Optimizing diffusion data-loading using ROCm rocAL library

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Abstract:

The process of training large-scale deep neural networks can be costly, both in terms of time and resources. It often requires the use of multiple GPUs and can involve significant data loading and preprocessing times, particularly when dealing with larger dataset and computationally intensive data-augmentation techniques. Given the high cost of GPU servers, any method to reduce training time is highly valuable. These issues can be especially problematic in real-world applications, where training performance bottlenecks can limit productivity. As most research has been focused on training performance, many model workflows face bottlenecks in data loading and preprocessing. To address these challenges, the AMD ROCm Augmentation Library (rocAL) was developed to optimize data loading and reduce GPU wait times**.**

In this case study, we are comparing the performance difference between two data loaders for a diffusion training benchmark[2]: baseline Pytorch dataloader and the rocAL dataloader. By using fused augmentation kernels, and comparing two data loaders for a diffusion training benchmark, we found that the use of rocAL led to training efficiency improvements of 3% on AMD MI250X and MI300X GPUs coupled with AMD EPYC CPU processors. These findings suggest that rocAL could be a valuable tool for enhancing the performance of deep learning models, particularly those requiring extensive data augmentation. Further research and development in this area may yield even greater benefits for the AI community.

Introduction:

A key factor behind the tremendous success of deep learning (DL) is the availability of large and diverse datasets, combined with substantial computing power, primarily from GPUs. Leading machine learning frameworks like MXNet, TensorFlow, and PyTorch leverage these resources by iteratively feeding GPUs with batches of data samples from various sources such as images, videos, and text. Before GPUs can efficiently process this data, it must be loaded into memory and undergo a series of transformations, including decoding, cropping, resizing, and normalizing.

To make full use of the GPU parallelism available today, this data preprocessing must be highly efficient to keep up with the GPUs' demands. Unfortunately, many studies focus primarily on the training phase, often overlooking the importance of the data preprocessing pipeline.

The popular DL frameworks share similar data preprocessing pipelines with consistent data formats and structures. However, different DNN models vary in data preprocessing and training performance. Some models take longer for pre-processing, where this becomes a bottle neck for the training pipeline.

While most of the major frameworks handle data preprocessing on CPUs and training on GPUs, rocAL offers improved performance by enabling CPU-GPU co-processing for data preparation. rocAL provides both CPU-based and GPU-based data loaders, allowing data reading and augmentation to be performed on either CPU or GPU cores. However, if a single time-consuming step, such as image decoding (currently handled by rocAL on the CPU), dominates the pipeline execution time, GPUs may remain idle waiting for data. To address this issue, additional CPU resources might be required, but rocAL supports decoding images on the CPU while performing augmentations on the GPU, thereby reducing this bottleneck.

Related work:

Deep learning applications require complex, multi-stage data processing pipelines that include loading, decoding, cropping, resizing, and many other augmentations. These data processing pipelines, which are currently executed on the CPU, have become a bottleneck, limiting the performance and scalability of training and inference.

The NVIDIA Data Loading Library (DALI)[3] is a GPU-accelerated library for data loading and pre-processing to accelerate deep learning applications. It supports reading data in multiple formats and provides data iterators in popular deep learning frameworks.

The torchvision[4] package consists of popular datasets, model architectures, and common image transformations for computer vision. Torchvision supports common

computer vision transformations. Transforms can be used to transform or augment data for training or inference of different tasks (image classification, detection, segmentation, video classification).

TensorFlow Datasets[5] is a collection of datasets ready to use, with TensorFlow or other Python ML frameworks, such as Jax. All datasets are exposed as tf.data.Datasets, enabling easy-to-use and high-performance input pipelines. The tf.data API enables you to build complex input pipelines from simple, reusable pieces.

Overall Design:

Dataloader bottlenecks
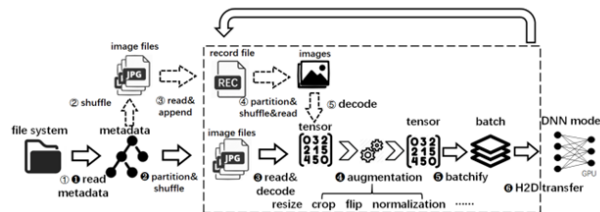
(Reference: arXiv:2304.08925)

The remainder of the paper examines the advantages of using a specialized tool like rocAL for data loading management.

Data loading is a critical component of neural network model training. It involves transferring data from secondary storage, such as a SSD Drive, to primary memory, like Random Access Memory. The data loading process also includes additional tasks, such as data augmentation, to prepare the data for the model.

Two main issues arise in the data loading process: (i) inefficiency in reading data directly from files, and (ii) CPUs are overloaded from resource allocation for extra operations on the data. Directly reading data from individual files is inefficient, especially when the entire dataset isn't cached in local memory. This is due to the overhead of opening, reading, and closing each file sequentially.

