# Accelerating Billion-Scale ANNS On Modern Hardware

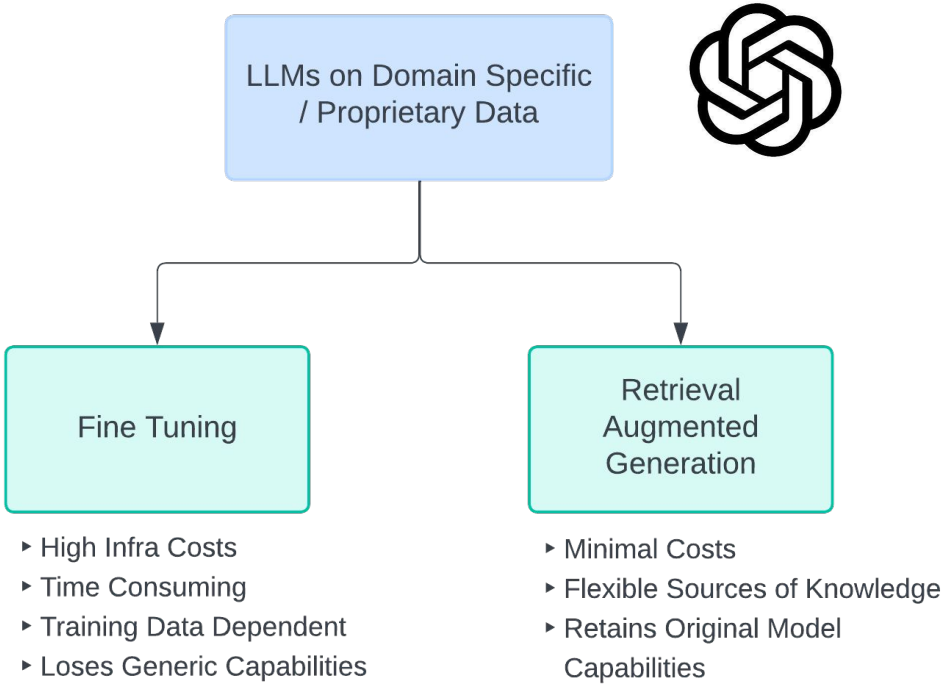
*Jayjeet Chakraborty, Heiner Litz*
*Center for Research in Systems and Storage*
*University of California, Santa Cruz*

UC SANTA CRUZ BaskinEngineering

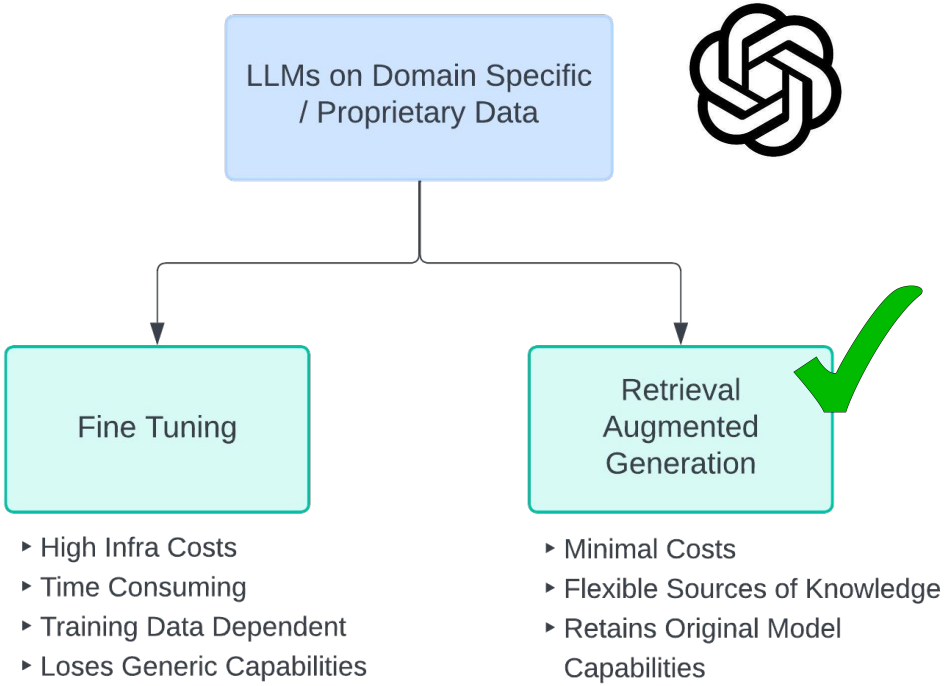
Center for Research in Systems and Storage

