

AI Memory at Meta: Challenges and Potential Solutions

Presented by Chris Petersen

AI at Meta

🔗 Across many applications/services and at scale → driving a portion of our overall infrastructure (both HW and SW)

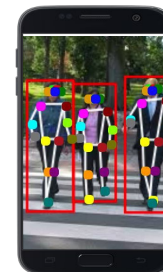
✂ Ranking and recommendation - Video, Ranking, Search...

✂ Content understanding - Computer vision, Speech, Translation, NLP, Video...

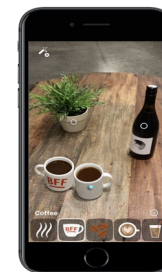
🔗 From data centers to the edge



Keypoint
Segmentation

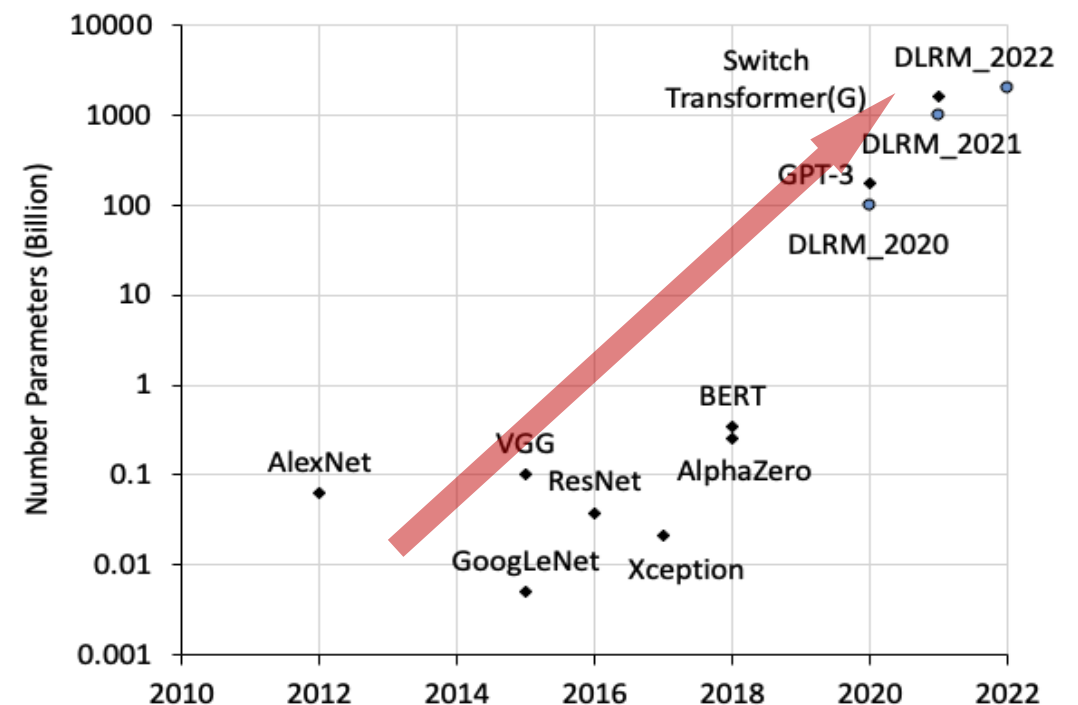
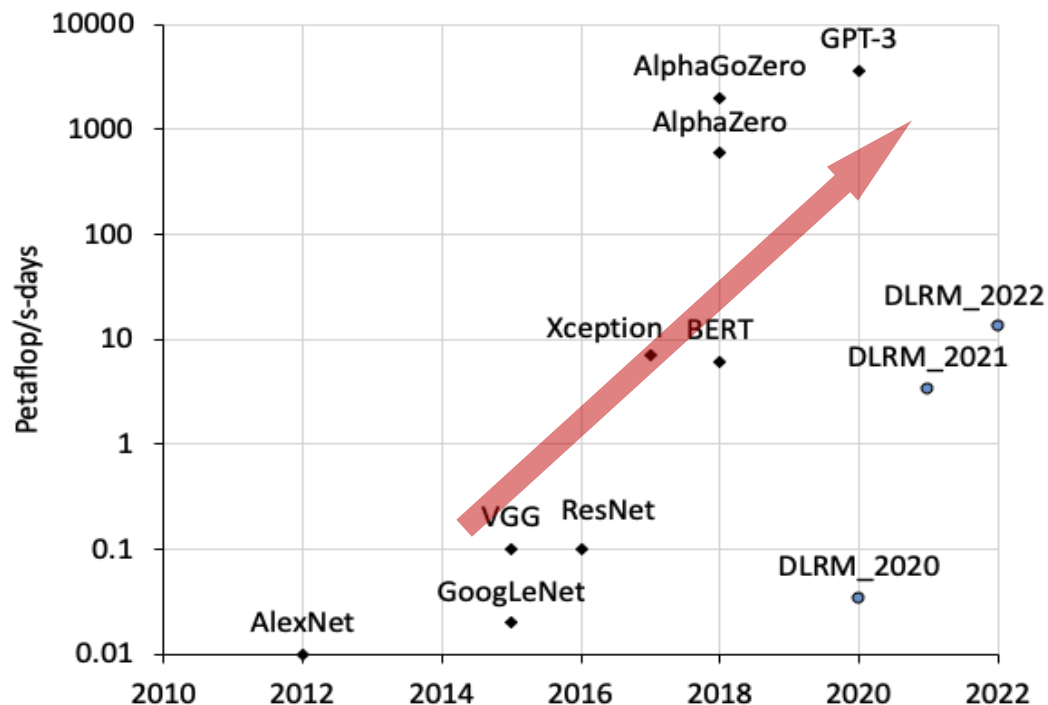


