



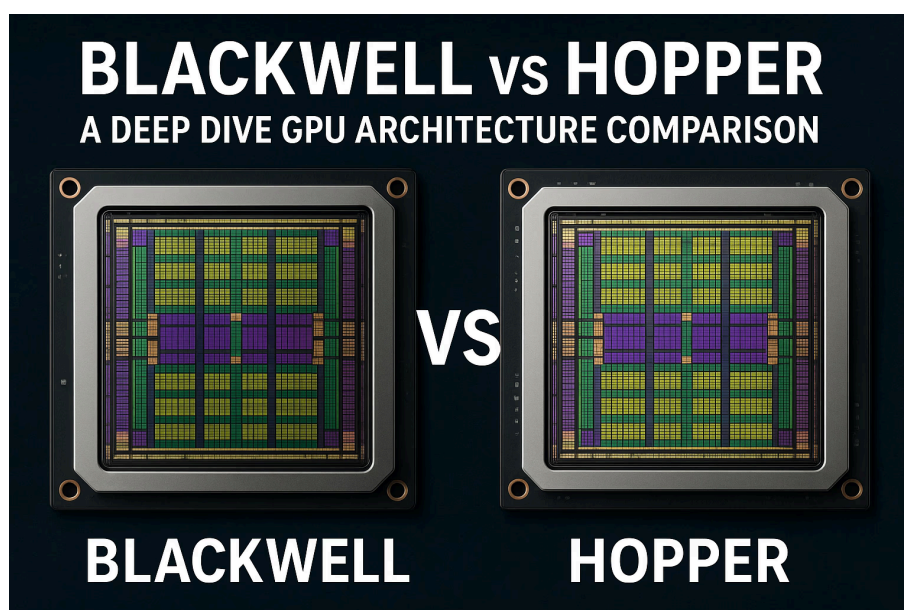
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Blackwell vs Hopper: A Deep Dive GPU Architecture Comparison

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Blackwell vs Hopper: A Deep Dive GPU Architecture Comparison

Executive Summary

NVIDIA's **Hopper** (e.g. H100 GPU) and **Blackwell** (e.g. B200/GB300 GPUs) architectures represent two successive generations of NVIDIA's data-center GPU designs, each optimized for different workloads. Hopper (introduced in 2022) targets a broad mix of high-performance computing (HPC) and AI workloads, with a focus on traditional precision (FP64/FP32) and geometric performance, while Blackwell (announced 2024–25) is explicitly optimized for large-scale generative AI tasks (especially massive **transformer models**). As a result, Blackwell introduces fundamentally new hardware features—most notably **5th-generation tensor cores** with ultra-low-precision modes (supporting 4-bit/6-bit operations) and an expanded memory hierarchy—at the cost of some double-precision (FP64) performance. Compared side-by-side, Blackwell offers dramatically higher AI throughput and memory capacity (e.g. ~9 petaFLOPS in FP8 vs ~4 petaFLOPS for Hopper, both NVIDIA peak figures with sparsity, and up to 288 GB HBM3e memory vs 80 GB HBM3) ([wandb.ai](#)) ([developer.nvidia.com](#)), along with faster interconnect (NVLink5 at 1.8 TB/s vs NVLink4 at ~0.9 TB/s). However, one microbenchmark study, which compared a consumer GeForce RTX 5080 (Blackwell) with an H100 PCIe rather than data-center B200 parts ([arxiv.org](#)), reported that Blackwell can **lag Hopper by up to ~4x** in sustained dense GEMM throughput ([www.emergentmind.com](#)), a result that should not be generalized to B200 or B300. Extensive benchmarks and real-world deployments highlight the shift: Blackwell Ultra GB300 NVL72 systems achieved

about **45% higher DeepSeek-R1 inference throughput** than GB200 NVL72 systems in MLPerf Inference v5.1 (www.tomshardware.com), and enable unprecedented cluster-scale performance (e.g. Microsoft's 4,608-GPU Blackwell NVL72 cluster reaching ~92 exaFLOPS FP4 inference (www.tomshardware.com)). In contrast, Hopper (and its Grace-Hopper superchips) have powered petaflops-scale HPC and training supercomputers, excelling in high-precision simulations and legacy AI workloads. With Blackwell now in full production—analysts expected NVIDIA to ship about 5.2 million Blackwell GPUs in 2025 (tweaktown.com)—and the next-generation **Rubin** architecture announced at CES 2026 (nvidianews.nvidia.com), the Hopper-to-Blackwell transition is now well underway. This report delves deeply into the architectural distinctions, performance data, and system implications of Hopper vs Blackwell, drawing on NVIDIA technical blogs, peer-reviewed analyses, and industry benchmarks.