NSF

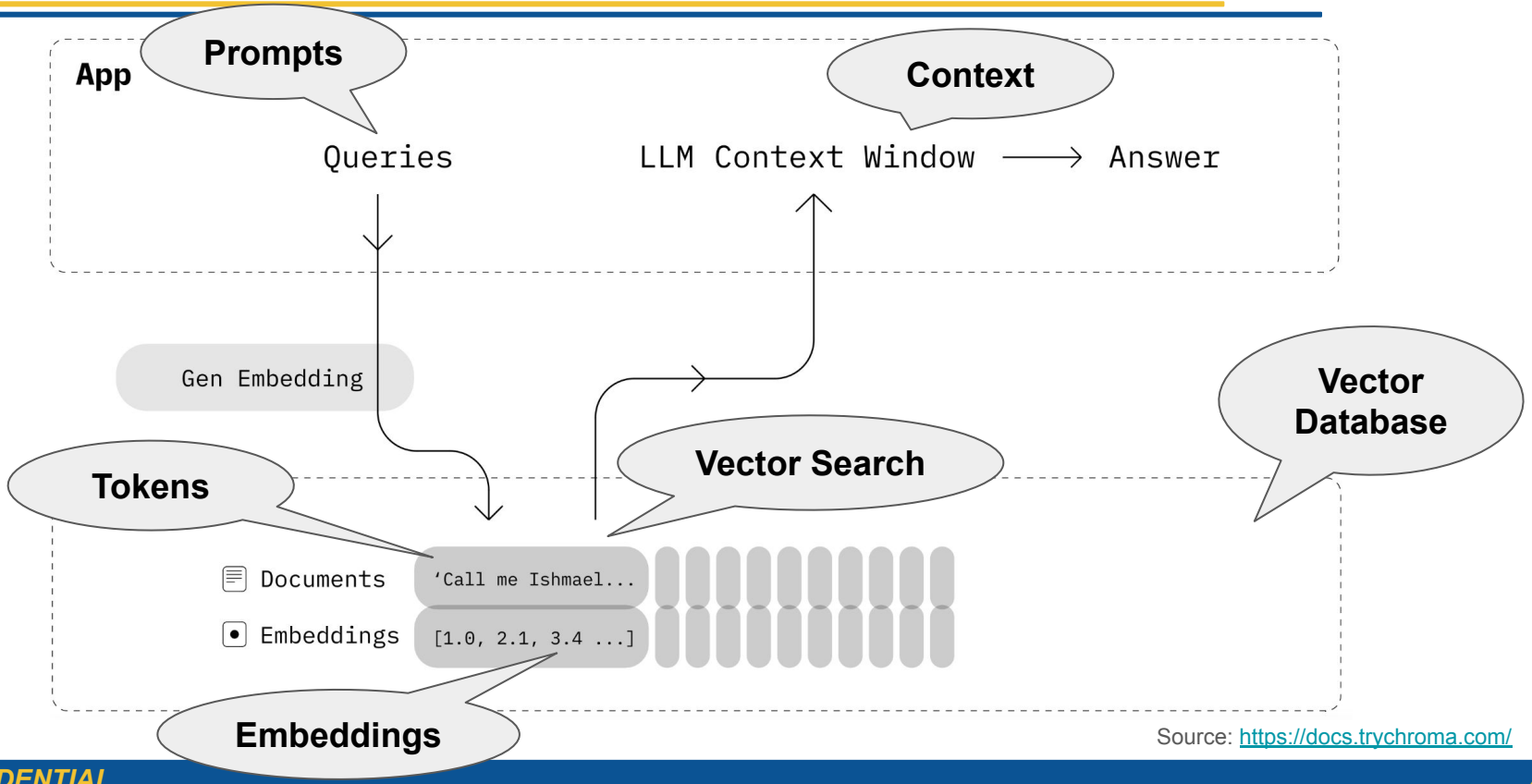
# Custom Language Models



# Custom Language Models

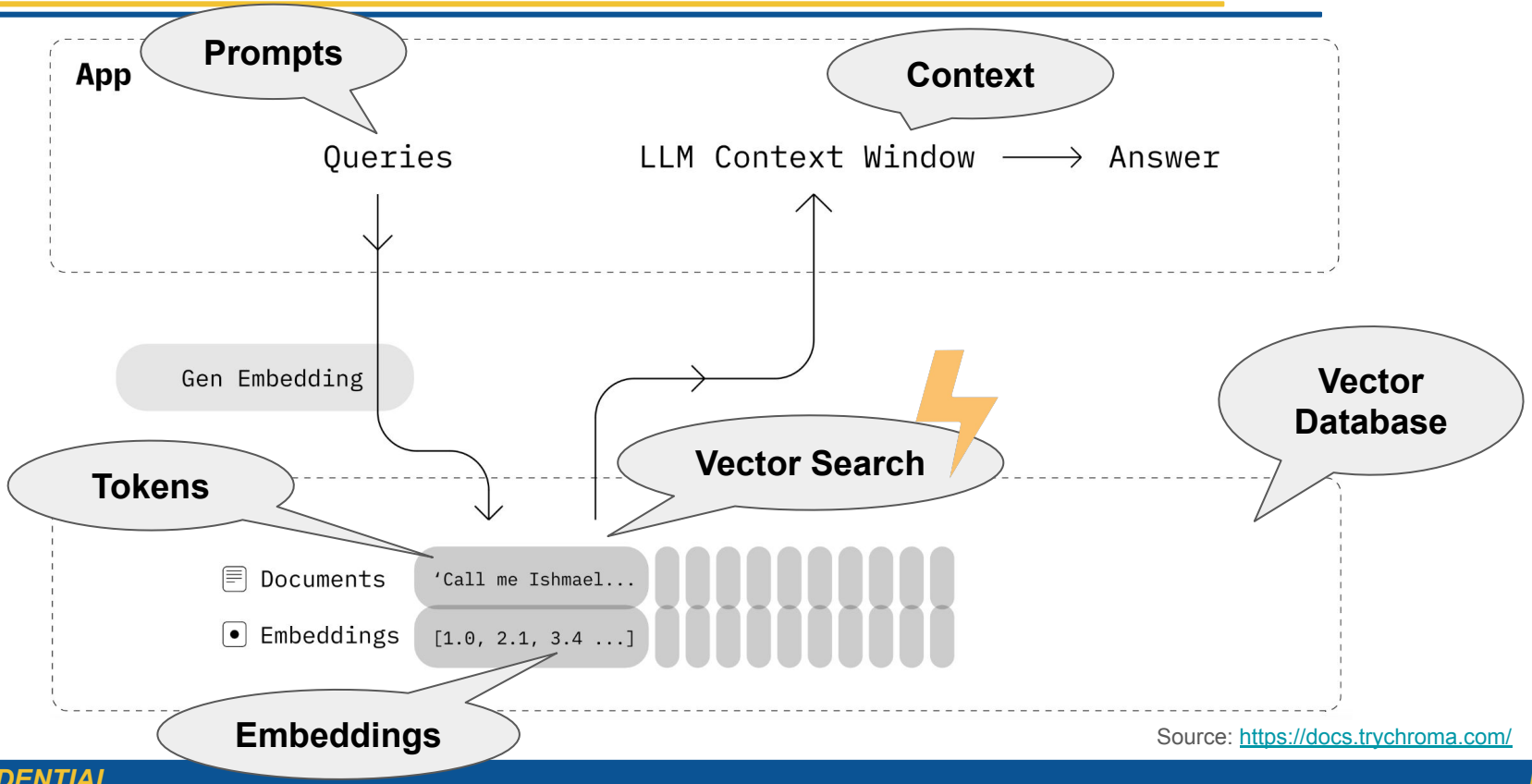


# Retrieval Augmented Generation




Source: https://docs.trychroma.com/

