

Poster: SWIFT: Expedited Failure Recovery for Large-scale DNN Training

Yuchen Zhong¹, Guangming Sheng¹, Juncheng Liu², Jinhui Yuan², Chuan Wu¹

¹The University of Hong Kong, China, ²OneFlow Inc., China

{yczhong,gmsheng,cwu}@cs.hku.hk,{liujuncheng,yuanjinhui}@oneflow.org

Abstract

As the size of deep learning models gets larger and larger, training takes longer time and more resources, making fault tolerance critical. Existing state-of-the-art methods like CheckFreq and Elastic Horovod need to back up a copy of the model state in memory, which is costly for large models and leads to non-trivial overhead. This paper presents SWIFT, a novel failure recovery design for distributed deep neural network training that significantly reduces the failure recovery overhead without affecting training throughput and model accuracy. Instead of making an additional copy of the model state, SWIFT resolves the inconsistencies of the model state caused by the failure and exploits replicas of the model state in data parallelism for failure recovery. We propose a logging-based approach when replicas are unavailable, which records intermediate data and replays the computation to recover the lost state upon a failure. Evaluations show that SWIFT significantly reduces the failure recovery time and achieves similar or better training throughput during failure-free execution compared to state-of-the-art methods without degrading final model accuracy.

CCS Concepts: • Computing methodologies → Distributed artificial intelligence.

Keywords: Distributed DNN Training; Failure Resilience

1 Introduction

Large deep neural networks (DNNs) have recently been shown to improve model performance [2], but training these models is prone to failures due to the use of many machines (e.g., hundreds of GPU machines) and long training time (e.g., days to months). Currently, the most common method for fault tolerance in deep learning frameworks is global checkpointing, which periodically saves the entire model state (i.e., parameters and optimizer states) and restarts from the latest checkpoint in the event of a failure. Depending

on the checkpointing frequency, this often results in several hours of lost computation time [8]. CheckFreq [9] achieves more frequent checkpoints by splitting the operation into two phases: first, the model state is copied into the GPU memory, called a *snapshot*, or to the CPU memory if the GPU memory is insufficient; next, the snapshot is written to the disk asynchronously. Elastic Horovod [1], a framework for elastic training, adopts a similar approach but without the second phase. The reason is that Elastic Horovod assumes distributed data-parallel training, where each worker maintains a replica of the model state; during failure recovery, one of the surviving workers broadcasts the snapshot to other workers, and all workers restart training from the snapshot. Taking a snapshot is necessary for Elastic Horovod to prevent a corrupted state: if a failure occurs during the model update, the surviving workers are in an awkward situation - some parameters are updated while the others are not. We identify this problem as the *crash-consistency problem*. However, we found that both methods can slow down training due to the overhead of snapshotting, as shown in Figure 1.

This paper studies a better failure resilience design for distributed DNN training that significantly reduces the recovery overhead without affecting training throughput and final model accuracy. SWIFT uses a combination of replication-based recovery and logging-based recovery to achieve this goal. We implement SWIFT in PyTorch [10] and the code is publicly available at <https://github.com/jasperzhong/swift>.

2 SWIFT Design

First, SWIFT uses a novel method called *update-undo* that resolves model state inconsistencies caused by the failure and thus enables *replication-based recovery* using replicas of the model state in data parallelism without creating additional snapshots. Second, SWIFT proposes *logging-based recovery* to achieve expedited failure recovery in pipeline parallelism.

2.1 Update-undo

Many update operators in optimizers like SGD and Adam [6] are mathematically *invertible*, meaning that there is an inverse operator that can reverse the operation of the original operator. For example, linear operators like element-wise addition and scalar multiplication are all invertible. However, some optimizers involve non-linear operators, such as the LAMB optimizer [13] which scales gradients with the L2 norm of the parameters. In this case, it is necessary to save the L2 norm as a scalar for recovery purposes. In the

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

PPoPP '23, February 25-March 1, 2023, Montreal, QC, Canada

© 2023 Copyright held by the owner/author(s).

