GPU Domain Specialization via Composable On-Package Architecture

YAOSHENG FU, EVGENY BOLOTIN, NILADRISH CHATTERJEE, DAVID NELLANS, and STEPHEN W. KECKLER, NVIDIA, USA

As GPUs scale their low-precision matrix math throughput to boost deep learning (DL) performance, they upset the balance between math throughput and memory system capabilities. We demonstrate that a converged GPU design trying to address diverging architectural requirements between FP32 (or larger)-based HPC and FP16 (or smaller)-based DL workloads results in sub-optimal configurations for either of the application domains. We argue that a **Composable On-Package GPU** (COPA-GPU) architecture to provide domain-specialized GPU products is the most practical solution to these diverging requirements. A COPA-GPU leverages multi-chip-module disaggregation to support maximal design reuse, along with memory system specialization per application domain. We show how a COPA-GPU enables DL-specialized products by modular augmentation of the baseline GPU architecture with up to 4× higher off-die bandwidth, 32× larger on-package cache, and 2.3× higher DRAM bandwidth and capacity, while conveniently supporting scaled-down HPC-oriented designs. This work explores the microarchitectural design necessary to enable composable GPUs and evaluates the benefits composability can provide to HPC, DL training, and DL inference. We show that when compared to a converged GPU design, a DL-optimized COPA-GPU featuring a combination of 16× larger cache capacity and 1.6× higher DRAM bandwidth scales per-GPU training and inference performance by 31% and 35%, respectively, and reduces the number of GPU instances by 50% in scale-out training scenarios.

CCS Concepts: • **Computer systems organization** → **Processors and memory architectures; Neural networks**;

Additional Key Words and Phrases: GPU computing, multi-chip module

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1 INTRODUCTION

Deep learning (DL) has revolutionized computer vision, natural language processing, speech recognition, and recommendation systems [7, 20, 26, 27] and reshaped the automotive, robotics, e-commerce, and healthcare industries [23, 72, 73, 75]. GPUs have become the de facto platform of choice for DL applications due to their relative ease of programming, rich set of optimized

Authors' address: Y. Fu, E. Bolotin, N. Chatterjee, D. Nellans, and S. W. Keckler, NVIDIA Corporation, 2788 San Tomas Expy, Santa Clara, CA USA 95051; emails: {yfu, ebolotin, nchatterjee, dnellans, sheckler}@nvidia.com.

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Fig. 1. (a) A converged monolithic GPU for HPC and DL. (b) An HPC-specialized COPA-GPU with similar capabilities to converged GPU. (c) A DL-specialized COPA-GPU featuring a large capacity, high-bandwidth on-package cache, and scaled DRAM resources.

software libraries, and good balance between compute and off-chip memory bandwidth [66]. GPU acceleration can reduce the training time of DL applications from months to minutes [57]. However, GPU architectures must keep evolving to satisfy the unprecedented expansion in DL computing demand, fueled by the growing complexity of both model and dataset sizes [40].

GPU vendors have long enjoyed the benefits of shrinking process technologies that increased transistor density, while also manufacturing ever larger dies [58, 61, 63, 64, 66]. Thanks to technology scaling, architects have had ample resources to add domain-specialized hardware to computer-graphics-oriented GPUs, resulting in today's converged GPU design that serves multiple application domains. To cater to **High-Performance Computing (HPC)**, GPUs added costly high-precision arithmetic (FP64) units, advanced error detection and correction hardware, **high-bandwidth memories (HBMs)**, and fast I/O such as NVIDIA's NVLINK [6, 62, 64, 66]. Similarly, specialized hardware such as NVIDIA Tensor Cores and AMD Matrix Cores were added for DL, while RT Cores were added to accelerate next-generation ray tracing capabilities [6, 64–66].

The recent dramatic improvement in low-precision math throughput on GPUs is driven by research work showing the feasibility of high-accuracy DL training and inference while utilizing lower-precision arithmetic [30, 44, 54]. For example, NVIDIA's V100 GPU introduced DL Tensor Cores improving FP16 throughput by 6× in one GPU generation [64]. NVIDIA's Turing GPU family went even further, integrating INT4/8 support into the Tensor Cores [65]. Most recently, NVIDIA's A100 GPU increased the FP16 throughput by an additional 2.5× over V100 [66].

This work demonstrates that converged GPU designs fail to satisfy the diverging requirements, in terms of memory bandwidth to compute throughput, between FP32/FP64-based HPC applications and low-precision-based DL networks. Moreover, the slowdown in transistor scaling along with reticle limitations in silicon lithography is restricting transistor and die area growth, making it ever harder to deliver competitive performance in multiple application domains with a single

converged GPU design. Future off-chip bandwidth scaling is also at risk as the die edge scales sub-linearly with increasing die size, limiting the off-chip DRAM and I/O bandwidth available to individual dies [8].

The growing importance of DL domain-specific acceleration in the datacenter is demonstrated by a proliferation of accelerators targeted exclusively at DL algorithms [25, 34, 36, 38, 43, 46, 47]. We believe that the combination of technology trends and an ultra-competitive DL landscape has created an inflection point at which GPU manufacturers must embrace more domain-specialized GPU designs to continue providing competitive performance, while also maximizing design reuse and minimizing **non-recurring engineering (NRE)** costs.

In this work we examine historical trends and project future ratios that show a strong divergence between high- and low-precision math throughput on GPUs. We show that this gap makes it difficult to design a memory system that efficiently supports both HPC and DL use cases. Thus, we propose a **Composable On-Package GPU (COPA-GPU)** architecture as a practical solution for building a new class of domain-optimized GPUs. Leveraging **multi-chip module (MCM)** integration [8, 12, 28, 39, 55, 59] along with emerging circuit technology innovations [28, 48, 52], we propose to replace the single converged GPU that serves both HPC and DL domains with composable, semi-specialized designs as shown in Figures 1(b) and 1(c).

A COPA-GPU that is specialized for HPC (similar to Figure 1(b)) uses the baseline **GPU module (GPM)** and a memory system module providing similar or scaled-down capabilities as in the converged GPU today. Augmenting the memory system modules with a very large on-package cache accessible at high on-package bandwidth and additional off-chip DRAM resources (Figure 1(c)) results in a substantially different COPA-GPU design point that is well suited for bandwidth-hungry DL workloads. This level of specialization is not free, as it requires both intelligent architectural disaggregation of the GPU memory system and employing emerging circuit and packaging techniques. This work aims to shed light on the architectural choices available to designers when building and specializing composable GPU designs.

