

Exploring Innovations in Storage & Memory Compression at Hyperscale

Presenter:

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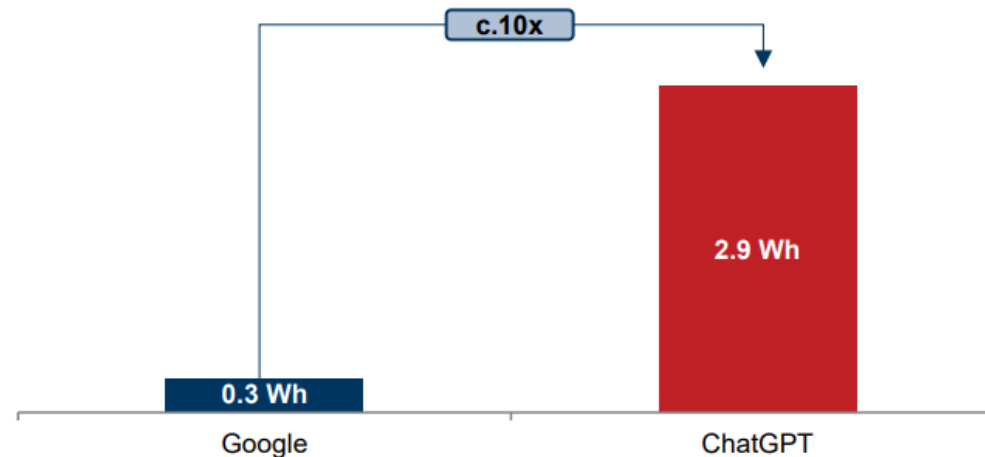
Problem: The AI Energy Efficiency Challenge

Schneider Electric estimate	2023	2028
Total data center power consumption	57 GW	93 GW
AI power consumption	4.5 GW	14.0-18.7 GW
AI power consumption (% of total)	8%	15-20%
AI workload (Training vs Inference)	20% Training, 80% Inference	15% Training, 85% Inference

Source: Schneider Electric White Paper 110, *The AI Disruption: Challenges and Guidance for Data Center Design*

ChatGPT queries are 10x as power intensive as Google searches

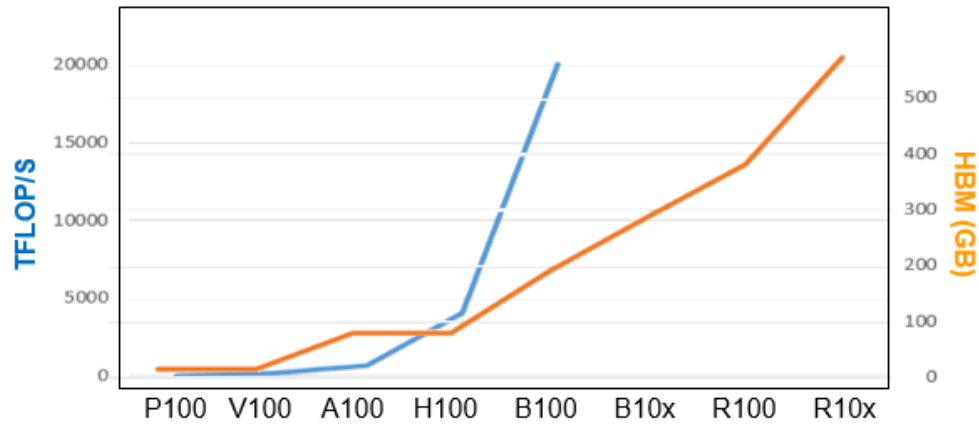
Power consumption per query/search, Watt-hour (Wh)



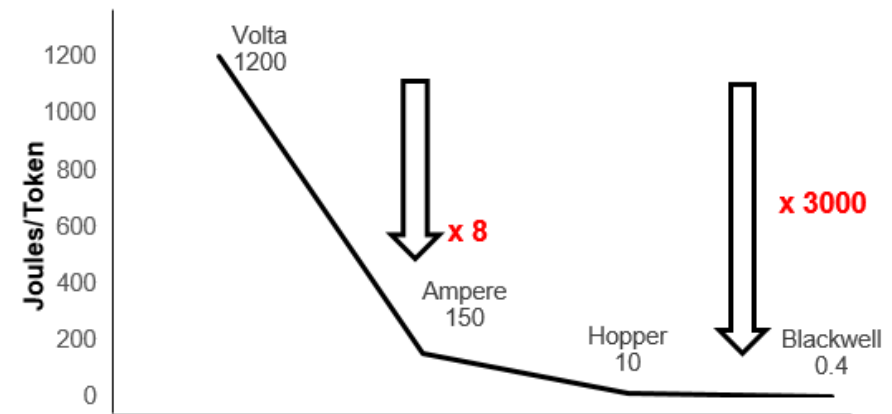
Source: Google, SemiAnalysis, compiled by Goldman Sachs GIR.



