

# Conference Paper Title\*

\*Note: Sub-titles are not captured in Xplore and should not be used

1 <sup>st</sup> André Lucena Ribas Ferreira	1 <sup>st</sup> Carlos Eduardo da Silva Machado	1 <sup>st</sup> Gonalo Manuel Maia de Sousa
<i>University of Minho</i>	<i>University of Minho</i>	<i>University of Minho</i>
Braga, Portugal	Braga, Portugal	Braga, Portugal
pg52672@uminho.pt	pg52675@uminho.pt	pg52682@uminho.pt

**Abstract**—This document is a model and instructions for L<sup>A</sup>T<sub>E</sub>X. This and the IEEEtran.cls file define the components of your paper [title, text, heads, etc.]. \*CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract.

**Index Terms**—component, formatting, style, styling, insert

## I. INTRODUCTION

- Machine learning has increased in popularity
  - image classification
  - natural language processing
- studies have tried to analyze I/O patterns in DL Workflows (source)
- I/O Characterization has served to produce diverse assumptions about DL I/O behavior, like high overhead for random reads, which are commonly used to justify various types of optimization explorations ([1], [2], [3]). Application-specific storage characterization is required to find unique and worthwhile solutions for newer performance problems.
- very few get down to kernel level
- eBPF are ...
- we seek to provide a tool to Characterize DL workloads using eBPF's

## II. BACKGROUND

*Deep learning* is a subset of machine learning algorithms based on neural networks with many layers. Training is done by passing all data through the entire network to calculate a loss, this is called the forward pass, the network parameters are then updated using the calculated loss, this is called backpropagation.

To accelerate the training process computation can be distributed among several workers, this is called Distributed Parallel learning and involves cloning the model parameters among all the workers, each of the individually processes a subset of the data, the loss is then averaged and all the workers update their parameters with the same loss, ensuring consistency among all workers.

- DL involves iterating multiple times (epochs) through a dataset
- DL is a subset of machine learning algorithms based on neural networks

- for accuracy, all data is read exactly once per one epoch and is done in random reads(I/O intensive)
- passing it through all the layers to calculate a loss (forward pass)
- use calculated loss to update the learnable parameters of the network (backpropagation)
- SGD is an optimizer for loss function minimization widely used for its lower computation compared to working through the whole dataset
- increasing batch-size in the last years, from the usual range of 32-256 [2]
- DL is usually I/O-bound [need source], due to the use of accelerators (GPU), size of the data and random reads
- pytorch is a DL framework with some particularities (Dataloader, ...)
- Tensorflow is also a DL framework, with other particularities...
- Imagenet
- Distributed DNN training (data parallelism)
- checkpointing involves saving the model state
- in pytorch its done explicitly with torch.save() and in official workloads is done in-between epochs
- eBPF's

## III. RELATED WORK

- papers que usam darshan/tf-darshan, como per-file statistics, para caracterizar padres [4] [5]
- MLPerf Storage/tese de um aluno da Oana
- DIO e tools de observabilidade que usam eBPF e outras (related work do DIO), LD PRELOAD, captura de de I/O request por instrumentao do cdigo fonte.
- Utilizar a descrio do I/O pipeline de Tensorflow workloads para benchmark [6]
- Caracterizar o I/O de LMDB, que  anloga  do PyTorch e do Tensorflow, a **database** usada como base do Caffe, baseada em *mmap* e numa *B+-tree*. [1]
- Comparar o overhead das leituras no treino inteiro com e sem shuffling. [7]
- Que mtricas analisam principalmente?
  - I/O skew por processo;
  - tempo de leitura por processo;
  - bandwidth do read por cada I/O block size;
  - nmero de context switches;

- latência com/sem shuffle
- O que falta fazer?
  - Análise empírica dos padrões de I/O como parte do processo de treino ao longo do tempo
  - Análise da cache como interveniente no processo de I/O
  - Testes de Rede (para modelos distribuídos)
  - Analisar PyTorch com o nível de detalhe que analisaram outras
  - Analisar kernel-level I/O calls

#### IV. DESIGN

- high level description of the system

#### V. EVALUATION METHODOLOGY

- dstat, nvidia-smi to get cost of using the tool
- python parser and plots
- grafana dashboard to get data

#### VI. EVALUATION RESULTS

#### VII. CONCLUSION

#### REFERENCES

- [1] S. Pumma, M. Si, W.-C. Feng, and P. Balaji, “Scalable deep learning via i/o analysis and optimization,” *ACM Trans. Parallel Comput.*, vol. 6, no. 2, Jul. 2019. [Online]. Available: <https://doi.org/10.1145/3331526>
- [2] Y. Zhu, W. Yu, B. Jiao, K. Mohror, A. Moody, and F. Chowdhury, “Efficient user-level storage disaggregation for deep learning,” in *2019 IEEE International Conference on Cluster Computing (CLUSTER)*, 2019, pp. 1–12.
- [3] F. Chowdhury, Y. Zhu, T. Heer, S. Paredes, A. Moody, R. Goldstone, K. Mohror, and W. Yu, “I/o characterization and performance evaluation of beegfs for deep learning,” in *Proceedings of the 48th International Conference on Parallel Processing*, ser. ICPP ’19. New York, NY, USA: Association for Computing Machinery, 2019. [Online]. Available: <https://doi.org/10.1145/3337821.3337902>
- [4] S. W. D. Chien, A. Podobas, I. B. Peng, and S. Markidis, “tf-darshan: Understanding fine-grained i/o performance in machine learning workloads,” in *2020 IEEE International Conference on Cluster Computing (CLUSTER)*, 2020, pp. 359–370.
- [5] T. Wang, S. Byna, G. K. Lockwood, S. Snyder, P. Carns, S. Kim, and N. J. Wright, “A zoom-in analysis of i/o logs to detect root causes of i/o performance bottlenecks,” in *2019 19th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID)*, 2019, pp. 102–111.
- [6] S. W. D. Chien, S. Markidis, C. P. Sishtla, L. Santos, P. Herman, S. Narasimhamurthy, and E. Laure, “Characterizing deep-learning i/o workloads in tensorflow,” in *2018 IEEE/ACM 3rd International Workshop on Parallel Data Storage & Data Intensive Scalable Computing Systems (PDSW-DISCS)*, 2018, pp. 54–63.
- [7] F. Chowdhury, J. Liu, Q. Koziol, T. Kurth, S. Farrell, S. Byna, and W. Yu, “Initial characterization of i/o in large-scale deep learning applications,” in *3rd Joint International Workshop on Parallel Data Storage and Data Intensive Scalable Computing Systems (PDSW-DISCS’18) at the International Conference on High Performance Computing, Networking, Storage and Analysis*, 2018.