

# Streaming DiLoCo with overlapping communication

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## Abstract

Training of large language models (LLMs) is typically distributed across a large number of accelerators to reduce training time. Since internal states and parameter gradients need to be exchanged at each and every single gradient step, all devices need to be co-located using low-latency high-bandwidth communication links to support the required high volume of exchanged bits. Recently, distributed algorithms like DiLoCo (Douillard et al., 2024a) have relaxed such co-location constraint: accelerators can be grouped into “workers”, where synchronizations between workers only occur infrequently. This in turn means that workers can afford being connected by lower bandwidth communication links without affecting learning quality. However, in these methods, communication across workers still requires the same peak bandwidth as before, as the synchronizations require all parameters to be exchanged across all workers. In this paper, we improve DiLoCo in three ways. First, we synchronize only subsets of parameters in sequence, rather than all at once, which greatly reduces peak bandwidth. Second, we allow workers to continue training while synchronizing, which decreases wall clock time. Third, we quantize the data exchanged by workers, which further reduces bandwidth across workers. By properly combining these modifications, we show experimentally that we can distribute training of billion-scale parameters and reach similar quality as before, but reducing required bandwidth by two orders of magnitude.

## 1 Introduction

Scaling deep learning has led to significant leaps in capability (Team et al., 2024; OpenAI et al., 2024; Grattafiori et al., 2024). Although neural architectures have evolved over the past decade, the standard approach to optimization remains essentially unchanged from the days of Alexnet (Krizhevsky et al., 2012). Practitioners use minibatch stochastic gradient descent, with backpropagation through the model’s layers to compute the gradients. As in Alexnet, which already combined two hardware accelerators for parallel training, models are trained with multiple hardware accelerators.

However, modern training runs, for example for large language models (LLM), may use tens of thousands of accelerators, and this number increases year after year. Building and maintaining a data-center that can co-locate that many accelerators is expensive and leads to increasingly complex engineering challenges. Beyond the physical infrastructure, orchestrating the passage of gradients, parameters and intermediate states between these devices at each optimization step, while keeping all devices fully utilized is technically challenging from a software engineering perspective. Furthermore, the more devices that

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are used for each synchronous training step, the more chances there are that one of them fails, risking halting training, or introducing subtle numerical issues.

Recent publications (Douillard et al., 2024a; Jaghouar et al., 2024a), building on work by McMahan et al. (2017), have demonstrated that the co-location requirements of all accelerators can be loosened. These methods allow highly-performant training when accelerators are grouped into several “workers” with fast bandwidth intra-worker but with slow bandwidth inter-workers. The basic approach is to allow each worker to continue training for many minibatches, independently of the other workers; and then synchronize the parameters of the workers after a set number of these “inner” steps. The synchronization, in its simplest form (McMahan et al., 2017), is to average the parameters of the workers (Wortsman et al., 2022); but more sophisticated methods (Huo et al., 2020; Reddi et al., 2021) use the workers’ parameters to form a pseudo-gradient to update the shared parameters. The details of the formulation of the weight synchronization is important for machine-learning efficiency; see Section A.1.

However, in these approaches, the synchronization typically requires an all-reduce operation which fully synchronizes the model parameters on some step. This all-reduce results in two main issues: 1) a large peak bandwidth, and 2) a blocking of the workers while they wait to receive updated weights. In this work, dubbed *Streaming DiLoCo*, we propose three modifications to these approaches to practically reduce the peak bandwidth and mitigate worker-blocking without loss of learning efficiency:

**Contribution 1: *Synchronization.***

We synchronize subsets of parameters on a schedule, rather than all parameters at once. This contribution reduces the peak required bandwidth.

**Contribution 2: *Overlapping.***

We overlap worker computation and communication of synchronizations. This contribution increases the tolerated latency of communication.

**Contribution 3: *Quantization.***

We compress the outer gradients to four bits per parameters without loss of performance. This contribution reduces the total amount of bits exchanged.

We show experimentally that our model, Streaming DiLoCo, is strictly superior to the original DiLoCo (Douillard et al., 2024a), and achieves similar performance to the bandwidth-costly data-parallelism. Since we attain the same quality at negligible bandwidth, we consider our approach as an important stepping stone towards a form of *distributed free lunch*.

## 2 Model

We recommend the reader unaware of the previous literature on FedOpt (Reddi et al., 2021) and DiLoCo (Douillard et al., 2024a) to read our provided context in the appendix in subsection A.1.

For all algorithms, we denote the model parameters as  $\theta$ . We use the superscript notation  $\theta^{(t)}$  to indicate the parameters at a given step  $t$ , and the subscript notation  $\theta_m$  to denote a particular shard of the DiLoCo replica. For example,  $\theta_m^{(t)}$  indicates the parameters of DiLoCo replica  $m$  at step  $t$ . If no subscript is used, the parameters are replicated across DiLoCo replicas. Note that it is possible for parameters to not be replicated and yet to be of the same value.

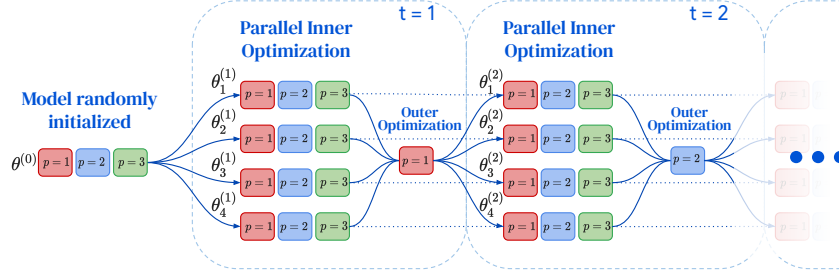


Figure 1: **Streaming DiLoCo**: each replica trains independently for dozen of inner optimization steps, and then synchronize a single fragment during outer optimization. In this figure, there are  $M = 4$  replicas with  $p = \{1, 2, 3\}$  fragments. Each fragment can be made of several transformer layers. Note that this figure only showcases the streaming partial updates (subsection 2.1) and not the quantized communication overlapping (subsection 2.2 and 2.3).

## 2.1 Streaming partial updates

Instead of communicating the full outer gradient vector ( $\Delta_m^{(t)}, \forall m \in \{1, \dots, M\}$ ) every  $H$  steps, we propose to share only a fragment  $p$  of it ( $\Delta_{m,p}^{(t)}$ ) more frequently, as highlighted in Figure 1. There is a huge possible space of choices for these fragments and specification of “more frequently”<sup>1</sup>; here we consider the simple partition of our network into  $P$  fragments made of several transformer blocks. Specifically, we study two fragment patterns, as shown in Figure 8 in the appendix: 1) *sequential* where each fragment comprises consecutive transformer blocks and 2) *strided* where each fragment is composed of interleaved transformer blocks. We will demonstrate in subsection 3.3 that the algorithm is robust to the particular choice of fragments. Since the stride version offers in practice slightly better compute utilization (less time spent communicating instead of computing), we will use it as the default choice in our experiments. As we increase model scale, the fragment definition (e.g., how many transformer blocks comprise a fragment) is maintained, which means that larger models have more fragments.

The resulting algorithm is shown in Algorithm 1 (and contrasted with the original version shown in Algorithm 2), where only a fragment  $p$  of the replica  $m$  is shared. We denote a fragment with a new lower script, thus  $\theta_{m,p}^{(t)}$  is the parameters of fragment  $p$  of the replica  $m$  at step time  $t$ .

The Streaming DiLoCo’s inner optimization (L3-5 of Algorithm 1) is identical to DiLoCo’s (L3-5 of Algorithm 2). However, the outer optimization (L12) is done per fragment. If a fragment  $p$  satisfies the condition  $t + t_p H = 0$ , where  $t_p$  is a time offset fragment-dependent, then it is synchronized. In this way, each fragment will always do  $H$  steps before being synchronized, but overall the model is synchronizing *some* fragment more frequently than every  $H$  steps. For example, with  $H = 100$  and  $P = 2$  fragments, the first fragment will be synchronized at step  $t = 100, t = 200, \dots$  ( $t_{p=1} = 0$ ); the second fragment will be synchronized at step  $t = 150, t = 250, \dots$  ( $t_{p=2} = 50$ ). While in practice, given an equal  $H$ , streaming DiLoCo communicates more often than DiLoCo, the peak communication is reduced by a factor of  $|p|/L$  with  $|p|$  the size of a fragment in *layers* and  $L$  the total number of layers.

## 2.2 Overlapping communication with computation

To further maximize the time spent doing computation v.s. communication, we propose to overlap the communication of the outer gradient fragment with the inner optimization computation; the overlap happens with a strictly positive  $\tau$  in Algorithm 1, lines 10-12. At

<sup>1</sup>For example, an extreme version might be to send a constant bitstream of random choices (according to some optimization-useful distribution) of parameters.

**Algorithm 1** Streaming DiloCo

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**Require:**  $M$  replicas  
**Require:** Number of inner steps  $H$   
**Require:** Fragments  $p \in \{1, \dots, P\}$  with their respective synchronization offset  $t_p$   
**Require:** Model replicas  $\{\theta_1^{(t)}, \dots, \theta_M^{(t)}\}$   
**Require:** Inner overlap delay  $\tau < H$   
**Require:** Data shards  $\{\mathcal{D}_1, \dots, \mathcal{D}_M\}$   
**Require:** Optimizers InnerOpt and OuterOpt

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1: parallel for replica  $m = 1 \dots M$  do
2:   for step  $t = 1 \dots T$  do
3:      $x \sim \mathcal{D}_m$ 
4:      $\mathcal{L} \leftarrow f(x, \theta_m^{(t-1)})$ 
5:      $\theta_m^{(t)} \leftarrow \text{InnerOpt}(\theta_m^{(t-1)}, \nabla_{\mathcal{L}})$ 

6:   if  $\exists p$  s.t.  $t - t_p H == 0$  then
7:      $\Delta_{m,p}^{(t)} \leftarrow \theta_{m,p}^{(t-H)} - \theta_{m,p}$ 
8:      $\Delta_p^{(t)} \leftarrow \text{async-send}[\frac{1}{M} \sum_{m=1}^M (\Delta_{m,p}^{(t)})]$ 

9:   if  $\exists p$  s.t.  $t - t_p - \tau H == 0$  then
10:    block-receive $[\Delta_p^{(t-\tau)}]$ 
11:     $\tilde{\theta}_{m,p}^{(t)} \leftarrow \text{OuterOpt}(\theta_{m,p}^{(t-\tau-H)}, \Delta_p^{(t-\tau)})$ 
12:     $\theta_{m,p}^{(t)} \leftarrow \alpha \theta_{m,p}^{(t)} + (1 - \alpha) \tilde{\theta}_{m,p}^{(t)}$ 
  
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the beginning of outer step  $t + 1$ , instead of waiting for the communication of the fragment block-receive, we immediately start the new round of optimization. After  $\tau - 1$  inner steps (L3-5), we block-wait for the exchanged fragment (L10), apply the outer optimizer on the previously synchronized fragment ( $\theta_{m,p}^{(t-\tau-H)}$ ), and merge it with the currently optimized fragment with a mixing factor  $\alpha$ .  $\alpha = 1$  is equivalent to no communication between replicas,  $\alpha = 0$  discards any updates done in the first  $\tau$  steps on the fragment  $p$ , and  $\alpha = 0.5$  does a uniform average between the local fragment parameters and the globally shared one.