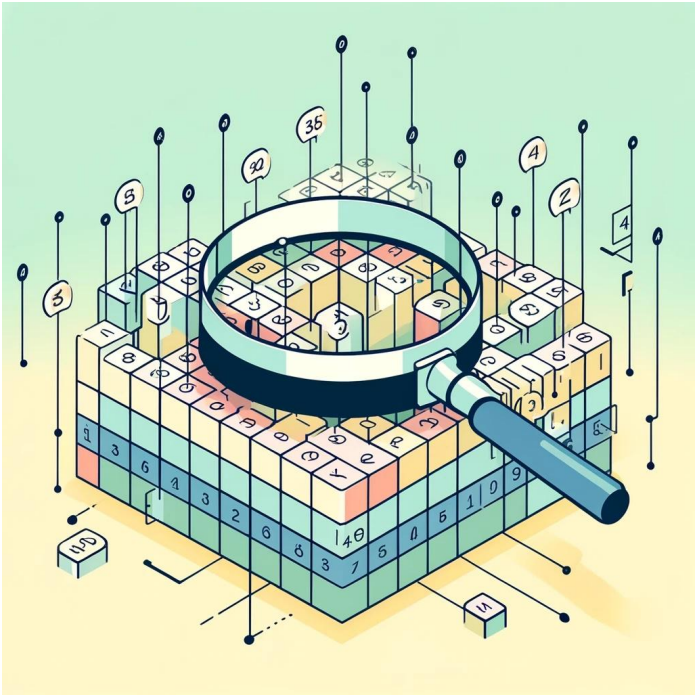
# Retrieval Augmented Generation




Source: https://docs.trychroma.com/

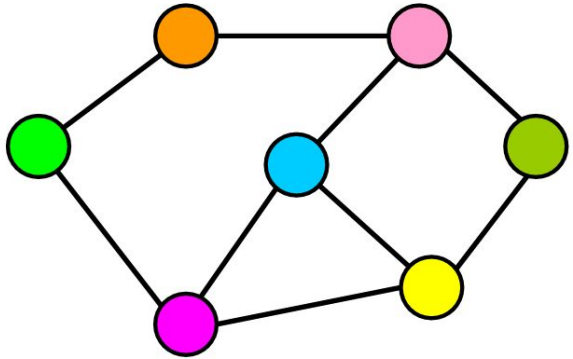
# Vector Search

- Find tokens similar to a query using nearest neighbor searches
- Traditionally, **KNN** has been used
  - But on millions & billions of data points, not feasible
- Using **ANN** (Approximate Nearest Neighbor) algorithms allows trading off **accuracy** for **search speed**

