

The logo for the 2024 Embedded VISION Summit is centered on the left side of the slide. It features a white octagonal background with a colorful, multi-layered border in shades of purple, blue, green, yellow, and orange. The text "2024" is at the top, "embedded" is below it, "VISION" is in large, bold, dark blue letters with a gradient, and "SUMMIT" is at the bottom.

2024
embedded
VISION
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The Importance of Memory for Breaking the Edge AI Performance Bottleneck

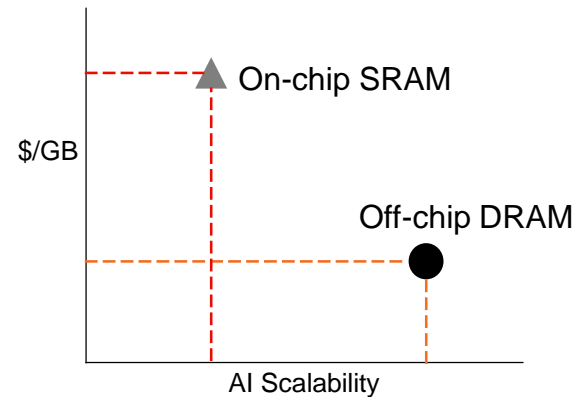
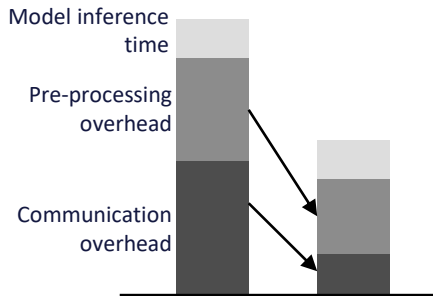
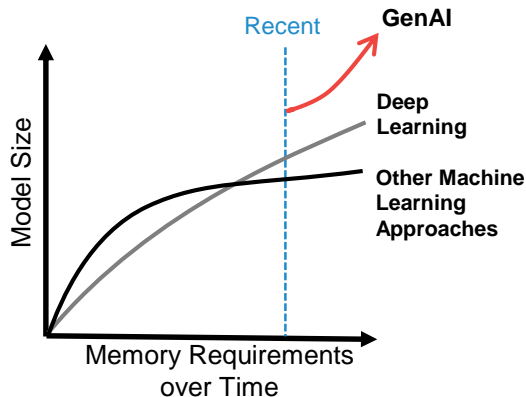
Wil Florentino