### 2.3 Low-precision outer gradients

The previous methods, streaming and overlapping communication with computation, reduce peak bandwidth and wall-clock time, respectively. To reduce total amount of bits exchanged, we use lower-precision in the outer gradients exchanged by workers (while still using FP32 for computing gradients), up to a float with 4 bits (1 sign bit, 3 exponent bits, and 0 mantissa bit) called E3M0 (Agrawal et al., 2024). Across a wide variety of experiments, we found no sign of performance regression when employing such low precision numbers during communication, even at the billion scale. This compression is applied when sending each replica’s unreduced outer gradients to minimize the amount bits communicated (L8 of Algorithm 1), but once received by a replica, importantly, the accumulation is done in FP32 for stability.

## 3 Experiments

We run experiments demonstrating the compute utilization benefits of our approach in a bandwidth and compute simulation in Section 3.1. In Section 3.2 we show in practice the model learning outcomes. Finally, in Section 3.3 we show results with variations of the three main contributions of the paper, ablating their relative importance.



Figure 2: Simulation of a schedule interleaving forward passes (in blue), backward passes w.r.t. activations and parameters (resp. in light green and dark green), and (outer) gradient reduction (in purple).

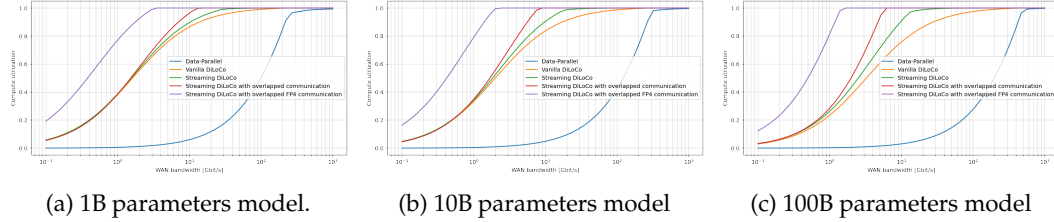


Figure 3: **Compute Utilization** simulated across a range of bandwidth. A compute utilization of 0.8 means 80% of the time is spent in computation, and 20% in communication. Our best method reaches a compute utilization of 95% for models 1B, 10B, and 100B with a bandwidth roughly constant between 1 and 5 Gbit/s. Data-Parallel on the other hand requires 100, 200, and 300Gbit/s.

### 3.1 Compute utilization

To highlight the impact of our contributions in a controlled setting, we built a simulator to estimate the **compute utilization** of each method: how much time is spent doing computation v.s. communication. The simulation is a DAG with four different types of nodes as seen in Figure 2: forward in blue, backward w.r.t activations and parameters in green, (outer or not, for resp. DiLoCo and Data-Parallel) gradients reduction in purple. Each node represent a single layer. Therefore, the total number of nodes, for a single step, is  $4 \times L - 1$  (because we don't need the backward w.r.t activations of the first layer). The overall training is represented by a DAG made of such nodes. We use this simulator to estimate the **compute utilization** of each method: how much time is spent doing computation v.s. communication. Ideally this number is close to 1.0: No time is spent waiting for communication. It is more useful than just reporting the reduction in data transferred because our overlapping method (subsection 2.2) reduces the latency while keeping the amount of data exchanged constant.

In Figure 2, we report:

- **Data-Parallel**: the baseline which communicates gradients of the full model at every step;
- **DiLoCo**: which communicating outer gradients of the full model once in a while (in this example, every  $H = 2$  steps);
- **Streaming DiLoCo**: which communicates outer gradients only for a subset of the model (here the fragment size is a single layer and there are two fragments) every  $H = 2$  steps;
- **Streaming DiLoCo with overlapping communication and computation**: This is similar to the above but gradients sent across workers are only needed after  $\tau$  steps (in this example  $\tau = 1$ ).

Method	1 GiB/s	10 GiB/s	100 GiB/s	1000 GiB/s
Data-Parallel	21 days	2 days	10 hours	5 hours
DiLoCo	12 hours	6 hours	5 hours	5 hours
Streaming DiLoCo with overlapped FP4 com.	6 hours	5 hours	5 hours	5 hours

Table 1: **Wallclock time** for Data-Parallel, DiLoCo, and our method for 1B model spending 0.1s of computation per step and doing 186,250 steps under various bandwidth profile..

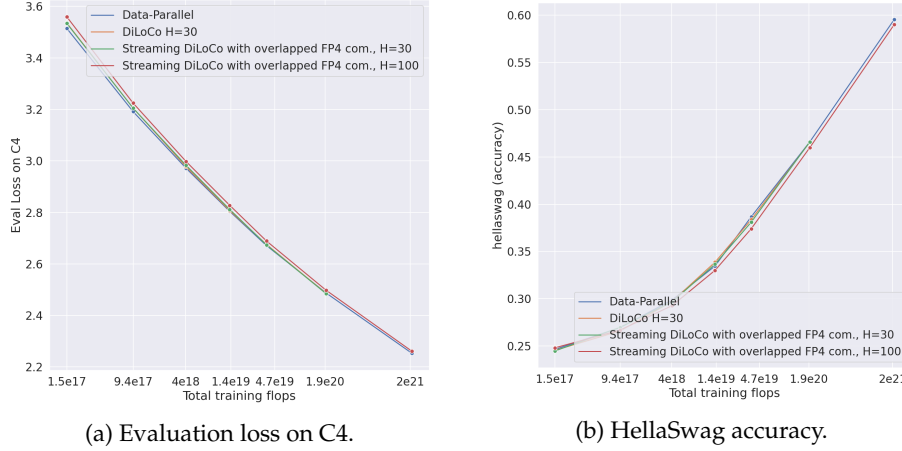


Figure 4: **Scaling** models from 35M to 4B on C4.

The simulated compute utilization (CU) depends on some factors, listed as columns in Table 5. For the model scales 10B and 100B, we estimate step time (pure compute) based on the flops profile, a reasonable MFU (40%), and hardware theoretical flops per seconds. We simulate training of each method, across three scales (1B, 10B, and 100B) under various bandwidth profiles Figure 3.

We make several observations: 1) Streaming DiLoCo (in green) improves the CU of DiLoCo (in orange) despite exchanging as much data, because it reduces the latency by splitting the communication of the outer gradients across fragments. 2) only overlapping communication with computation can reach full 100% compute utilization. 3) the required bandwidth can become *lower* as the model scale gets *larger* when overlapping communication with computation, because longer compute step time (forward & backward) will provide more time to perform the synchronization across workers.

The last point may seem counter-intuitive at first glance, but is the main advantage of our method, exploiting the *square-cube law of distributed training* (Ryabinin et al., 2023) where computation scales worse than communication ( $O(n^3)$  vs  $O(n^2)$  for a square matrix  $n \times n$ ). We provide in the appendix, in Figure 16, the simulated compute utilization for a 100B model across various step time.

**Remark: simulation vs reality.** Of course this is only a simulation of what we expect to happen in practice. Such simulation is not perfect because for instance we consider only the bandwidth between datacenters and not the local bandwidth between devices. We believe however, that this is still a useful tool<sup>2</sup> to estimate device utilization. We show in Table 1 the real wallclock under various bandwidth for the 1B model only.

**Remark: pipeline parallelism.** We focus here solely on distributing the *data* axis and don't include pipeline parallelism. Our goal, achievable with the former, is to decouple instances of the model to facilitate fault tolerance. The latter isn't best suited for that purpose.

<sup>2</sup>[https://en.wikipedia.org/wiki/Bonini%27s\\_paradox](https://en.wikipedia.org/wiki/Bonini%27s_paradox)



Method	Token Budget	Hours spent w/ $+\infty$ Gbits/s	Hours spent w/ 1 Gbits/s	Terabytes exchanged	Eval Loss $\downarrow$	HellaSwag $\uparrow$	Piqa $\uparrow$	Arc Easy $\uparrow$
Data-Parallel	25B	0.67	109	441	2.67	<b>42.09</b>	67.35	<b>40.42</b>
	100B	2.7	438	1,767	2.52	49.78	69.15	<b>44.03</b>
	250B	6.75	1097	4,418	<b>2.45</b>	53.86	70.45	<b>44.21</b>
Streaming DiLoCo with overlapped FP4 communication	25B	0.67	0.88	1.10	<b>2.66</b>	42.08	<b>67.46</b>	38.42
	100B	2.7	3.5	4.42	<b>2.51</b>	<b>49.98</b>	<b>69.96</b>	<b>44.03</b>
	250B	6.75	8.75	11.05	<b>2.45</b>	<b>54.24</b>	<b>71.38</b>	41.92

Table 2: **Overtraining** Data-Parallel and our method on Dolma with a 1 billion parameters model.

### 3.2 LLM Scaling Experiments

We perform our experiments with a Chinchilla architecture (Hoffmann et al., 2022). Following Wortsman et al. (2023) and Jaghouar et al. (2024a), we use QKNorm (Henry et al., 2020) and a Z-loss (Chowdhery et al., 2023) with a factor of  $1e-4$  to stabilize training. We report in Table 3 the architecture hyperparameters and token budget at each scale. Unlike recommended in Post-Local SGD (Lin et al., 2020), we train all our models from scratch. The main hyperparameter of DiLoCo is its outer learning rate; we tuned it to be optimal at small scale at 0.4, and kept it fixed across all scales. Likewise, for the simplicity, and to show that Streaming DiLoCo is a drop-in replacement of DiLoCo, we used the same outer learning rate, without further hyperparameters tuning.