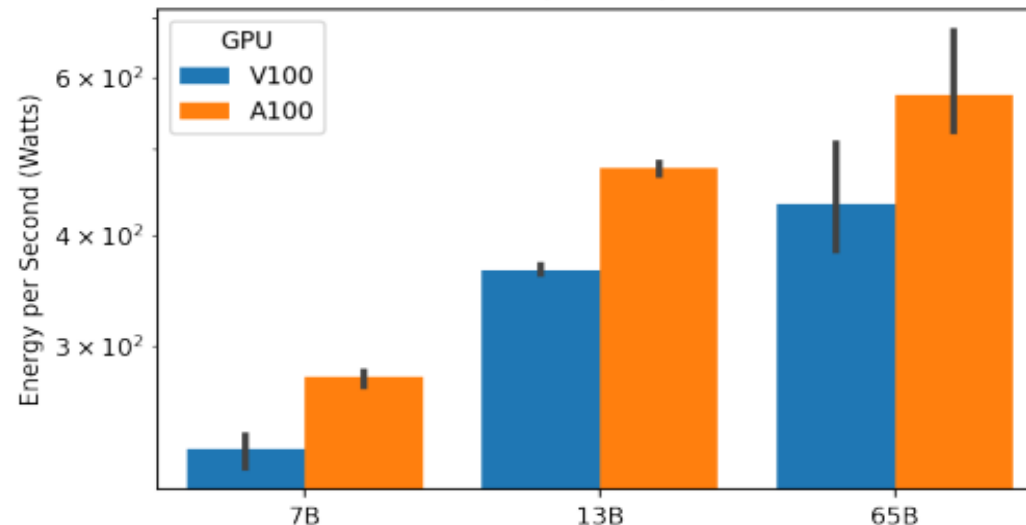
Can GPU solve the energy program?



Nvidia GPU Generation



Nvidia GPU Inferencing Energy (GPT-1.8T)