This work makes the following contributions:

- We examine historical GPU trends and perform a detailed performance analysis of diverging HPC and DL benchmarks. We show that due to the converged nature of GPUs and future DL scaling requirements, the GPU's memory bandwidth will become the primary performance bottleneck for GPU-based DL training and inference, while being under-utilized for most HPC applications.
- We propose the development of domain-specialized composable GPU architectures. COPA-GPUs provide high levels of GPU design reuse across the HPC and DL domains, while enabling specifically optimized products for each domain. We describe both the architectural modifications and the landscape of technologies needed to enable COPA-GPUs.
- We evaluate the performance potential of COPA-GPU in the context of DL training and inference and show that very large cache capacity can dramatically improve DL-inference, but both cache and DRAM improvements (available only through COPA designs) are necessary to significantly improve DL-training.
- Finally, we propose a specific COPA-GPU design boosting per-GPU training and inference performance by up to 31% and 35%, respectively, while also significantly reducing the cost of scale-out GPU training in datacenters.

2 MOTIVATION AND BACKGROUND

The commercial importance of deep learning is undeniable, and numerous companies are now designing targeted DL training and inference accelerators, such as Google's TPU [36–38],

Table 1. GPU and DL Accelerator Compute and Memory System Trends, Including a Forward-looking GPU Projection (GPU-N)

GPU Architecture	FP32 [TFLOPS]	FP16 [TFLOPS]	L2 [MB]	-	DRAM BW [GB/s]
NVIDIA P100	11	21	4	-	732
NVIDIA V100	16	125	6		900
NVIDIA A100	20	312	40	-	1,555
GPU-N	24	779	60	-	2,687

DL Accelerator	FP32 [TFLOPS]	FP16 [TFLOPS]	On-chip Memory [MB]	On-chip Memory BW [TB/s]	DRAM BW [GB/s]
Graphcore IPU	31	125	304	45	N/A
Graphcore IPUv2	62	250	896	45	N/A
Cerebras WSE	-	-	214	107	N/A
Cerebras WSE-2	-	-	476	238	N/A
Groq TSP	-	250	220	80	N/A
Google TPUV2	5	46	32	-	700
Google TPUV3	14	123	32	-	900
Google TPUV4i	-	138	144	-	614

We report the attributes of Cerebras as 1/84 tiles in a wafer to provide area-similar comparisons.

Graphcore's IPU [34, 43], Cerebras' WSE [46, 47], and Groq's TSP [25]. These application-specific architectures need not maintain a legacy of high performance in other domains, allowing them to make heavily specialized architectural choices compared to GPU architectures that currently serve multiple domains. To better understand the divergence of GPU and DL accelerator design trends, we examined recent GPU scaling trends, projected a plausible future GPU configuration, and now compare it to several dedicated DL accelerators.

2.1 DL Architecture Trends and Projections

Table 1 summarizes several key compute and memory system characteristics across the three most recent generations of NVIDIA Tesla GPUs targeting both HPC and DL domains. We then forward-project the hardware capabilities of a hypothetical **next-GPU configuration (GPU-N)** using evolutionary scaling. We calculate the compute and memory bandwidth of GPU-N by linearly extrapolating these parameters from V100 to A100 [64, 66]. We calculate the GPU-N L2 capacity using the lower scaling rate of 1.5 $\times$ from P100 [63] to V100 (instead of 6.7 $\times$ from V100 to A100) since GPU-N is highly unlikely to be able to fit hundreds of MB of SRAM on a single GPU die. Note that we are not trying to accurately project the exact configuration of a future GPU, but rather demonstrate the effect of expected scaling rates on compute and memory bandwidths. Table 1 makes it clear that while the memory bandwidth to FP32 throughput ratios have generally increased across GPU generations (from 67 $\times$ in P100 to 112 $\times$ in GPU-N), the memory bandwidth to FP16 ratio has diminished to only 3.4 $\times$ in GPU-N.

In addition to several GPU generations, Table 1 provides attributes of several DL accelerators. The Graphcore, Cerebras, and Groq products all feature very large on-chip SRAMs as main memory, while Google TPUs use off-chip DRAM (HBM). In contrast to GPUs and TPUs, DL accelerators with DRAM-less memory system can provide substantially higher memory bandwidth to FP16 ratios reaching 180 $\times$ and 320 $\times$ in IPUv2 and TSP, respectively, albeit providing much lower total memory capacity that may prove to be inadequate for rapidly growing memory footprint demands

Fig. 2. GPU-N performance bottleneck analysis using the MLPerf DL training and inference suites, for both large-batch and small-batch settings.

of DL applications [40]. The designers of the future DL training and inference platforms will have to strike the right architectural balance between relatively large on-package SRAM caches for performance and energy efficiency and high-capacity DRAM to provide an adequate amount of device memory suitable for the growing DL requirements.

2.2 Diverging DRAM Bandwidth Requirements

To understand the diverging DRAM bandwidth requirements of future GPUs, Figure 2 presents a simulation performance bottleneck analysis of the DL workloads from the MLPerf suite (details described later in Section 4.1) for both small and large batch sizes on GPU-N. Figure 2 presents a breakdown of the total execution time, with each colored bar segment representing the performance overhead introduced by a hardware component (or a group of related hardware components) during execution. For example, the blue “DRAM BW” bars show the performance overhead attributed to non-ideal DRAM bandwidth when compared to infinite DRAM bandwidth. Similarly, the orange bars represent the performance penalty caused by all other components in the memory subsystem being non-ideal in terms of bandwidth and latency. The gray bars represent the performance penalty caused by dynamic SM under-utilization (idle SMs) versus an ideal GPU with 100% SM utilization, reflecting inefficiencies such as imperfect work scheduling or lack of sufficient parallelism (sometimes only in phases) within the workload itself. Finally, the green bars show the relative execution time spent in Math units, which should be 100% utilized in the ideal case.