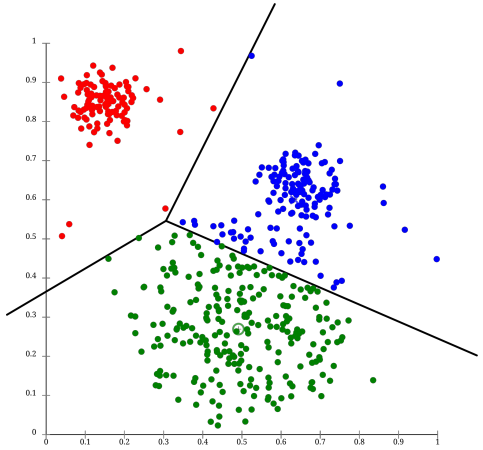


Source: Generated by DALL-E

# Categories of ANN Algorithms



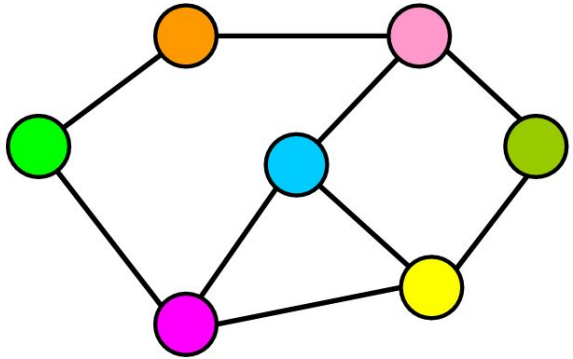
Graph-based



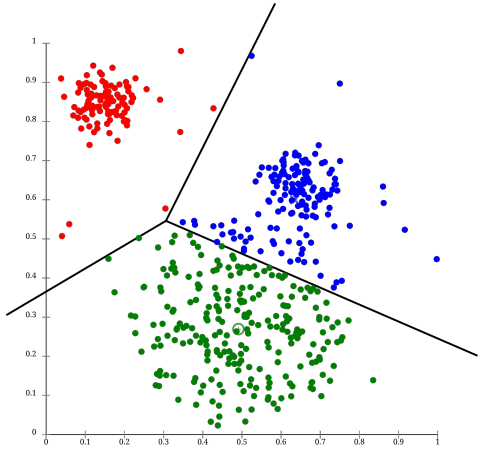
Cluster-based

Source: Google Images

# Categories of ANN Algorithms



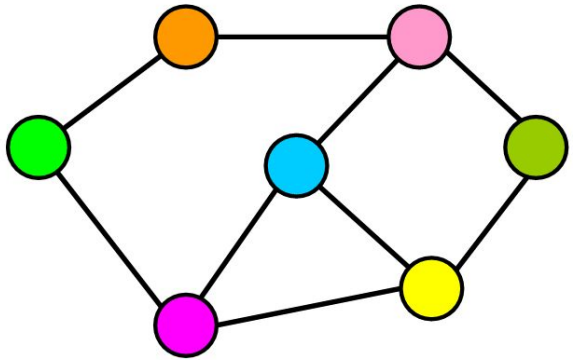
Ex: NSG, HNSW



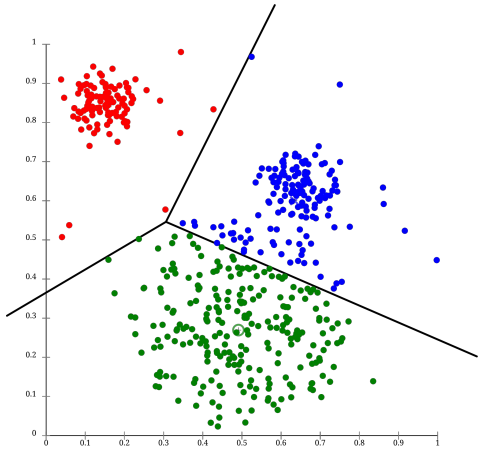
Ex: IVF, IVF-PQ

Source: Google Images

# Categories of ANN Algorithms



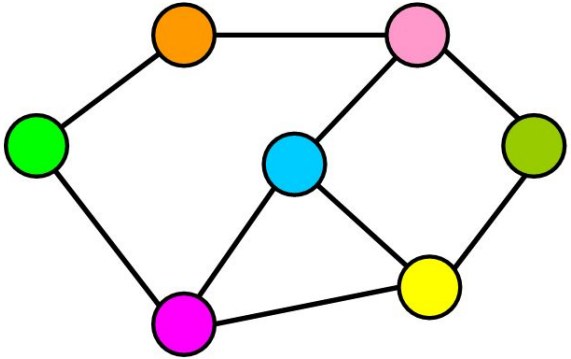
**Branchy** Character,
Better suited for **CPUs**