Llama 7B/13B/65B inferencing Power for fixed # of Tokens

TDP
 V100: 300W
 A100: 400W

Transformer Inference
 Arithmetic Intensity is very low
 → Memory bound

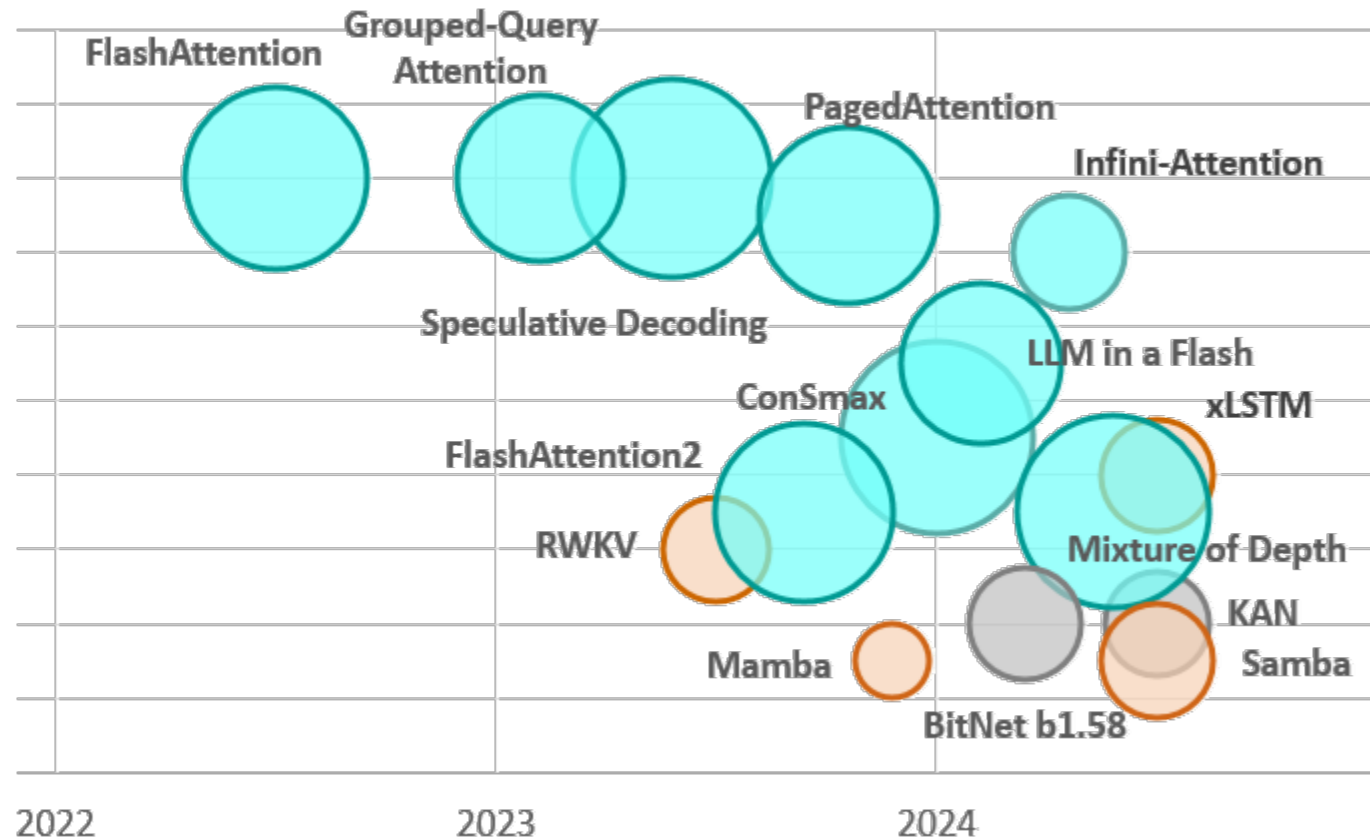
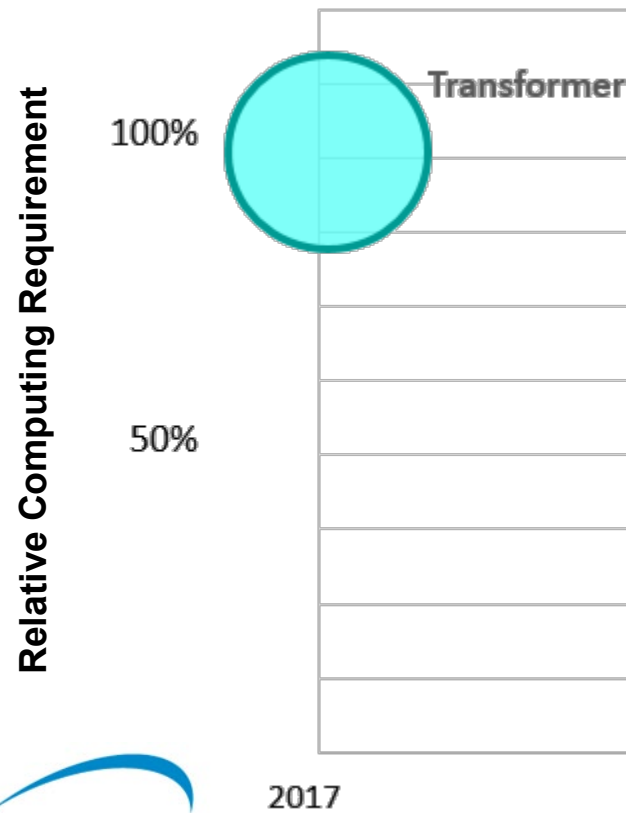


AI Algorithm Evolution

Transformer

Non Transformer

Computing Optimization



AI Algorithm Computing Requirement

*The circle size is relative memory requirement



Energy Efficient Memory Solutions

- Compute-In-Memory
- Process-In-Memory
- Processing-Near-Memory (Computational Memory System)



Compute-In-Memory

Computation happens in the memory cells

High cell density & capacity
Bit-serial computation (Limited OP/s)
Massive parallel operation

Compute-In-Memory (CIM)

Compute-In New Memory (NVM)
(ReRAM, MRAM, FeRAM...)

