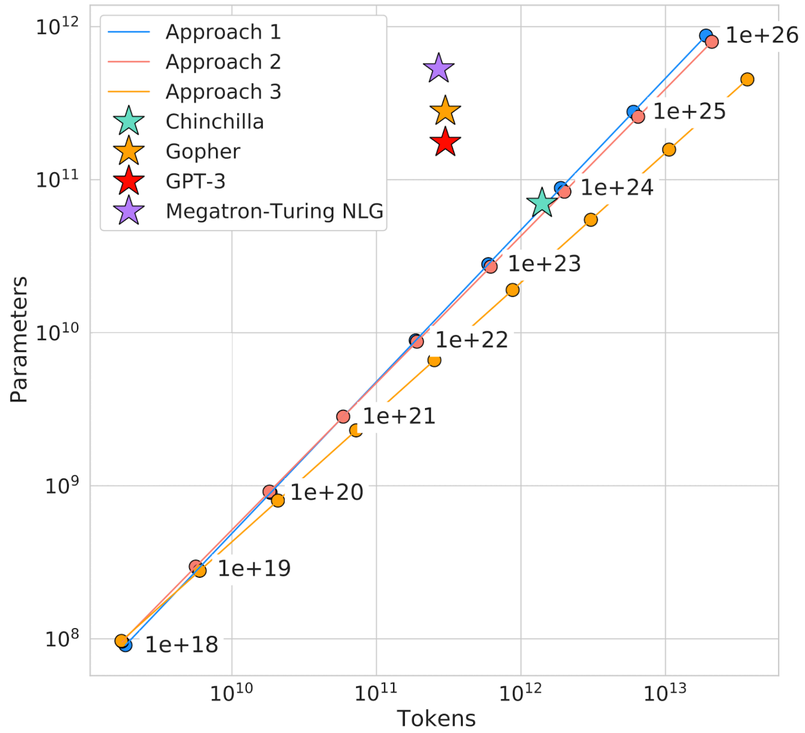

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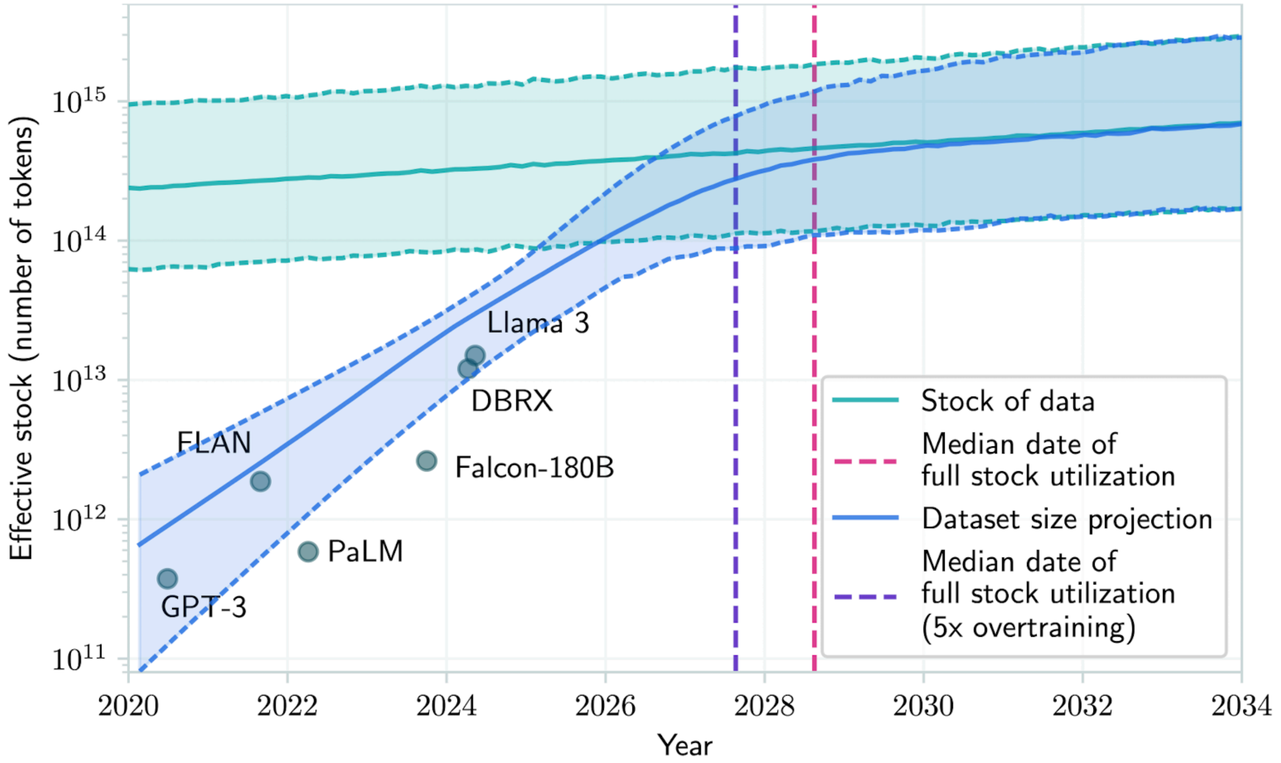

[5] Will we run out of data? An analysis of the limits of scaling datasets in Machine Learning (Villalobos et al., '22)

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[4] Beyond Chinchilla-Optimal: Accounting for Inference in Language Model Scaling Laws (Sardana, L., et al., '24)
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LLMs and FL - Related Works