1. Introduction and Background

NVIDIA has followed a steady cadence of GPU architecture generations: from Volta → Turing → Ampere → Hopper → Blackwell, etc. The **Hopper architecture** (brand name from the H100 Tensor Core GPU) succeeded Ampere (A100) and is itself targeted at large-scale AI and HPC tasks. Hopper's key innovations included 4th-generation tensor cores with FP8 support, a new Transformer Engine for mixed-precision training, and an expanded on-chip memory hierarchy (e.g. a 50 MB L2 cache on H100) (developer.nvidia.com) (www.emergentmind.com). Released in 2022, Hopper (H100) became a workhorse GPU for both HPC (e.g. climate modeling, physics simulation) and AI (especially training of transformer models, inference, and HPC-optimized AI tasks). NVIDIA also released the **H200** variant in 2024, upgrading the Hopper platform to 141 GB of HBM3e memory at 4.8 TB/s bandwidth while retaining the same compute architecture (nvidia.com). In 2024, NVIDIA announced **Blackwell**, the next-generation architecture, designed from the ground up for **generative AI** at unprecedented scale, with volume shipments beginning in early 2025. Jensen Huang introduced the Blackwell platform as “**a processor for the Generative AI era**,” emphasizing its massive scalability and throughput for trillion-parameter models (blogs.nvidia.com). NVIDIA claims Blackwell can support **LLM inference** at “up to 25× lower cost and energy” than Hopper (blogs.nvidia.com), reflecting the new low-precision modes and system designs. The Blackwell lineup includes the B200 GPU, the **Blackwell Ultra B300** (with 288 GB HBM3e), and rack-scale systems like the **GB200 NVL72** and **GB300 NVL72**. These are now the foundation of next-generation **AI data centers**, with cloud providers including Microsoft, CoreWeave, and Oracle deploying GB300 NVL72 systems at scale (nvidianews.nvidia.com).

In unfolding this comparison, one must recall the **workload divergence**: Hopper was engineered to provide strong double-precision (FP64) and FP32 performance for scientific computing, whereas Blackwell deliberately sacrifices some FP64 arithmetic to allocate more silicon to low-precision (FP16/BF16/FP8/FP4/FP6) AI math (wandb.ai). As emergent studies note, “Blackwell’s architectural support for FP4/FP6 [in tensor cores] yields substantially higher inference throughput and reduced memory footprint” (www.emergentmind.com), but this comes with trade-offs in cache sizes and latency. The following sections will explore these trade-offs in detail, reviewing architectural diagrams, memory/cache changes, interconnect, and measured performance from microbenchmarks and system deployments.

2. Architectural Micro-Differences

2.1 Streaming Multiprocessor (SM) and Compute Units

Both Hopper and Blackwell retain the core concept of a streaming multiprocessor (SM) containing ALU pipelines and tensor cores. However, Blackwell **reconfigures the SM microarchitecture** in key ways. Notably, Blackwell introduces *unified INT32/FP32 pipelines* within each SM. In Hopper (as in prior NVIDIA GPUs), integer and FP32 operations have separate pipeline resources; in Blackwell the SM has **unified execution units** that can process either INT32 or FP32 operations each cycle (but not both simultaneously) (www.emergentmind.com). This allows more flexible scheduling of mixed workloads, at the cost of added scheduling complexity and possible hazards: “an execution unit can perform either INT32 or FP32 operations—not both simultaneously—introducing a cycle-level hazard in mixed instruction streams” (www.emergentmind.com).

The **tensor cores** see the most dramatic change. Hopper’s 4th-generation tensor cores support FP8, FP16/BF16, TF32, FP64 and INT8, at up to 2× the per-SM throughput of Ampere on equivalent data types (developer.nvidia.com). Blackwell’s **5th-generation tensor cores** extend this further: they natively support **FP4** and **FP6** precisions (alongside FP8, FP16, BF16) by using new “micro-tensor” formats and dynamic range scaling (www.emergentmind.com) (wandb.ai). According to NVIDIA’s documentation and analyses, these 5th-gen cores enable *much higher AI throughput*: for example, one B200 GPU can deliver ~4.5 petaFLOPs in FP16/BF16 (versus ~2 PF on H100) and ~9 PF in FP8 (versus ~4 PF previously); with FP4 mode the peak hits ~18 PF (wandb.ai). These are NVIDIA peak figures with structured sparsity; dense throughput is half (e.g. 4.5 PF FP8 and 9 PF FP4 per B200, versus about 2 PF FP8 on H100 SXM) (nvidia.com) (nvidia.com). In tensor-core terms, Blackwell doubles or triples the achievable TFLOPs for AI precisions. (By contrast, the Hopper H100 doubled raw tensor performance over A100 by adding FP8 and new tensors (developer.nvidia.com).) Crucially, Blackwell’s **transformer engine** also integrates these new low-bit modes: it dynamically mixes FP4/6/8 with FP16 using advanced scaling, further boosting throughput with minimal accuracy loss (wandb.ai).