Augmented Reality
with Smart Camera



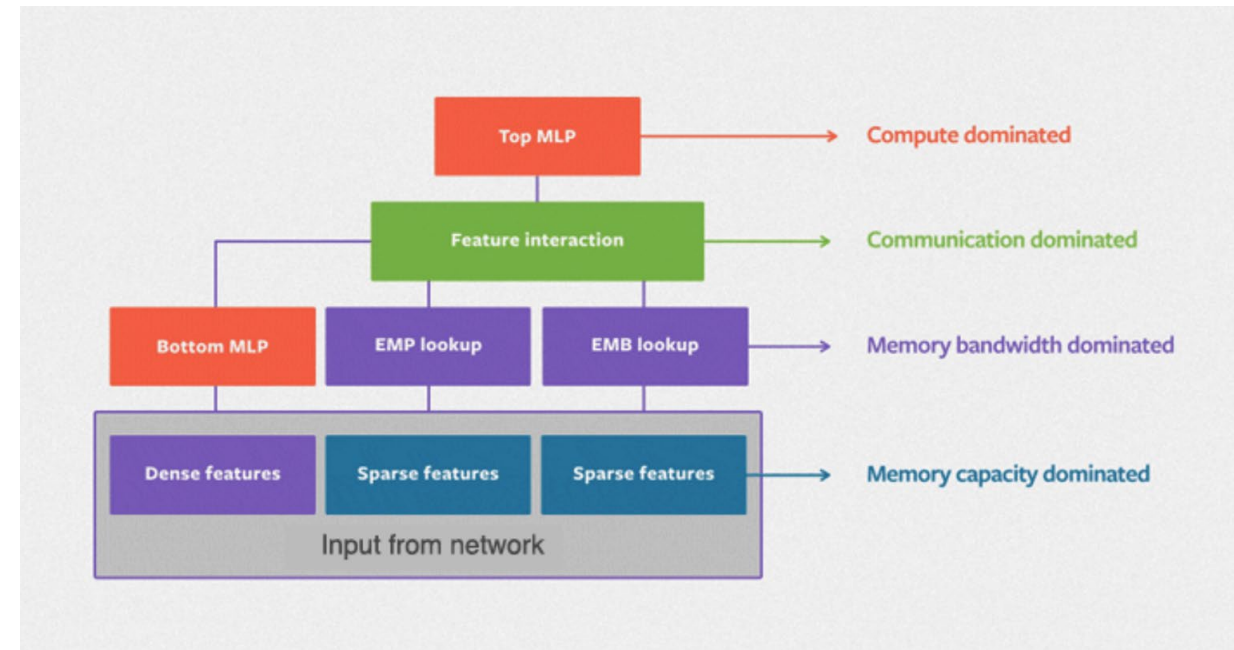
Problem Statement: AI workloads scale rapidly