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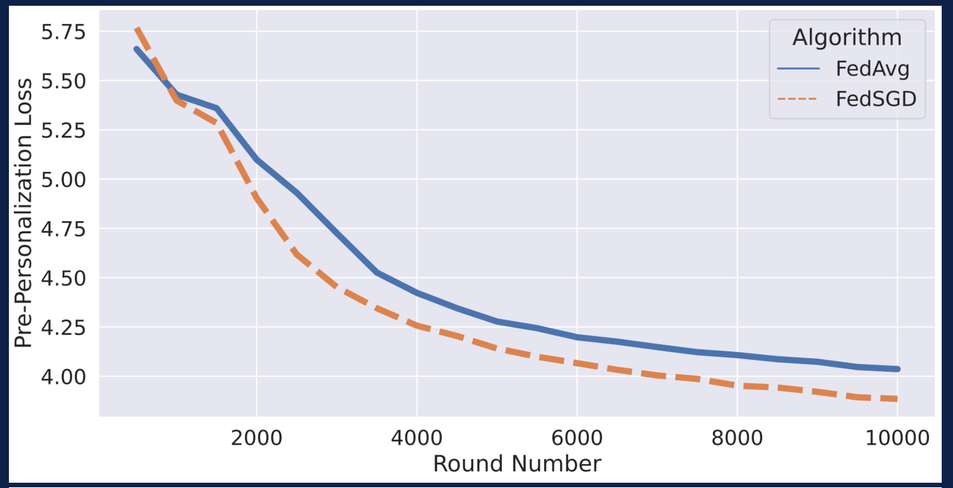
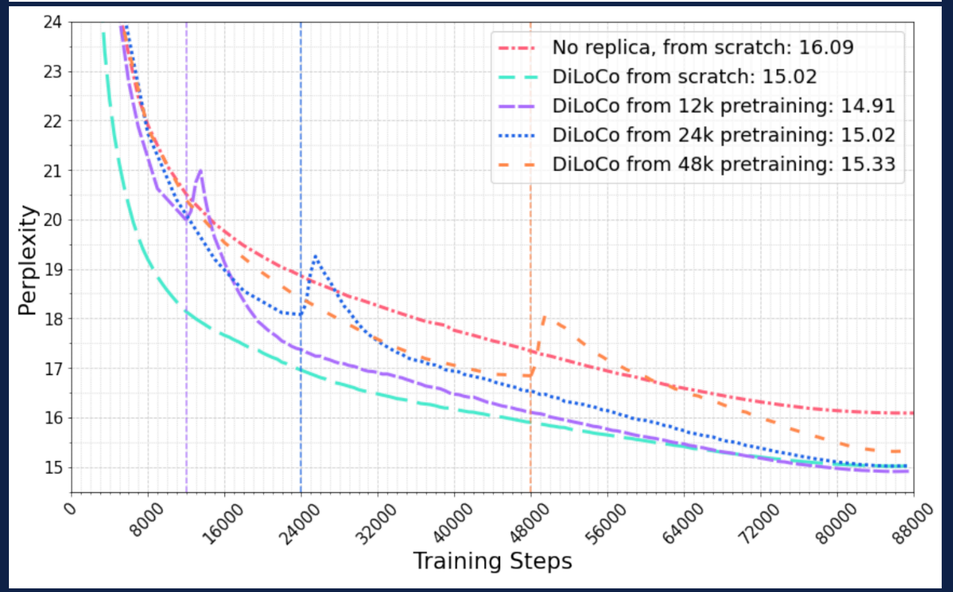
- **Pre-training LLMs in federated settings**
  ⇒ Dataset Grouper [6]
  ⇒ DiLoCo-DiPaCo (semi-federated) [7,8]





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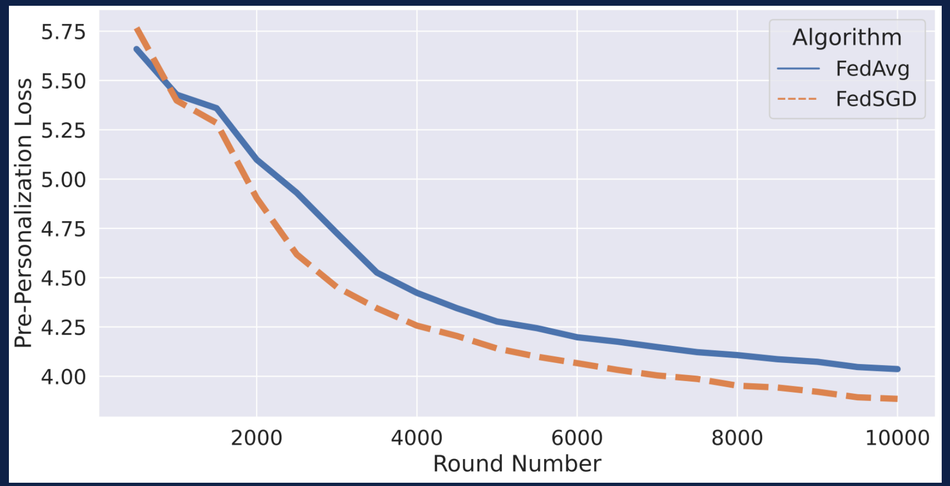
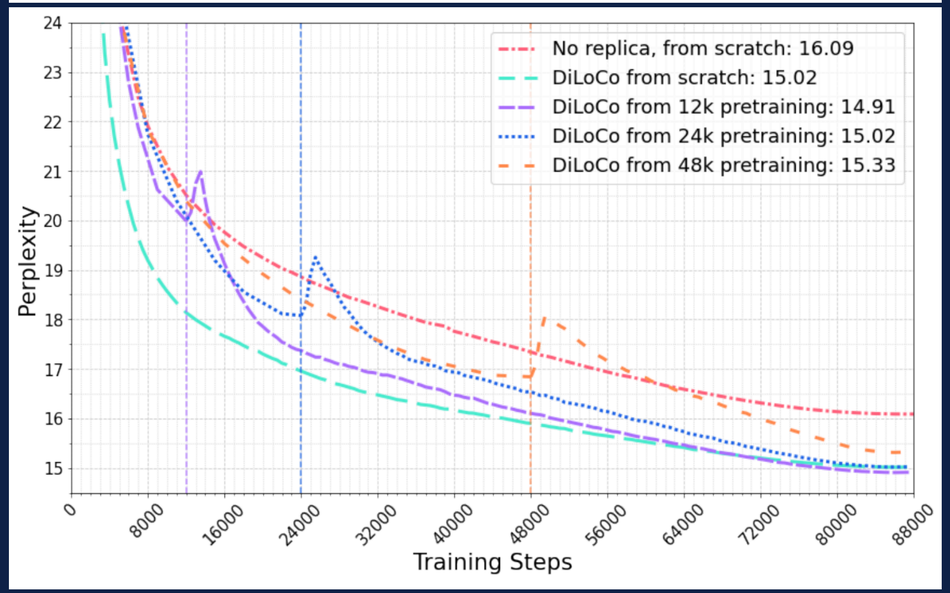
- Federated Fine-tuning of LMs
  ⇒ FL > centralized | some heterogeneous settings

- Federated PEFT and Federated LoRA
  ⇒ communication and computation efficiency

- Federated Prompt Tuning
  ⇒ improve generalization





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!?