Except mentioned otherwise, we use the C4 dataset (Raffel et al., 2020) and train models from 35 million to 4 billion parameters, all with a sequence length of 1,024. Each scale is trained with the chinchilla-optimal number of steps. We use 2 DiLoCo replicas, each of them performing FSDP (Zhao et al., 2023) across their respective closely located devices.

Our code is based on NanoDO codebase (Liu et al., 2024b) and uses DrJax (Rush et al., 2024) to parallelize inner steps across replicas.

#### 3.2.1 Scaling

We perform scaling experiments on C4, with models ranging from 35 millions parameters to 1 billion parameters, all with a sequence length of 1,024. For Data-Parallel and Streaming DiLoCo with  $H = 100$ , we also provide results on a 4 billion parameter model. At each scale, we use the Chinchilla-optimal number of steps. We highlight in Figure 4 the evaluation loss (lower is better) and HellaSwag (Zellers et al., 2019) accuracy (higher is better).

First, we observe in Figure 4 that Data-Parallel (in blue), DiLoCo with  $H = 30$  inner steps (in orange), and Streaming DiLoCo with  $H = 30$  (green) perform all similarly across both loss (at 1B parameters, respectively 2.49, 2.49, and 2.48) and accuracy metrics (resp. 46.6%, 46.5%, and 46.6%). Streaming DiLoCo with more inner steps  $H = 100$  (in red) has slightly worse performance initially but use significantly less bandwidth and the loss improves proportionally better as we scale: scaling law slope for Data-Parallel is -0.13149 while -0.13539 for Streaming DiLoCo. We report in the appendix Table 6 all metrics, and include two more downstream tasks: Piqa (Bisk et al., 2020) and Arc-Easy (Clark et al., 2018). Moreover, Table 7 considers an increased number of DiLoCo replicas.

#### 3.2.2 Overtraining on Dolma

The previous experiments were performed on C4 dataset using the chinchilla-optimal number of tokens. Using a 1 billion parameter model, this yields a token budget of 25 billion. However, language models are now usually *overtrained* (Gadre et al., 2024). Therefore we perform a comparison of a Data-Parallel baseline vs our full model (streaming DiLoCo with overlapped FP4 communication) on the Dolma dataset (Soldaini et al., 2024) with a 1 billion parameter model and with a token budget of 25, 100, and 250 billions tokens (resp.  $1.9e20$ ,  $7.6e20$ , and  $1.9e21$  flops) using a sequence length of 2,048. In that larger, more realistic setting, we set the number of inner steps between synchronization to  $H = 100$  to further minimize communication.

We report results in Table 2, and note that both our method and the baseline perform similarly w.r.t loss and accuracy on downstream tasks (HellaSwag, Piqa, Arc-Easy). In addition

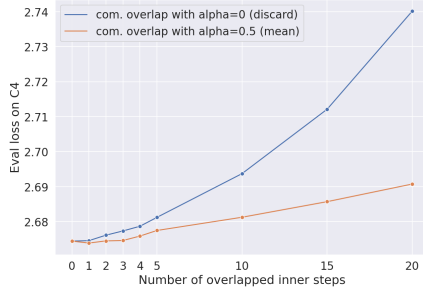


Figure 5: Varying the number of overlapped inner steps  $\tau$  for  $\alpha = \{0, 0.5\}$ . A larger  $\tau$  requires a significantly lower bandwidth, see also Figure 13.

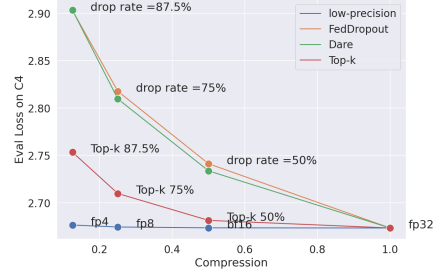


Figure 6: Compressing the outer gradients with either value dropping (FedDropout, Dare) or using lower-precision floating point numbers.

of being neutral in term of ML performance: 1) the amount of bits exchanged between non-located devices over the course of training is  $400\times$  higher for Data-Parallel; 2) the peak bandwidth (amount of bits exchanged at given moment) is reduced by  $\frac{\text{num\_layers}=24}{\text{fragment\_size}=3} = 8\times$ ; and 3) while Data-Parallel ideally hopes for a 0 second latency when communicating, our overlapping scheme allows us a latency as long as a full forward/backward pass, which is several seconds at large scale. For those reasons, we believe our work is step towards a truly “distributed free lunch”.

### 3.3 Ablations

To ablate the importance of each component of Streaming DiLoCo, we perform all our ablations on a model of size 500 million parameters using the C4 dataset with the chinchilla-optimal number of steps and a token budget of 11 billions.

We split our ablations section in three parts, corresponding to the three improvements brought in this paper: namely 1) Streaming synchronization, 2) overlapping communication with computation, and 3) finally quantized communication.

**Number of synced layers per fragment** We ablate in Figure 7 in the appendix the fragment size, *i.e.*, how many transformer blocks are included in a fragment. Based on this analysis, we choose a fixed fragment size of 3 layers, striking a desirable trade-off between ML performance and reduction of peak bandwidth (for which the smaller the fragments the better). We also consider whether to have a sequential or strided pattern (see illustration in Figure 8 for a reference). We choose the latter for several reasons: 1) ML performance is slightly better for the fragment size we consider, 2) deeper networks, with a small fragment size (e.g. 3), should benefit more from striding by spreading out up-to-date synchronized layers across the full depth of the network. Finally, 3) it slightly improves the compute utilization (see Figure 10) by allowing better overlapping schedule, as clearly seen in Figure 9 in the appendix.

**Overlapping** We first vary the number of inner steps,  $\tau$  we use to overlap communication with computation (see subsection 2.2). Figure 5 shows results varying  $\tau$  from 1 to 20, with  $\alpha = 0$  (discarding any intermediary inner updates) and  $\alpha = 0.5$  (uniform merging). We can see that the degradation in evaluation loss is negligible up to an overlap of 10 inner steps ( $< 0.2\%$ ). By checking the compute utilization of a 100B model in Figure 13, we observe little gain in compute time after an overlap of 5 inner steps. Therefore, we advise practitioners to limit the overlap to 5 inner steps. In our main experiments, we used 1 step for simplicity.

**Compressing outer gradients** We ablate in Figure 6 two ways of compressing the outer gradients: either by setting to zero some values (FedDropout (Wen et al., 2022), Dare (Yu et al., 2024), and Top-K selection) or by lowering the precision. In all cases, we accumulate



the outer update in float32. We report the evaluation loss on C4. Interestingly, lowering the precision, from float32 to float4 does not affect the performance, while setting some values to zero is significantly worse, particularly when zero-ing out at random. We also considered Ties-Merging’s pruning method (Yadav et al., 2023) but preliminary experiments showed it also underperformed; however this approach might become advantageous with larger number of replicas  $M$ .

## 4 Related Works

**Federated learning / local SGD.** While model merging (Wortsman et al., 2022) proposes to combine several models once, FedAvg (McMahan et al., 2017) and Local SGD (Stich, 2019) do it multiple times with the goal of reducing bandwidth requirements: they operate by performing local training (typically via SGD) across workers for some number of steps before doing some kind of synchronization of worker parameters, or aggregation of parameters across workers. In their original forms, both FedAvg and Local SGD simply averaged the parameters across workers. As shown by Reddi et al. (2021), the synchronization is more effective when each worker calculates a “model delta”, and these are aggregated over workers to produce a pseudo-gradient (Reddi et al., 2021; Ilharco et al., 2022) or *outer gradient*, which is then fed to a first-order optimizer. This yields a bi-level optimization scheme with inner optimizers and an outer optimizer, referred to as FedOpt by Reddi et al. (2021), who propose using SGD as the inner optimizer and adaptive methods like Adam (Kingma & Ba, 2014) as the outer optimizer in resource-constrained FL settings.

**Distributed training for LLMs.** The increased requirements of training large language models (LLMs) hastened the need for distributed methods, for both inference (Borzunov et al., 2023) and training (Presser, 2020; Diskin et al., 2021; Ryabinin et al., 2021). More recently, DiLoCo (Douillard et al., 2024a) proposed a particular instantiation of FedOpt (Reddi et al., 2021) with AdamW (Loshchilov & Hutter, 2019) as inner optimizer and Nesterov (Sutskever et al., 2013) as outer optimizer (Huo et al., 2020). This simple formulation proved to be effective for distributed training with LLMs, where the number of replicas is small ( $\leq 100$ ) and without replica sampling, closer to cross-silo federated learning (Kairouz et al., 2021). The FedOpt algorithm was also shown to be effective in training LLMs in settings that looked more like cross-device federated learning (Charles et al., 2024). The empirical success of DiLoCo has been reproduced multiple times (Jaghoul et al., 2024b; Sani et al., 2024b) and has been successfully scaled up to 10 billion parameter models (Jaghoul et al., 2024a). Related, a simple change on how the outer Nesterov accumulates outer gradients proved to handle well asynchronicity between workers of different speeds (Liu et al., 2024a). DiLoCo adds a new axis of parallelism to distributed training (Shoeybi et al., 2020), and is compatible (Jaghoul et al., 2024a) with other existing axes like FSDP (Zhao et al., 2023), or even another level of federated learning (Sani et al., 2024a). CO2 (Sun et al., 2024) proposes also to overlap communication, however using stale communication and for a full outer step. We saw in our work that overlapping only for a few inner steps reap most of the bandwidth reduction benefits while keep the performance stable.

**Partial communication.** Communicating a subset of the network is often used in federated learning to provide *personalized* models per user, see FedPart (Arivazhagan et al., 2019). DiPaCo (Douillard et al., 2024b) recently proposed a distributed mixture-of-experts where subsets of the model is synchronized with subsets of the replicas, according to a sharing pattern that is optimized with Expectation-Maximization style of algorithm during training. WASH (Fournier et al., 2024) and later Sparta (Baoumy & Cheema, 2025) propose to frequently exchange a random subset of the neurons. Finally FedPart (Wang et al., 2024), developed at the same time as Streaming DiLoCo, also proposes to share per-layer fragments. However, they argue that for a given communication round, non-shared fragments should not undergo inner optimization, a strategy which we show slows down convergence. Note that all partial communication methods can be seen as a form of *structured* (outer) gradients compression.