Our bottleneck analysis is conducted by gradually idealizing one or more architectural features of the system starting with DRAM bandwidth and moving inward toward the SM, then using the performance differential between the idealized and the real system to determine the extent to which each component impacts overall performance. We start with the baseline GPU-N and first idealize the DRAM bandwidth to estimate the overhead of insufficient off-chip bandwidth. Then with the DRAM bandwidth remaining idealized, we idealize the rest of the memory subsystem, effectively modeling a perfect GPU memory system in which all memory requests return immediately to the SM. Finally, to quantify the effect of SM under-utilization due to load imbalance or an insufficient amount of work, we simulate a GPU-N with just one SM and a perfect memory system, and then divide the execution time by the original number of SMs to mimic the case where all SMs achieve full occupancy. The primary reason for gradual simultaneous idealization, as opposed to idealizing only one component at a time, is to understand the full potential performance of removing a bottleneck once all the bottlenecks that are downstream from it (until the DRAM)

Fig. 3. Performance speedup of various DRAM bandwidths for HPC applications on a GPU-N configuration where dashed lines represent geomean speedups for corresponding configurations.

are removed. Obviously, these results can depend on the order in which the idealization steps are applied. However, as our primary focus is on the memory system, we idealize these components first to minimize the interference by idealizing other parts of the system. Our method has some overlap with the bottleneck breakdown in GSI [5]; however, our analysis goes beyond the memory subsystem and extends to SM utilization and Math units.

Figure 2 shows that indeed DRAM bandwidth is the primary performance limiter (excluding Math) for DL training on GPU-N, contributing 28% of the total execution time on average across large-batch and small-batch cases. DRAM bandwidth is also the main performance bottleneck for large-batch DL inference and accounts for 30% of the total execution time. However, at small batch sizes, SM under-utilization accounts for 41% of total execution time and serves as the primary performance bottleneck rather than DRAM bandwidth. This is because MLPerf small-batch inference does not expose enough parallelism to fill an entire GPU that was designed for the data-center. Moreover, due to small-batch inference’s relatively small memory footprints, the majority of each workload’s data can be buffered on-chip, and thus DRAM bandwidth is not the primary bottleneck.

We also use the same simulator to simulate the converged GPU-N configuration across varying DRAM bandwidth settings using 130 HPC benchmarks from differing sources including the CORAL [50] and CORAL-2 [51] benchmarks, Amber18 benchmarks [4], FUN3D [60], SPECfem3D Cartesian [3], GROMACS [1], Laghos [49], and RELION [2]. As shown in Figure 3, in stark contrast to DL applications, most HPC applications are quite insensitive to changes in DRAM bandwidth. When DRAM bandwidth is increased to infinite, a geometric mean speedup of only 5% is achieved. When DRAM bandwidth is decreased, $0.75 \times \text{BW}$ and $0.5 \times \text{BW}$ result in 4% and 14% slowdown, respectively. This implies that future increases in DRAM bandwidth will go largely underutilized by most HPC applications if converged GPU designs targeting both DL and HPC domains remain the de facto standard.

2.3 Very Large Caches for DL-optimized GPUs

Because the memory bandwidth demands of DL applications are likely to exceed what evolutionary DRAM scaling can provide, GPU designers must pursue alternative methods to meet aggressive bandwidth targets. Historically, the GPU’s LLC has remained relatively small because HPC workloads have good spatial locality and the majority of the off-chip bandwidth filtering potential can be captured within last-level caches that are measured in tens of megabytes. In DL workloads data locality spans multiple temporal and spatial scales, requiring much larger capacities.

Fig. 4. DRAM traffic reduction versus LLC capacity, normalized to the baseline GPU-N configuration with 60MB of LLC.

To understand how much LLC capacity GPU-N would need to effectively shield the GPU’s DRAM system, we examine the off-chip DRAM traffic reduction achieved when sweeping GPU-N’s LLC capacity from 60MB to 4GB. Figure 4 shows that doubling the LLC capacity to 120MB provides up to 53% reduction in off-chip DRAM traffic in DL training. Further growth to 960MB reduces off-chip BW demand by 82% (5× reduction). We will later show that DRAM traffic reduction from larger caches correlates well with improved training performance. Compared to DL training, large LLC capacities are even more beneficial for DL inference because they enable a larger portion of the workload’s weights and activations to be cached on-chip. For example, in large-batch inference, a 960MB LLC achieves a 16× DRAM traffic reduction, while a 240MB LLC is sufficient to capture all available data reuse data on-chip for small-batch inference because of its smaller memory footprint.

Because modern GPUs are already area limited [8], implementing hundreds of additional megabytes of on-die LLC without severely sacrificing other functionalities is not feasible. Even if it could be done, such an architecture would be out of balance for optimal HPC performance. Because of the different sensitivities to off-chip GPU bandwidth and on-GPU cache capacities between HPC and DL workloads, we now explore the potential benefits of a composable GPU architecture that can satisfy the unique demands of each domain while maximizing design reuse through a modular on-package design.

3 COMPOSABLE GPU ARCHITECTURE

A COPA-GPU architecture has two primary goals: (1) to largely preserve the existing GPU architecture to minimize design effort and maximize reuse, and (2) to provide flexibility in specializing the GPU memory system for diverging requirements across application domains. Specifically, we aim to improve the GPU’s memory system with substantially more cache and memory bandwidth than is required for domains such as HPC, to unlock deep learning performance on GPUs. To achieve this range of GPU system capabilities, we leverage on-package multi-chip-module integration to couple a GPU-core die with different memory system dies, each having different allocations of on-package cache and memory resources.

3.1 Practical GPU Disaggregation with COPA-GPU

We propose to disaggregate today’s monolithic GPU into a basic GPM on-package that is reused without modifications across domain-specialized COPA-GPU instances and a domain-specialized **Memory System Module (MSM)** tailored for the specifics of each application domain. The main

Fig. 5. GPU MCM disaggregation options for practical and composable domain specialization.

challenge with on-package disaggregation for GPUs is striking the right balance between the degree of composability and the practicality of effectively shifting the burden of high-bandwidth intra-GPU communication from the on-chip to on-package wires.

Figure 5(a) depicts a generic monolithic GPU architecture, with **streaming multiprocessors (SMs)** and corresponding L1 caches connected to a distributed L2 cache via the GPU **network on chip (NoC)**. L2 cache slices are attached to **Memory Controllers (MCs)** driving the off-chip DRAM memory interface. While contemporary off-chip DRAM interfaces provide a few TB/s of memory bandwidth (2.7 TB/s in GPU-N), the on-chip interconnects of a modern GPU are designed to transport many tens of TB/s of on-chip bandwidth between the SMs and the on-chip memory hierarchy.