FL scale like centralized

!?

!?

model the token-to-parameter optimality in FL

Burning question?

FL and architecture-wise optimizations (MoEs, split learning, etc.)

!?

!?

multilinguality
meta learning
plasticity

!?

FL scale like centralized

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Photon's Fantastic Four [7]

The design principles for obtaining an inclusive FL system for LLM pre-training

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- data >> compute: data-rich but compute-poor is welcome
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Scalable Local Training Pipeline

- many sizes, many scales, one recipe

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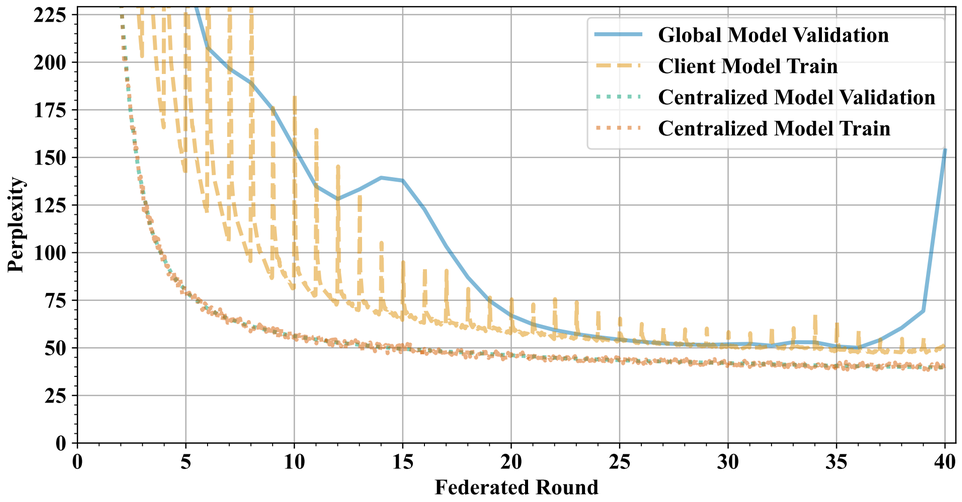
FL robust at different model scales

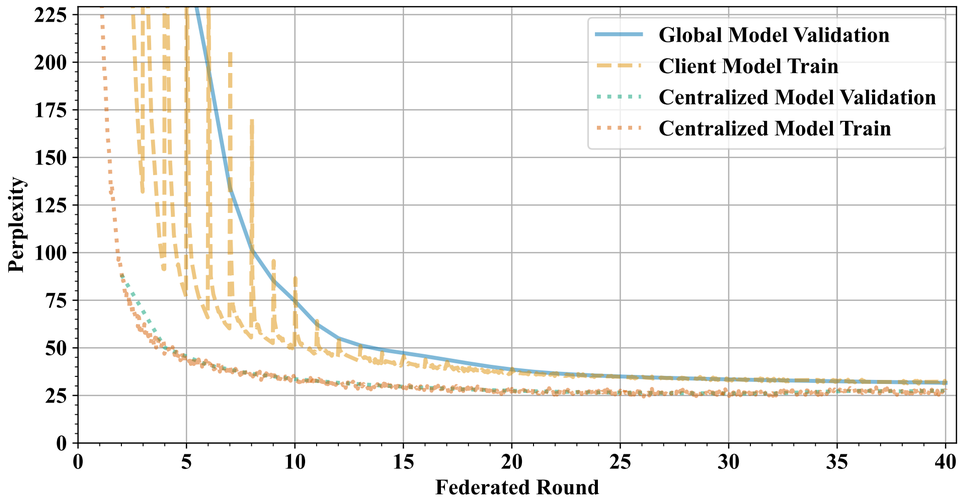
!?

!?