Sr. Segment Marketing Manager
Micron Technology



Edge AI reveals memory as the bottleneck

Trend toward memory-bound applications



Model complexity vs. memory bandwidth

- Transformer size growth 410x / 2 years
- AI HW memory bandwidth 2x / 2 years¹

Pre-processing latency in AI execution

- Data pre-preprocessing overhead² impacts latency

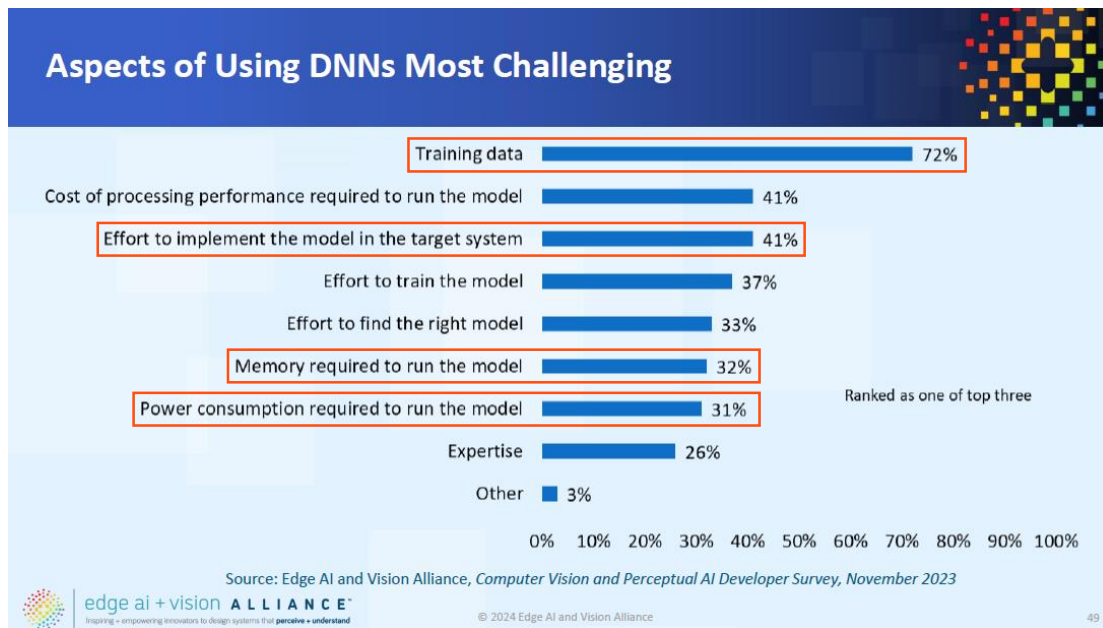
\$/GB vs. scalability

- SRAM: \$5,000/GB
- DRAM: \$50/GB³

DNN challenges relate back to memory and storage

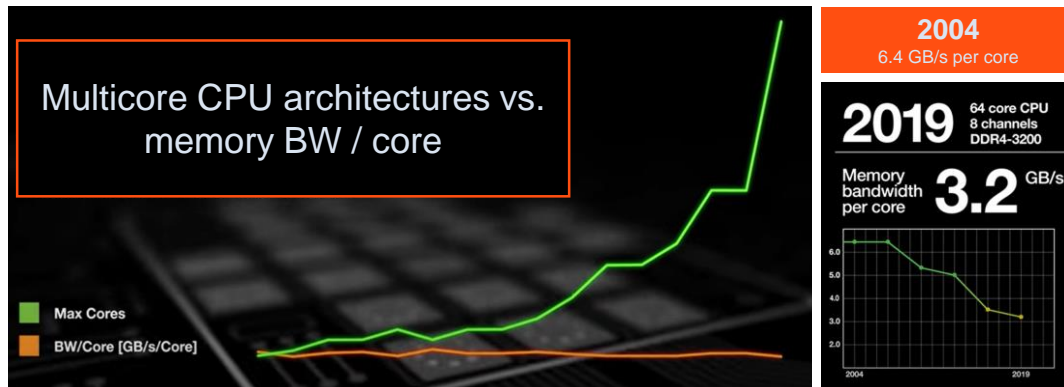
Edge AI and Vision Alliance report on DNN implementation challenges

- Training data trade-offs between cost of storage on-premise vs. cloud
- Complexity of on-device implementation in target
- Type of and memory performance influence the efficiency of running the model
- Power consumption



DRAM memory bandwidth per core has been declining

- CPU core counts are increasing at a rate that minimizes available memory bandwidth per core
- New memory technologies are required to meet next-generation bandwidth-per-core requirements in multi-core CPUs
- Edge AI inference compute requires additional memory consideration



Source: Micron. bandwidth normalized to x64 interface, 64Byte random accesses, 66% reads, dual-rank x4 simulation, 16Gb. Best estimates; subject to change.

The many levers of a memory device

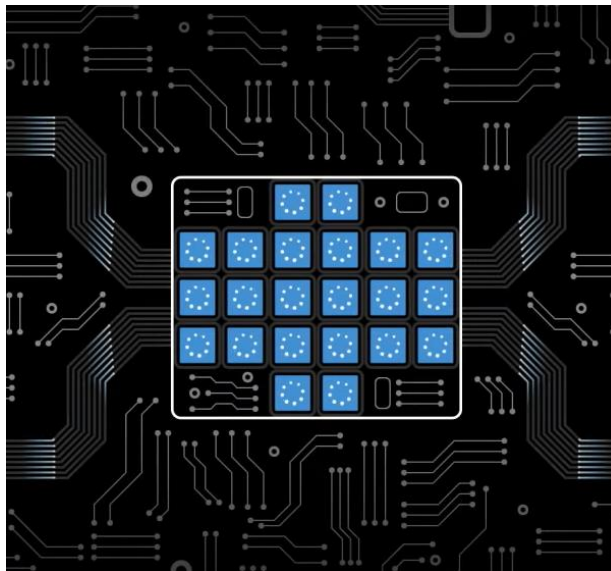
Complex design considerations for memory improve performance and lower costs

Configuration

- Density per die
- Die per package
- I/O width
- Bank groups
- Technology node

Performance

- Speed/pin
- Number of channels
- Prefetch size
- Burst length
- Read latency



Operational

- On-die Error Correction
- Thermal profile
- Refresh management
- Power reduction modes
- Active vs. standby power (picojoule/bit)