The three possible GPU disaggregation options are shown in Figure 5(b). Option (I), denoted by GPM+MSM(L2+MC), features a GPM containing SMs, L1s, and the GPU NoC, while the MSM includes the L2 cache and the memory controllers. This design can provide more effective die area and die edge than single reticle-limited die to support bigger L2 cache and higher DRAM bandwidth when needed. Option (II), denoted by GPM+MSM(NoC+L2+MC), is similar to (I) but shifts the GPU NoC from the GPM onto the MSM. However, options (I) and (II) are impractical as they both require many tens of TB/s of NoC traffic to instead traverse on-package wires, which Section 3.5 later shows is not realizable using current or known proposed technologies.

Thus, we choose option (III), denoted by GPM+MSM(L3+MC), for exploring a practical COPA-GPU design as it relies on existing L2 cache bandwidth filtering within the GPM to achieve feasible levels of off-GPM inter-die bandwidth. Additionally, we propose to add an additional layer of L3 cache between the L2 cache and MC, and to have both the L3 cache and the MC implemented on the MSM. Such composable design re-organization can provide more than 4× higher post-L2 bandwidth using previously proposed package integration technologies.

3.2 COPA-GPU Architectures and Packaging

The architectural domain customization in our proposed COPA-GPU is achieved through integration of a GPM with a dedicated domain-optimized MSM using 2.5D or 3D on-package integration that could leverage either planar or vertical die stacking approaches. We consider COPA-GPU architectural options spanning both integration strategies while taking into account the unique interdependency between architectural and package technology choices, distilling the advantages and disadvantages of each approach.

Fig. 6. COPA-GPU architectural options spanning 2.5D and 3D integration domains.

Figure 6(a) shows a high-level top and side view of a modern GPU architecture, including a maximum-sized GPU die with the L2 cache and memory controllers on-die and HBM sites attached via 2.5D on-silicon interposer integration. The same diagram shown in Figure 6(a) also describes the basic COPA-GPU GPM, pre-equipped to be 3D integrated with an MSM die to provide a 3D DL-optimized COPA-GPU variant.

Figure 6(b) illustrates a 3D organization of a DL-optimized COPA-GPU where the GPM die from Figure 6(a) is integrated with an MSM carrying additional L3 cache. The MSM is vertically attached via a **3D ultra-high-bandwidth (3D-UHB)** link using high-density intra-die bonding, with up to 14.7TB/s of bandwidth, further detailed in Section 3.5. The MSM is positioned between the GPU and silicon interposer and provides all the essential connectivity between the GPM and the silicon interposer via **through silicon vias (TSVs)**, as shown in Figure 6(b:side-view). The composable nature of a 3D COPA-GPU allows for designs both with (for DL) and without (for HPC) additional L3. The primary disadvantage of a 3D COPA-GPU organization is that it cannot provide any additional die edge to improve DRAM scaling.

Figure 6(c) shows a basic 2.5D COPA-GPU integrating a GPM with up to two MSM modules in a 2.5D organization targeting HPC. The design of a 2.5D COPA-GPU retains most of its original functionality on the base GPM but offloads the **memory controllers (MCs)** and HBM I/O to new (small) in-package MSMs. A 2.5D COPA-GPU has the advantage that offloading of GPM area allocated to MC and HBM I/O frees up die area for the implementation of UHB links and additional compute resources in the baseline COPA-GPU.

Figure 6(d) augments the 2.5D COPA-GPU in Figure 6(c) with a large L3 cache and additional DRAM stacks, subject to package area limitations. The same GPM die is reused between Figures 6(c) and 6(d), and this 2.5D DL-optimized organization has several advantages compared to a 3D organization. First, it can provide up to $2\times$ more L3 capacity than the 3D organization. Second, the additional MSM geometry increases the total available die-edge of the design. This die-edge can provide up to $1.7\times$ or $2.3\times$ higher HBM BW and larger capacity, via 10 total HBM sites, or 14 total HBM sites using maximally sized MSMs (not shown).

3.3 COPA-GPU Microarchitectures

Figure 7 presents the microarchitecture of the proposed memory systems for both the 3D and 2.5D COPA-GPU designs. Figures 7(a) and 7(b) outline the main components of a 3D COPA-GPU with and without an extended L3 MSM. The most significant difference between current GPU

Fig. 7. L3 cache microarchitecture in COPA-GPU designs.

architectures and the 3D COPA-GPU is the addition of a new switching component that steers requests from the L2 to the on-chip memory controller or to the UHB links, depending on whether the MSM is present in-package.

If the MSM is not present (Figure 7(a)), the switch is configured to steer the memory requests directly from the L2 to its local MC, similarly to today's GPUs. If the MSM is present (Figure 7(b)), the switch is reconfigured to steer post-L2 traffic to the L3 via the UHB link. This design requires the MSM to implement its own MC that connects to HBM I/O, with silicon area overheads stemming from adding the UHB link, the TSV-based I/O, and power delivery between GPM and the silicon interposer dies. In the 2.5D COPA-GPU designs without and with additional L3 capacity on the MSM (Figures 7(c) and 7(d)), the GPM is completely stripped of its original MC and HBM I/O, and post-L2 traffic is always routed to the MSM modules over on-package UHB links. Both of the 2.5D COPA-GPU configurations consist of the same GPM but are equipped with different versions of the MSM to serve different application classes (i.e., with or without L3 and additional HBM sites).

In both designs, the L3 cache is architecturally implemented as yet another level of memory-side cache that (when present) backs the existing L2. It is neither inclusive nor exclusive, nor does it require coherence with the L2 because the L2 already serves as the point of coherence in GPU systems. Lines present in the L2 always supercede lines in the L3 from the GPU's perspective and are written back to the L3 upon eviction from the L2. No requests are routed to the L3 without first being serviced at the L2.

3.4 Costs and Benefits of the COPA-GPU

The major drawback of a 2.5D COPA-GPU organization is that it increases the package size. Conversely, the 3D COPA organization has minimal impact on package complexity (same top view), but the base GPM must now account for the implementation of the distributed on-die UHB link bonding used for vertical inter-die communication (Section 3.5) and the TSV overheads used for traversing through the MSM die. We estimate that in the 3D case, the cost of providing as much as 14.7TB/s bandwidth of UHB I/O will consume less than 4% of silicon surface and metal layers for inter-die communication bonding. The majority of the active area and lower-level metals under the 3D bonding can likely be reused for other logic in the GPM. In 2.5D designs, the maximally sized links result in approximately 6% area overheads assuming a 20Gbps signaling rate. Section 3.5 provides further details on these assumptions.