75M

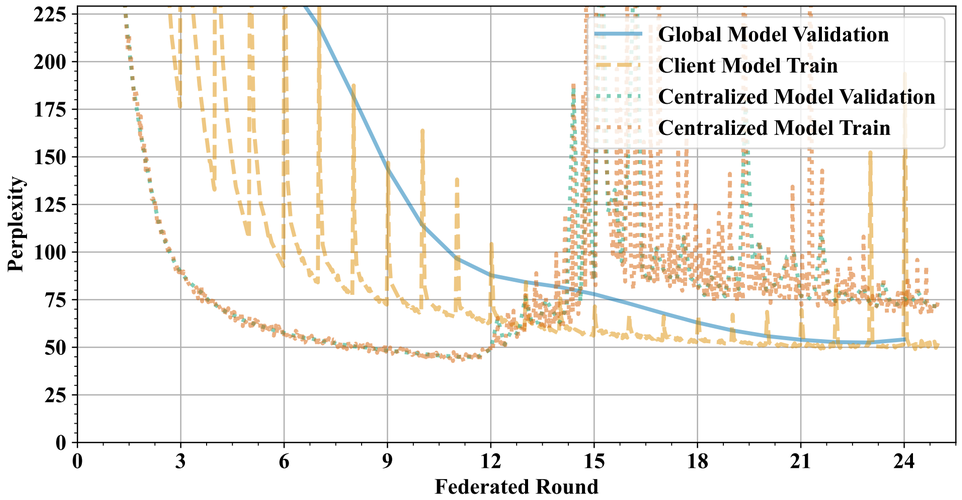
125M



C4 (IID) - P = 8 clients - 100% sampling rate

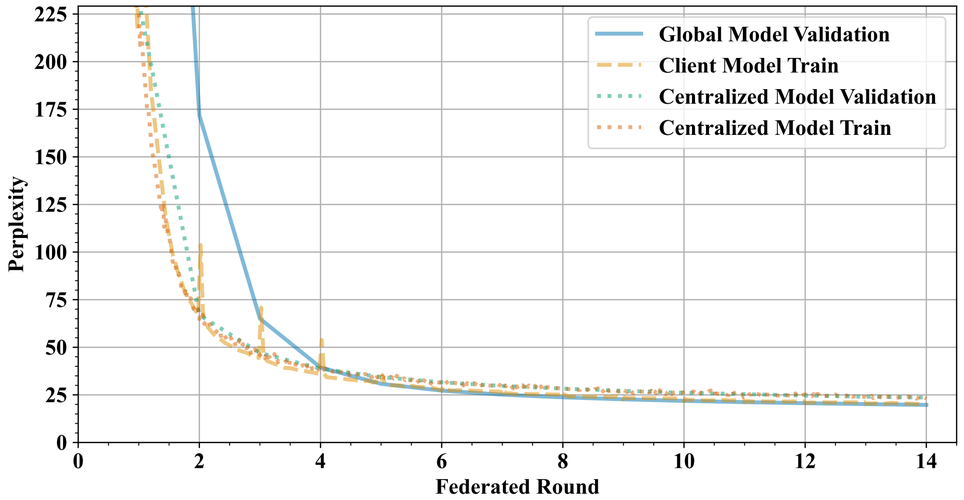
ServerOpt ⇒ SGD + Nestorov

ClientOpt ⇒ AdamW + cos LR with warmup



350M

1.3B



75M
64
clients
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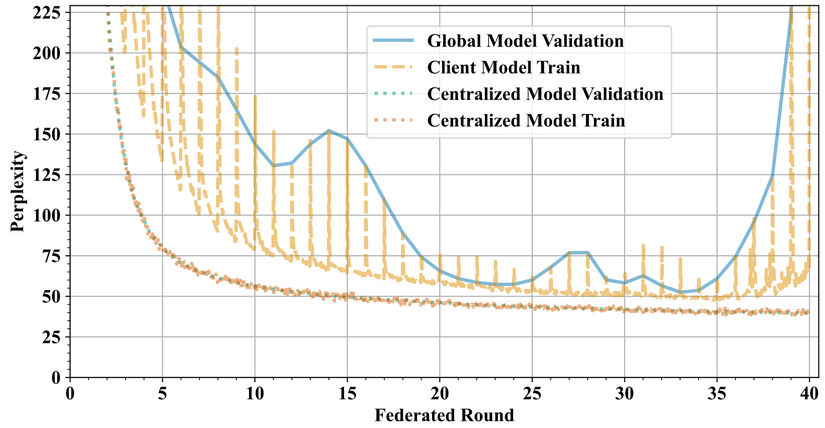

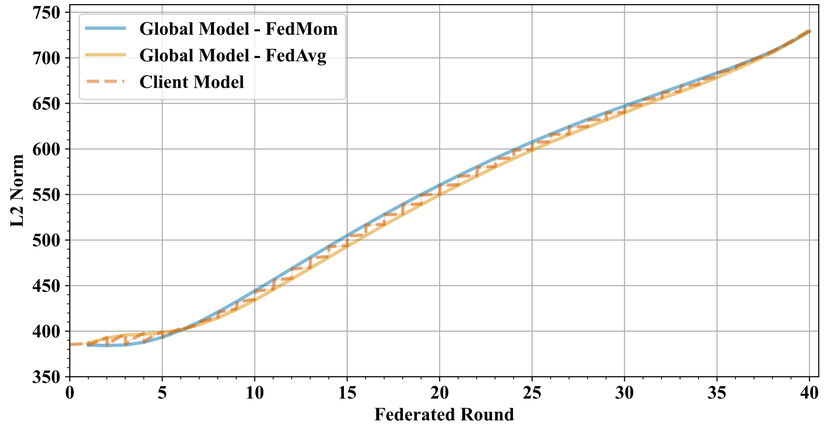

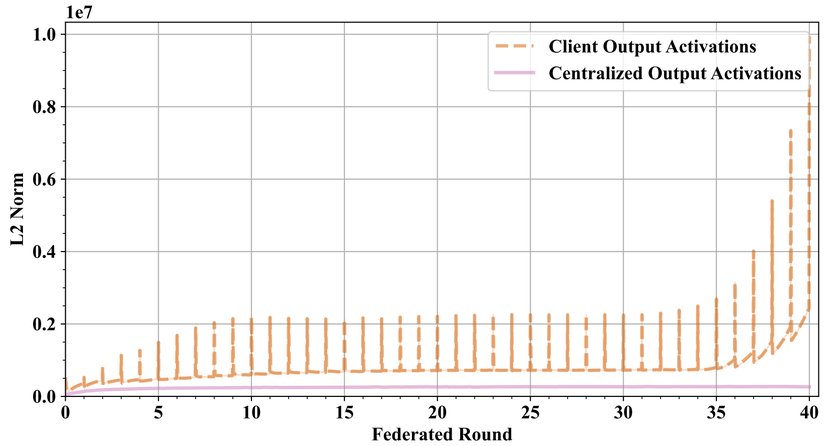

characterizing the blow-up
and
varying server learning rate

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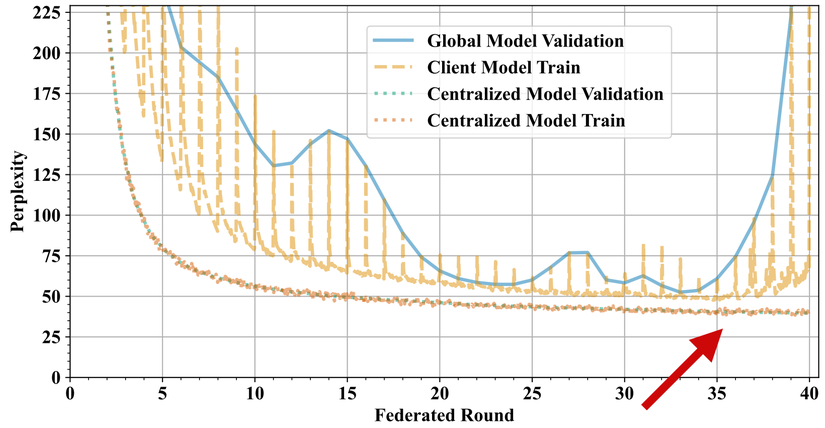