- ❧ Compute, Memory BW, Memory Capacity, all scale for frontier models
 - ❧ Scaling typically is faster than scaling of technology
- ❧ The rapid scaling requires more vertical integration from SW requirements to HW design



Recommendation models (e.g. DLRM)

- One of the main drivers of AI HW platforms
- Most of the memory capacity is contributed by sparse features (embedding tables)
 - Dense
 - Requires high BW at low capacity
 - Sparse
 - Requires high capacity at high BW



<https://ai.facebook.com/blog/dlrm> -an-advanced-open-source-deep-learning-recommendation-model/

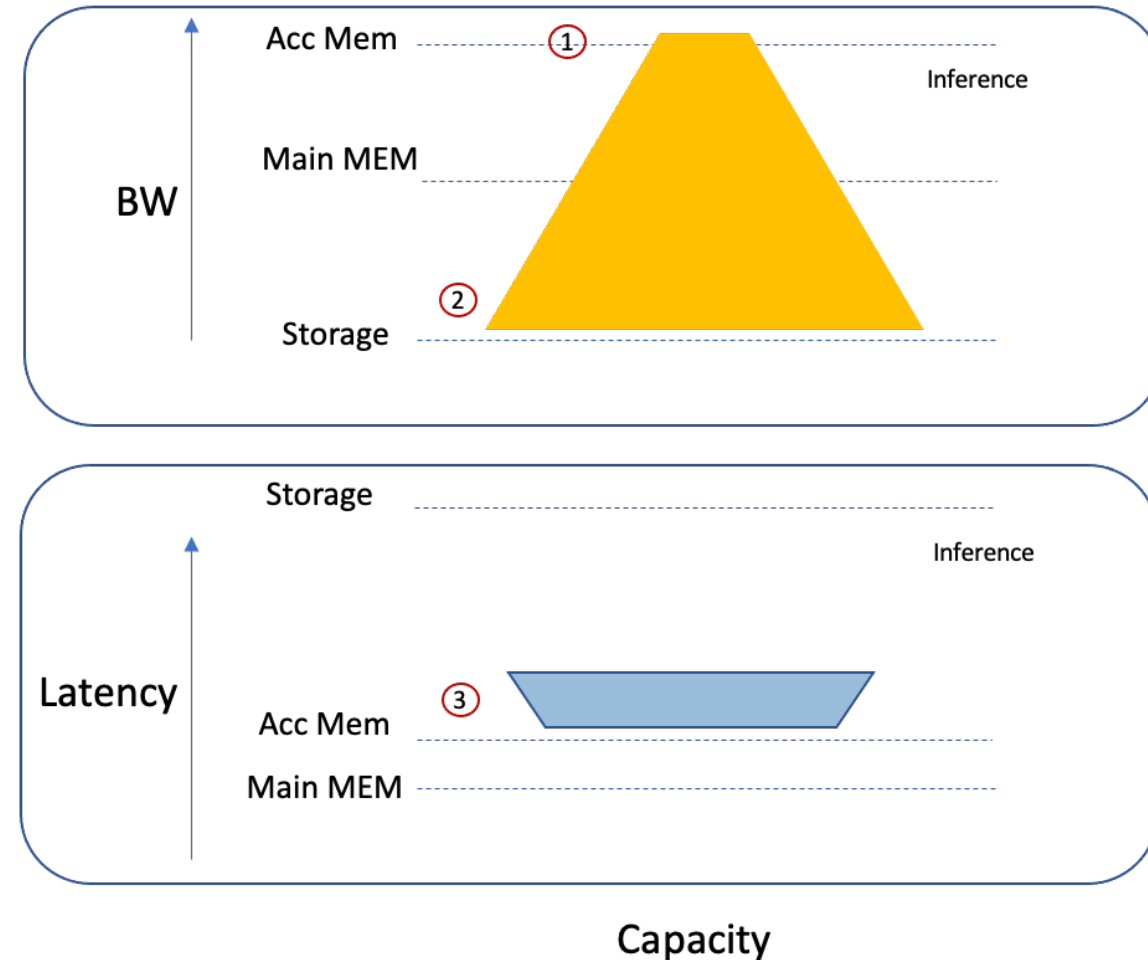
DLRM Requirements

Bandwidth

1. Considerable portion of capacity needs high BW Accelerator memory.
2. Inference has a bigger portion of the capacity at low Bandwidth. More so than training.