Compute In DRAM

Compute In SRAM

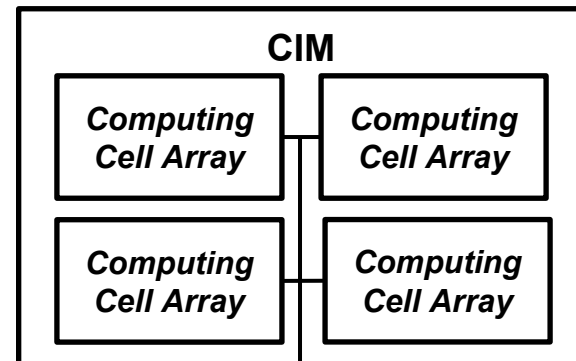
Low cell density (reached its limit)
Limited capacity
Great TOPS/W (~ 10X than GPU)

Digital

Analog

Digital

Analog



PHY

PHY

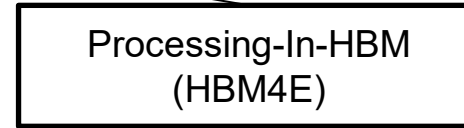
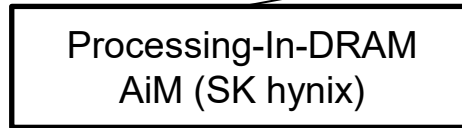
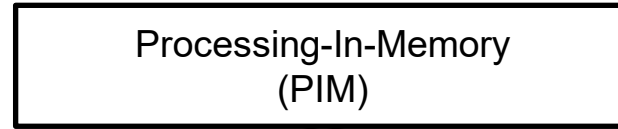
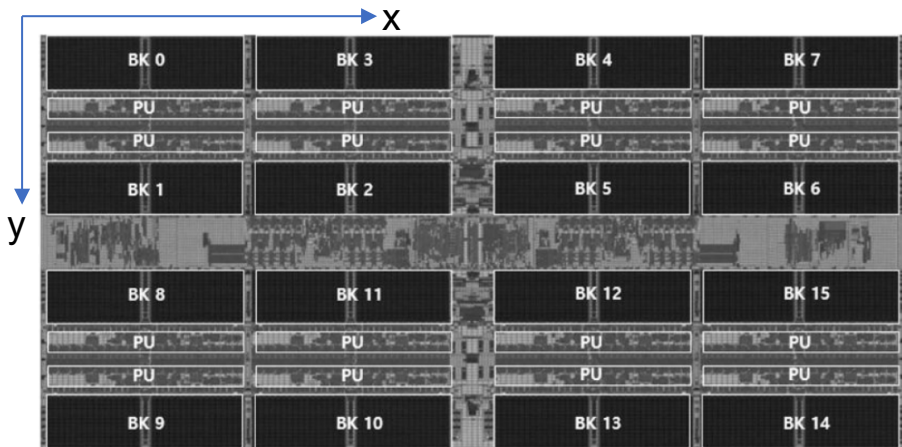
Memory Controller



Process-In-Memory (PIM)

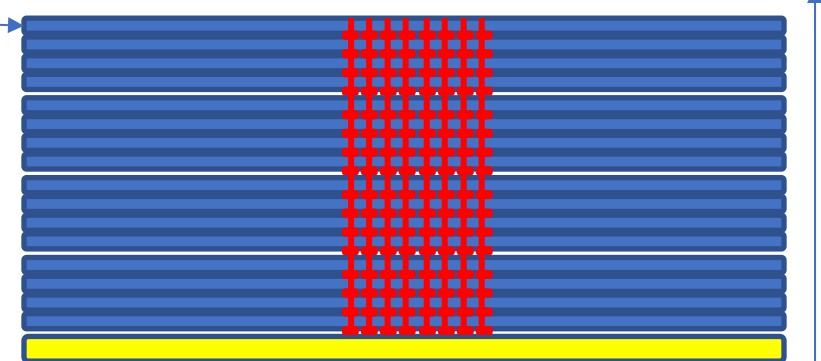
Computation happens in the memory package