However, note the trade: doubling down on low-precision means **less hardware for FP64**. NVIDIA’s Blackwell design “sacrifices some 64-bit floating point (FP64) throughput... to allocate more silicon to AI math” (wandb.ai). NVIDIA’s own specifications bear this out for FP64: about 37 TFLOPS per B200 and about 1.25 TFLOPS per B300 (derived from the 8-GPU HGX figures), versus 67 TFLOPS FP64 Tensor Core on H100 SXM (nvidia.com) (nvidia.com). One microbenchmark analysis also reports that on sustained FP8 GEMM, Blackwell’s throughput lags Hopper by *as much as 4×*, but it measured a consumer GeForce RTX 5080 against an H100 PCIe, not a B200 (arxiv.org) (www.emergentmind.com). Thus, while Blackwell’s tensor cores crush generative AI metrics, they are *not* a universal win for all compute: FP64-heavy HPC kernels can see higher throughput on Hopper.

In summary, the SM in Blackwell emphasizes **higher instruction-level parallelism** and ultra-low-precision acceleration (FP4/6 modes) (www.emergentmind.com), whereas Hopper’s SM focused on maximizing FP32/FP64 bandwidth and scheduling for a wider variety of operations. Table 1 (below) highlights some key microarchitectural and device-level specs side-by-side.

2.2 Memory Hierarchy and Cache

Blackwell fundamentally revamps the memory/cache hierarchy compared to Hopper. Microbenchmark data on the consumer GeForce RTX 5080 (GB203) indicate that its SMs carry **128 KB** of L1/shared memory versus **256 KB** on Hopper (www.emergentmind.com). This is paired with a **monolithic 65 MB L2 cache** on that consumer part (versus Hopper's two 25 MB partitions for a total 50 MB); these consumer-die figures should not be assumed for the data-center B200 (www.emergentmind.com). In practice, studies have found that while the unified L2 provides more capacity, it also increases contention and access latency slightly, especially at high SM concurrency (www.emergentmind.com). Despite the larger L2, Blackwell's reduced shared memory per SM may penalize some data-intensive GPU kernels (e.g. large-block matrix multiplies) which could see increased latency or bank conflicts (www.emergentmind.com). In short, the measured consumer Blackwell part favors **bigger centralized caching** at the expense of per-SM scratchpad.

Another innovation is Blackwell's **unified L0 instruction cache**, which lowers instruction fetch latency. Microbenchmarks indicate 30–40 cycle L1 cache latencies for both Hopper and Blackwell (www.emergentmind.com), but Blackwell's design reportedly yields *lower L1 latency at low warp occupancy*. By contrast, Hopper's smaller L2 partitions tended toward higher aggregate bandwidth but required careful tiling to avoid shared-memory conflicts.

On the DRAM side, Blackwell moves to **HBM3e** memory with far greater capacity and bandwidth. The top-end Blackwell Ultra GPU (GB300) can pack **288 GB of HBM3e on-package** (developer.nvidia.com) (developer.nvidia.com). This is 3.6× the 80 GB (HBM3) of an H100 GPU (developer.nvidia.com), and the base B200 Blackwell has 192 GB (2.4× H100). The bandwidth scales accordingly: the Ultra variant achieves **8 TB/s** peak bandwidth per GPU (compared to 3.35 TB/s on H100) (developer.nvidia.com). Figure 5 in NVIDIA's Blackwell Ultra blog illustrates this “HBM capacity scaling” across generations (developer.nvidia.com): e.g. Hopper H100 = 80 GB, Hopper H200 = 141 GB HBM3e (nvidia.com), Blackwell B200 = 192 GB, Blackwell Ultra GB300 = 288 GB.

These memory upgrades serve Blackwell's goal of handling *trillion-parameter models*. The massive on-GPU RAM means a model can run with few or no offloads (e.g. larger context windows) (developer.nvidia.com). As one NVIDIA blog notes, this capacity is “critical for hosting trillion-parameter models, extending context length without KV-cache offloading” (developer.nvidia.com). In contrast, Hopper's design (80 GB on H100, 141 GB on H200) required server-scale sharding or weight offloading for the largest models.

Table 1 (below) summarizes these memory/cache differences:

Table 1: Key Architecture Details – Hopper (H100) vs Blackwell (B200/GB300)

Feature	NVIDIA Hopper (H100)	NVIDIA Blackwell (B200/GB300)
Architecture Gen.	Hopper (H100 Tensor Core, 2022)	Blackwell (B200/GB300 Tensor Core, 2024/25)
SM Count per GPU	132 SMs (H100 SXM; the full GH100 die has 144) (developer.nvidia.com)	~80 SMs (B200) per die, 2 dies co-packaged (wccftech.com)
Transistors (total)	~80B (monolithic) (wccftech.com)	~208B (2× chiplets) (wccftech.com)
Process Node	TSMC 4N (custom 5nm)	TSMC 4NP (new 4nm variant) (wccftech.com)