**Gradient compression.** Data-Parallel (with gradients) and Federated learning (with outer gradients) often share similar methods to compress the communication (Lin et al., 2018): from randomly dropping values (Wen et al., 2022), to combining multiple compression schemes (e.g. dropping, top-k, low-precision) (Wang et al., 2023), to use low-rank compression (Vogels et al., 2019; Zhao et al., 2024), or recently to keep only the fast moving components with DCT but communicates via an all-gather collective instead of an all-reduce (Peng et al., 2024).

## 5 Conclusion and Future Work

In this paper, we introduced three improvements over DiLoCo: we synchronize a only subset of the parameters at a time, we overlap the communication of this synchronization over several computation steps, and we compress the outer gradients to communicate to low-precision with only four bits. All these innovations combined together leads to a training with similar ML-performance as a classical Data-Parallel training, while using  $400\times$  less bandwidth, reducing the peak bandwidth compared to DiLoCo’s bursts of communication, and allowing communication to have an ideal non-zero latency by overlapping it with computation.

In sum, we can reach a similar compute utilization as the widely used Data-Parallel using two orders of magnitude less Gbit/s bandwidth, while performing comparably in term of training loss and downstream evaluation accuracies as Data-Parallel.

**Next.** In our view, the ubiquity of co-located Data-Parallel training is likely due to the hardware lottery (Hooker, 2020), when “*a research idea wins because it is suited to the available software and hardware and not because the idea is superior to alternative research directions*”. Data-Parallel training has been extensively studied, tuned, and scaled (Kaplan et al., 2020), and it is hard to beat the wisdom-of-the-crowd of thousands of researchers. In contrast, the federated learning literature has mainly studied smaller scale models, primarily due to its focus on edge devices. There are huge opportunities for bringing the ideas from the federated learning literature to the new world of large scale training for LLMs. A critical next work is to study how new distributed methods like ours should be tuned and scaled across multiple axes (e.g. model size, overtraining factor, number of replicas). In particular, how to scale efficiently the number of DiLoCo replicas given an equivalent token budget is most needed.

More generally, reducing the communication problem to a minor obstacle allows new classes of co-designed architectures and training paradigms (for example Douillard et al. (2024b)) maximizing available compute (Sutton, 2019): we hope to see the training of modular constellations of small models loosely connected (Dean, 2021) across heterogeneous devices, using compute arbitrage spread world-wide.

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## A Supplementary Materials

### A.1 Context: FedOpt and DiLoCo

FedOpt (Reddi et al., 2021) is a generic framework to perform federated learning with a bi-level optimization.  $M$  local replicas perform  $H$  steps of *inner* independent optimizations on a different subset of the data (L3 to L5 in Algorithm 2). Every  $H$  steps, each replica computes an *outer gradient*  $\Delta_m^t = \theta_m^{(t-H)} - \theta_m^{(t)}$  (L7), a delta in the parameters space, and communicates to all other replicas. This communication can be performed through a central parameter server or through direct communication of each worker to the others (e.g. with a ring all-reduce), and results in each worker obtaining  $\Delta^t = 1/M \sum_{m=1}^M \Delta_m^t$  (L7-9). This outer gradient is applied on a set of *outer parameters*, the previously synchronized parameters  $\theta_m^{(t-H)}$ , with an *outer optimizer* (L10). The full algorithm is shown in Algorithm 2.

The costly communication between non-located devices happens during the averaging of outer gradients, in L8-9 of Algorithm 2. It is as costly as in Data-Parallel, but instead of being executed at every step, it is done every  $H$  (e.g. one hundred) steps, thus amortizing the communication cost.

DiLoCo is a successful instantiation of FedOpt applied to language models where the inner optimizer is Adam (Kingma & Ba, 2014) and the outer optimizer is SGD with Nesterov momentum (Sutskever et al., 2013). In this work, which focuses on distributed optimization, and unlike in the federated learning literature (as discussed in FedOpt), the workers aren’t sampled; but instead all workers will be present at each step.

### A.2 Discussions

**Memory overhead.** In an SPMD<sup>3</sup> model, the memory overhead of the Data-Parallel baseline is the parameters ( $1\times$ ) + Adam state ( $2\times$ ). (Streaming or not) DiLoCo’s memory overhead is the parameters ( $1\times$ ), the Adam state ( $2\times$ ), the outer global parameters ( $1\times$ ), and the outer Nesterov state ( $1\times$ ). Thus, our method requires 66% ( $5/3$ ) more memory compared to Data-Parallel. However, in the case of Streaming DiLoCo, only a *subset* of the outer parameters and outer optimizer state is needed at a given time. Therefore, this

<sup>3</sup>[https://en.wikipedia.org/wiki/Single\\_program,\\_multiple\\_data](https://en.wikipedia.org/wiki/Single_program,_multiple_data)

**Algorithm 2** FedOpt / DiLoCo

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**Require:**  $M$  replicas  
**Require:** Synchronization frequency  $H$   
**Require:** Model replicas  $\{\theta_1^{(t-1)}, \dots, \theta_M^{(t-1)}\}$   
**Require:** Data shards  $\{\mathcal{D}_1, \dots, \mathcal{D}_M\}$   
**Require:** Optimizers InnerOpt and OuterOpt

```

1: parallel for replica  $m = 1 \dots M$  do
2:   for step  $t = 1 \dots T$  do
3:      $x \sim \mathcal{D}_m$ 
4:      $\mathcal{L} \leftarrow f(x, \theta_m^{(t-1)})$ 
5:      $\theta_m^{(t)} \leftarrow \text{InnerOpt}(\theta_m^{(t-1)}, \nabla \mathcal{L})$ 

6:   if  $tH == 0$  then
7:      $\Delta_m^{(t)} \leftarrow \theta_m^{(t-H)} - \theta_m^{(t)}$ 
8:      $\Delta^{(t)} \leftarrow \text{async-send}[\frac{1}{M} \sum_{m=1}^M (\Delta_m^{(t)})]$ 
9:     block-receive $[\Delta^{(t)}]$ 
10:     $\theta_m^{(t)} \leftarrow \text{OuterOpt}(\theta_m^{(t-H)}, \Delta^{(t)})$ 

```

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overhead can be alleviated by offloading the additional bits onto CPU memory (Beaumont et al., 2022). The memory overhead to hold in HBM at any point in time is the size of a fragment  $|p|$  times two, for the outer parameters and outer optimizer state. For a 100 billion parameter model for instance, with  $|p| =$  three layers and with a total of 108 layers, that amounts to a 2% increase of memory (additional 20 GB to 1,117 GB<sup>4</sup>). This extra memory is used when there are no activations or gradients in live memory, and thus should fit in HBM without any problem.

Furthermore, the communication schedule is deterministic and known prior to training. Thus, we can start the transfer from RAM to HBM of a fragment (and its associated outer optimizer state) while finishing the previous (inner) gradients passes. Given that only a small subset is required at a given time, the memory transfer cost is negligible. With an H100 with PCIe<sup>5</sup>, characterized by 2 TB/s of bandwidth speed, and without any sharding, this transfer is done in less than 10 milliseconds.

**Future work.** In our view, the ubiquity of co-located Data-Parallel training is likely due to the hardware lottery (Hooker, 2020), when “a research idea wins because it is suited to the available software and hardware and not because the idea is superior to alternative research directions”. Data-Parallel training has been extensively studied, tuned, and scaled (Kaplan et al., 2020), and it is hard to beat the wisdom-of-the-crowd of thousands of researchers. In contrast, the federated learning literature has mainly studied smaller scale models, primarily due to its focus on edge devices. There are huge opportunities for bringing the ideas from the federated learning literature to the new world of large scale training for LLMs. A critical next work is to study how new distributed methods like ours should be tuned and scaled across multiple axes (e.g. model size, overtraining factor, number of replicas). In particular, how to scale efficiently the number of DiLoCo replicas given an equivalent token budget is most needed.

More generally, reducing the communication problem to a minor obstacle allows new classes of co-designed architectures and training paradigms (for example Douillard et al. (2024b)) maximizing available compute (Sutton, 2019): we hope to see the training of modular

---

<sup>4</sup>The size in GB of the parameters & inner Adam optimizer state is the number of parameters  $\times 3 \times 4$  (FP32). The size in GB of the additional fragment and its outer Nesterov optimizer state is the number of parameters  $\times 2 \times 4 \times \frac{3}{108}$ .

<sup>5</sup><https://www.nvidia.com/en-gb/data-center/h100/>

constellations of small models loosely connected (Dean, 2021) across heterogeneous devices, using compute arbitrage spread world-wide.

**Discussion on model merging.** Model merging, a subfield within the broader study of linear mode connectivity, explores the potential of linearly interpolating between parameters of multiple models to synthesize a unified model that inherits the strengths of its constituents (Matena & Raffel, 2021; Wortsman et al., 2021). A key finding in this domain is the existence of low-loss pathways within the parameter space (Frankle et al., 2020; Neyshabur et al., 2020) that connect independently trained models, effectively circumventing the anticipated loss barriers. For instance, Wortsman et al. (2022) demonstrated that averaging the parameters of models fine-tuned from a common pre-trained initialization on diverse tasks (Ramé et al., 2023a) or with varying hyperparameters (Wortsman et al., 2022) yields a performant merged model. This approach, initially demonstrated in computer vision, has been successfully extended to natural language processing (Li et al., 2022), reinforcement learning with human feedback (Ramé et al., 2023b), noisy label learning (Rebuffi et al., 2022), and out-of-distribution generalization (Ramé et al., 2023c). Recent research has further investigated alternative strategies for mitigating loss barriers in model merging, including techniques based on parameter space transformations and other model surgery methods aiming to resolve merging conflicts (Jordan et al., 2023; Stoica et al., 2023; Jin et al., 2023; Ainsworth et al., 2023; Yadav et al., 2023; Yu et al., 2024).

### A.3 Implementation details

**DrJax.** For training we use a modified version of the NanoDO codebase (Liu et al., 2024b) that uses DrJax (Rush et al., 2024) to parallelize inner steps across replicas. The inner optimization is done with an annotated variant of `jax.vmap` for the optimization step, with parameters having an extra leading axis for the DiLoCo replicas. The outer optimization is implemented with an all-reduce, without any central parameter server.