Monolithic Die
Limited PU area & lower cell density

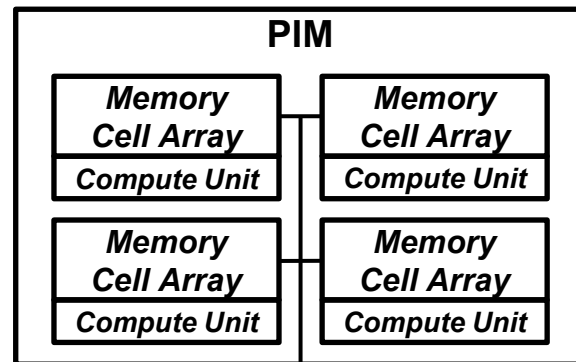


3D Packaging (Hybrid Bonding)
Thermal issues
Connection issues

DRAM Die



Logic Die (Processing Unit)

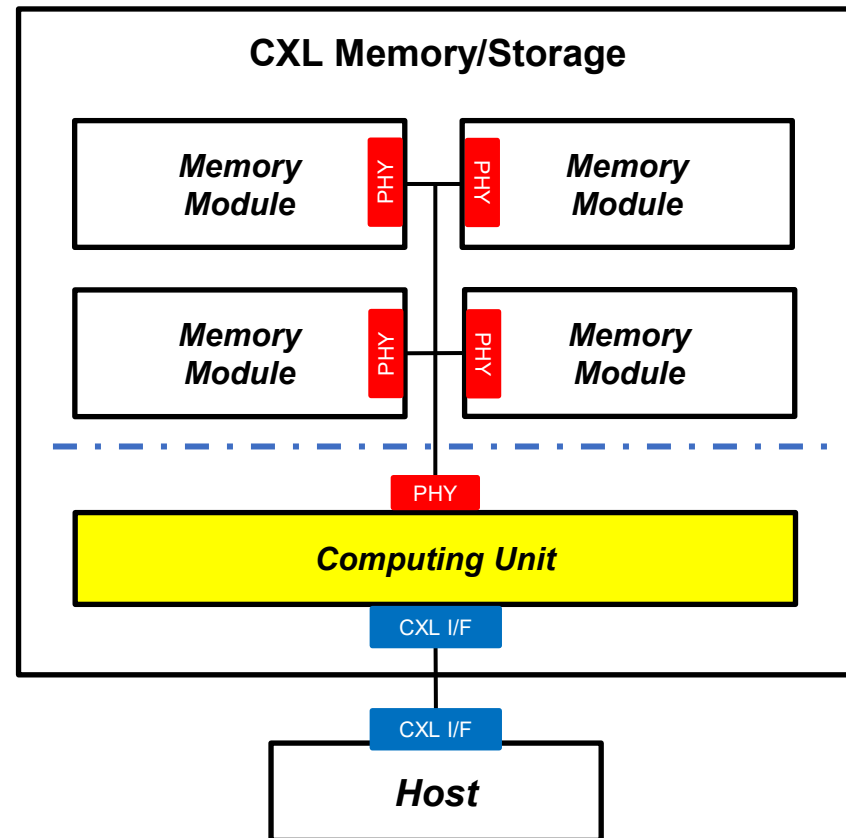


PHY

PHY



Computational Memory System



- Bandwidth Improvement
- (De)compression
 - Model training computation



Hyperscale Data Challenge/ compression

Hyperscalers spending significant \$\$ on software based compression

Hyperscaler requirement:
hardware accelerated compression is a MUST-have