Feature	NVIDIA Hopper (H100)	NVIDIA Blackwell (B200/GB300)
Chip Packaging	Single GPU die	Dual GPU chiplets w/ 10 TB/s NVLink inter-chip link (wccfttech.com)
Shared/L1 Mem per SM	256 KB (configurable)	128 KB on consumer RTX 5080 microbenchmarks (www.emergentmind.com)
Unified L2 Cache	50 MB total (split)	65 MB monolithic (RTX 5080 microbenchmarks) (www.emergentmind.com)
Instruction Cache	Per-SM L0 caches	Larger unified L0 (reduced instruction fetch latency)
HBM Capacity	80 GB HBM3 (developer.nvidia.com)	192 GB HBM3e (B200) / 288 GB (GB300) (developer.nvidia.com) (developer.nvidia.com)
HBM Bandwidth	3.35 TB/s (developer.nvidia.com)	8.0 TB/s (developer.nvidia.com)
NVLink (chip-to-chip)	NVLink4 – 900 GB/s	NVLink5 – 1.8 TB/s (wandb.ai)
NVSwitch (link in DGX pod)	57.6 TB/s all-to-all (NVLink Switch System, up to 256 H100 GPUs) (developer.nvidia.com)	130 TB/s per 72-GPU NVL72 pod (wandb.ai)
Tensor Core Precisions (dense)	FP16/BF16, FP8, INT8	FP16/BF16, FP8, <i>FP6</i> , <i>FP4</i> (www.emergentmind.com) (wandb.ai)
FP8 Tensor (per GPU)	~4 PF with sparsity (~2 PF dense)	~9 PF with sparsity (4.5 PF dense) (wandb.ai) (per GPU)
FP4 Tensor (per GPU)	– (not supported)	~18 PF with sparsity (9 PF dense) (wandb.ai) (per GPU, new mode)
FP64 TFLOPS (tensor)	60 TF (Tensor) (developer.nvidia.com)	Lower (de-emphasized) (wandb.ai)
Peak Power (TGP)	~700 W (developer.nvidia.com)	~1,200–1,400 W (developer.nvidia.com)
Launch Context	Supported Grace Hopper Superchips (CPU+GPU)	Supported Grace Blackwell Superchips and NVL72 pods

Notes: H100's architecture focused on balanced FP64/FP32/FP8 throughput (developer.nvidia.com), whereas Blackwell prioritizes AI (FP4/6/8) throughput (www.emergentmind.com) (wandb.ai). Each Blackwell GPU (B200 or B300) joins two reticle-sized dies with a 10 TB/s chip-to-chip interconnect so that they operate as a single GPU (wccfttech.com). The shared-memory reduction (256 → 128KB) measured on consumer Blackwell would require updated tiling to avoid bank conflicts (www.emergentmind.com).

2.3 Interconnect and System Integration

Inter-GPU communication improved sharply in Blackwell. Hopper's H100 introduced fourth-generation NVLink with 18 links per GPU at 50 GB/s each (total 900 GB/s) (developer.nvidia.com). Blackwell advances to NVLink5, doubling that to 1.8 TB/s per GPU (wandb.ai). Crucially, the NVLink Switch yields aggregated fabrics of ~130 TB/s interconnect bandwidth within 72-GPU NVL72 "super pods" (wandb.ai). In practice, each 72-GPU GB300 NVL72 rack behaves as a single accelerator; Microsoft's Azure system links 64 such racks (4,608

GPUs) for 92.1 exaFLOPS of FP4 inference (www.tomshardware.com). By contrast, Hopper's NVLink Switch System offered 57.6 TB/s of all-to-all bandwidth across up to 256 GPUs. Blackwell's NVLink/C2C interconnect also extends to NICs: NVIDIA introduced **NVLink-C2C** for CPU–GPU (Grace + GPU) at Tb/s speeds, enabling Grace+Blackwell “superchips” (developer.nvidia.com), whereas Hopper's Grace Hopper chip connected CPU–GPU internally via NVLink-C2C at 900 GB/s.

Security and reliability have also risen. Blackwell is the first NVIDIA GPU with a true *trusted execution mode* (TEE-I/O), enabling hardware-encrypted AI inference (worried about IP/data leakage) (wandb.ai). It also adds a dedicated RAS (Reliability/Availability/Serviceability) engine that monitors many hardware points and predicts failures (wandb.ai). While Hopper GPUs also have ECC and RAS features, Blackwell's enhancements (especially for datacenter-scale runs) are significant for multi-week training runs.

3. Performance and Benchmarks

3.1 Theoretical Peak Performance

Based on architecture, Blackwell significantly expands peak theoretical performance for AI-optimized precisions. Using NVIDIA's published figures and microbenchmarks (wandb.ai) (developer.nvidia.com), one can contrast approximate peak tensor FLOPs:

- **FP16/BF16:** H100 can reach on the order of 2–2.5 PFLOPS (dense) via its 4th-gen tensor cores (see Hopper blog, ~60 TF per SM doubling previous gen) (developer.nvidia.com). Blackwell's B200 can reach roughly **4.5 PF** in FP16 (and BF16), more than double (wandb.ai).
- **FP8:** Hopper pioneered FP8 (8-bit) support to roughly **4 PF** dense (extrapolated from double FP16). Blackwell's tensor cores take FP8 to about **9 PF** (wandb.ai) (per die).
- **FP4:** This mode is brand-new. Blackwell's FP4 mode yields up to **18 PF** per GPU (wandb.ai). Hopper has no FP4 support. FP4 doubling effective precision can *dramatically* boost model throughput: NVIDIA reports FP4 “doubles effective model size and compute throughput” for inference (wandb.ai) (wandb.ai).