Table 2. Bandwidth and Energy Characteristics Assumptions for 2.5D and 3D Ultra-high Bandwidth (UHB) in This Work

Technology	BW Density	Max Bisection BW	Energy/bit
2.5D	256GB/s/mm	14.7TB	0.3 pJ/b
3D	512GB/s/mm ²	>14.7TB	0.05 pJ/b

Even though both COPA-GPU approaches introduce 4% to 6% area overhead due to new MCM communication interfaces, this area (and thus cost overhead) will be more than offset by the savings in the HPC-oriented variants by not carrying forward the unnecessary and expensive DL-oriented memory subsystem. Moreover, we believe that in the future even non-composable GPU designs will turn to MCM organizations due to looming reticle limitations, effectively introducing similar MCM link overheads into *all* GPU designs. The main challenge with such modular GPU designs going forward is its growing integration complexity, effectively shifting focus from on-die integration onto advanced assembly, test, and continuous innovation in on-package interconnect and packaging technologies.

Adding new communication interfaces that memory system requests must traverse, however, comes with an additional energy tax. We estimate that the 2.5D organized UHB-link consumes less than 9 watts, assuming peak 100% bandwidth utilization at 0.3pJ/b with a 25% wire toggle-rate. Consequently, the 3D link consumes less than 2 watts, due to its more efficient link technology and overall shorter communication distances (see Section 3.5 for further details).

A large L3 reduces the number of DRAM accesses, more than offsetting the additional cost of the UHB link traversal and L3 accesses. Figure 4 shows that the 960MB and 1.9GB L3 configurations reduce overall DRAM traffic by up to 94% and 98%, respectively. We estimate that fetching a cache line from an SRAM-based COPA-GPU L3 into the GPM will consume approximately 4× less energy than accessing HBM memories. These estimates fully account for the energy associated with traveling to an SRAM sub-array on an MSM-die and back, as well as the energy consumed by the SRAM sub-array [9, 11, 41, 77]. Consequently, we estimate that either COPA-GPU design (utilizing a 960MB L3 cache) will reduce the total HBM-related GPU energy consumption by up to 3.4×. While left for future exploration, the cost of the MSM caching modules could be reduced by implementing them in older and less expensive processes.

3.5 COPA-GPU Enabling Technologies

The feasibility of COPA-GPUs depends on several technologies reaching maturity for industrial implementation.

Cache Technology Projections: Large caches can be realized through high-density **Embedded DRAM (eDRAM)** [10] or SRAM technologies [13, 24]. IBM recently implemented a 960MB cache on a 696mm² die using a 14nm eDRAM technology [10]. Graphcore’s recently announced second-generation IPU [43] integrates 896MB of SRAM along with thousands of cores on a single 823mm² die using TSMC’s 7nm process. Cache density is dictated by a combination of the bitcell area, control overheads, and the bandwidth requirements. Because the COPA-GPU’s L3 is designed to provide lower bandwidth than L2, we estimate that a future reticle limited 826-mm² MSM die (the same die size as an NVIDIA A100 GPU [66]) can provide up to 2GB of L3 cache, though the remainder of this work assumes a conservative projection of a 960MB L3 on an 826mm² die, which implies a maximum of 960MB L3 in a 3D COPA-GPU with single MSM die and 1920MB L3 in a 2.5D COPA-GPU with two MSM dies.

High-Bandwidth 2.5D and 3D Interconnects: High-speed links that enable 2.5D integration are rapidly maturing [19, 22, 48, 76]. Chen et al. [19] recently demonstrated 20Gbps signaling rates

Table 3. MLPerf Training and Inference Benchmarks

Benchmark	Type	Small-batch		Large-batch	
		Per-GPU Batch Size	Memory Footprint	Per-GPU Batch Size	Memory Footprint
resnet	training	12	989MB	128	6GB
ssd	training	4	559MB	128	7.9GB
maskrcnn	training	1	2.1GB	6	9.9GB
minigo	training	128	105MB	2,048	1.5GB
gnmt	training	32	3GB	256	8.3GB
transformer	training	640	4.5GB	5120	7.9GB
ncf	training	65,526	657MB	1,048,576	4.5GB
resnet	inference	1	49MB	232	1.1GB
mobilenet	inference	1	16MB	704	2GB
ssd-small	inference	1	24MB	288	2GB
ssd-large	inference	1	136MB	6	562MB
gnmt	inference	1	300MB	128	961MB

Table 4. Detailed GPU Configurations

Configuration	NVIDIA V100	NVIDIA A100	GPU-N
SMs	80	108	134
GPU frequency (GHz)	1.4	1.4	1.4
FP32 (TFLOPS)	15.7	19.5	24.2
FP16 (TFLOPS)	125	312	779
L2 cache (MB)	6	40	60
DRAM BW (GB/s)	900	1,555	2,687
DRAM Capacity (GB)	16	40	100

across a 2.5mm silicon interposer layer at 0.3pJ/b, resulting in a $\sim 200\text{GB/s/mm}$ bandwidth density per layer, which can be further increased at shorter distances. This work assumes a 2.5D COPA-GPU UHB link with a bandwidth density of 256GB/s/mm ; thus, the dedicated edges of the 826mm^2 GPM module can provide up to 14.7TB/s of off-GPM bandwidth as described in Figure 6(d). While this bandwidth to the MSM far exceeds the actual L3 bandwidth requirement, it provides headroom for future increases in off-die communication.

3D integration is also maturing [14, 29, 31, 33, 79]. For example, TSMC’s **System on Integrated Chips (SoIC)** is expected to provide ultra-dense 3D interconnects [14, 29] with greater than 1TB/s/mm^2 of inter-die bandwidth, assuming a 1 Gbps signaling rate. We conservatively assume 3D-UHB links with 512GB/s/mm^2 of bandwidth density at 0.05pJ/b. Achieving the assumed 14.7TB/s of data bandwidth for a 2.5D COPA-GPU would require 28.7mm^2 (less than 4%) of silicon area for the inter-die communication bonding. Table 2 summarizes the UHB link characteristics for both 2.5D and 3D scenarios.