CPU cycles used for compression



4.6%



Google Cloud

3%



OPEN
Compute Project

Hyperscale CXL Tiered Memory Expander Specification

Revision 1

Version 1.0

Base Specification Template v1.2

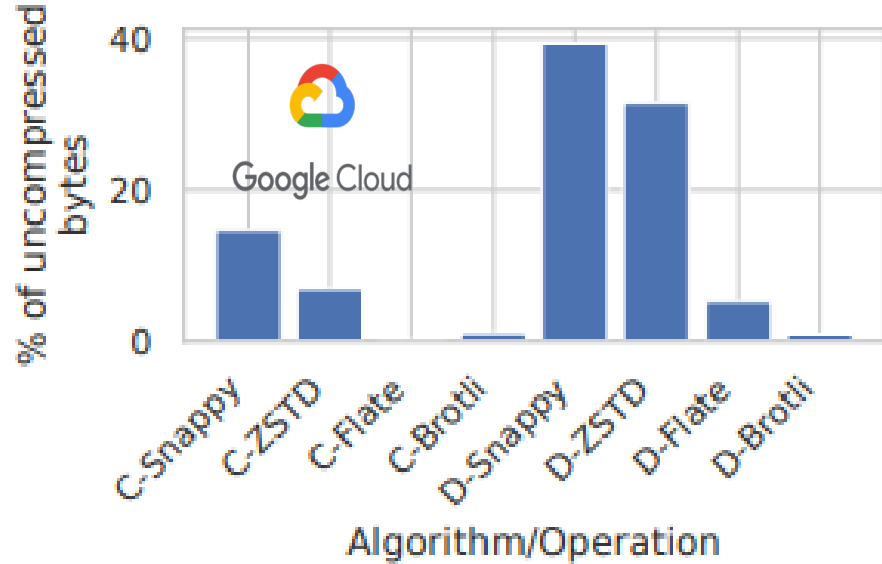
Effective October 27, 2023



**OCP Hyperscale CXL Tiered
Memory Expander Spec**

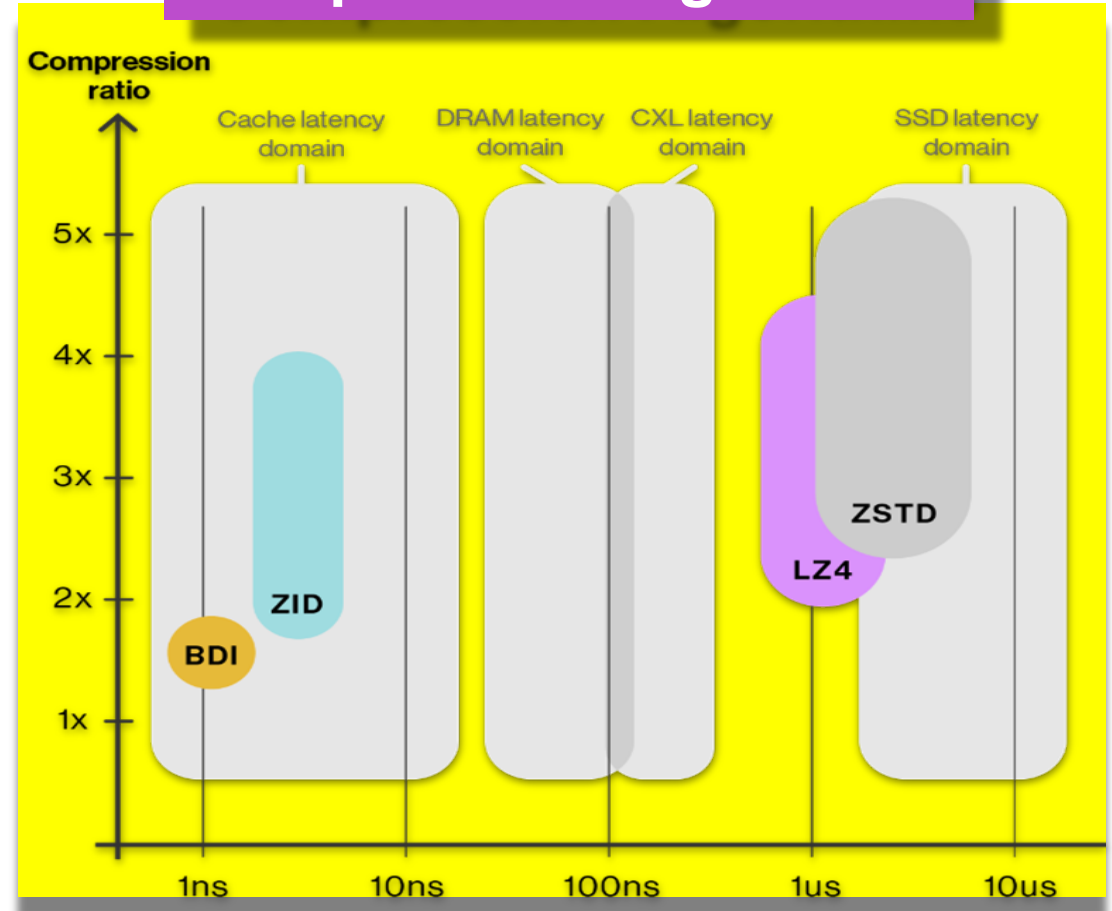
Compression Algorithms: Memory, storage

[Google Fleetwide De\(compression\)](#)



(a) Fleet-wide uncompressed bytes handled by (de)compression, broken down by algo.