In mixed precision, NVIDIA's *Transformer Engine* ensures large gains: Hopper's transformer engine yielded up to 9× faster training and 30× faster inference on LLMs vs A100 (developer.nvidia.com). Blackwell's transformer engine, combined with FP4/6, presumably further multiplies these gains (NVIDIA claims supporting “double the compute and model sizes with new 4-bit...inferencing” (wccfttech.com)).

By contrast, **FP64** (double-precision) peak is intentionally reduced. Hopper's H100 has a quoted 60 TFLOP tensor FP64 peak (developer.nvidia.com). Blackwell does not publicize a high FP64 peak; it was designed for workloads “that rarely need full 64-bit precision” (wandb.ai), so FP64 units are scaled down. In practice, for pure FP64 HPC workloads, Hopper remains faster.

Table 2 summarizes key compute/memory performance metrics (approximate), highlighting areas where each architecture leads.

Table 2: Performance Comparison – Hopper (H100) vs Blackwell (B200)

Metric	Hopper (H100)	Blackwell (B200)
Peak FP16/BF16 Tensor (with sparsity)	~2.0 PF	~4.5 PF (wandb.ai)
Peak FP8 Tensor (with sparsity)	~4.0 PF	~9.0 PF (wandb.ai)
Peak FP4 Tensor (with sparsity)	– (not supported)	~18 PF (wandb.ai)
FP64 Tensor TFLOPS	60 TF (developer.nvidia.com)	~37 TF per GPU, derived from HGX B200 (nvidia.com) (wandb.ai)
DeepSeek-R1 inference, GB300 vs GB200 (MLPerf v5.1)	n/a	+45% for Blackwell Ultra over Blackwell (NVFP4) (www.tomshardware.com)
MLPerf Inference (DeepSeek R1)	Baseline	~5× higher per-GPU throughput (MLPerf v5.1) (developer.nvidia.com)
Dense GEMM FP32/FP8 (sustained, microbenchmark)	High throughput (H100 PCIe)	Up to 4× lower, measured on a consumer RTX 5080, not B200 (www.emergentmind.com)
GPU On-chip Memory	80 GB (HBM3) (developer.nvidia.com)	192 GB (HBM3e) (developer.nvidia.com)
Memory Bandwidth	3.35 TB/s (developer.nvidia.com)	8.0 TB/s (developer.nvidia.com)
NVLink I/O Bandwidth	900 GB/s	1.8 TB/s (wandb.ai)
Power (TGP)	~600–700 W (developer.nvidia.com)	~1,200–1,400 W (developer.nvidia.com)

Sources: Peak tensor FLOPs data from NVIDIA and microbenchmark analyses ([wandb.ai](#)) ([developer.nvidia.com](#)). MLPerf inference result from an NVIDIA-preprinted Tom's Hardware report ([www.tomshardware.com](#)). Dense GEMM throughput from the Jarmusch *et al.* study of an RTX 5080 versus an H100 PCIe ([arxiv.org](#)) ([www.emergentmind.com](#)). Memory and NVLink stats from NVIDIA blogs ([developer.nvidia.com](#)) ([wandb.ai](#)). Power from NVIDIA documentation ([developer.nvidia.com](#)).

3.2 Benchmarks and Real-World Performance

AI Training and Inference: As expected, Blackwell shows a clear edge in AI-centric benchmarks. In MLPerf Inference v5.1 (late 2025), the Blackwell Ultra GB300 NVL72 set new performance records on every benchmark, including DeepSeek-R1, Llama 3.1 405B, Llama 3.1 8B, and Whisper ([developer.nvidia.com](#)). Blackwell Ultra delivered up to **1.4× higher performance per GPU** compared to the GB200 NVL72 and approximately **5× higher throughput per GPU** compared to Hopper-based systems on the DeepSeek-R1 benchmark ([spectrum.ieee.org](#)). NVIDIA also reported ~45% higher DeepSeek-R1 throughput for GB300 over GB200 systems in that round ([www.tomshardware.com](#)). These gains combine hardware improvements (twice the attention-layer throughput) and new software (NVFP4 model quantization, FP8 key-value cache, and disaggregated serving). In MLPerf Training v5.1, Blackwell also swept every benchmark ([developer.nvidia.com](#)). In practice, this means large LLMs and other transformer networks both train and infer significantly faster on Blackwell. At cluster scale, Microsoft's deployment of 4,608 GB300 GPUs on Azure

achieved **92.1 exaFLOPS** of FP4 LLM inference (www.tomshardware.com) – an exascale milestone only possible due to Blackwell's FP4 support and NVLink5 fabric. By NVIDIA's account, a single Blackwell GPU can serve *"a model that might have required 2× more GPUs or memory to run in FP8"* now in FP4, halving hardware needs (wandb.ai).