ACM ISBN 979-8-4007-0015-6/23/02.

<https://doi.org/10.1145/3572848.3577510>

event of a failure during model updates, if some parameters at the workers have been updated and others have not, the surviving workers can *undo* the update for the updated parameters. In addition to restoring the model parameters, it is also necessary to restore optimizer states such as momentum to ensure consistency across all workers. With update-undo, replicas of the model state can be used for failure recovery in data parallelism, called *replication-based recovery*.

2.2 Logging-based Recovery

We propose logging-based recovery for pipeline parallelism. This involves logging the inter-machine communication (i.e., intermediate activations in the forward pass and the gradients in the backward pass), as well as metadata such as the sender and the receiver and the timestamp (i.e., the current training iteration and the current micro-batch being trained). Our logging method is similar to upstream backup [5], where the sender rather than the receiver logs the message to ensure that the intermediate data needed for recovery is not lost upon a failure. Logging is done asynchronously in the background using a dedicated CUDA stream. A queue is set up for each worker. The worker keeps pushing outgoing tensors into the queue during training, while another background thread keeps reading tensors from the queue and doing the logging. In addition, we perform logging during the bubble time in synchronous pipeline-parallel training. In this way, logging is *off the critical path*. Note that global checkpointing is still used to limit the logging size because all logging files are obsoleted after a global checkpointing.

In the event of a failure, the surviving upstream workers flush the queue of uncompleted logging tasks when detecting a failure in the training job. The upstream workers then upload their logging files to global storage (e.g., HDFS). The replacement workers for the failure workers then download the necessary logging files from the global store, load the latest checkpoint, and replay previously received tensors from the logging file in the exact order of their timestamps. If necessary, the surviving workers will undo the update. This method allows for a more limited scope of recovery, focusing on the local computation graph on the failed machine rather than the entire computation graph compared to pure global checkpointing, resulting in faster recovery. Note that logging requires the computation to be deterministic (i.e., the same input leads to the same output).

Parallel recovery. To further improve the recovery process, we utilize the surviving workers to assist in the recovery of the failed workers. By logging the intermediate results of all micro-batches, we can use data-parallel training based on the logged data to expedite the recomputation of lost states.

Selective logging. We next investigate a trade-off between the storage space and the recovery time with selective logging. Our idea is to group machines and log inter-group communication but not intra-group communication. The original approach is a particular case where each machine

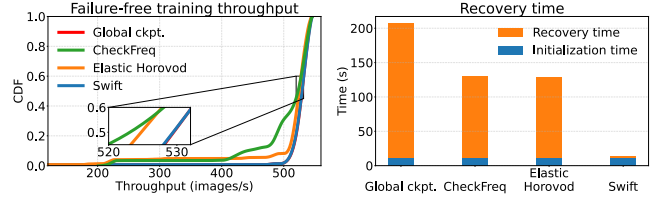


Figure 1. Replication-based recovery for Wide-ResNet-50.

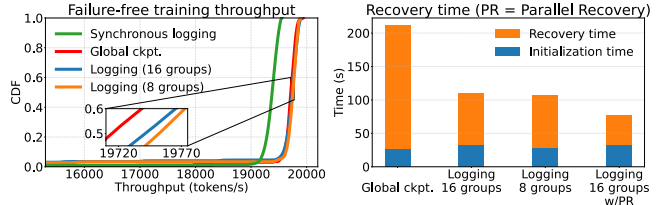


Figure 2. Logging-based recovery for BERT-128.

forms a group. If one machine in a group fails, training on the entire group of machines needs to be rolled back from the latest checkpoint, and the recovery time will be longer.