Application focus

- Functional safety
- Reliability/Availability/Serviceability
- Extended temperature
- Validation and testing
- Product lifecycle
- Industrial rated
- Auto validated

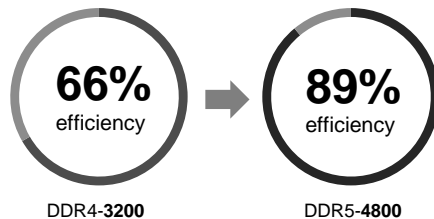
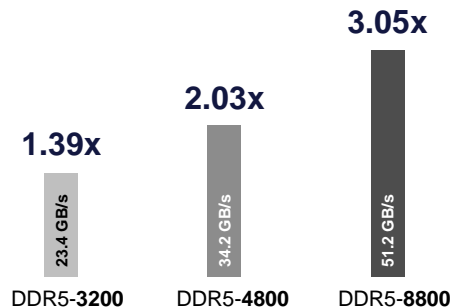
DDR5 for data-intensive training workloads

2x
capability

- Burst length
- Bank groups
- Banks

DDR5 memory comparisons

Increased bandwidth more than 3x¹



Higher bus efficiency **up to 90%**¹
Faster transfer speed **up to 8800 MT*/s²**

Improved overall workload performance³



Cloud
Virtualization 40%



Data center
Business apps 45%



High-performance computing
HPC modeling >200%



128GB high-capacity RDIMM
using monolithic 32Gb DRAM

Compute bandwidth requirements by edge solution

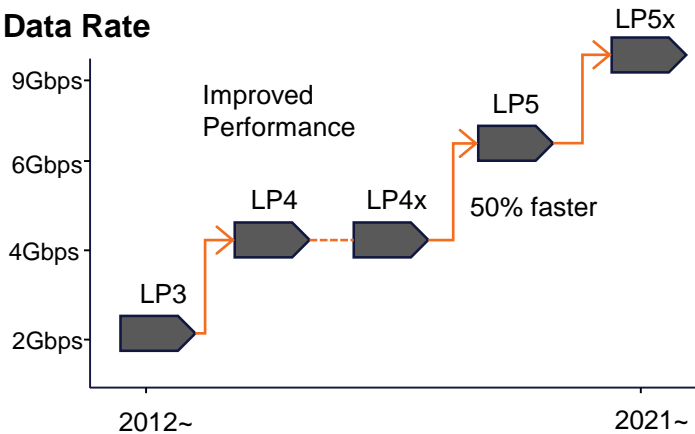
AI TOPs* vs. number of LPDDR4 devices scenarios

● x16 ● x32 ● x64

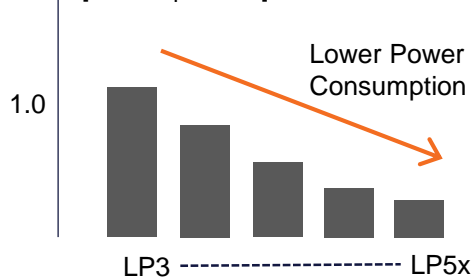
	Sensor edge IoT sensors and ultra low power devices (TinyML)	Device edge Cameras, machines and industrial/SFF PC/server	Network edge Industrial PC/server, network equipment, NVR/VMS appliances	Compute edge Server/NVR/VMS appliances
Power	<1W	2W <= 15W	15W <=75W	15W <= 75W+
SoC/ASIC IO width (typical)	x16	x32	x64	x128
DLA INT 8 TOPS	<4	4–20	20–50	50–100
Est. bandwidth to full utilization of accelerator [saturate accelerator**]	18 GB/s	90 GB/s	225 GB/s	451 GB/s
BW of LP4 @ 4.2Gbps/pin IO per device (x16/x32/x64)	8 GB/s ●	17 GB/s ●	33 GB/s ●	33 GB/s ●
Number of LP4 packaged devices	3	6	7	14!