**Architecture hyperparameters** We detail the architecture across model scales in Table 3. The token budget per scale is computed from the chinchilla-optimal amount of flops (Hoffmann et al., 2022).

Model scale	Hidden dim	Num layers	Num heads	Token budget
35M	2,048	6	8	700M
100M	3,072	9	12	1.5B
200M	4,096	12	16	3.5B
300M	5,120	15	20	6B
500M	6,144	18	24	11B
1B	8,192	24	32	25B
4B	12,288	36	48	83B

Table 3: **Architecture hyperparameters:** we consider model from 35M to 4B with the following hyperameters and chinchilla-optimal token budget. For all model scale, the vocabulary size is 32,000.

### A.4 Additional details

### A.5 Streaming DiLoCo.

**Pattern.** We illustrate in Figure 8 the two considered patterns in subsection 2.1: namely *sequential* and *strided*. Each has slightly different ML performance (see ??) but also compute utilization. It’s better seen on the schedules of Figure 9, where we can see that a strided pattern can more often overlap communication with the next step computation, resulting in slightly better utilization (see Figure 10).

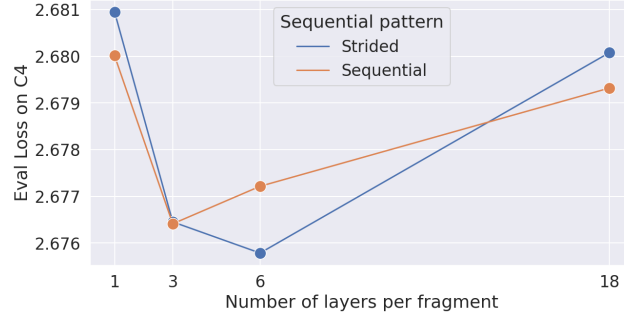


Figure 7: **The fragment’s size** will determine the peak bandwidth but also the learning dynamics. We choose in practice 3 layers per fragment across all model scales.

**Comparison to FedPart.** Streaming DiLoCo bears similarity with concurrent work dubbed FedPart (Wang et al., 2024), where a subset of the model is also exchanged at each round. However, FedPart argues that non-shared layers should be frozen during inner optimization. We believe this is rather flops-inefficient: For an 18 layer model, with 3 layers per fragment, 15 layers (83%) are frozen at any point in time despite doing forward/backward computation. We ran comparison of Streaming DiLoCo with and without the frozen pattern proposed by FedPart, reaching respectively on the C4 eval loss 3.2145 and 2.6749. Freezing the  $18 - 3 = 15$  layers that won’t be synchronized at the given round therefore results in a 20% increase of the evaluation loss. These results confirm our intuition that while freezing layers may help merging, this incurs a significant flop inefficiency, which might not be acceptable in training compute-bound settings (which are typical in current large scale training of LLMs).

**Number of replicas** We perform our main experiments with 2 replicas for simplicity but showcase in Figure 11 an ablation of DiLoCo vs Streaming DiLoCo where the number of replicas  $M$  vary from 2 to 8. Contrarily to (Douillard et al., 2024a), we keep the total token budget constant. In Figure 11a, we keep the global batch size constant, and thus reduce the local per-replica batch size). In Figure 11b, we keep the local per-replica batch size constant, and thus increase the global batch size but also reduce the total number of steps.

**Number of inner steps** The number of inner steps  $H$ , has an engineering effect and a learning effect: a larger  $H$  means less frequent synchronization and thus less required bandwidth. On the other hand, a too small  $H$  produce noisy small-normed outer gradients and a too high  $H$  will see replicas drifting apart. Therefore, some middle ground needs to be found. We ablate in Figure 12 and find that while Streaming DiLoCo has similar behavior as DiLoCo when  $H$  increases, it is more robust to low values of  $H$ .

**Which parameters to evaluate** We considered multiple subset of the parameters to use for evaluation: 1) the arbitrarily chosen first replica ( $\theta_1$ ), 2) an average of all replicas ( $\frac{1}{M} \sum_{m=1}^M \theta_m$ ), or 3) the globally shared outer parameters ( $\theta$ ). Note that the latter is made of fragments that were synchronized at different points in time. We show the performance of each subset in Table 4: The difference here between these methods is small, but the outer parameters yield slightly better performance.

## A.6 Communication overlapping

**Impact of overlapping on compute utilization.** We show in Figure 13, various degrees of communication overlapping and their impact on compute utilization. While more is obviously better, there are clear diminishing returns starting from 5 inner steps, which is also where the ML performance starts to degrade.



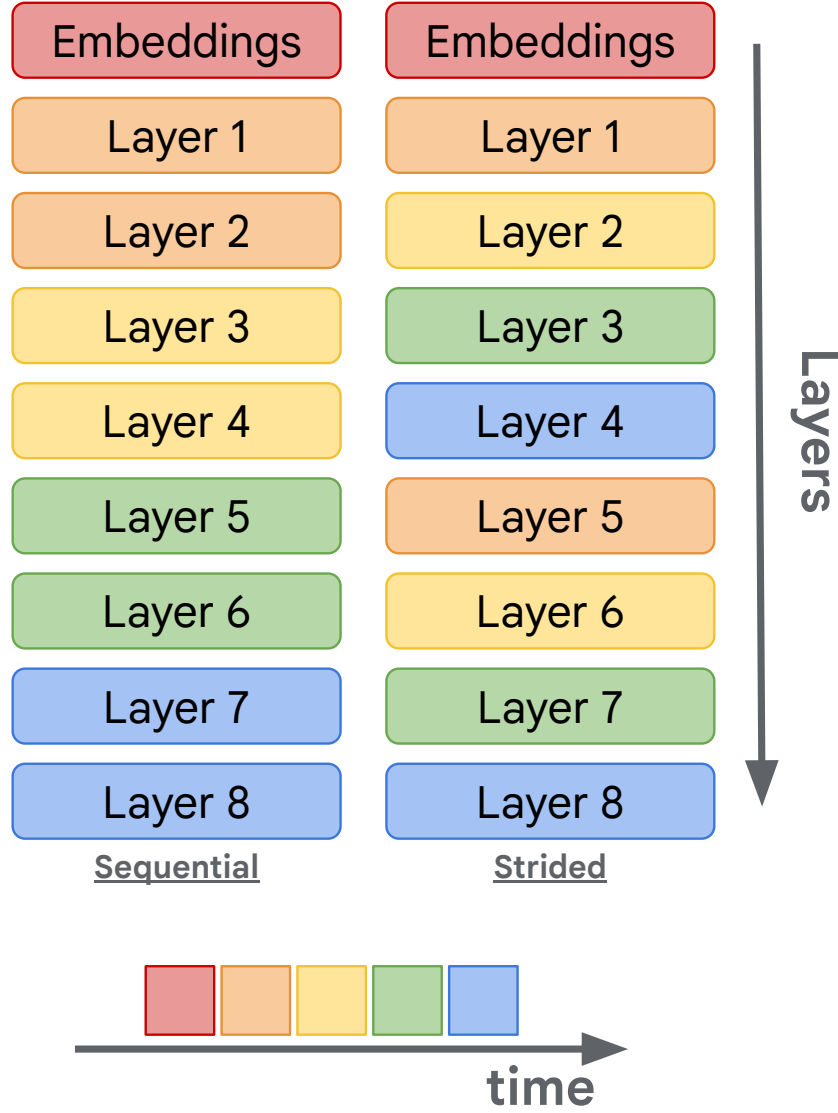


Figure 8: **Streaming pattern:** sequential (left) and strided (right). Colors denotes the fragment. A different fragment is synchronized each time.

**Overlapping with some slack between workers** If workers use heterogeneous device types (e.g. TPUv5e vs TPUv6e) or are just placed in different environments, their execution speed might vary and it would be inefficient to force them to synchronize at the same optimization step. In this case, we could grant workers with some slack. For instance, in a 2 DiLoCo replicas setting, both workers could send their respective outer gradients at the same step (but not necessarily at the same time) and they could receive the update at a different step (Liu et al., 2024a). We accomplish this by simply using a different  $\tau$  per worker ( $\tau_1$  and  $\tau_2$ ) as shown in line 7-9 in Algorithm 1. We show in Figure 14 the evaluation loss when  $\tau_1 = 1$  and varying  $\tau_2$ . Similarly to Figure 5, the loss degradation is limited under a delay of up to 5 inner steps. This result suggests that Streaming DiLoCo is rather robust and could support training of large models on several heterogeneous workers.

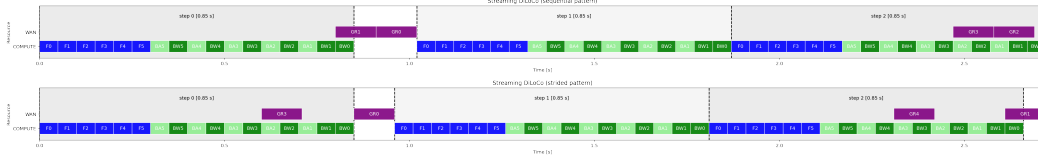


Figure 9: Simulation of a schedule interleaving forward passes (in blue), backward passes w.r.t. activations and weights (resp. in light and dark green), and (outer) gradient reduction (in purple) for Streaming DiLoCo, respectively with a sequential and strided pattern.

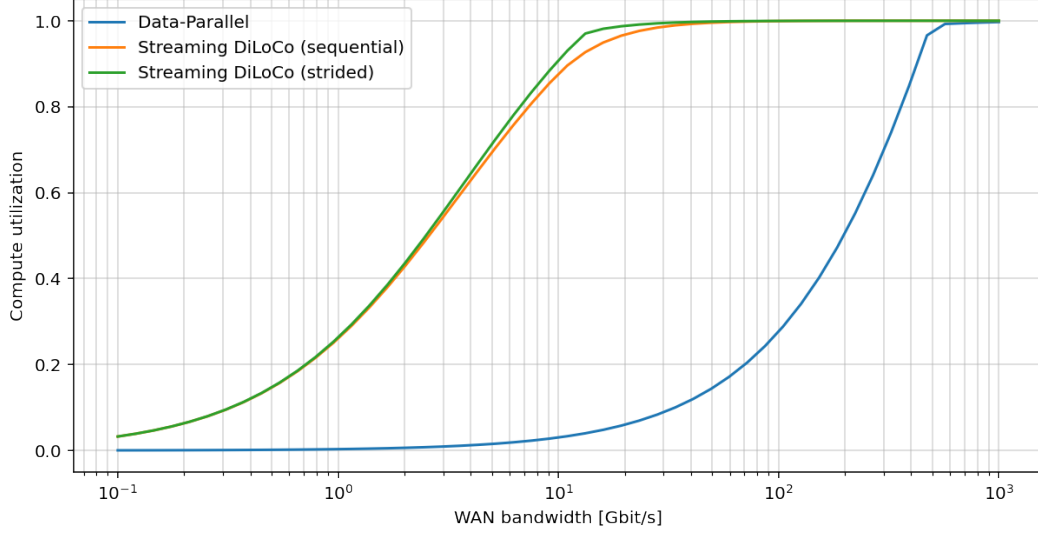


Figure 10: **Compute utilization profile** of sequential vs strided pattern for a 100 billion parameters model.