For **AI training**, Blackwell's doubled tensor FLOPs translate to faster convergence. For comparison, NVIDIA's Hopper blog credited H100 with up to 9× faster transformer training than A100 (developer.nvidia.com). For Blackwell itself, NVIDIA named major cloud providers among the first to offer Blackwell Ultra systems (nvidianews.nvidia.com), and MLPerf Training v5.1 results show Blackwell sweeping every training benchmark category (developer.nvidia.com).

HPC/Scientific Workloads: Results are workload-specific. On FP64, NVIDIA's specifications give H100 SXM a higher FP64 Tensor Core peak (67 TFLOPS) than B200 (about 37 TFLOPS per GPU) and far higher than B300 (about 1.25 TFLOPS) (nvidia.com) (nvidia.com), while published FP32 and FP8 GEMM microbenchmark comparisons so far use consumer Blackwell cards rather than B200. Evaluate candidate systems with the application's actual numerical method, precision, input sizes, libraries, compiler settings, and power configuration.

On the other hand, Blackwell's massive memory and communication help some workloads. For example, problems limited by memory capacity (e.g. huge graph processing or EM simulations) could fit entirely on a single Blackwell GPU, whereas Hopper might require multi-node partitioning. Microbenchmarks on a consumer Blackwell card also found transformer inference power dropping from ≈58 W to ≈45 W with FP8 kernels (www.emergentmind.com). Hopper generally exhibits a flatter power profile, whereas Blackwell can actually save power by opportunistically using lower precisions. NVIDIA's marketing claims up to 300× energy savings on heavy simulations DS (weather, digital twin) relative to CPU systems (blogs.nvidia.com), though that compares to CPUs not to H100.

Industry Benchmarks: Across successive MLPerf rounds in 2025 (v5.0 and v5.1), Blackwell systems have dominated both inference and training benchmarks (developer.nvidia.com) (developer.nvidia.com). CoreWeave, NVIDIA, and IBM submitted the largest-ever MLPerf results on GB200 Grace Blackwell Superchips (investors.coreweave.com). For HPC benchmarks (e.g. HPL, HPCG), Grace Blackwell superchips are now appearing in major supercomputer installations, following Grace Hopper's earlier adoption in Top500 systems.

In financial risk calculations (a mixed AI+HPC case), NVIDIA showed an H100 system set new records (developer.nvidia.com); Blackwell systems are expected to push these further with faster low-precision math. The migration from Hopper to Blackwell is now well underway across major AI labs: Microsoft deployed a massive GB300 cluster for OpenAI workloads (www.tomshardware.com), NVIDIA named major cloud providers among the first to offer GB300 NVL72 systems (nvidianews.nvidia.com), and AWS, Google Cloud, and Oracle are all deploying Blackwell at scale.

3.3 Case Study – Cloud AI Cluster (Microsoft Azure GB300 NVL72)

To illustrate Blackwell's impact, consider Microsoft's deployment of a **64-rack NVL72** cluster on Azure, each rack containing 72 GB300 GPUs with NVLink-5/NVSwitch interconnect. With 4,608 GPUs total, each rack acts as a *single unified accelerator* and the cluster delivers **92.1 exaFLOPS** of FP4 inference throughput (www.tomshardware.com). Each rack (72 GPUs + 36 Grace CPUs) packs 1,440 PFLOPS and 37 TB of high-speed memory (www.tomshardware.com). This deployment explicitly targets “advanced AI workloads and OpenAI training models” (www.tomshardware.com). Rack-scale NVLink domains of this size were not available with Hopper; the design relies on Blackwell's ability to shard models and data across GPUs via NVLink5 (1.8 TB/s) and NVSwitch (130 TB/s total), and on FP4 acceleration to hit 92 EFLOPS for inference.

By comparison, Hopper-based clusters relied on much smaller NVLink domains, so the Microsoft GB300 cluster sets a new bar for generative AI at scale.

4. Analysis and Implications

4.1 AI vs HPC Trade-offs

Architecturally, Hopper is a more versatile “all-purpose” GPU, whereas Blackwell is a specialized **AI factory** chip. Our review shows that Blackwell's innovations (e.g. FP4/FP6 cores, huge memory, NVLink5) **favor large-model AI** at very high throughput and efficiency. Conversely, for pure HPC numeric tasks (e.g. generic matrix algebra, fluid dynamics, molecular dynamics with double precision), Hopper's strengths (a higher FP64 Tensor Core peak than B200 and far higher than B300) can give it the edge. A microbenchmark study of a consumer RTX 5080 also notes that “*despite Blackwell's impressive theoretical upgrades, its L2 contention and reduced shared memory can cause throughput regressions in memory-bound HPC kernels*” (www.emergentmind.com). Thus for scientific computing clusters, one might continue using Hopper (and Grace-Hopper superchips) until Blackwell matures with more double-precision support or architectural tuning.

