SHADE: Enable Fundamental Cacheability for Distributed Deep Learning Training

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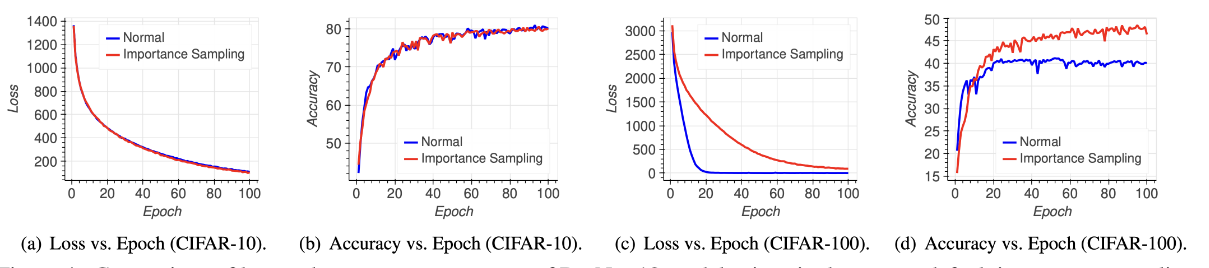
Abstract

Deep learning training (DLT) applications exhibit unique I/O workload behaviors that pose new challenges for storage system design. DLT is I/O intensive since data samples need to be fetched continuously from a remote storage. Accelerators such as GPUs have been extensively used to support these applications. As accelerators become more powerful and more data-hungry, the I/O performance lags behind. This creates a crucial performance bottleneck, especially in distributed DLT. At the same time, the exponentially growing dataset sizes make it impossible to store these datasets entirely in memory. While today's DLT frameworks typically use a random sampling policy that treat all samples uniformly equally, recent findings indicate that not all samples are equally important and different data samples contribute differently towards improving the accuracy of a model. This observation creates an opportunity for DLT I/O optimizations by exploiting the data locality enabled by importance sampling. To this end, we design and implement SHADE, a new DLTaware caching system that detects fine-grained importance variations at per-sample level and leverages the variance to make informed caching decisions for a distributed DLT job. SHADE adopts a novel, rank-based approach, which captures the relative importance of data samples across different minibatches. SHADE then dynamically updates the importance scores of all samples during training. With these techniques, SHADE manages to significantly improve the cache hit ratio of the DLT job, and thus, improves the job's training performance. Evaluation with representative computer vision (CV) models shows that SHADE, with a small cache, improves the cache hit ratio by up to 4.5x compared to the LRU caching policy.

Problem Statement and Research Objectives

DL Training with Importance Sampling

- Recently, researchers found that in SGD-based DL training, **a specific set of training samples tend to generate little-to-no impact** on the model quality and, therefore, can be ignored.
- The process of finding the set of training samples that are more important than others is known as **importance sampling**.
- Difficulty in Importance Sampling
  1. Default importance sampling (importance sampling considered in prior works) assigns per-minibatch scores, which are too coarse-grained and inaccurate.
  2. Even if important samples are identified properly, aggressively feeding the DL model with repetitive samples might make training model biased.
  3. Importance scores are constantly changing and may get stale quickly. The same sample in a later minibatch may contribute differently toward the model than it did in an earlier minibatch.



(a) Loss vs. Epoch (CIFAR-10). (b) Accuracy vs. Epoch (CIFAR-10). (c) Loss vs. Epoch (CIFAR-100). (d) Accuracy vs. Epoch (CIFAR-100).

Figure 4: Comparison of loss and accuracy convergence of ResNet-18 model using single process default importance sampling against baseline training on the CIFAR-10 and CIFAR-100 datasets.

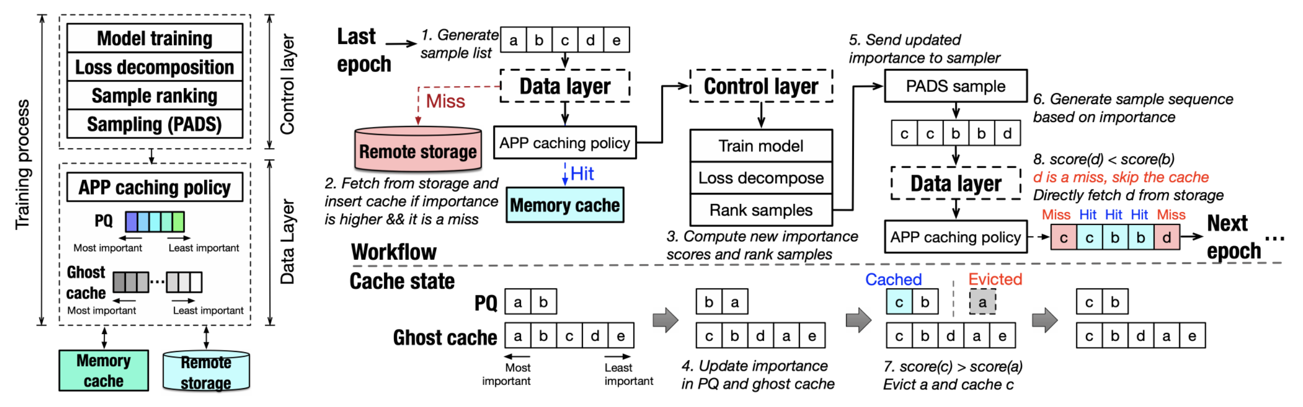
Proposed Method

1. Control Layer

- It calculates the importance scores associated with data samples
- It samples the data for different training processes.