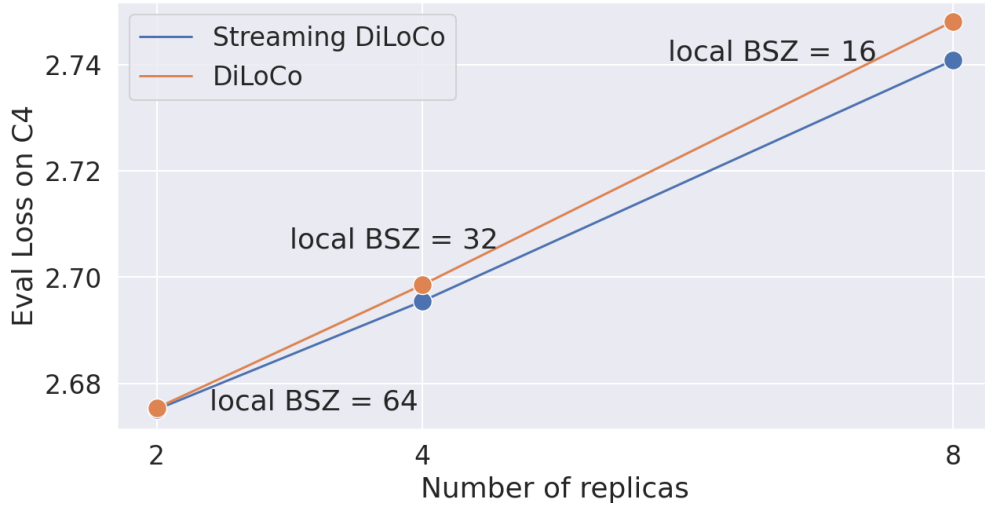
## A.7 Quantized communication

**Loss and accuracy.** We show in Figure 15 the impact of compressed outer gradient communication on both the loss on C4 and accuracy on HellaSwag.

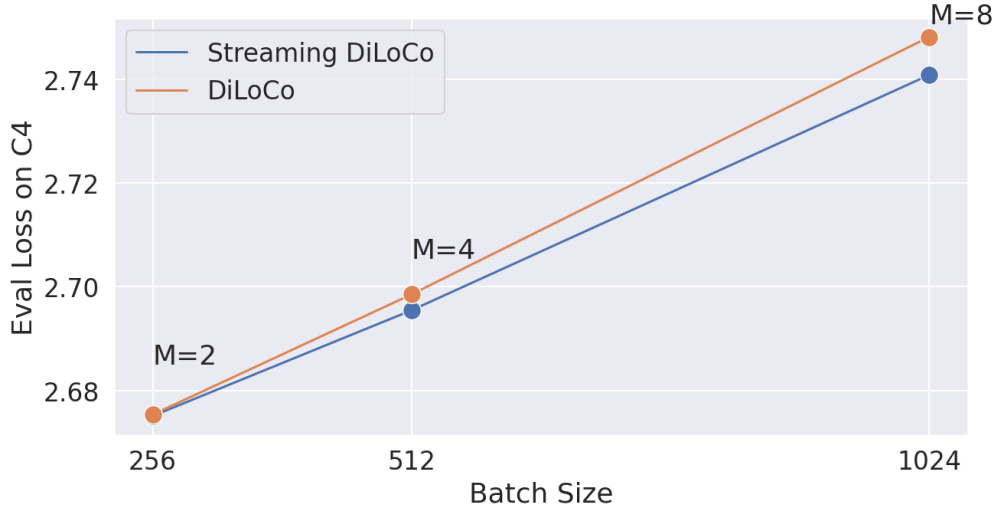
## A.8 Compute Utilization

**Compute utilization.** We report in Table 5 the amount of Gbit/s required, per method, to reach a certain level of compute utilization. See Figure 3 for a figure view of this table. For DiLoCo and Streaming DiLoCo (and variants thereof), we use  $H = 100$  inner steps. For Streaming DiLoCo (and variants thereof), we use a fixed fragment size of 3 layers; therefore, deeper networks have more fragments: for 1B, 10B, and 100B model scales, it is respectively 8, 16, and 36 fragments. Also, respectively per model scales, a fragment is synchronized every 11, 5, and 2 steps. While the synchronization seems to be more frequent for deeper networks, from the perspective of particular fragment, it is synchronized roughly every  $H = 100$  steps. To estimate the compute utilization in Table 5 and Figure 3, the time spent per step doing computation (forward & backward) is critical: we report respectively 0.1s, 0.8s, and 4.9s based on each model scale flops profile, a reasonable amount of chips, and a MFU of 60%.

**Compute utilization with various speeds.** Varying the time spent per step to do pure computation (forward & backward) affects the compute utilization: e.g. for a fixed bandwidth and thus fixed communication time, longer step time, will improve compute utilization.



(a) Keeping the *global* batch size constant, and thus decreasing the *local* per-replica batch size.



(b) Keeping the *local* per-replica batch size constant, and thus increasing the *global* batch size.

Figure 11: **Scaling the number of DiLoCo replicas  $M$  from  $M = 2$  to  $M = 4$ .** For all experiments, the token budget is kept constant.

Parameters evaluated	Eval Loss	HellaSwag
First replica	2.77	37.77
Replicas average	2.68	37.72
Outer parameters	<b>2.67</b>	<b>37.78</b>

Table 4: **Which parameters to evaluate?:** Evaluating the outer parameters, where each fragment has been synchronized at a different moment in time, yields better performance than any inner parameters.

We report in Figure 16, simulated compute utilization when using, at 100B model scale, a compute step time of 1 second, 5 seconds, and 10 seconds.

**Compute Utilization on Llama and DeepSeek.** We estimate in Figure 17, the compute utilization of our method vs baselines on top of Llama405 (Grattafiori et al., 2024) and

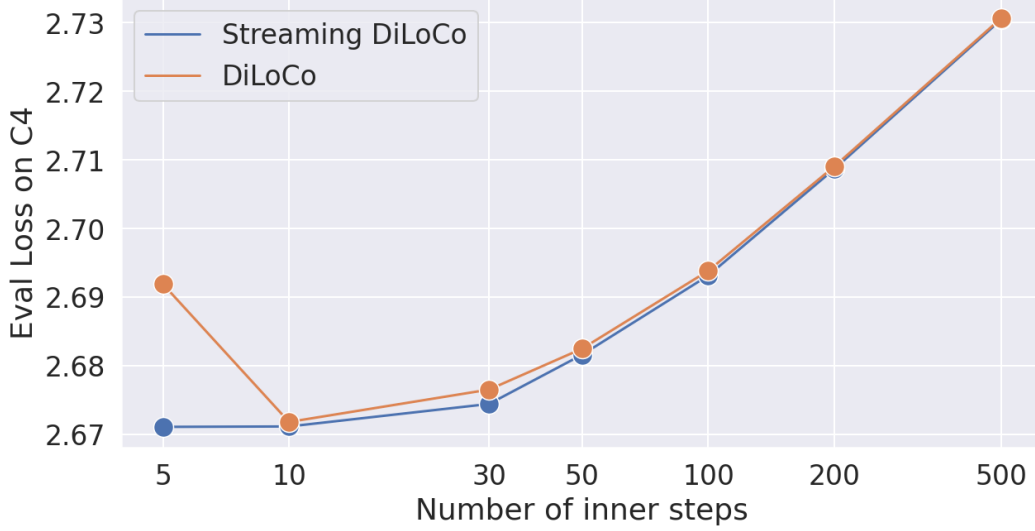


Figure 12: Varying the number of inner steps  $H$  for DiLoCo and Streaming DiLoCo while keeping the total number of steps constants. A lower  $H$  means more communication rounds to be done.

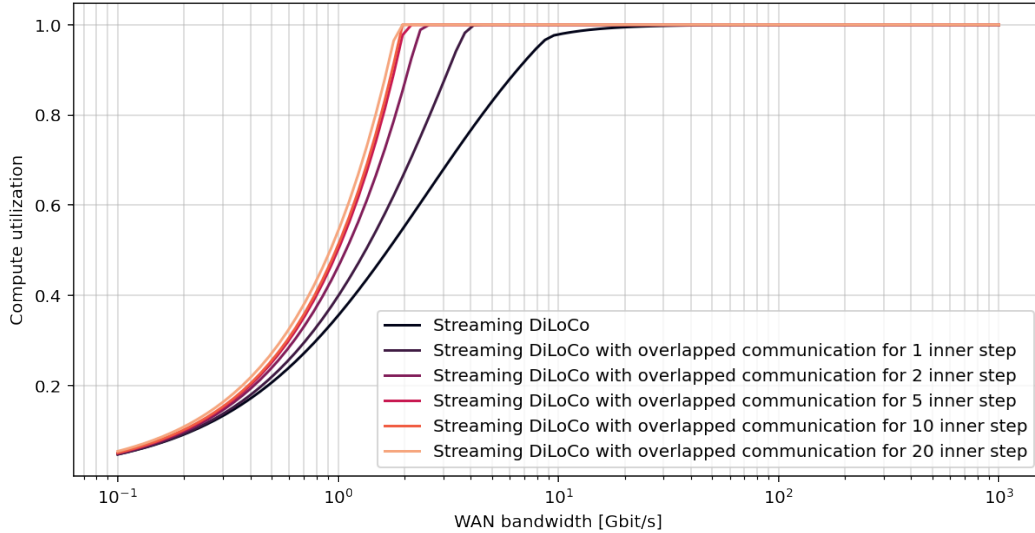


Figure 13: Estimated compute utilization for a 100B model when increasing  $\tau$ , the number of inner steps which overlap with communication.