LPDDR5 offers a leap in performance and possibilities

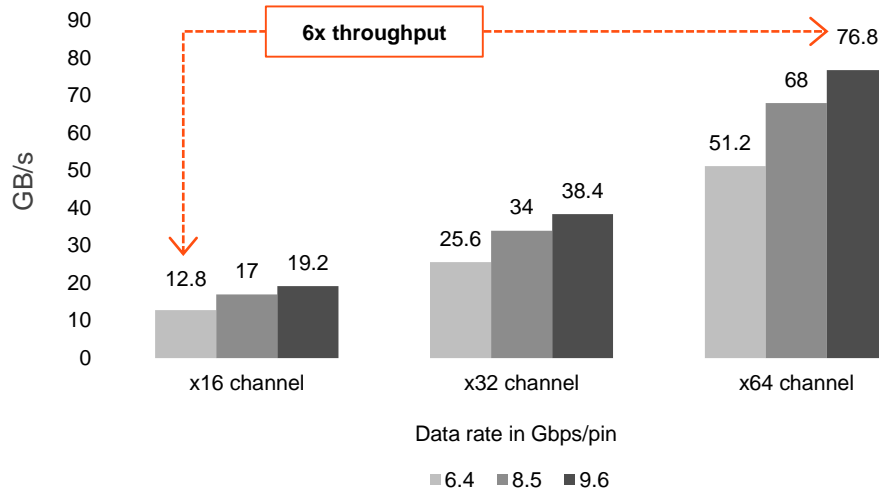
Data Rate



Improved Power Savings Features [mW/GBps index]



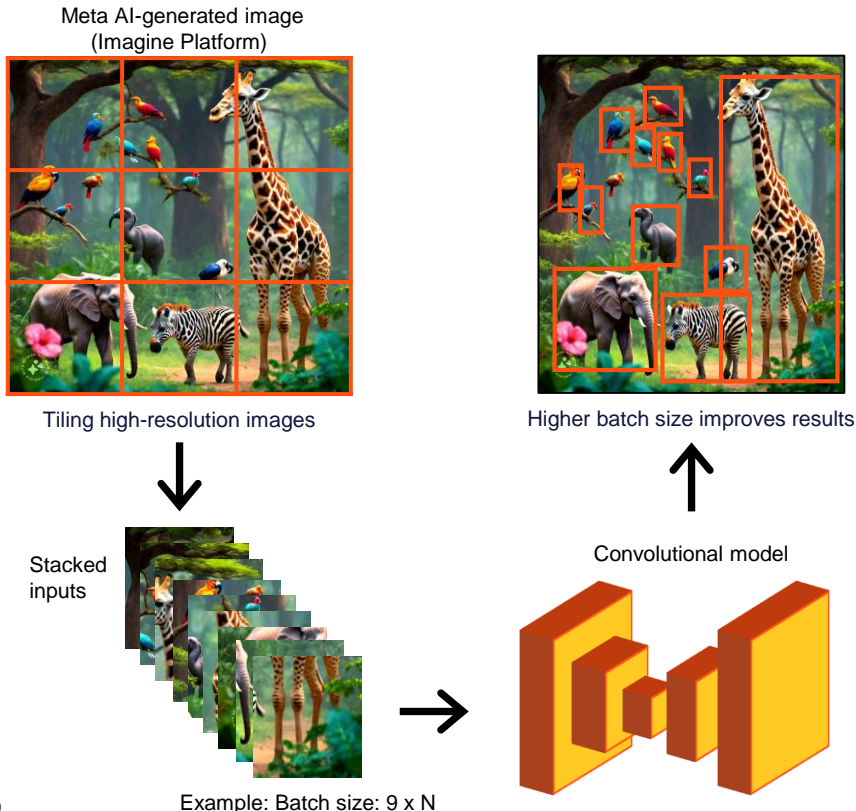
LPDDR5X bandwidth at different channel and pin speed



- Reduces number of components to get to same bandwidth
- Improved architecture
- Lower power [pj/bit]

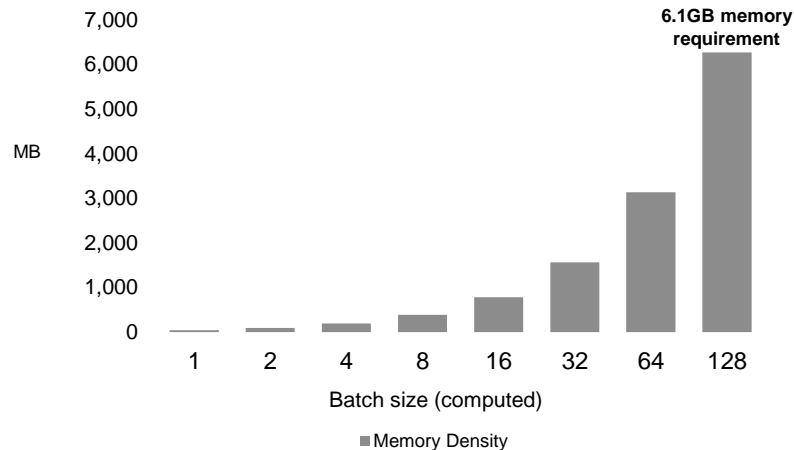
Memory footprint as a function of batch size

