

# Errata for “Cerebro: A Data System for Optimized Deep Learning Model Selection”

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We discovered that there was an inconsistency in the communication cost formulation for the decentralized fine-grained training method in **Table 2** of our paper [1]. We used Horovod as the archetype for decentralized fine-grained approaches, and its correct communication cost is higher than what we had reported. So, we amend the communication cost of decentralized fine-grained to  $2km(p-1)|S|\left\lceil\frac{|D|}{bp}\right\rceil$ , instead of  $kmp|S|\left\lceil\frac{|D|}{bp}\right\rceil$ .

With this correction, **Table 2** of our paper should be corrected as follows, which uses the same notation.

**Table 2: Communication cost analysis of MOP and other approaches. \*Full replication. †Remote reads. ‡Parameters for the example:  $k = 20$ ,  $|S| = 20$ ,  $p = 10$ ,  $m = 1\text{GB}$ ,  $\langle D \rangle = 1\text{TB}$ , and  $|D|/b = 100\text{K}$ .**

	Comm. Cost	Example <sup>‡</sup>
Model Hopper Parallelism	$kmp S  + m S $	4 TB
Task Parallelism (FR <sup>*</sup> )	$p\langle D \rangle + m S $	10 TB
Task Parallelism (RR <sup>†</sup> )	$k S \langle D \rangle + m S $	400 TB
Bulk Synchronous Parallelism	$2kmp S $	8 TB
Centralized Fine-grained	$2kmp S \left\lceil\frac{ D }{bp}\right\rceil$	80 PB
Decentralized Fine-grained	$2km(p-1) S \left\lceil\frac{ D }{bp}\right\rceil$	72 PB

Also, the last two paragraphs of Section 2 that refer to the above table should be corrected as follows:

All PS-style approaches have *high communication* due to their centralized all-to-one communications, which is proportional to the number of mini-batches and orders of magnitude higher than BSP, e.g., **10,000x** in Table 2.

Decentralized Fine-grained. The best example is Horovod. It adopts HPC-style techniques to enable synchronous all-reduce SGD. While this approach is bandwidth optimal, communication latency is still proportional to the number of workers, and the synchronization barrier can become a bottleneck. The total communication overhead is also proportional to the number of mini-batches and orders of magnitude higher than BSP, e.g., **9,000x** in Table 2.

The above amendments are purely in the conceptual exposition and do not affect any technical findings, empirical results, or conclusions in the paper.

## REFERENCES

- [1] Supun Nakandala, Yuhao Zhang, and Arun Kumar. 2020. Cerebro: A Data System for Optimized Deep Learning Model Selection. *Proc. VLDB Endow.* 13, 12 (July 2020), 2159–2173. <https://doi.org/10.14778/3407790.3407816>

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