# DIRECT: Enabling Scalable Processing-In-Memory via DPU-to-DPU Communication

A Hierarchical, CPU-Bypass Architecture with Hardware Synchronization

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#### **Motivation & Problem**

- Scaling ML training is gated by data movement and synchronization overheads.
- Result: **poor scalability**, energy waste, and low parallel efficiency at cluster scale.

**Goal:** Enable direct DPU-to-DPU communication with hardware-level sync, preserving locality and bypassing CPU.

## **Baseline Communication Cost (Conventional PIM)**

$$T_{\mathsf{comm}} = 2 N_{\mathsf{DPU}} igg( L_{\mathsf{DPU-CPU}} + rac{M}{B_{\mathsf{DPU-CPU}}} igg) + Q_{\mathsf{cont}} + Q_{\mathsf{sync}}$$

#### Where:

- N<sub>DPU</sub> = number of Data Processing Units
- L<sub>DPU-CPU</sub> = DPU-to-CPU communication latency
- *M* = message size (bytes)
- B<sub>DPU-CPU</sub> = available DPU-to-CPU bandwidth
- $Q_{\text{cont}}$  = queuing delays from contention
- O<sub>sync</sub> = synchronization overhead

#### **Key Issues:**

- Each transfer pays latency + bandwidth cost to the CPU.
- Queuing (Q<sub>cont</sub>) and software barriers (O<sub>sync</sub>) worsen at scale.

## **DIRECT: Key Idea & Contributions**

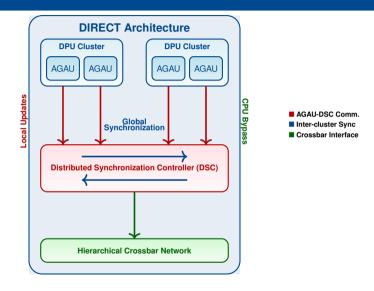
Idea: CPU-free DPU-to-DPU communication via a hierarchical crossbar, with hardware primitives for local & global sync.

- AGAUs: in-memory atomic gradient accumulation and reduction.
- DSC: distributed synchronization controller with token-based arbitration.
- Locality-aware protocol: minimize global sync; favor cluster-local updates.

#### **At 2048 DPUs**

- 2.9× speedup vs. SOTA
- 65% lower energy
- 92% parallel efficiency

## **System Overview**



#### **AGAU: Atomic Gradient Accumulation Units**

- 256-bit SIMD for parallel accumulation.
- Hardware reduction tree:  $O(\log n)$  averaging within a cluster.
- Local parameter cache + coherence directory.
- Atomic primitives: FETCH\_ADD, COMPARE\_SWAP.

## **Impact**

- Cuts intra-cluster communication and software overhead.
- Delivers ~45% of end-to-end speedup (see later breakdown).

## **DSC: Distributed Synchronization Controller**

- Token-based permissions for cross-cluster updates.
- Adaptive sync interval using gradient staleness metrics.
- Hardware barriers: local/global modes.
- Priority arbitration to avoid hotspots.

#### **Impact**

- Reduces global coordination cost;
- $\sim$ **35%** of total speedup contribution.

## **Locality-Aware Communication Protocol**

$$T_{ ext{comm, DIRECT}} = egin{cases} L_{ ext{local}} + rac{M}{B_{ ext{local}}} & ext{(same cluster)} \ L_{ ext{global}} + rac{M}{B_{ ext{global}}} + O_{ ext{dsc}} & ext{(inter-cluster)} \end{cases}$$

- Prefer **local updates**; escalate selectively when staleness exceeds threshold.
- Hierarchical crossbar minimizes hops; DSC trims sync overhead.