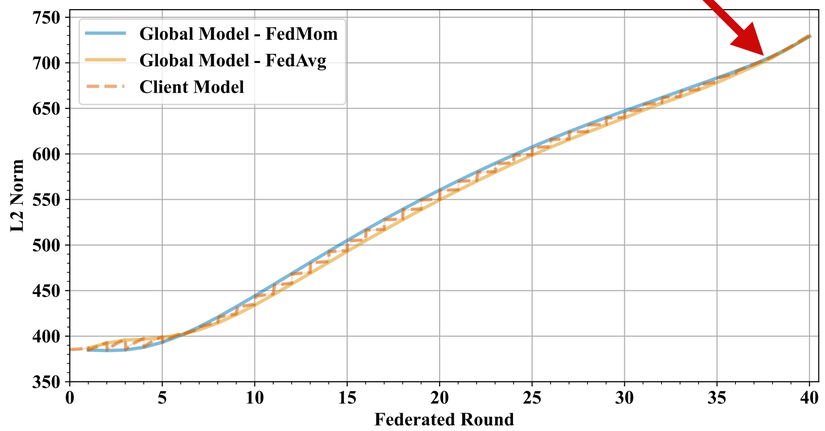

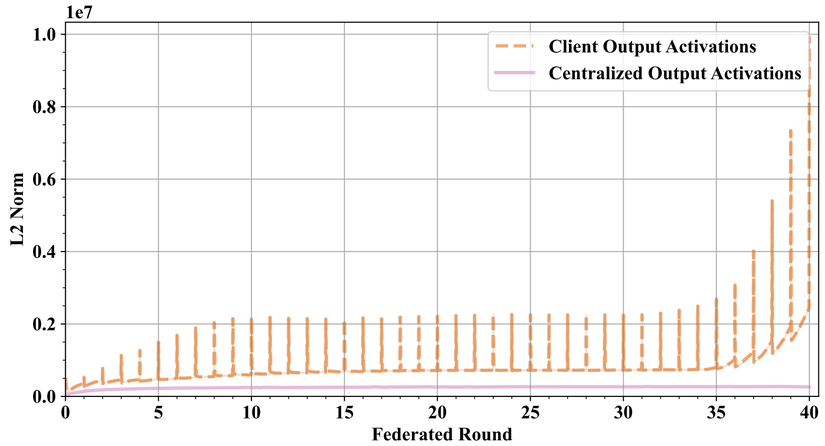

characterizing the blow-up and varying server learning rate

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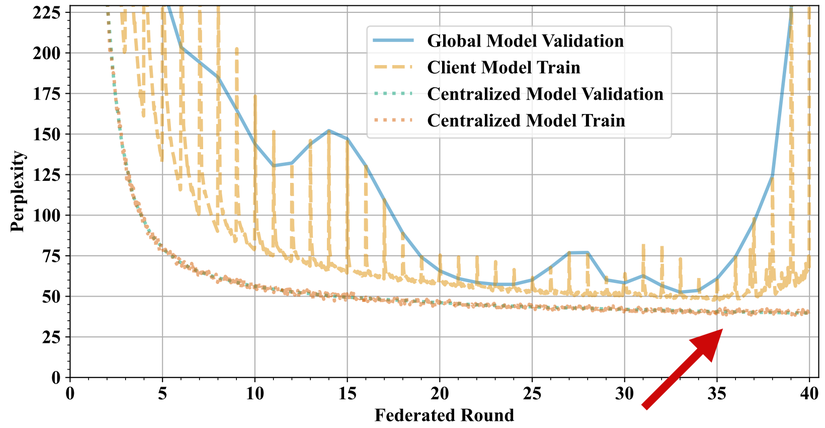