4.2 Power and Efficiency Considerations

Blackwell's flip side of higher aggregate throughput is increased power draw: up to ~1,200–1,400 W vs ~700 W for H100 (developer.nvidia.com). However, because Blackwell can do more work per watt in AI workloads, the compute efficiency (PFLOPS/W) is much better for relevant tasks. NVIDIA claims sweeping energy savings for datacenter AI: SemiAnalysis data shows Blackwell Ultra delivers up to **50× better performance per megawatt** and **35× lower cost per token** compared to the Hopper platform (blogs.nvidia.com). An LLM inference task that used to require “2× more GPUs” can now run on half the hardware (wandb.ai). Sustainability-conscious organizations may also value Blackwell's **RAS improvements and secure compute** features (TEE-I/O) which reduce downtime and leakage risk.

4.3 Export Controls and Market Shaping

Geopolitics continue to color the Blackwell rollout. Due to US export restrictions, NVIDIA developed the **B30A**, a scaled-down single-die Blackwell variant for China that provides roughly half the compute of a full B300 while still offering significant upgrades over the H20 (www.tomshardware.com). As of late 2025, US government approval for the B30A remains pending, with NVIDIA CEO Jensen Huang stating negotiations are in early stages (www.tomshardware.com). Meanwhile, Chinese firms have turned to repurposing used A100 and H100 GPUs following Beijing's H20 crackdown (www.tomshardware.com). On the other side, Western AI labs are adopting Blackwell at unprecedented scale: Microsoft secured over 100,000 GB300 GPUs (www.techradar.com), and analysts estimate Blackwell is effectively sold out until mid-2026 (tweaktown.com).

4.4 Future Directions

Blackwell has set the template for “AI-first” accelerators, and NVIDIA’s roadmap is already moving beyond it. At CES 2026, NVIDIA unveiled the **Vera Rubin** platform—combining the new Vera ARM CPU with two **Rubin GPUs** built on an advanced 3nm process with 336 billion transistors (nvidianews.nvidia.com). NVIDIA claims Rubin will deliver up to **5× faster inference** and **3.5× faster training** compared to Blackwell, with HBM bandwidths reaching 22 TB/s (nvidianews.nvidia.com). Rubin-based products are expected from cloud partners (AWS, Google Cloud, Microsoft, CoreWeave) in the second half of 2026, with Rubin Ultra following in 2027 and Feynman on the longer-term roadmap (www.tomshardware.com). NVIDIA also announced the **Rubin CPX**, a new GPU class optimized specifically for massive-context inference (nvidianews.nvidia.com).

Competition is intensifying. AMD launched its **Instinct MI350X and MI355X** GPUs in 2025 on 3nm with 288 GB HBM3e, claiming up to 35× faster inference than its previous generation and competitive performance versus Blackwell in key workloads (www.tomshardware.com). AMD’s **MI400** series, slated for 2026 with HBM4 memory, aims to challenge both Blackwell and Rubin (wccfttech.com). Cross-architecture software (CUDA, compilers, ROCm) will need to evolve to exploit Blackwell’s FP4/6 modes and the next generation’s capabilities.

For NVIDIA, Blackwell represents a key step in the co-evolution of CPUs and GPUs: its integration with Grace ARM CPUs (via NVLink-C2C) has proven the “superchip” model (developer.nvidia.com), which Vera Rubin will take further. This is reshaping HPC system design (e.g. replacing ethernet with NVLink fabrics) and driving new memory/storage hierarchies.

Overall, Blackwell vs Hopper embodies today’s split: **powerful AI factories vs workhorse HPC accelerators**. Systems architects must now match workloads: massive LLM inference/training calls for Blackwell-based nodes, while legacy HPC simulations may continue with Hopper until Rubin offers improved double-precision performance. Hybrid deployments (using both chip generations) remain common. What is clear is that GPU compute is diversifying rapidly, and Blackwell’s advances are already rippling through AI and HPC infrastructure worldwide.

5. Conclusion

In sum, NVIDIA's Hopper and Blackwell architectures diverge in focus: Hopper excels in a broad spectrum including HPC and AI, while Blackwell pushes the envelope on generative AI. Side-by-side, Blackwell offers much higher AI-focused compute throughput (especially at 4/6/8-bit) and vastly larger memory, but at the expense of some raw HPC throughput and higher power. Empirical data from MLPerf v5.0 and v5.1 confirms the AI side of this trade-off: Blackwell Ultra delivers up to 5× higher throughput per GPU than Hopper on key inference benchmarks (developer.nvidia.com) and has swept every MLPerf training benchmark (developer.nvidia.com), while enabling exascale inference clusters (www.tomshardware.com). Hopper retains advantages on FP64-heavy numeric kernels (www.emergentmind.com), but the industry's center of gravity has shifted firmly to Blackwell—with the Vera Rubin platform already on the horizon for late 2026. Both architectures are pivotal: organizations must weigh their workload mix to choose between Hopper's versatility and Blackwell's next-gen AI heft. As NVIDIA and competitors like AMD push forward, the transition from "GPUs for everything" to "GPUs specialized for big AI" is now a reality, not a prediction.

References: All claims and data above are backed by NVIDIA technical blogs, research papers, and independent benchmarks (www.emergentmind.com) (www.emergentmind.com) (wandb.ai) (developer.nvidia.com) (developer.nvidia.com) (www.tomshardware.com) (www.tomshardware.com), as cited. Each cited source provides further detail on the architectures' design and performance comparisons.