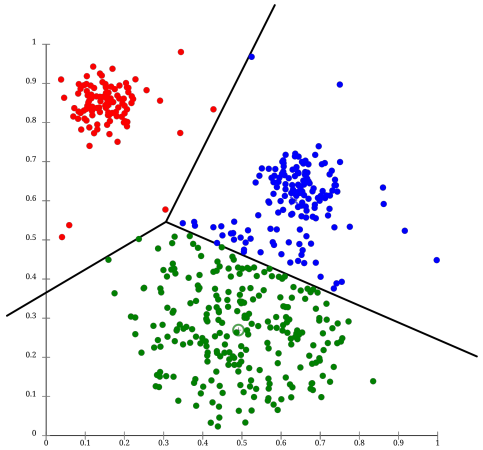
**Data Parallel** Character,
Better suited for **GPUs**

Source: Google Images

# Categories of ANN Algorithms



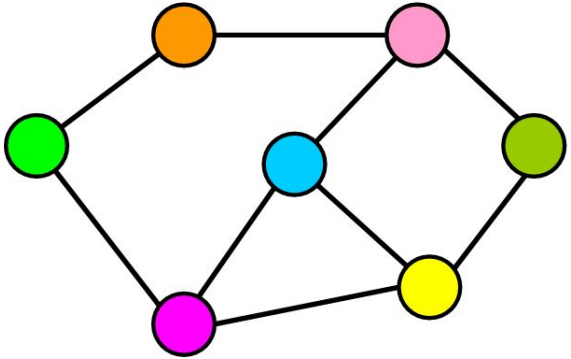
Inter-query parallelism & limited Intra-query parallelism