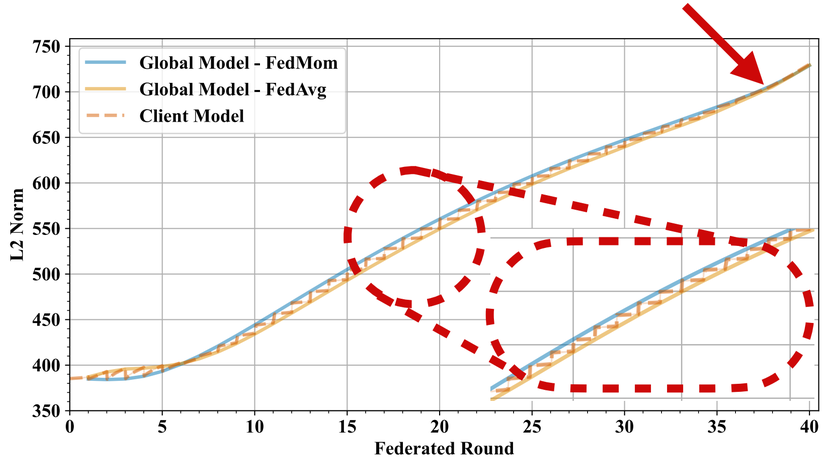

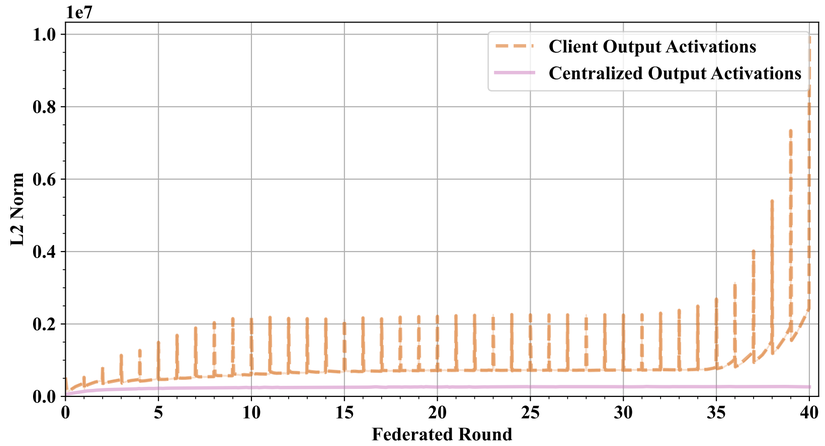

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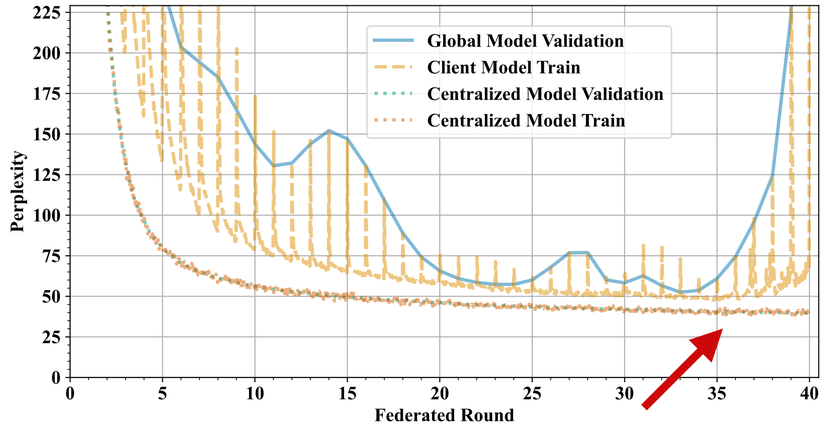

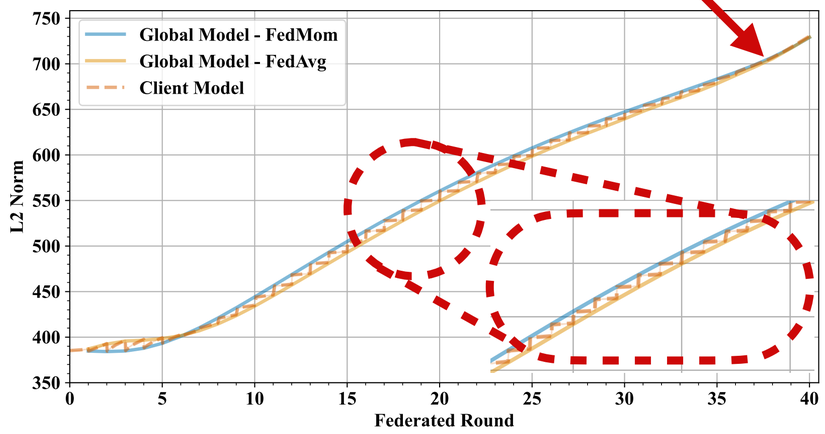

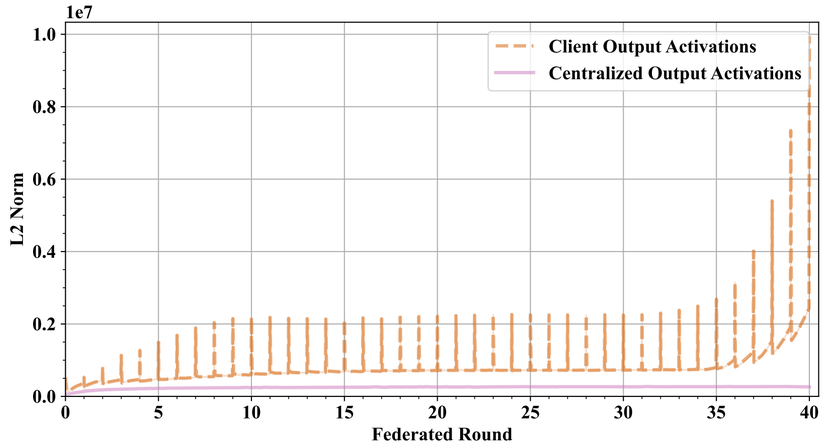

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Takeaways:

1. observe global model norms after aggregation

2. conservative server LRs help by slowing down

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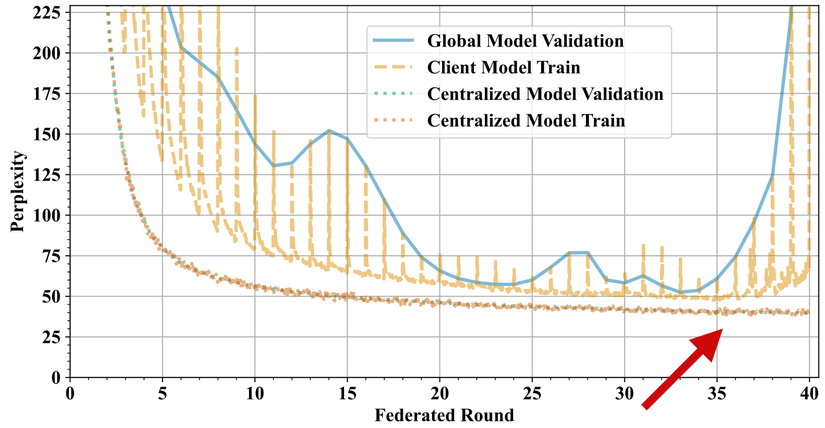