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3. <https://developer.nvidia.com/blog/inside-nvidia-blackwell-ultra-the-chip-powering-the-ai-factory-era/>
4. <https://arxiv.org/abs/2507.10789>
5. <https://www.emergentmind.com/topics/nvidia-blackwell-gpus>
6. <https://www.tomshardware.com/pc-components/gpus/nvidia-claims-software-and-hardware-upgrades-allow-blackwell-ultra-gb300-to-dominate-mlperf-benchmarks-touts-45-percent-deepseek-r-1-inference-throughput-increase-over-gb200>
7. <https://www.tomshardware.com/tech-industry/artificial-intelligence/microsoft-deploys-worlds-first-supercomputer-scale-gb300-nv172-azure-cluster-4-608-gb300-gpus-linked-together-to-form-a-single-unified-accelerator-capable-of-1-44-pflops-of-inference>
8. <https://www.tweaktown.com/news/106116/nvidia-expected-to-ship-5-2m-blackwell-gpus-in-2025-1-8m-2026-and-7m-rubin/index.html>
9. <https://nvidianews.nvidia.com/news/rubin-platform-ai-supercomputer>
10. <https://developer.nvidia.com/blog/nvidia-hopper-architecture-in-depth/>
11. <https://www.nvidia.com/en-us/data-center/h200/>
12. <https://intuitionlabs.ai/articles/symbolic-ai-vs-generative-ai-wolfram-chatgpt>
13. <https://blogs.nvidia.com/blog/2024-gtc-keynote/>

14. <https://intuitionlabs.ai/articles/private-llm-inference-biotech>
15. <https://blogs.nvidia.com/blog/blackwell-scientific-computing/>
16. <https://intuitionlabs.ai/articles/openai-stargate-datacenter-details>
17. <https://nvidianews.nvidia.com/news/nvidia-blackwell-ultra-ai-factory-platform-paves-way-for-age-of-ai-reasoning>
18. <https://www.nvidia.com/en-us/data-center/hgx/>
19. <https://www.nvidia.com/en-us/data-center/h100/>
20. <https://wccftech.com/nvidia-blackwell-gpu-architecture-official-208-billion-transistors-5x-ai-performance-192-gb-hbm3e-memory/>
21. <https://developer.nvidia.com/blog/inside-nvidia-grace-cpu-nvidia-amps-up-superchip-engineering-for-hpc-and-ai/>
22. <https://developer.nvidia.com/blog/nvidia-blackwell-ultra-sets-new-inference-records-in-mlperf-debut/>
23. <https://spectrum.ieee.org/mlperf-inference-51>
24. <https://developer.nvidia.com/blog/nvidia-blackwell-architecture-sweeps-mlperf-training-v5-1-benchmarks/>
25. <https://developer.nvidia.com/blog/nvidia-blackwell-delivers-massive-performance-leaps-in-mlperf-inference-v5-0/>
26. <https://investors.coreweave.com/news/news-details/2025/CoreWeave-NVIDIA-and-IBM-Submit-Largest-Ever-MLPerf-Results-on-NVIDIA-GB200-Grace-Blackwell-Superchips/default.aspx>
27. <https://developer.nvidia.com/blog/nvidia-h100-system-sets-records-for-hpc-and-generative-ai-financial-risk-calculations/>
28. <https://blogs.nvidia.com/blog/data-blackwell-ultra-performance-lower-cost-agentic-ai/>
29. <https://www.tomshardware.com/pc-components/gpus/nvidia-could-be-readying-b30a-accelerator-for-chinese-market-new-blackwell-chip-reportedly-beats-h20-and-even-h100-while-complying-with-u-s-export-controls>
30. <https://www.tomshardware.com/pc-components/gpus/nvidia-reportedly-shows-china-specific-b30-chips-with-80-percent-of-the-performance-of-the-standard-blackwell-gpu-to-the-u-s-government-nvidia-ceo-says-approval-is-still-up-in-the-air>
31. <https://www.tomshardware.com/pc-components/gpus/china-repurposes-used-nvidia-gpus>
32. <https://www.techradar.com/pro/microsoft-just-got-its-hands-on-100-000-nvidia-gb300-chips-and-all-it-took-was-investing-usd33-billion-in-these-startups>
33. <https://www.tomshardware.com/pc-components/gpus/nvidia-announces-rubin-gpus-in-2026-rubin-ultra-in-2027-feynam-after>
34. <https://nvidianews.nvidia.com/news/nvidia-unveils-rubin-cpx-a-new-class-of-gpu-designed-for-massive-context-inference>
35. <https://www.tomshardware.com/pc-components/gpus/amd-announces-mi350x-and-mi355x-ai-gpus-claims-up-to-4x-generational-gain-up-to-35x-faster-inference-performance>
36. <https://wccftech.com/amd-details-plans-for-instinct-ai-gpu-lineup-mi350-to-now-release-by-mid-2025-mi400-lineup-slated-for-2026/>

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