Tiling for small object detection in high-resolution vision



Batch size impacts the memory footprint

Memory for inference YOLOv8x across* batch sizes



*Parameter size: 273MB

- [1] Small object detection: An image tiling based approach, Medium, 2021 [\[Link\]](#)
- [2] S. Ngyuyen, et al., "Dynamic tiling: A model-agnostic, adaptive, scalable, and inference-data-centric approach for efficient and accurate small object detection," arXiv:2309.11069v1, 2023
- [3] F. Akyon, et al., "SAHI: Slicing aided hyper inference and fine-tuning for small object detection," IEEE ICIP, 2022
- [4] F. Unel, et al., "The power of tiling for small object detection," CVPR, 2019
- [5] Training vs. inference - Memory consumption by neural networks [\[Link\]](#)
- [6] GitHub: TorchInfo [\[Link\]](#)
- [7] Model not quantized (fp32). Memory footprint of two largest consecutive layers.

Why memory is important for generative language

- Models are very large and often need to fit in DRAM
- Bandwidth is critical to quality of service
 - Tokens/sec is highly correlated with DRAM bandwidth

LLAVA 7B with 8-bit quantization* ~5 seconds

LP4 4.2 (x32): 17 GB/s



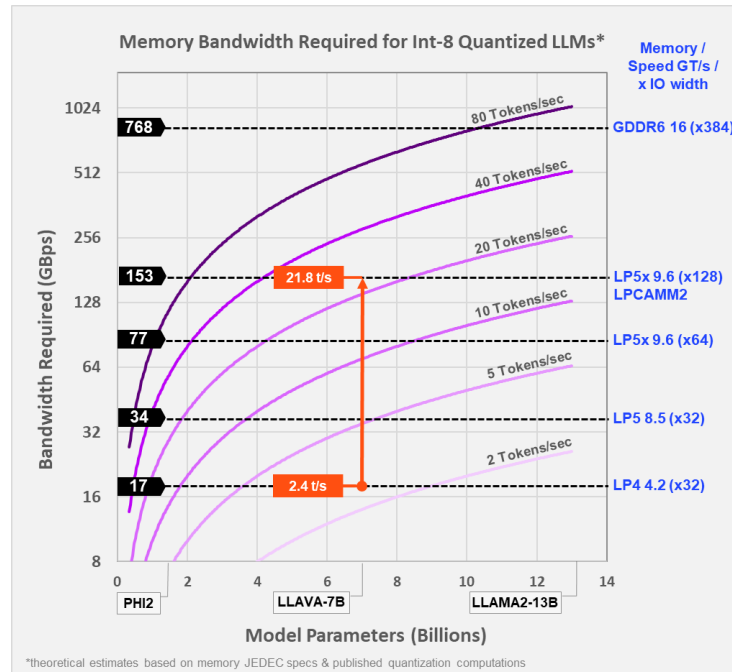
The image shows a person ironing clothes on a...

LP5X 9.6 (x128): 153 GB/s



The image depicts an unusual scene where a man is ironing clothes on an ironing board placed on the back of a moving vehicle, specifically a yellow SUV. This is not a typical activity one would expect to see on a city street, as ironing is usually done indoors in a stationary position to ensure safety and to prevent accidents. The man's actions are not only unconventional but also potentially dangerous due to the risk of falling or being hit by other vehicles or pedestrians. Additionally, the presence of a taxicab in the background adds to the urban environment, which makes the scene even more out of the ordinary.

