

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

Supun Nakandala, Yuhao Zhang, and Arun Kumar
University of California, San Diego
{snakanda, yuz870, arunkk}@eng.ucsd.edu

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 1: 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 [‡] |
|-------------------------------------|--|----------------------|
| Model Hopper Parallelism | $kmp S + m S $ | 4 TB |
| Task Parallelism (FR*) | $p\langle D \rangle + m S $ | 10 TB |
| Task Parallelism (RR [†]) | $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 refers 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.

1. REFERENCES

- [1] S. Nakandala, Y. Zhang, and A. Kumar. Cerebro: A data system for optimized deep learning model selection. *Proc. VLDB Endow.*, 13(12):21592173, July 2020.

This work is licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License. To view a copy of this license, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>. For any use beyond those covered by this license, obtain permission by emailing info@vldb.org. Copyright is held by the owner/author(s). Publication rights licensed to the VLDB Endowment.

Proceedings of the VLDB Endowment, Vol. 13, No. 11

ISSN 2150-8097.

DOI: <https://doi.org/10.14778/3407790.3407816>