4 EVALUATION

We now present our simulation methodology, examine the performance sensitivity of the baseline COPA-GPU architecture to DRAM bandwidth and on-package LLC capacity, and evaluate several specific DL-specialized COPA-GPU configurations in both training and inference scenarios.

4.1 Methodology

To provide performance projections for DL workloads, we perform our studies using unmodified workloads from the MLPerf training and inference benchmark suites [53, 70] for one end-to-end iteration of the workloads, rather than using disjoint and isolated GPU kernel calls. This approach allows us to characterize the overall throughput and capture inter-layer activation and weight reuse in the L3 that will drive future memory system design on GPUs. MLPerf is the de facto standard for DL benchmarking and is maintained by major DL chip vendors including NVIDIA, Google, and Intel. Table 3 shows the seven MLPerf training benchmarks and the five inference benchmarks used, taken from NVIDIA's publicly available MLPerf training v0.6 and MLPerf inference v0.5 submissions [56, 57]. These codes are highly optimized for NVIDIA GPUs by exploiting high-throughput Tensor Cores [64] and have demonstrated performance scalability from a single to thousands of GPUs.

To build a complete picture of future deep learning scenarios, we run all our DL benchmarks in two different configurations. For DL training, we use a large per-GPU batch size to characterize a single-GPU training situation and a small per-GPU batch size to represent a large-scale training system. For DL inference, we use a large per-GPU batch size to represent a datacenter processing inference task with large numbers of concurrent queries and a small per-GPU batch size for a latency-sensitive scenario with real-time processing requirements. Although small-batch inference workloads are less common on the large datacenter-grade GPUs we evaluate in this article, we include them in our studies for completeness as future GPU designs could be scaled down (in aggregate) to build niche-specific GPU products in traditional or COPA-GPU form, and also there has been a lot of recent work [16, 17, 21, 80] focusing on efficient small-batch inference for latency-sensitive DL workloads.

The batch sizes we choose for each scenario are taken from NVIDIA's MLPerf submissions and are shown in Table 3. For our evaluations, we execute each application on a single NVIDIA Tesla V100 and collect a GPU execution trace from a full end-to-end iteration. We focus on the per-GPU workload analysis and omit the all-reduce synchronization overheads when projecting performance for large-scale DL training. All-reduce performance largely depends on the implementation of the inter-GPU network, which is beyond the scope of this work but is also receiving attention within the architecture community [42, 45].

We simulate these workloads using a modified version of NVIDIA's NVArchSim [78]. NVArchSim provides very fast simulation of deterministic portions of an application without sacrificing simulation accuracy or correctness during non-deterministic application phases and has high accuracy for the MLPerf workloads we focus on in this work. Our analysis focuses on the projected GPU-N configuration described in Table 4. GPU-N's SM count growth beyond NVIDIA A100's is proportional to the projected FP32 throughput (from Table 1) with a constant SM frequency. GPU-N's DRAM capacity is projected based on a linear extrapolation similar to the projections done for the DRAM bandwidth.

4.2 DL Performance Sensitivity to DRAM Bandwidth

We perform a detailed sweep of the DRAM bandwidth settings for the basic COPA-GPU design without L3 (similar to GPU-N) from half of its nominal bandwidth (1.3TB/s) up through infinite bandwidth. Figure 8 summarizes the overall performance normalized to the 2.7TB/s baseline. Workload performance scales steadily with growing DRAM bandwidth up to a $3 \times \text{BW}$ (8.1TB/s) setting in most of the training and inference scenarios, with diminishing returns beyond this point. Small-batch inference applications are less sensitive to DRAM bandwidth due to their relatively small footprint (more details in Section 4.3), while the remaining DL training and inference workloads

Fig. 8. Performance of a basic COPA-GPU with varying DRAM bandwidth for large-batch (*lb*) and small-batch (*sb*) settings, normalized to the baseline GPU-N performance.

show that even a relatively modest 1.5 $\times$ increase in DRAM bandwidth from 2.7TB/s to 4TB/s would lead to notable speedups of up to 18% for training and 21% for inference.

We notice that some applications are more sensitive to DRAM bandwidth at small-batch scenarios, while others are more sensitive at large-batch scenarios. There are multiple factors that determine the sensitivity of an application to DRAM bandwidth as the batch size changes. In general, smaller batch sizes mean less data reuse at the batch dimension, thereby lowering the compute intensity (FLOPS/byte) of the application and making it more memory-bound. As a result, small-batch settings would be more sensitive to DRAM bandwidth. However, smaller batch sizes could also result in further SM underutilization as shown in Figure 2, which would consequently lead to a lower DRAM bandwidth pressure. In addition, for applications with small memory footprint (as shown in Table 3), smaller batch sizes also allow a significantly larger portion of the model data (activations and weights) to be stored on-chip, reducing the DRAM bandwidth pressure. The sensitivity of an application to bandwidth is impacted by all these factors and thus can vary across different applications.

From these results we conclude that modern GPUs are on track to be severely DRAM bandwidth limited and that additional raw DRAM bandwidth is the most powerful tool for scaling DL performance. However, because evolutionary improvement in HBM memory frequency and pin density is unlikely to provide a substantially higher bandwidth scaling ratio than our aggressively projected 1.7 $\times$ (for GPU-N), we explore the potential of a very large- and high-bandwidth on-package cache to close this gap in future COPA-GPUs.

4.3 DL Performance Sensitivity to Cache Capacity

To understand the impact of large caches on DRAM bandwidth reduction in future GPUs, we sweep the LLC (L2) cache capacity of the basic COPA-GPU without L3 from 60MB to 3,840MB. A perfect L2, where all requests hit in the L2 caches, serves as the upper bound on performance. Figure 9 shows the performance of these different L2 configurations, normalized to the 60MB baseline. Increasing the L2 capacity results in performance gain equivalent to large increases in DRAM bandwidth, primarily because of the significant off-chip DRAM traffic reduction, as shown in Figure 4.

Fig. 9. Performance of a basic COPA-GPU with varying LLC capacities for both large-batch (*lb*) and small-batch (*sb*) settings, normalized to the baseline GPU-N performance.