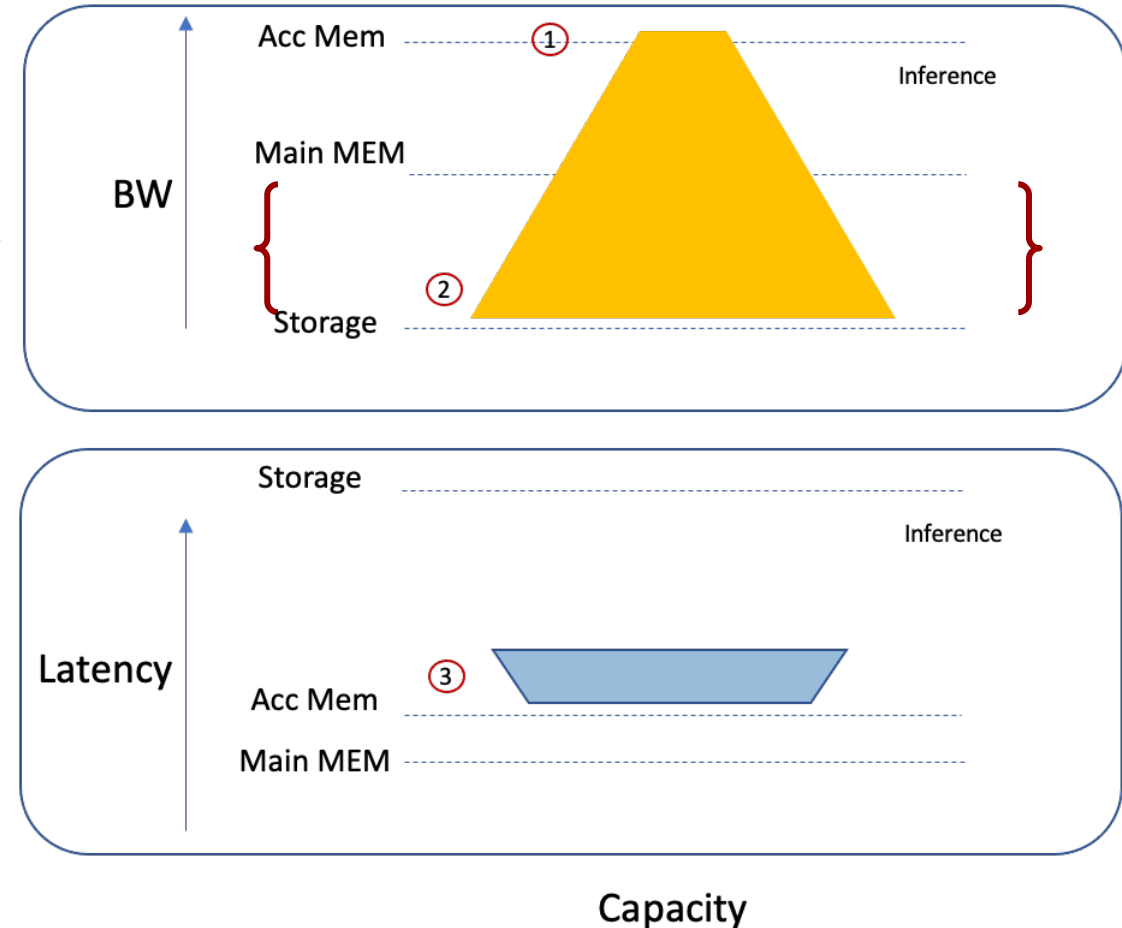
Latency

3. Inference has a tight latency requirement, even on the low BW end



System Implications of DLRM Requirements

- ✎ A tier of memory **beyond HBM and DRAM** can be leveraged, particularly for inference
 - ✧ Higher latency than main memory. But still tight latency profile (e.g TLC Nand Flash does not work)
 - ✧ Trade off performance for capacity
 - ✧ This does not negate the Capacity and BW demand for HBM and DRAM



How does it fit in the whole e2e system?