DeepSeek-V3 (DeepSeek-AI et al., 2024). For each, we estimate their step time from the respective paper: 26.9 seconds for Llama (first stage of pretraining) and 20.1 seconds for DeepSeek, using the most charitable estimation everytime. Notably, for DeepSeek-V3 (Figure 17b), only 35 billion parameters are activated per token due to their MoE architecture (Shazeer et al., 2017). However, the total 671 billion parameters are synchronized between replicas, massively increasing the amount of bits to transfer. In that case, in our simulation, our method (in red) can be close to 100% compute utilization with 4 Gbits per second vs 1 Tbit per second for Data-Parallel.

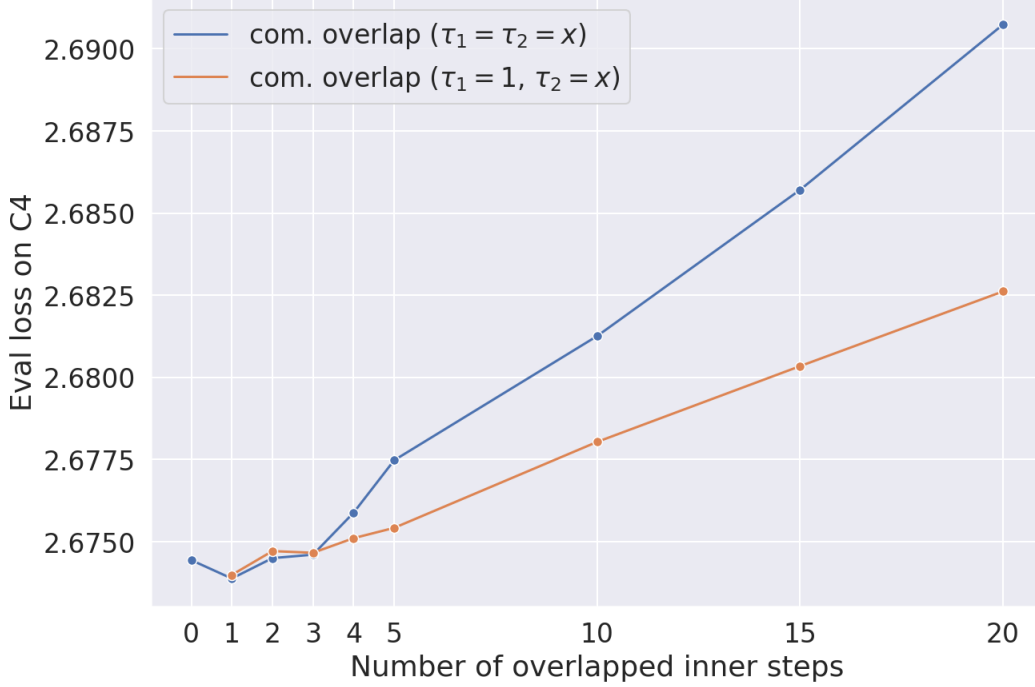


Figure 14: Varying the number of overlapped inner steps  $\tau_2$  for the second worker while keeping  $\tau_1 = 1$ . For all data points,  $\alpha = 0.5$ . Training is very robust for values of  $\tau_2$  less than 5.

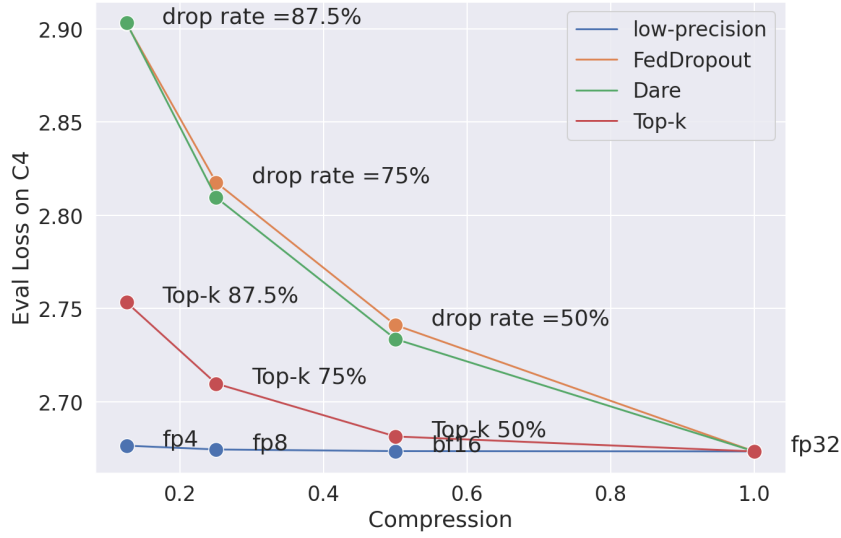
Model size	# layers	Step time	Method	Gbit/s to reach a compute utilization CU = ?				
				50%	80%	90%	95%	99%
1B	24	0.1s	Data-Parallel	86.8	152.6	184.2	222.3	569.0
			Vanilla DiLoCo	1.4	6.2	13.3	23.3	86.8
			Streaming DiLoCo	1.4	5.2	9.1	16.0	28.1
			Streaming DiLoCo w/ overlapped com.	1.4	4.3	6.2	9.1	11.0
			Streaming DiLoCo w/ overlapped FP4 com.	0.4	0.9	1.7	2.0	3.0
10B	48	0.8s	Data-Parallel	104.8	222.3	222.3	268.3	471.5
			Vanilla DiLoCo	1.7	7.5	16.0	33.9	104.8
			Streaming DiLoCo	1.7	5.2	9.1	13.3	19.3
			Streaming DiLoCo w/ overlapped com.	1.7	3.6	5.2	6.2	7.5
			Streaming DiLoCo w/ overlapped FP4 com.	0.4	0.9	1.4	1.4	1.7
100B	108	4.9s	Data-Parallel	184.2	323.8	390.7	390.7	471.5
			Vanilla DiLoCo	3.0	11.0	23.3	49.4	184.2
			Streaming DiLoCo	2.4	6.2	9.1	11.0	19.3
			Streaming DiLoCo w/ overlapped com.	1.7	3.6	4.3	5.2	5.2
			Streaming DiLoCo w/ overlapped FP4 com.	0.5	0.9	1.1	1.1	1.4

Table 5: **Simulation:** we estimate the step time (pure compute) of 10B and 100B based on the required flops using [Kaplan et al. \(2020\)](#) rule and using a MFU of 60%. For all DiLoCo and Streaming DiLoCo-variants, we use  $H = 100$ . For all Streaming DiLoCo-variants, we use a fragment size of 3 layers.

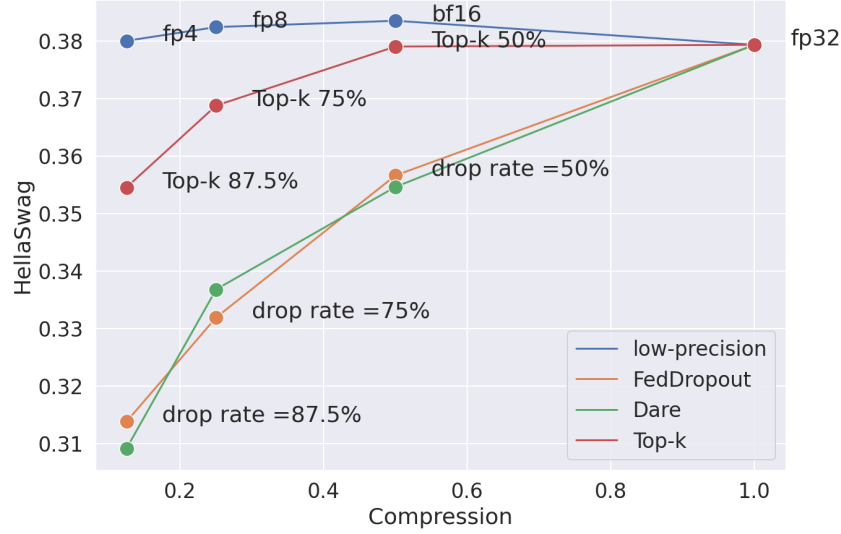
## A.9 Additional numbers

**Scaling performance.** We report in [Table 6](#), the evaluation loss on C4 and accuracy on HellaSwag ([Zellers et al., 2019](#)), Piqa ([Bisk et al., 2020](#)), and Arc-Easy ([Clark et al., 2018](#)), for four different methods across 6 model scales. See [subsection 3.2.1](#) for the initial discussion. Performance across scales are roughly similar among all considered methods, with usually a slight advantage for Data-Parallel. We found in practice this advantage to disappear when doing a more realistic overtraining with larger token budget in [subsection 3.2.2](#).





(a) C4 evaluation loss



(b) HellaSwag accuracy

Figure 15: **Compressing the outer gradients** with either value dropping (FedDropout, Dare) or using lower-precision floating point numbers.

**Scaling with variable number of replicas.** Contrarely to Data-Parallel, changing the number of replicas for DiLoCo is not mathematically equivalent due to the local training, happening independently for each replicas. We display in Table 7, a scaling from 35 million parameters to 1 billion parameters on the C4 dataset of our method, Streaming DiLoCo with overlapped FP4 communication, with different number of replicas  $M = \{2, 4\}$  and different frequencies of synchronization  $H = \{30, 100\}$ . Likewise, in Table 8, we showcase token budget overtraining at 1 billion parameters on the Dolma dataset.

#### A.10 Miscellaneous

**Outer gradients' cosine similarity,** We observe in Figure 18 the cosine similarity per scale between each replica's outer gradients for respectively all parameters but the embeddings (Figure 18a) and only the embeddings (Figure 18b). For both, the cosine similarity starts from slightly correlated ( $\approx 0.1$ ), spends of the training time to be close to orthogonal ( $\approx 0.0$ ),

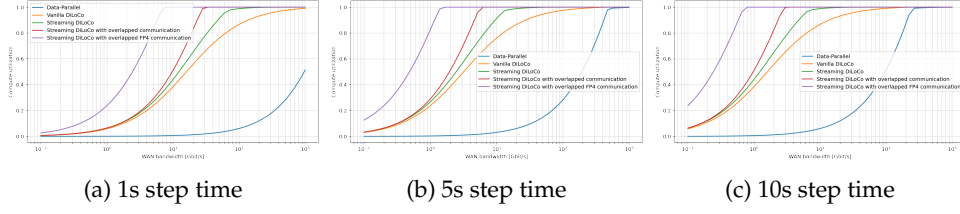


Figure 16: **Compute Utilization** for a 100 billion parameters when the step time (pure compute) is 1 second, 5 seconds, and 10 seconds.