## Training Algorithm on DIRECT

## **Algorithm 1** DIRECT Locality-Aware Training (per epoch)

```
Require: Learning rate \eta, batch size B, staleness threshold \tau
 1: for each DPU cluster G in parallel do
          g_{local} \leftarrow \mathsf{AGAU}.\mathsf{Reduce}(\sum_{i \in G} \mathsf{ComputeGradient}_i(B))
          if DSC.STALENESS() > \tau then
 3:
 4:
               t \leftarrow \mathsf{DSC}.\mathsf{AcquireToken}()
               g_{\text{global}} \leftarrow \mathsf{CROSSBARREDUCE}(g_{\text{local}})
 5:
 6:
               \mathbf{w} \leftarrow \mathbf{w} - \eta \cdot \mathbf{g}_{\text{global}}
               DSC.BroadcastUpdate(w); DSC.ReleaseToken(t)
 8:
          else
 9:
               \mathbf{w} \leftarrow \mathbf{w} - \eta \cdot \mathbf{g}_{local}
10:
          end if
11: end for
```

#### **Simulation Setup**

- **Simulator**: gem5 with PIM extensions (AGAU, DSC, hierarchical crossbar).
- Scale: up to 2048 DPUs; cycle-accurate.
- Baselines: PIM-Opt (State-of-the-art PIM architecture for accelerating ML workloads); NVIDIA A100 GPU.

#### **Workloads**

- Linear Model: YFCC100M-HNfc6 (sparse, memory-bound).
- ResNet-18: ImageNet (compute-heavy).

#### **Metrics**

- Time, Energy, Staleness, Accuracy
- Parallel efficiency @ scale
- Area/Power overheads

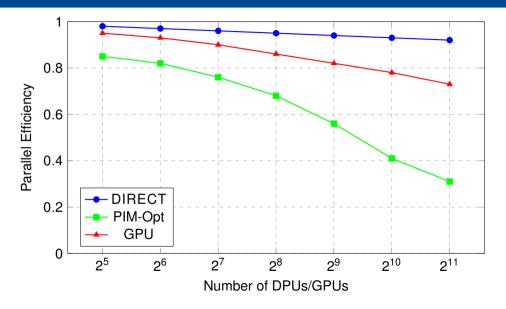
# **Experimental Configuration**

Value
Up to 2048
4
Token-based DSC
Parallel accumulation & reduction
Cycle-accurate
ResNet-18, YFCC100M-HNfc6

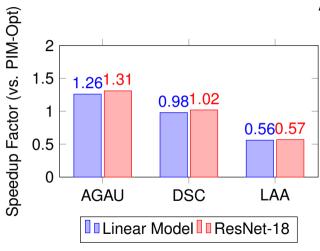
# **Main Results (Per-Epoch)**

Metric	YFCC100M-HNfc6			ResNet-18		
	PIM-Opt	DIRECT	GPU	PIM-Opt	DIRECT	GPU
Time (s/epoch)	245	87.5	120	1240	428	650
Energy (J/epoch)	892	312	560	4350	1522	2740
Staleness (ms)	475	128	220	685	178	380
Accuracy (%)	84.2	84.5	84.3	76.1	76.3	76.2
	Paralle	el Efficiency	/ @ <b>20</b> 4	8		
Compute	0.82	0.95	0.88	0.78	0.93	0.85
Comm.	0.25	0.92	0.72	0.22	0.89	0.68
Overall	0.31	0.93	0.76	0.28	0.91	0.73
Area Overhead (mm <sup>2</sup> )	0.42	0.51	_	0.42	0.51	_
Power Overhead (mW)	185	205	_	185	205	_

# Scaling: Parallel Efficiency vs. System Size



## Where the Speedup Comes From



#### As a percentage of total gains:

- AGAU: efficient local reductions (~ 45%).
- DSC: low-overhead global synchronization (~ 35%).
- LAA: locality-aware algorithm (~ 20%).

## Takeaways & Industry Relevance

#### **Key Takeaways**

- DIRECT delivers **CPU-free** DPU-to-DPU communication at scale.
- Achieves 2.9× speedup, 65% energy reduction, 92% efficiency @ 2048 DPUs.
- Minimal overhead: **0.51 mm**<sup>2</sup>, **205 mW** (28nm process).

#### Why it Matters for Industry

- Cut training costs by slashing interconnect traffic.
- Boost sustainability through large-scale energy savings.
- **Drop-in scalability** for next-gen heterogeneous accelerators.
- Future-ready for on-memory AI training workloads.

## **Thank you!** Questions welcome.