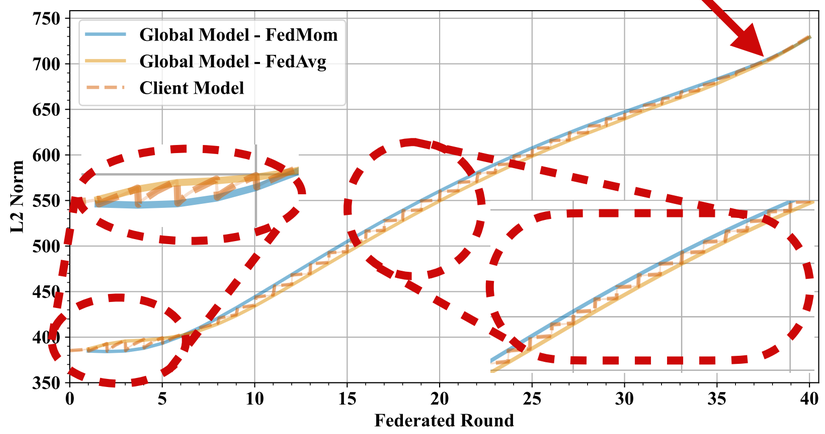

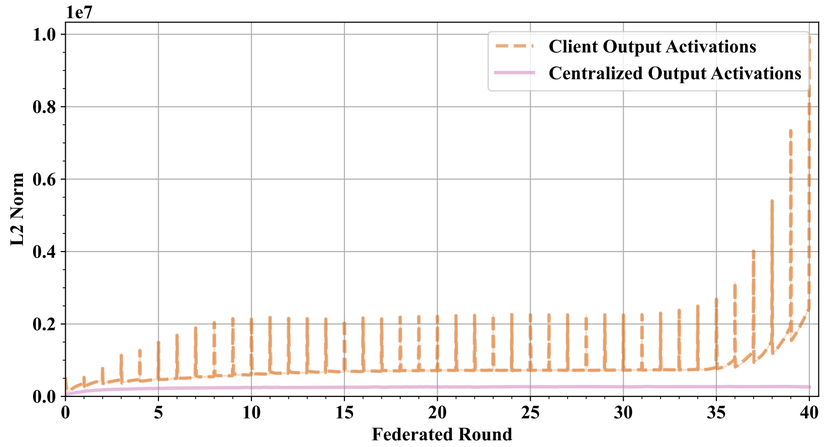

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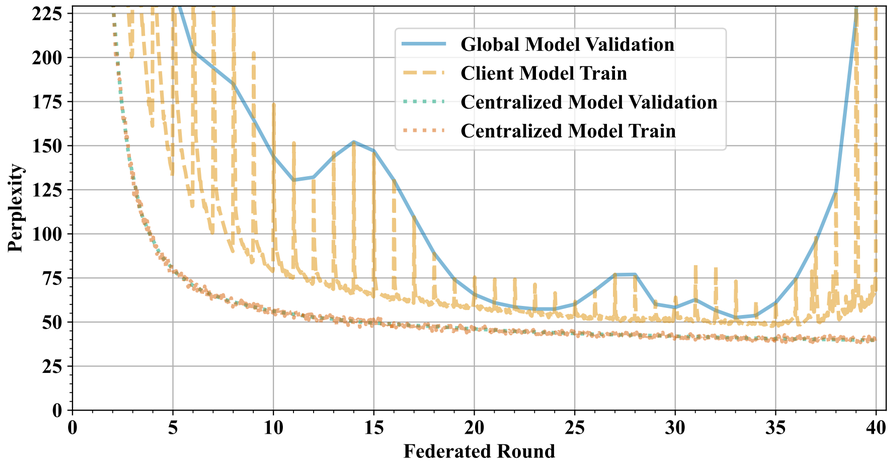
Heterogeneous Datasets



C4 (IID) - 64 clients - 6.25% sampling rate

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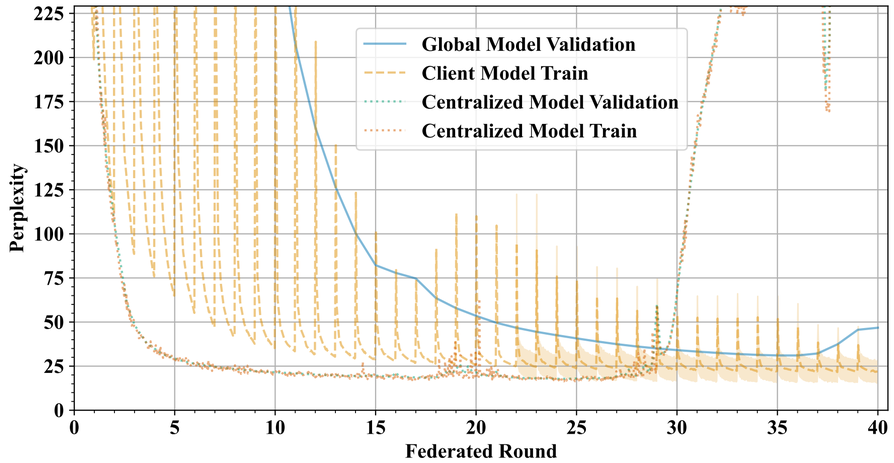
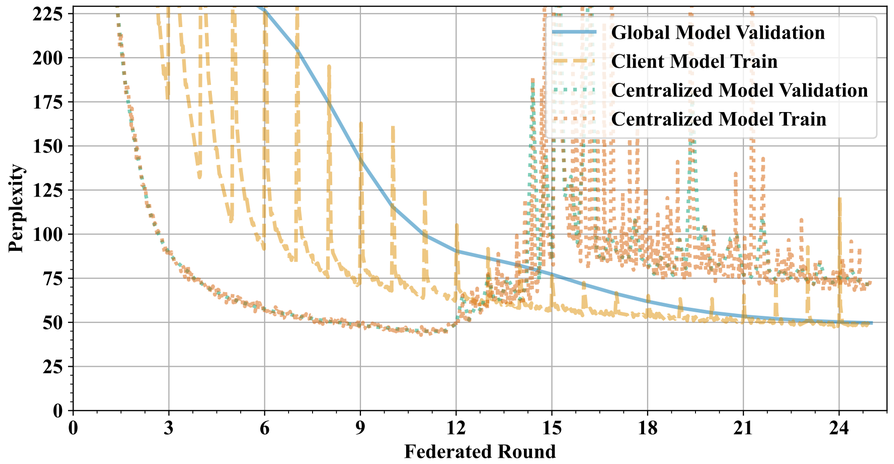