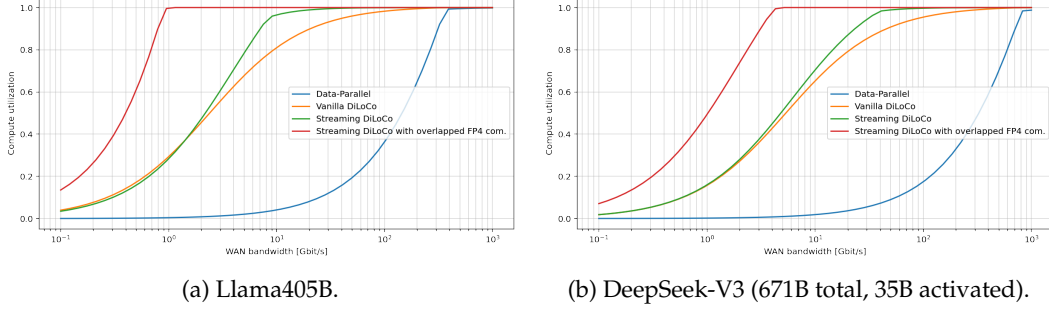


Figure 17: **Compute Utilization** simulated across a range of bandwidth for Llama405 and DeepSeek-V3, using step time estimated from respective papers.

and ends slightly inversely correlated ( $\approx -0.1$ ) as we reach the fluctuation phase. Note also that the larger the model size, the lower is overall the cosine similarity.

We also plot in [Figure 19](#) the cosine similarity per scale and per transformer layer. Notably, the first transformer layer at each scale has a significantly higher similarity, at every model scales.

Model size	Flops	Method	Eval Loss ↓	HellaSwag ↑	Piqa ↑	Arc Easy ↑
35M	1.5e17	Data-Parallel	3.51	24.62	57.89	29.65
		DiLoCo H=30	3.54	24.53	58.11	29.65
		Streaming DiLoCo with overlapped FP4 com., H=30	3.53	24.46	57.67	30.53
		Streaming DiLoCo with overlapped FP4 com., H=100	3.56	24.80	57.89	29.12
100M	9.4e17	Data-Parallel	3.19	26.94	60.12	30.35
		DiLoCo H=30	3.21	26.59	60.50	29.12
		Streaming DiLoCo with overlapped FP4 com., H=30	3.21	26.97	59.58	31.40
		Streaming DiLoCo with overlapped FP4 com., H=100	3.22	26.68	60.39	31.93
200M	4e18	Data-Parallel	2.97	29.86	63.71	35.44
		DiLoCo H=30	2.98	29.71	62.30	33.68
		Streaming DiLoCo with overlapped FP4 com., H=30	2.98	29.67	61.92	34.39
		Streaming DiLoCo with overlapped FP4 com., H=100	3.00	29.27	62.13	34.21
300M	1.4e19	Data-Parallel	2.80	33.46	64.69	34.91
		DiLoCo H=30	2.81	33.87	64.74	34.74
		Streaming DiLoCo with overlapped FP4 com., H=30	2.81	33.66	63.49	35.09
		Streaming DiLoCo with overlapped FP4 com., H=100	2.83	33.00	63.71	34.39
500M	4.7e19	Data-Parallel	2.67	38.68	66.49	37.19
		DiLoCo H=30	2.68	38.37	65.61	36.32
		Streaming DiLoCo with overlapped FP4 com., H=30	2.67	38.10	66.21	34.91
		Streaming DiLoCo with overlapped FP4 com., H=100	2.69	37.40	65.51	34.74
1B	1.9e20	Data-Parallel	2.49	46.60	68.93	39.65
		DiLoCo H=30	2.49	46.56	68.82	36.84
		Streaming DiLoCo with overlapped FP4 com., H=30	2.48	46.60	69.04	39.12
		Streaming DiLoCo with overlapped FP4 com., H=100	2.50	46.00	68.82	38.42
4B	2e21	Data-Parallel	2.25	59.56	72.42	43.51
		DiLoCo H=30	-	-	-	-
		Streaming DiLoCo with overlapped FP4 com., H=30	-	-	-	-
		Streaming DiLoCo with overlapped FP4 com., H=100	2.26	59.02	72.52	43.16

Table 6: **Scaling** from 35 million parameters to 4 billion parameters using a chinchilla-optimal number of flops/tokens. We train on the C4 dataset, and report the evaluation loss on its validation set.

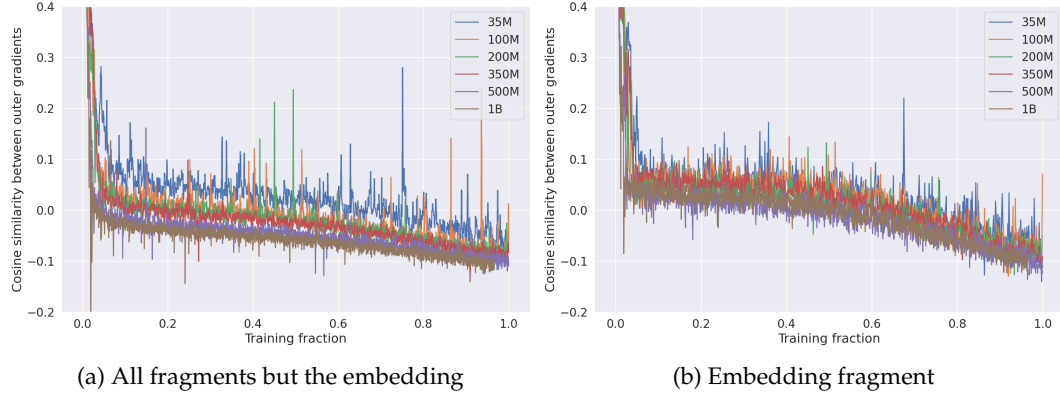


Figure 18: **Cosine similarity between the outer gradients** across scales.

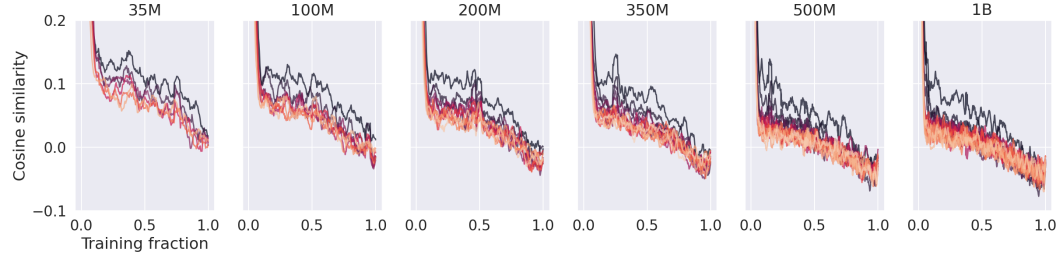


Figure 19: **Cosine similarity between the outer gradients** across scales. Each line is a transformer layer, with darker colors being earlier layers and lighter colors later layers.

Model size	Flops	$M$	$H$	Eval Loss ↓	HellaSwag ↑	Piqa ↑	Arc Easy ↑
35M	1.5e17	2	30	3.53	24.46	57.67	30.53
		4	30	3.60	24.50	56.09	28.60
		2	100	3.56	24.80	57.89	29.12
		4	100	3.64	24.67	56.75	26.84
100M	9.4e17	2	30	3.21	26.97	59.58	31.40
		4	30	3.25	26.24	59.74	32.63
		2	100	3.22	26.68	60.39	31.93
		4	100	3.29	26.54	60.34	29.82
200M	4e18	2	30	2.98	29.67	61.92	34.39
		4	30	3.02	29.09	62.89	35.44
		2	100	3.00	29.27	62.13	34.21
		4	100	3.05	28.53	61.10	33.51
300M	1.4e19	2	30	2.81	33.66	63.49	35.09
		4	30	2.84	32.54	64.42	34.74
		2	100	2.83	33.00	63.71	34.39
		4	100	2.87	32.02	64.25	35.44
500M	4.7e19	2	30	2.67	38.10	66.21	34.91
		4	30	2.70	36.95	65.72	35.26
		2	100	2.69	37.40	65.51	34.74
		4	100	2.73	36.02	66.27	35.09
1B	1.9e20	2	30	2.48	46.60	69.04	39.12
		4	30	2.50	45.25	67.95	39.12
		2	100	2.50	46.00	68.82	38.42
		4	100	2.53	44.74	68.34	38.25

Table 7: **Scaling** from 35 million parameters to 1 billion parameters Streaming DiLoCo with overlapped FP4 communication and with two different synchronization frequencies  $H = \{30, 100\}$  and number of DiLoCo replicas  $M = \{2, 4\}$ .

Method	Token Budget	Terabytes exchanged ↓	Eval Loss ↓	HellaSwag ↑	Piqa ↑	Arc Easy ↑
Data-Parallel	25B	441	2.67	<b>42.09</b>	67.35	<b>40.42</b>
	100B	1,767	2.52	49.78	69.15	<b>44.03</b>
	250B	4,418	<b>2.45</b>	53.86	70.45	<b>44.21</b>
Our method, M=2	25B	1.10	<b>2.66</b>	42.08	<b>67.46</b>	38.42
	100B	4.42	<b>2.51</b>	<b>49.98</b>	<b>69.96</b>	<b>44.03</b>
	250B	11.05	<b>2.45</b>	<b>54.24</b>	<b>71.38</b>	41.92
Our method, M=4	25B	0.55	2.73	38.93	66.92	39.64
	100B	2.21	2.54	48.35	69.42	40.52
	250B	5.52	2.47	52.20	70.29	42.45

Table 8: **Overtraining** on the Dolma dataset with a 1 billion parameters model, and with an increasing token budgets (25B, 100B, and 250B). We report here for our model both with  $M = 2$  and  $M = 4$  DiLoCo replicas. With twice more replicas, the global batch size is doubled, and twice less steps are done. It is also thus roughly twice faster, but come with slightly worse performance. Our method is the final model: Streaming DiLoCo with overlapped FP4 communication.