* LLaVA (llava-vl.github.io) | Assume 1 token/word | Excluding time to first token



¹ Assumes GGML Quantization: ggml.ai. ² Kim, Sehoon, et al. "Full stack optimization of transformer inference: a survey." arXiv preprint arXiv:2302.14017 (2023)

LPCAMM2 for AI-equipped systems



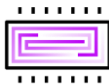
Performance

- LPDDR5x speed of up to **9.6Gbps**
- **Full 128-bit**, dual-channel, low-power modular memory solution



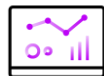
Power efficiency

- Consumes **57%-61%**¹ less active power and up to **80%**¹ less system standby power compared to DDR5 SODIMM
- Thermal efficiency, fanless computers



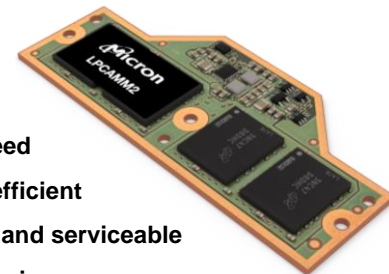
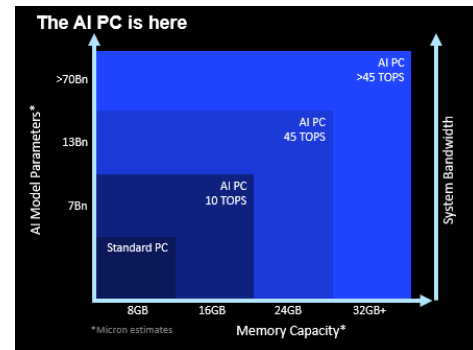
Modularity

- Flexibility to **upgrade system memory capacity**
- Single PCB for all memory configurations



Form factor

- Up to **64%**² space savings
- Space savings for industrial PCs, embedded single-board computers, AIoT systems

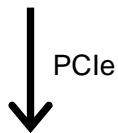
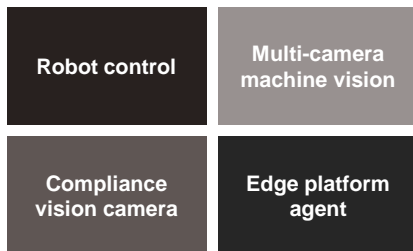


- High speed**
- Energy efficient**
- Modular and serviceable**
- Space savings**

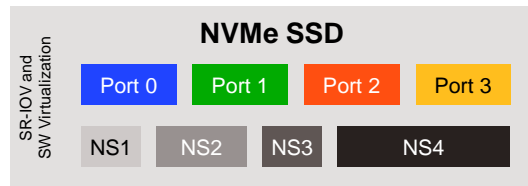
Multiport SSD as centralized storage

Supporting multiple subsystems in a single storage device

Multiple HW and SW subsystems
(different AI models)



Single multiport centralized storage



4150AT product highlights

- **Configurable multiport** (single, dual, triple and quad)
- **SR-IOV** allowing for shared and private namespaces
- **Design flexibility** to match system usage models with TLC, SLC and HE-SLC endurance modes
- Up to **600K read and 100K write** IOPS performance
- **-40 C to 115 C Tc** operating temperature range
- **Fast boot** with TTR <100ms

Micron AI memory and storage portfolio

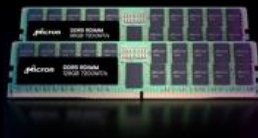
Leadership products to enable AI workloads



High-bandwidth in-package memory
HBM3E



High-performance graphics memory
GDDR6X



High-capacity DRAM
128GB DDR5 using monolithic 32Gb DRAM



Compute DRAM
DDR5



Low-power memory
LPCAMM2



Low-power memory
LPDDR5X



Universal flash storage
UFS 4.0



Memory expansion with CXL™
CZ120



High-performance data center NVMe™ SSD
Micron 9400



High-capacity data center NVMe™ SSD
Micron 6500 ION

Summary

Micron memory enables all forms of AI embedded solutions

AI at the edge (outside the data center) reveals memory as a bottleneck

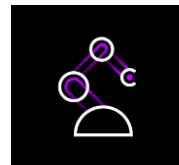
- Disproportionate growth between transformer size vs. memory bandwidth
- Data pre-preprocessing overhead impacts latency
- On-chip SRAM is cost prohibitive vs. external DRAM

Memory technology influences AI model execution performance

- Edge AI devices TOPS showcase memory bandwidth gap
- Tiling activation requires in-line memory density resources
- In generative language, bandwidth is required for quality of service

Leading memory technologies offer the best mix of solutions for edge AI applications

- DDR5 for AI training workloads
- LPDDR4 and LPDDR5 for neural network compute
- LPCAMM2 to leverage LPDDR5X performance with DIMM modularity
- Multiport SSD to support different AI models and compute in a single storage



Smart factory and robotics



Industrial AR/VR



Smart grid and clean energy



AI-enabled video security and analytics



Low earth orbit (LEO) communication



Drones and industrial transport

Thank You