Compression Algorithms



[LZ4, ZSTD IP](#)

Room for Innovation

Legacy

Case Study: Implementations



Intel QAT: CPU [integrated \(De\)compression engine](#)



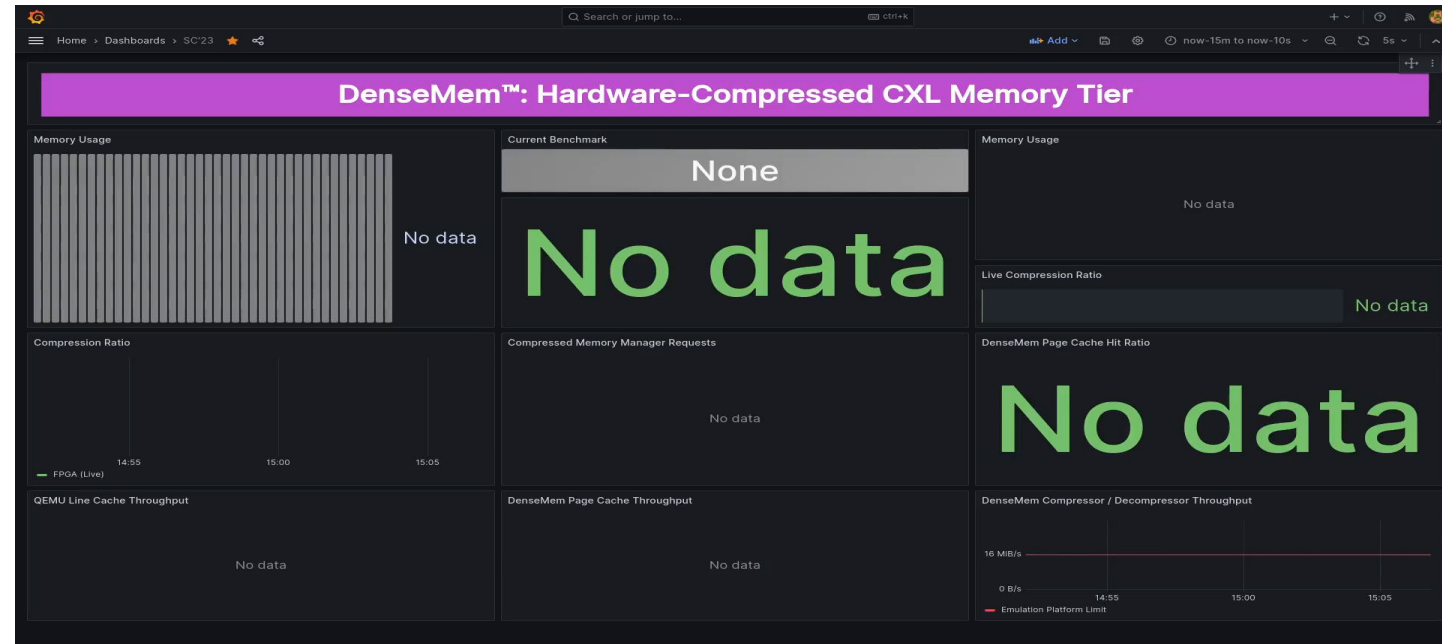
Nvidia Blackwell : [800GB/s embedded](#) Decompression engine

Solutions, Challenges and considerations

Compaction, Software Transparent
Address Translation – Dynamically
Adjusting Capacity