The CPU typically handles the entire data loading process, which can become a bottleneck in model training. This bottleneck is especially noticeable in multi-node, multi-GPU setups, where the time taken to load data batches can exceed the time needed for forward and backward propagation. rocAL addresses this issue by distributing some of the data loading tasks between the CPU and GPU, thus alleviating the CPU bottleneck.

In this case study, the diffusion data loader contains an image decoder and multiple augmentations like crop, resize, flip and normalize. In the pytorch native dataloader, the image is first read, decoded, cropped, resized, flipped, converted to (0-1) range and then undergoes mean std normalization.

The data loading is accelerated by the rocAL library by the usage of fused augmentations. The crop region is fixed for all images in the dataset so we use a fused crop_resize kernel which only resizes the crop region of the input image thus skipping the need for separate crop and resize augmentations. Likewise, we use a fused crop mirror normalization kernel for combining the flip and the normalization ((0,255)->(0,1)->(-1,1)) in the pytorch dataloader.

In general, rocAL contains multiple fused augmentation kernels in order to maximize GPU utilization and reduce CPU/GPU wait time due to data copies.

End-to-End training performance analysis

In this section, we present experimental results from end-to-end training of a diffusion benchmark[2]. We analyze how the data loading pipeline impacts overall performance and contributes to resource underutilization during training. Additionally, we highlight how the AMD rocAL library can enhance overall performance.

Experimental setup and Results

Hardware and Software setups: Our experiments use two different hardware configurations - an AMD EPYC 9654 96-Core Processor coupled with 8 AMD MI300X GPUs (each having 2432 compute units, 9728 Matrix Cores, and 192GB GPU memory) and an AMD EPYC 9A53 64-Core Processor coupled with 8 AMD MI250X GPUs (each having 1760 compute units, 880 Matrix Cores, and 128GB GPU memory)

OS and other software used include Ubuntu 22.04, ROCm 6.4.0, AMD rocAL 2.0, and PyTorch 2.6.0.

Preprocessing pipeline configurations: Our data preprocessing pipeline contains the following operators: image decode, crop, resize to (64,64), random horizontal flip, and normalize.

Models and datasets used: We train a Denoising Diffusion Probabilistic Model on CelebA dataset

Metrics: We measure data preprocessing and model training throughput, in E2E time. We also check the Fréchet inception distance (FID) metric to ensure the rocAL dataloading achieves the same accuracy as the baseline dataloader

We can observe that with rocAL dataloader, we observe a 3% improvement in E2E training times compared to the baseline pytorch dataloader which is bottlenecked by the dataloader.

S.no	System	Baseline pytorch	rocAL Host	rocAL HIP
1	AMD EPYC 7A53 64-Core CPU + 8 x MI250X GPUs	38:07:23	32:18:45	32:51:42
2	AMD EPYC 9654 96-Core CPU + 8 x MI300X GPUs	16:44:47	16:13:10	16:11:23
CelebA Diffusion training time (HH:MM:SS) | BS 128 | rocm6.4_ubuntu22.04_py3.10_pytorch_release_2.6.0 public docker				

Diffusion Model training times

S.no	System	Baseline pytorch	rocAL Host	rocAL HIP
1	AMD EPYC 7A53 64-Core CPU + 8 x MI250X GPUs	0:52:13	0:26:20	0:21:00
2	AMD EPYC 9654 96-Core CPU + 8 x MI300X GPUs	00:49:41	00:21:18	00:18:18
CelebA Dataloader time (HH:MM:SS) | BS 128 | rocm6.4_ubuntu22.04_py3.10_pytorch_release_2.6.0 public docker				

Diffusion Model data loading times

Conclusion

It is widely recognized that training deep neural networks (DNNs) demands significant resources, including GPUs/accelerators and network infrastructure. While much research has focused on improving training efficiency through better management of these resources, we argue that another crucial aspect has been largely overlooked: ensuring that data is fed to the accelerators in a manner that fully utilizes their capabilities.

Based on our performance results, we assert that the current pytorch data preparation pipeline for the diffusion benchmark is inefficient and often leads to significant resource waste, particularly in terms of under-utilizing costly GPU resources.

AMD rocAL provides an effective alternative to this data loading bottleneck. It provides a full pipeline of optimizations including data readers and multiple common training data augmentations on CPU and GPU.

References:

[1]: AMD ROCm Augmentation Library (rocAL) https://rocm.docs.amd.com/projects/rocAL/en/latest/index.html

[2]: Unofficial PyTorch Implementation of Denoising Diffusion Probabilistic Models (DDPM) https://github.com/tqch/ddpm-torch

[3] Nvidia DALI https://github.com/NVIDIA/DALI

[4] Torchvision https://github.com/pytorch/vision

[5] Tensorflow Datasets https://github.com/tensorflow/datasets