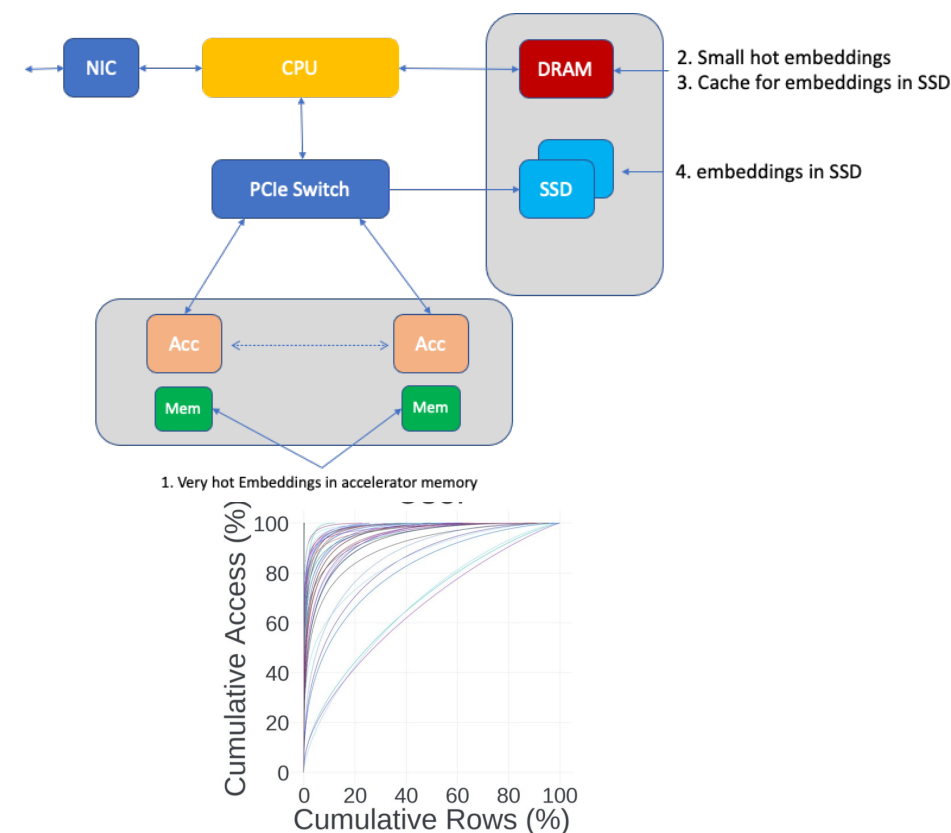
- ⌘ Perf / Watt and then Perf/\$ are important metrics
- ⌘ Different scenarios in real use cases
 - ✕ Simpler HW
 - ✕ Avoiding scale out
 - ✕ Facilitate Multi-tenancy

An Example Implementation

🔗 The published work below mainly focuses on the lowest memory tier (using NVMe SSDs)

🔗 Software Defined Memory backed by SSDs

- ✧ The BW demand required SCM SSDs
 - High IO rate at Smaller access granularity
- ✧ Application level Caching in main memory
 - Row cache due to lack of spatial locality
- ✧ Fast IO (io_uring)
- ✧ Placement policies among DRAM and SSDs
 - To improve overall performance



Impact Scenario #1: Save Power with Simpler HW

Deployment of a **143 GB** model with SDM enabled system, with simpler HW, can reach the same latency as deployment on a more complex model with more DRAM resulting in **20% power savings**.