2. Data Layer

The SHADE data layer provides mechanisms and policies for cache eviction and prefetching.



(a) SHADE's logical architecture. (b) SHADE's workflow.

Figure 6: SHADE architecture overview. (b) In illustration of how SHADE's components interact in a single epoch.

Evaluation and Results

- Cache hit ratio

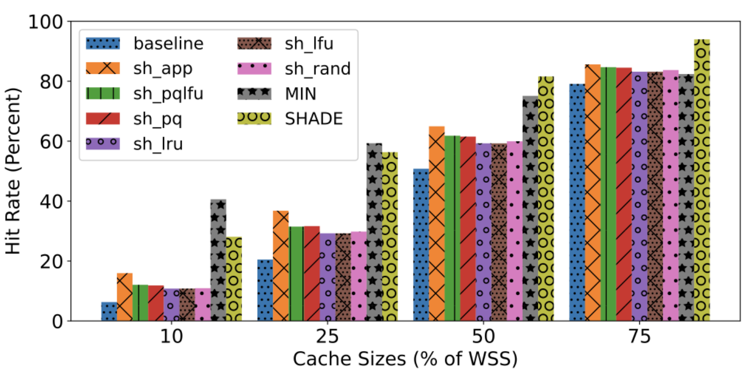
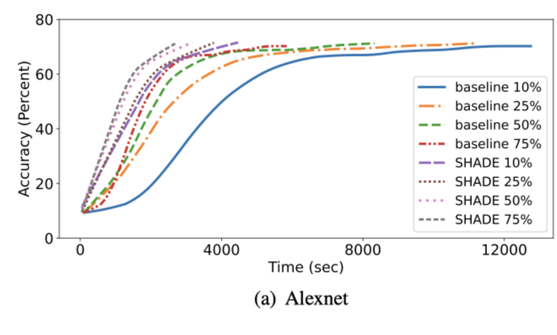
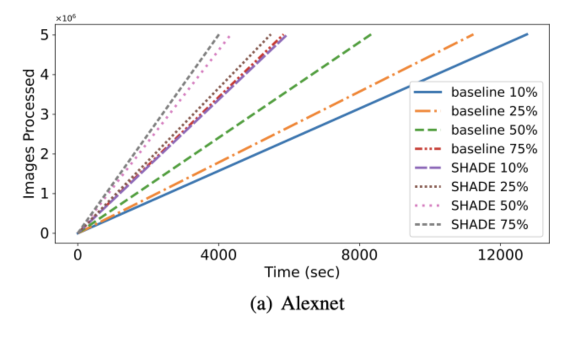


Figure 7: Comparison of the read hit ratio of various caching policies and cache sizes. The sh_ prefix denotes a baseline version of SHADE that uses the coarse-grained importance. SHADE denotes our contribution, SHADE, with all techniques enabled. WSS denotes working set size.

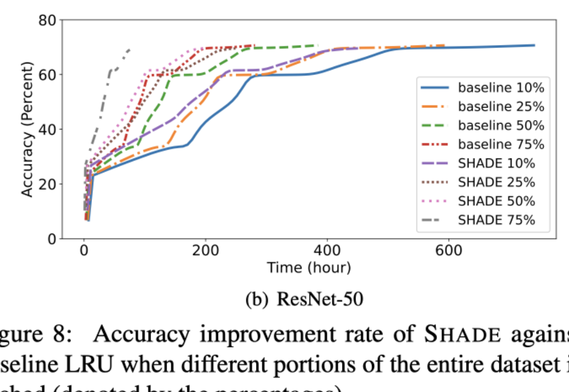
- Accuracy & Throughput



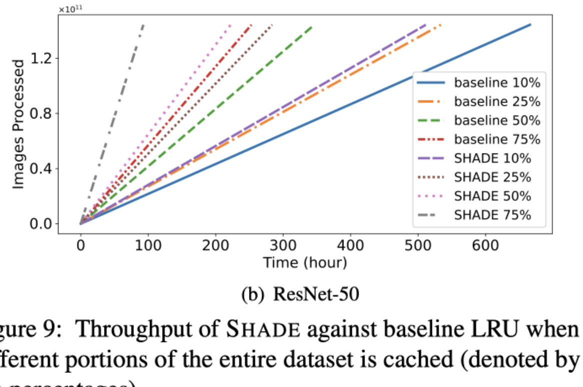
(a) Alexnet



(a) Alexnet



(b) ResNet-50



(b) ResNet-50

Figure 8: Accuracy improvement rate of SHADE against baseline LRU when different portions of the entire dataset is cached (denoted by the percentages).