Table 5. COPA-GPU Architectural Parameters

Architecture Configuration	LLC Capacity (MB)	DRAM BW (TB/s)	DRAM Capacity (GB)
GPU-N	60	2.7	100
COPA-GPU-1	960	2.7	100
COPA-GPU-2	960	4.5	167
COPA-GPU-3	1,920	2.7	100
COPA-GPU-4	1,920	4.5	167
COPA-GPU-5	1,920	6.3	233
Perfect L2	infinite	infinite	infinite

For DL training, 480MB of L2 performs slightly worse than a $1.5\times$ increase in DRAM bandwidth, and 960MB of L2 performs slightly worse than a $2\times$ increase in DRAM bandwidth (comparing to Figure 8). Yet larger L2 caches continue to incrementally improve the performance, but even a 3,840MB L2 still results in an 8% and 13% performance gap in large-batch and small-batch DL training workloads when compared to a perfect L2. Because DL inference applications generally have smaller memory footprint sizes than DL training, performance saturates once all workload data can be cached. The saturation points are 1,920MB and 240MB for large- and for small-batch inference, respectively, which correspond to their memory footprints listed in Table 3.

We conclude that a substantially larger LLC is an attractive solution for scaling DL performance within a COPA-GPU; however, closing the performance gap to a perfect L2 would require 4GB of on-package cache, which is impractical even under aggressive technology projections. As a result, to maximize DL performance, COPA-GPUs must not just utilize a very large L3 cache but also combine a large L3 and higher DRAM bandwidth made available with additional MSM-die edge in a 2.5D COPA-GPU design.

Fig. 10. Performance of a COPA-GPU-1 with varying UHB link bandwidth to the L3 cache, normalized to the baseline GPU-N performance.

4.4 DL Performance Scaling with COPA-GPU

Table 5 summarizes the DL-optimized COPA-GPU configurations that are enabled by architectural choices outlined in Section 3. The COPA-GPU-1 design provides 960MB of L3 cache through either 3D stacking with a single maximum-sized MSM die or 2.5D stacking with two MSM dies, each set to half of the maximum die size. The COPA-GPU-2 option with more HBM resources applies only to 2.5D, by exploiting the extra MSM die edge area to provide a $1.7\times$ higher HBM bandwidth and a larger HBM capacity (10 HBM sites in total). With two maximally sized MSM dies in the 2.5D stacking scenario, the L3 cache capacity and the additional DRAM bandwidth can be scaled to up to 1,920MB and $2.3\times$ of the baseline DRAM bandwidth (via 14 HBM sites), respectively. As a result, we consider three additional COPA-GPU configurations with 1,920MB of L3 cache and varying HBM resources: COPA-GPU-3, COPA-GPU-4, and COPA-GPU-5, with 2.7TB/s, 4.5TB/s, and 6.3TB/s of DRAM bandwidth, respectively.

Before moving to overall results, we first analyze the UHB on-package link bandwidth requirements by sweeping the unidirectional L3 bandwidth in the COPA-GPU-1 configuration with half of its baseline DRAM bandwidth ($0.5 \times \text{RD} + 0.5 \times \text{WR}$, which sums to 2.7TB/s) up through infinite bandwidth. Figure 10 summarizes the geometric mean speedup of the MLPerf applications (training and inference), normalized to the baseline GPU-N (without L3). The performance increases substantially when the L3 bandwidth grows from $0.5 \times \text{RD} + 0.5 \times \text{WR}$ to $2 \times \text{RD} + 2 \times \text{WR}$, with diminishing returns beyond that point. Overall, the UHB bandwidth configuration of $2 \times \text{RD} + 2 \times \text{WR}$ (total 10.8TB/s) comes within 3% and 6% of the unlimited bandwidth settings for training and inference, respectively. This bandwidth is well within the capabilities of next-generation 2.5/3D interconnect technologies assumed in our designs.

We also evaluate the effect of the UHB link latency by varying the total round-trip latency between the L2 and L3 caches from $0.25\times$ to $1\times$ of the DRAM access latency. Our experiments (not shown) indicate that COPA-GPU architecture is not sensitive to L3 latency, as performance changes by less than 2% across this latency range. As a result, we set the UHB link bandwidth to be $2 \times \text{RD} + 2 \times \text{WR}$, for a total of 10.8TB/s and the round-trip latency between L2 and L3 (UHB link latency plus L3 access latency) to be half of the DRAM access latency for all the COPA-GPU configurations with L3 that are listed in Table 5.

Figure 11 summarizes the MLPerf training and inference performance of the COPA-GPU designs from Table 5 in large batch (*lb*) and small batch (*sb*) settings. Unsurprisingly, larger cache capacity and higher memory bandwidth universally improve both large-batch and small-batch training performance. For example, the additional cache capacity in COPA-GPU-1 improves large-batch and small-batch performance by 21% and 18%, respectively, making it an attractive 3D COPA-GPU

Fig. 11. Performance of DL-optimized COPA-GPUs with varying designs, normalized to the baseline GPU-N performance. Large-batch and small-batch cases are denoted by *lb* and *sb*.

design. Further, the additional HBM bandwidth provided by the COPA-GPU-2 configuration achieves an overall 31% and 27% speedup, making it an attractive 2.5D COPA-GPU design choice. COPA-GPU-3 doubles L3 capacity instead of scaling DRAM bandwidth and results in lower speedups than COPA-GPU-2 (by 4%) at both large- and small-batch scenarios, indicating that increasing L3 capacity alone is not the best approach for scaling DL training performance. Finally, ambitious DRAM options such as COPA-GPU-4 and COPA-GPU-5 result in marginal performance gains (4%) when compared to COPA-GPU-2 and do not justify the additional costs of these systems.

For large-batch inference, the large L3 capacity in COPA-GPU-1 improves the performance by 29% and COPA-GPU-3 can reach speedup as high as 40%. With 1,920MB of L3, further increases in HBM bandwidth are not beneficial because most of the DRAM traffic has already been filtered out by the large L3 cache. In fact, though not shown, we find that DRAM bandwidth could be even reduced by 50% without affecting the performance. For small-batch inference, because the performance saturation point is at 240MB of LLC, the performance improvement via the combination of L3 and HBM is just 9%.

Overall, we conclude that COPA-GPU-2, which combines a substantially larger L3 cache (960MB) and moderately higher DRAM bandwidth (4.5TB/s), is likely the most optimal COPA-GPU design that will perform well for both DL training (with 31% gain at large-batch and 27% gain at small-batch) and inference (with 35% gain at large-batch and 8% gain at small-batch) without adding significant unnecessary cost through overprovisioning of memory resources. Inference is more sensitive to cache capacity and less sensitive to DRAM bandwidth than DL training, and trading off additional HBM resources for increased LLC capacity could be a plausible strategy if designing a COPA-GPU specialized for just DL inference.