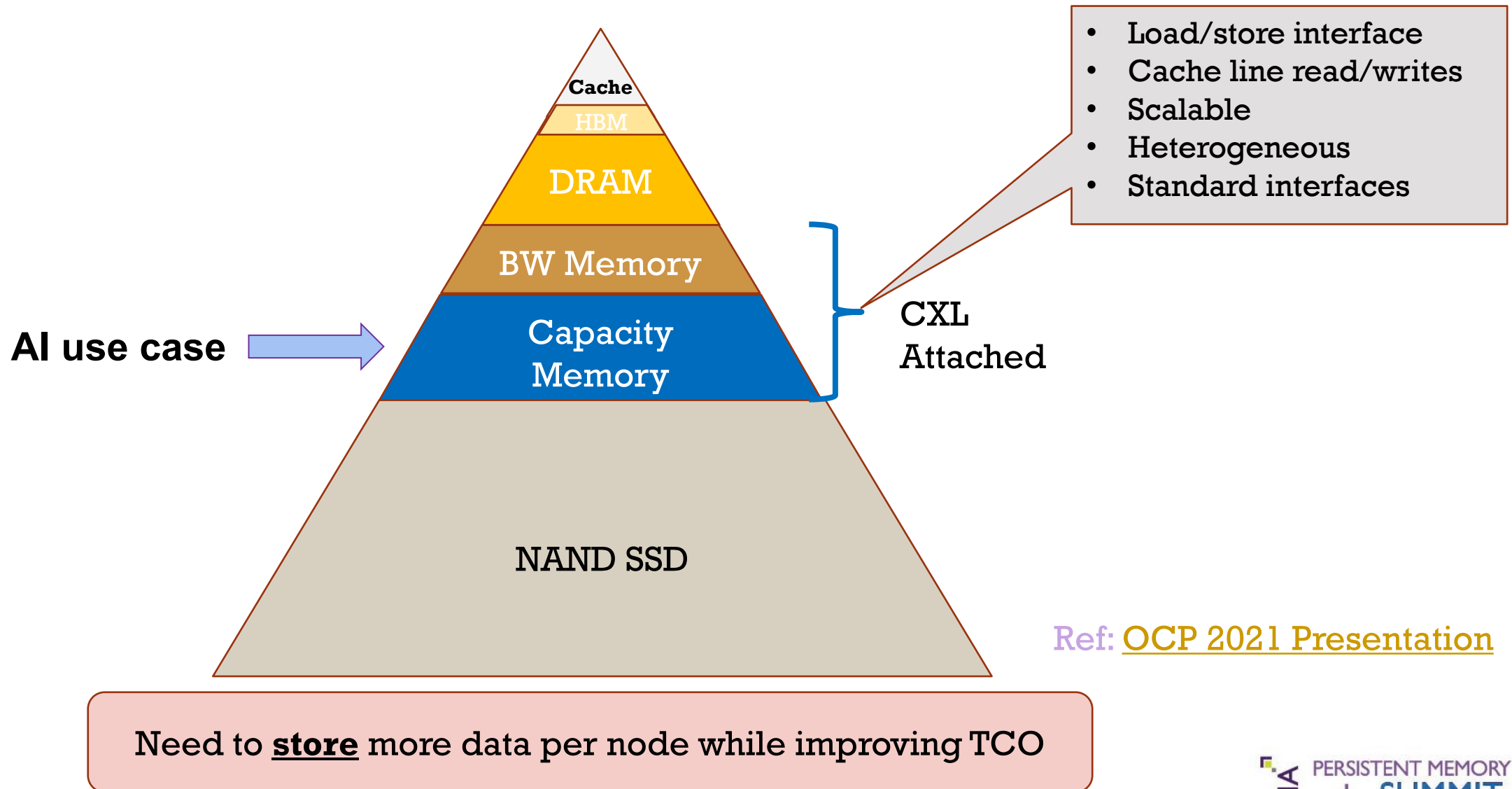
Scenario	QPS	Power	Total Hosts	Total Power
<u>Baseline</u>: 2-Socket, High Mem Capacity	240	1.0	1200	1200
<u>SDM system</u>: 1-socket, Low Mem Capacity + SDM	120	0.4	2400	960

Impact scenario #2: Save Power by Avoiding Scale out

- ❧ Systems with higher compute (e.g. using accelerators) require higher BW throughout the memory hierarchy
- ❧ Using SDM with a SCM SSD for a 150 GB model prevents scale out, **saves power by 5%**, and allows for a simpler serving paradigm

Scenario	QPS	Host Power	Total Hosts	E2E Power
<u>Baseline</u>: Scale Out	450	1.0+0.25	1500+300	100%
<u>Option 1</u>: Nand Flash	230	1.4	2978	189%
<u>Option 2</u>: SCM SSD	450	1.0	1500	95%

Memory Tiers at a High Level



Ref: [OCP 2021 Presentation](#)

Summary

- ❧ AI Models scale faster than the underlying memory technology
- ❧ Additional tiers of memory beyond host DRAM can help (aka Capacity Memory)
- ❧ This memory tier can trade off some performance for capacity
- ❧ CXL provides a viable option to enable this new memory tier

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