

Machine Learning Training on a Real Processing-in-Memory System

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ABSTRACT

Machine learning (ML) algorithms [1–6] have become ubiquitous in many fields of science and technology due to their ability to learn from and improve with experience with minimal human intervention. These algorithms train by updating their model parameters in an iterative manner to improve the overall prediction accuracy. However, training machine learning algorithms is a computationally intensive process, which requires large amounts of training data. Accessing training data in current processor-centric systems (e.g., CPU, GPU) implies costly data movement between memory and processors, which results in high energy consumption and a large percentage of the total execution cycles. This data movement can become the bottleneck of the training process, if there is not enough computation and locality to amortize its cost.

One way to alleviate the cost of data movement is *processing-in-memory* (PIM) [7–11], a data-centric computing paradigm that places processing elements near or inside the memory arrays. PIM has been explored for decades [9, 12–146]. However, memory technology challenges prevented from its successful materialization in commercial products. For example, the limited number of metal layers in DRAM [147, 148] makes conventional processor designs impractical in commodity DRAM chips [149–152].

Real-world PIM systems have only recently been manufactured and commercialized. The UPMEM company, for example, introduced the first general-purpose commercial PIM architecture [153–157], which integrates small in-order cores near DRAM memory banks. High-bandwidth memory (HBM)-based HBM-PIM [158, 159] and Acceleration DIMM (AxDIMM) [160] are Samsung’s proposals that have been successfully tested via real prototypes. HBM-PIM features *Single Instruction Multiple Data* (SIMD) units, which support multiply-add and multiply-accumulate operations, near the banks in HBM layers [161, 162], and it is designed to accelerate neural network inference. AxDIMM is a near-rank solution that places an FPGA fabric on a DDR module to accelerate specific workloads (e.g., recommendation inference). Accelerator-in-Memory (AiM) [163] is a GDDR6-based PIM architecture from SK Hynix with specialized units for multiply-accumulate and activation functions for deep learning. HB-PNM [164] is a 3D-stacked-based PIM architecture from Alibaba, which stacks a layer of LPDDR4 memory and a logic layer with specialized accelerators for recommendation systems.

These five real-world PIM systems have some important common characteristics, as depicted in Figure 1. First, there is a host processor (CPU or GPU), typically with a deep cache hierarchy, which has access to (1) standard main memory, and (2) PIM-enabled memory (i.e., UPMEM DIMMs, HBM-PIM stacks, AxDIMM DIMMs, AiM GDDR6, HB-PNM LPDDR4). Second, the PIM-enabled memory chip contains multiple PIM processing elements (PIM PEs), which have access to memory (either memory banks or ranks) with higher

bandwidth and lower latency than the host processor. Third, the PIM processing elements (either general-purpose cores, SIMD units, FPGAs, or specialized processors) run at only a few hundred megahertz, and have a small number of registers and relatively small (or no) cache or scratchpad memory. Fourth, processing elements may not be able to communicate directly with each other (e.g., UPMEM DPUs, HBM-PIM PCUs or AiM PUs in different chips), and communication between them happens via the host processor. Figure 1 shows a high-level view of such a state-of-the-art processing-in-memory system.

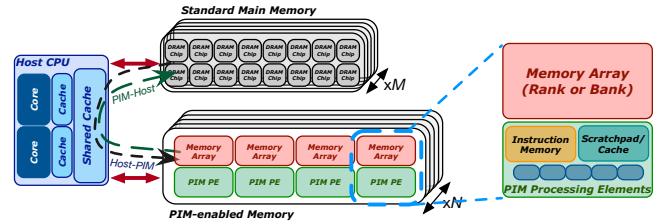


Figure 1: High-level view of a state-of-the-art processing-in-memory system. The host CPU has access to M standard memory modules and N PIM-enabled memory modules.

Our goal in this work is to quantify the potential of general-purpose PIM architectures for training of machine learning algorithms. To this end, we implement four representative classical machine learning algorithms (linear regression [165, 166], logistic regression [165, 167], decision tree [168], K-means clustering [169]) on a general-purpose memory-centric system containing PIM-enabled memory, specifically the UPMEM PIM architecture [153–157]. We do *not* include training of deep learning algorithms in our study, since GPUs and TPUs have a solid position as the preferred and highly optimized accelerators for deep learning training [89, 170–175].

Our PIM implementations of ML algorithms follow PIM programming recommendations in recent literature [154–156, 176]. We apply several optimizations to overcome the limitations of existing general-purpose PIM architectures (e.g., limited instruction set, relatively simple pipeline, relatively low frequency) and take full advantage of the inherent strengths of PIM (e.g., large memory bandwidth, low memory latency).

We evaluate our PIM implementations in terms of training accuracy, performance, and scaling characteristics on a real memory-centric system with PIM-enabled memory [153, 176, 177]. We run our experiments on a real-world PIM system [153] with 2,524 PIM cores running at 425 MHz, and 158 GB of DRAM memory.¹

¹The UPMEM-based PIM system has up to 2,560 PIM cores and 160 GB of DRAM.

Our experimental real system evaluation provides new observations and insights, including the following:

- ML training workloads that show memory-bound behavior in processor-centric systems can greatly benefit from (1) fixed-point data representation, (2) quantization [178, 179], and (3) hybrid precision implementation [163, 180] (without much accuracy loss) in PIM systems, in order to alleviate the lack of native support for floating-point and high-precision (i.e., 32- and 64-bit) arithmetic operations.
- ML training workloads that require complex activation functions (e.g., sigmoid) [181] can take advantage of *lookup tables* (LUTs) [98, 182, 183] in PIM systems instead of function approximation (e.g., Taylor series) [184], when PIM systems lack native support for those activation functions.
- Data can be placed and laid out such that accesses of PIM cores to their nearby memory banks are streaming, which enables better exploitation of the PIM memory bandwidth.
- ML training workloads with large training datasets can greatly benefit from scaling the size of PIM-enabled memory with PIM cores attached to memory banks. Training datasets can remain in memory without being moved to the host processor (e.g., CPU, GPU) in every iteration of the training process. Even if PIM cores need to communicate intermediate results via the host processor, this communication overhead is tolerable with proper overlap of computation and communication.

We compare our PIM implementations of linear regression, logistic regression, decision tree, and K-means clustering to their state-of-the-art CPU and GPU counterparts. We observe that memory-centric systems with PIM-enabled memory can significantly outperform processor-centric systems for memory-bound ML training workloads, when the operations needed by the ML workloads are natively supported by PIM hardware (or can be replaced by efficient LUT implementations).

Our extended paper [185] contains (1) detailed description of our PIM implementations of ML workloads; (2) comprehensive evaluation and comparisons to state-of-the-art CPU and GPU systems; and (3) more insights about the suitability of ML workloads to the PIM system, programming recommendations for ML software developers, and suggestions and hints for future PIM architectures. We aim to open-source all our PIM implementations of ML training workloads, training datasets, and evaluation scripts.

KEYWORDS

machine learning, processing-in-memory, regression, classification, clustering, benchmarking

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