Figure 9: Throughput of SHADE against baseline LRU when different portions of the entire dataset is cached (denoted by the percentages).

- Minibatch load time

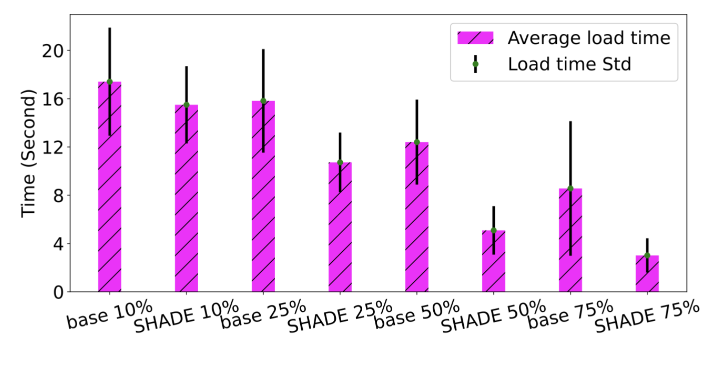
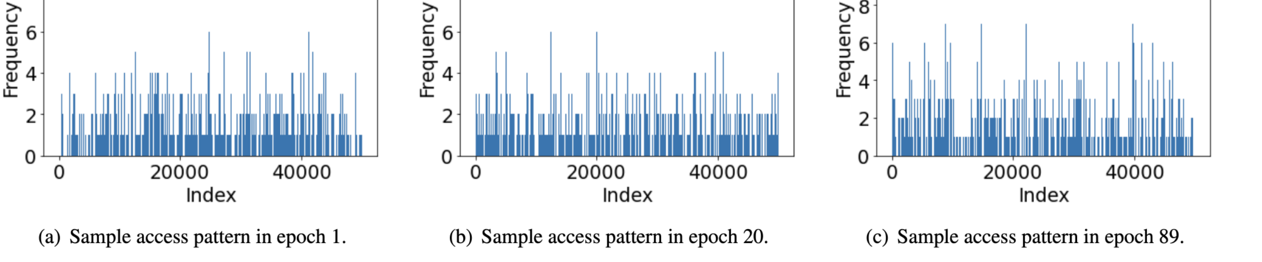


Figure 10: GPUs' minibatch load time when training ResNet-50. Percentages denote the amount of cached dataset.

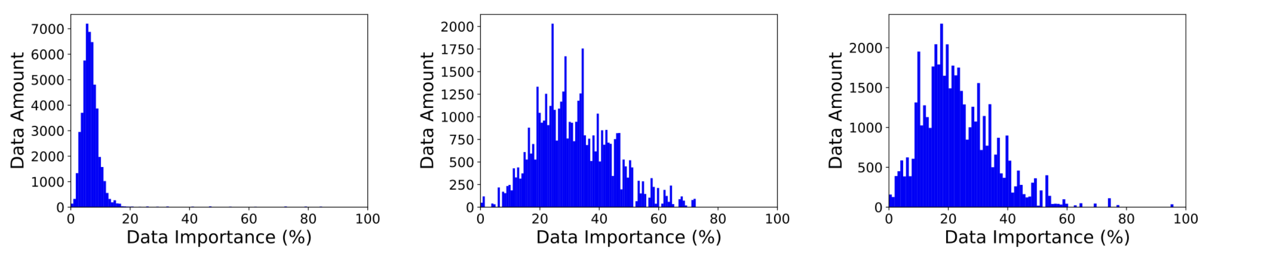
Notes

- It remains challenging to improve the I/O efficiency for distributed DLT as the I/O workloads of a DLT job exhibit unique patterns.
  1. full-object, sequential, read-only accesses at per-object level
  2. dominant, small, random I/Os spread across the whole training sample dataset.
  3. highly concurrent I/Os.
- Worse, conventional wisdom holds that the I/O workload of a DL training job is not cache-friendly due to the aforementioned I/O randomness and lack of data locality.



(a) Sample access pattern in epoch 1. (b) Sample access pattern in epoch 20. (c) Sample access pattern in epoch 89.

Figure 2: Frequency of samples accessed across different epochs in default single process importance sampling (CIFAR-10).



(a) Epoch 1. (b) Epoch 20. (c) Epoch 89.

Figure 3: Distribution of data importance as the number of epochs increases in single process default importance sampling on the CIFAR-10 dataset. Data importance is the ability of a sample to contribute towards improving the accuracy of a model.