Computational Programming

Standardized Data Movers

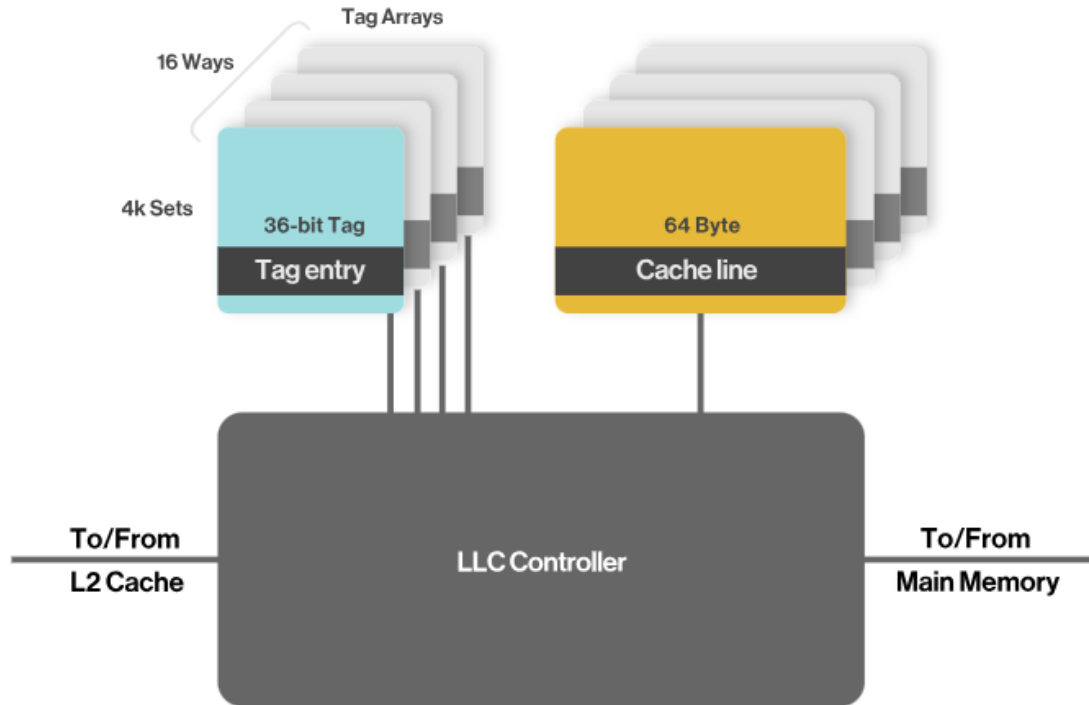


SNIA: [Data Mover Spec](#)



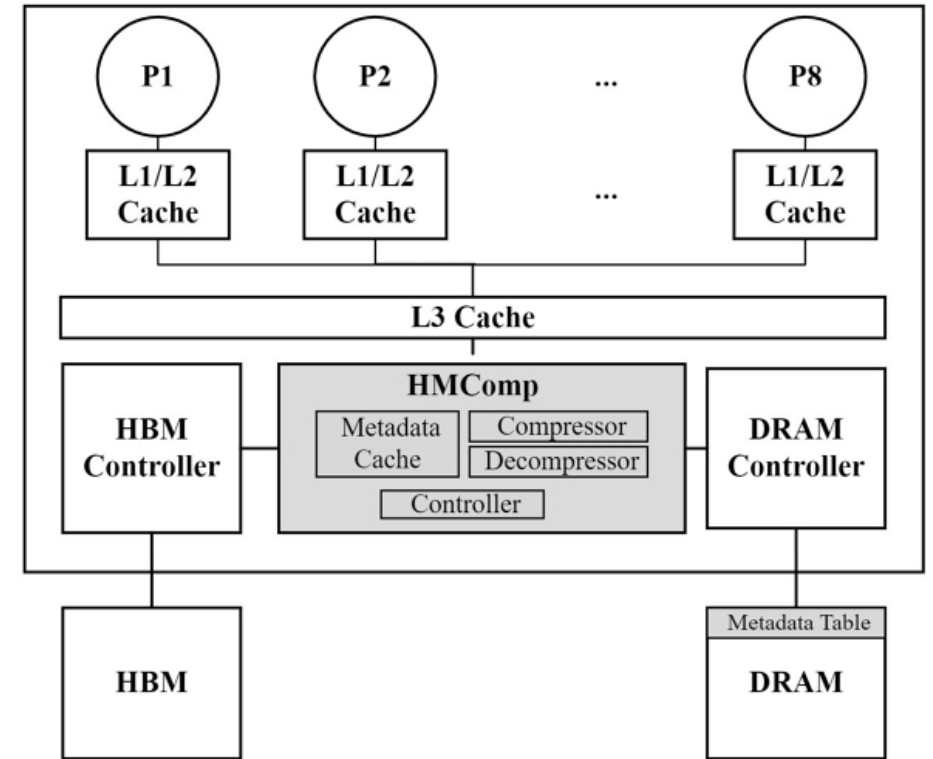
OCP [CMS Computational Programming Work¹ Group](#)

Future Trends / opportunities



[CacheMX Cache \(De\)compressor IP](#)

On chip SRAM cache compression



[HMComp](#): Extending Near-Memory Capacity using Compression in Hybrid Memory

HBM Compression

Summary Call to Action

- Joint Collaboration to accelerate Energy Efficient Solution deployment
- Start with Low hanging fruit : (De)Compression
- Prove out other use cases, influence/ shape standards