The Pile (non-IID) - 64 clients - 6.25% sampling rate



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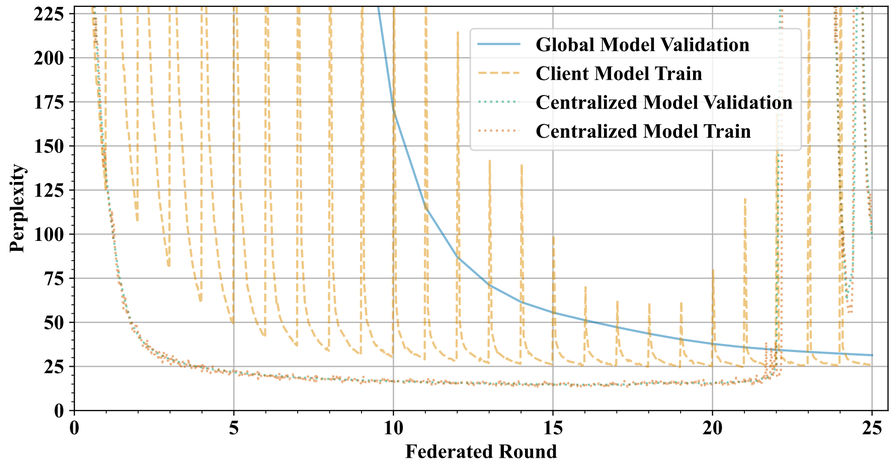

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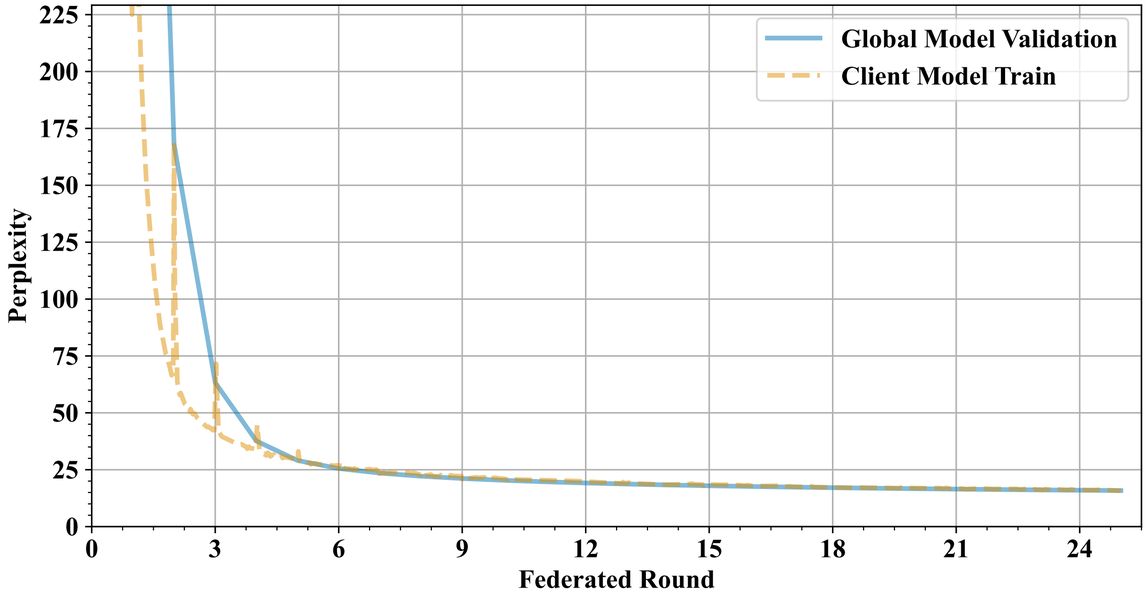

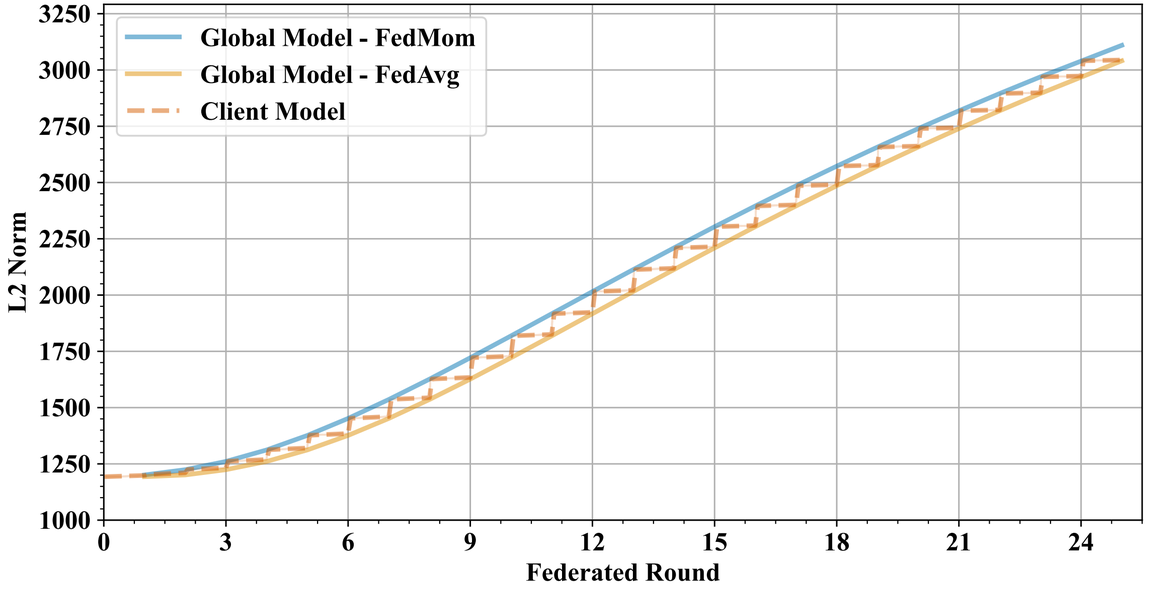

Next Steps and Open Questions

- **Distributed/Federated mixture,** what's best?
  ⇒ investigating different system configurations

  ⇒ how bandwidth and topology can impact our recipe

- More structured training recipe along the lines of **MoEs**
  ⇒ should we treat blocks and embedding layers the same way?

  ⇒ interplay between **multilingual** pre-training and FL?

- Fine-tuning and downstream performance of LLMs pre-trained on a federated population
  ⇒ more thorough **evaluation harness**

  ⇒ assess **meta-learning capabilities**

- **Privacy and memorization**

Thank you!

Any question?

reach me offline at: ls985@cam.ac.uk