A large COPA-GPU-enabled L3 reduces the total DRAM-related per-GPU energy consumption by up to 3.4 $\times$, as shown in Section 3.3. However, the improved DL-optimized COPA-GPU utilization may lead to increased total design power that may not be entirely mitigated by the power reduction within the memory system. To mitigate growing thermal density, we expect future high-end GPU systems will rely on liquid cooling technologies to enable increased thermal envelopes compared to those possible today [18, 67].

Fig. 12. Performance of DL-optimized COPA-GPU-2 designs versus additional data parallelism via 2×GPU-Ns and 4× GPU-Ns, normalized to the baseline GPU-N performance.

4.5 COPA-GPU Training Cost Efficiency at Scale

At scale, multi-GPU training performance is eventually limited by decreasing per-GPU compute efficiency and growing system-level synchronization overheads. To understand the scale-out efficiency of DL-optimized COPA-GPUs, we compare the performance of a COPA-GPU-2-based system with 2× and 4× larger systems composing the baseline GPU-Ns. We fix the global batch size across all configurations to maintain the same statistical efficiency [68]. Consequently, the per-GPU batch size drops to one-half and one-quarter for the baseline GPU-N configurations. We do not extrapolate the additional overheads of distributed gradient synchronization at larger scales, and thus our analysis favors the 2× and 4× GPU-N configurations.

Figure 12 shows that doubling and quadrupling the number of baseline GPU-N instances (2× GPU-Ns and 4× GPU-Ns) results in mean 29% and 43% performance gains, respectively, for our training workloads. We find that a DL-optimized COPA-GPU-2 configuration (with 27% performance gain) provides similar levels of performance to 2× GPU-Ns yet should cost significantly less than buying and hosting 2× larger installations of traditional GPU-Ns. Notice that at small-batch setting, *maskrcnn* has already reached the minimal batch size of 1 such that further data parallelism would not help. In general, applications that are less memory-bound and exploit more internal parallelism would benefit more from data parallelism.

When compared to GPU-N, even though COPA-GPU-2 doubles the area by adding close to 826mm² of silicon, it is dominated by regular SRAM cache arrays that are expected to achieve high manufacturing yields due to built-in redundancy and error recovery. Moreover, this aggregate area is split into two smaller dies, resulting in substantially lower cost per mm². COPA-GPU-2 integrates 1.6× more HBM memory resources, resulting in total aggregate cost lower than 2× of GPU-N. Thus, DL-optimized COPA-GPUs will provide substantially better cost performance at scale, saving on not just overall GPU cost but additional system-level collateral such as datacenter floorspace, CPUs, network switches, and other peripheral devices.

5 RELATED WORK

Leveraging high-capacity and high-bandwidth on-chip and on-wafer caches, or scratch memories, to store DL weights and activations has been well explored for DL training/inference architectures. DaDianNao [15] was designed with 36MB of on-chip eDRAM to cache model weights. Google’s TPUv1 [38] allocated 28MB of on-chip memory mostly for caching activations, while TPUv2 and TPUv3 [37] increased it to 32MB, and then TPUv4i [36] further increased it to 144MB. Recent DL accelerators such as Graphcore’s IPU [34, 43], Groq’s TSP [25], Alibaba’s HanGuang [35], and Cerebras’s WSE [46, 47] replaced off-chip memory with hundreds of MBs of high-bandwidth

on-chip SRAM to satisfy increasing memory bandwidth requirements. Unlike domain-specific accelerators that are highly tuned for DL workloads, COPA-GPUs provide high levels of GPU design reuse across application domains, while also enabling memory-system specialization for individual domains.

Multi-chip module (MCM) packaging has been extensively studied and deployed to integrate heterogeneous and homogeneous chips within a package, aiding the scaling of compute and memory bandwidths for a wide variety of legacy GPU and CPU applications. Prior work [8, 9, 55] has focused on developing MCM-GPU architectures to strong scale GPU performance beyond the limitations of a single monolithic die by leveraging on-package and on-board integration technologies. In a follow-on work [71, 81], the authors extend MCM-GPU architectures with advanced caching and HW/SW cache-coherency protocols to overcome NUMA limitations. MCM-3D-NoC [69] tackled the interconnect scalability issues of MCM integration over active interposers. In the CPU space, recent AMD CPU architectures [12, 59] leverage multi-module on-board integration to provide scalable and modular CPU architectures. Finally, Kannan et al. [39] proposed to disaggregate large monolithic CPU designs into smaller chips for cost reduction. In [74], the authors propose and quantify the costs and benefits of using MCMs with fine-grained domain-specific chiplets for DL inference.

General purpose CPU SoCs have already leveraged MCM designs with very large on-package eDRAM caches. Intel improved its mobile CPU performance by combining a CPU SoC and 128MB of on-package eDRAM organized as a victim cache [32], and IBM scaled up its Gen-Z mainframe performance with 960MB of L4 eDRAM cache [10].

While a COPA-GPU leverages the previously proposed concepts of on-package integration and large caches, our work is (1) the first to identify and solve the diverging architectural requirements between FP32 (or larger)-based HPC and FP16 (or smaller)-based DL workloads in GPUs and (2) the first to develop the reusable GPU architecture concept, enabling cost-effective GPU domain specialization for HPC and deep learning.

6 CONCLUSION

In this work, we demonstrate that diverging architectural requirements between the HPC and DL application domains put converged GPU designs on a trajectory to become significantly under-provisioned for DL and over-provisioned for HPC. We propose a new composable GPU architecture that leverages emerging circuit and packaging technologies to provide specialization, while maintaining substantial compatibility across product lines. We demonstrate that COPA-GPU architectures can enable selective deployment of on-package cache and off-chip DRAM resources, allowing manufacturers to easily tailor designs to individual domains. Our analysis shows that DL-optimized COPA-GPUs will provide impressive per-GPU training and inference performance improvements, while still efficiently supporting scaled-down HPC-targeted designs. DL-optimized COPA-GPUs will also result in reduced datacenter cost by minimizing the number of GPUs required to achieve scale-out training performance targets, making COPA-GPU an attractive paradigm for increasing individual and aggregate GPU performance without over-optimizing the product for any specific domain.

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