3 Evaluation

We experiment on 16 DGX-2 machines, each equipped with eight 32 GB V100 GPUs connected via 40Gbps Ethernet. We compare the performance of SWIFT with CheckFreq and Elastic Horovod for training a scaled-up version of the Wide-ResNet-50 model [14] (base channel size 320, 1.23 billion parameters) on the ImageNet dataset [12] using data parallelism, and with synchronous logging (i.e., saving a tensor before sending it) and global checkpointing for training a BERT-128 model [3] (128 transformer layers, 1.11 billion parameters) on the Wikipedia dataset [3] using pipeline parallelism. We simulate a failure by killing one machine at iteration 100. Figure 1 shows that SWIFT’s replication-based recovery significantly reduces recovery time by 98.1% compared to CheckFreq and Elastic Horovod for Wide-ResNet-50. Figure 2 shows that SWIFT’s logging-based recovery achieves similar throughput while reducing recovery time by up to 76.3% compared to global checkpointing for BERT-128. In addition, SWIFT demonstrates no loss of accuracy in end-to-end finetuning tasks for BERT-Large on the SQuAD dataset [11] and ViT-Base/32 [4] on the CIFAR-100 dataset [7], compared to its failure-free counterparts.

Simulation study. We calculate the expected end-to-end training time using traces collected in our experiments. We inject failures uniformly randomly during training, assuming a 17-hour median-time-between-failure [8]. Our results show that SWIFT can speed up end-to-end training for Wide-ResNet-50 and BERT-128 by 1.16x and 1.10x, respectively.

Acknowledgments

This work was supported in part by the Major Scientific Research Project of Zhejiang Lab (No.2019KD0AD01) and grants from Hong Kong RGC (HKU 17204619, 17208920).

References

- [1] The Horovod Authors. 2022. Elastic Horovod. https://horovod.readthedocs.io/en/stable/elastic_include.html.
- [2] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In *Proceedings of Advances in Neural Information Processing Systems*.
- [3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.
- [4] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2020. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In *Proceedings of International Conference on Learning Representations*.
- [5] Jeong-Hyon Hwang, Magdalena Balazinska, Alex Rasin, Ugur Cetintemel, Michael Stonebraker, and Stan Zdonik. 2005. High-availability Algorithms for Distributed Stream Processing. In *Proceedings of International Conference on Data Engineering*.
- [6] Diederik P Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In *Proceedings of International Conference on Learning Representations*.
- [7] Alex Krizhevsky, Geoffrey Hinton, et al. 2009. Learning Multiple Layers of Features from Tiny Images. (2009).
- [8] Kiwan Maeng, Shivam Bharuka, Isabel Gao, Mark Jeffrey, Vikram Saraph, Bor-Yiing Su, Caroline Trippel, Jiyan Yang, Mike Rabbat, Brandon Lucia, and Carole-Jean Wu. 2021. Understanding and Improving Failure Tolerant Training for Deep Learning Recommendation with Partial Recovery. In *Proceedings of the 4th Conference on Machine Learning and Systems*.
- [9] Jayashree Mohan, Amar Phanishayee, and Vijay Chidambaram. 2021. CheckFreq: Frequent, Fine-Grained DNN Checkpointing. In *Proceedings of the 19th USENIX Conference on File and Storage Technologies*.
- [10] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *Proceedings of Advances in Neural Information Processing Systems*.
- [11] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*.
- [12] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. 2015. Imagenet Large Scale Visual Recognition Challenge. In *Proceedings of International Journal of Computer Vision*.
- [13] Yang You, Jing Li, Sashank Reddi, Jonathan Hseu, Sanjiv Kumar, Srinadh Bhojanapalli, Xiaodan Song, James Demmel, Kurt Keutzer, and Cho-Jui Hsieh. 2020. Large Batch Optimization for Deep Learning: Training BERT in 76 Minutes. In *Proceedings of International Conference on Learning Representations*.
- [14] Sergey Zagoruyko and Nikos Komodakis. 2016. Wide Residual Networks. *arXiv preprint* (2016).