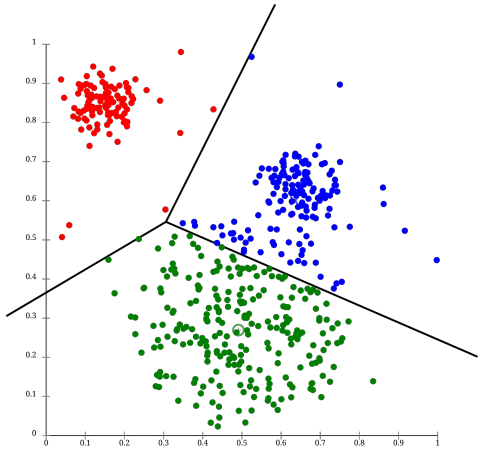
Good Intra & Inter-query parallelism

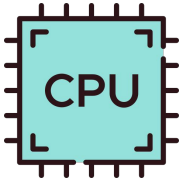
Source: Google Images

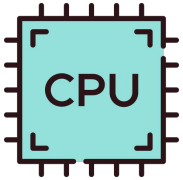
# Performance Characteristics



*faster* than

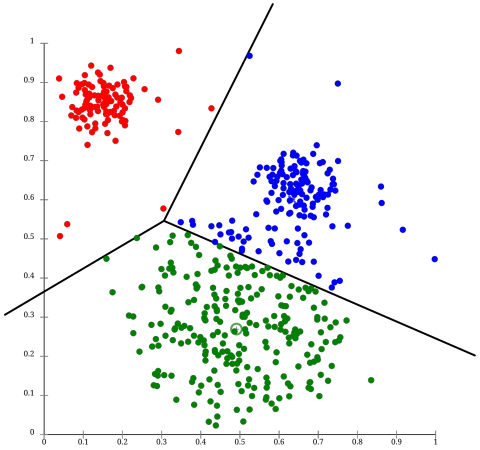


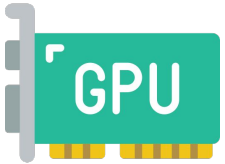


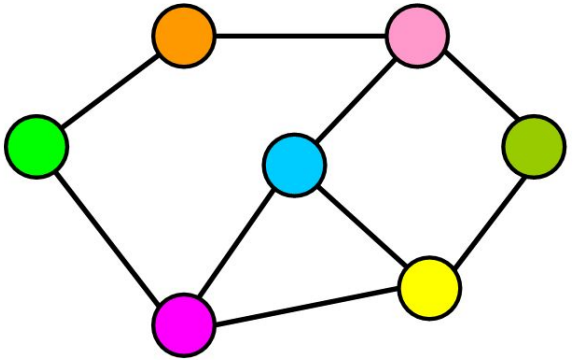

Source: Google Images, Flat Icons

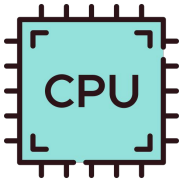
# Performance Characteristics





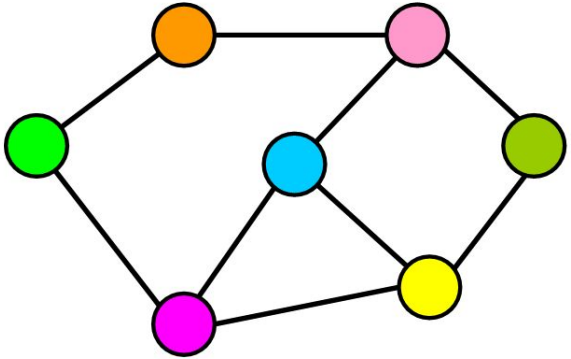

*faster* than



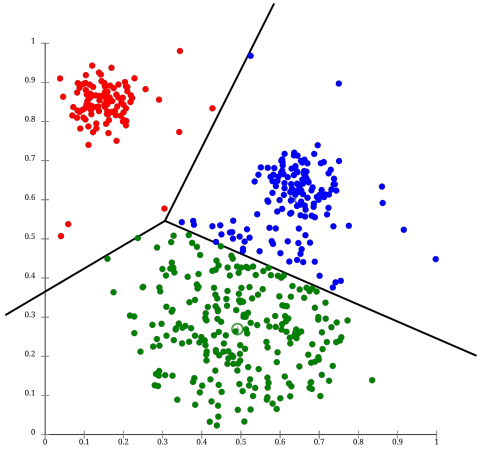


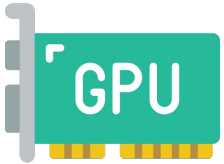

Source: Google Images, Flat Icons

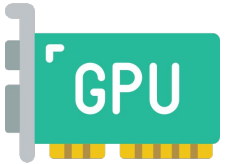
# Performance Characteristics



*faster* than

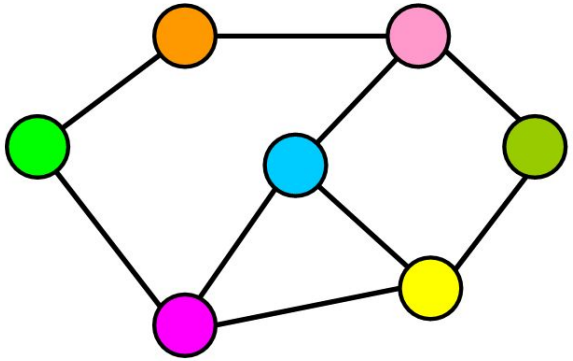


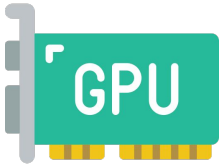



Source: Google Images, Flat Icons

# SOTA






Parallel Graph Construction and Search

Hand-tuned Kernels

GPU-friendly Data Structures

Utilizing register files, shared memory

Multi-stage pipelined execution using streams

Source: Google Images, Flat Icons

# SOTA

CAGRA: Highly Parallel Graph Construction and Approximate Nearest Neighbor Search for GPUs

SONG: Approximate Nearest Neighbor Search on GPU

GGNN: Graph-based GPU Nearest Neighbor Search

GPU-accelerated Proximity Graph Approximate Nearest Neighbor Search and Construction

# SOTA?

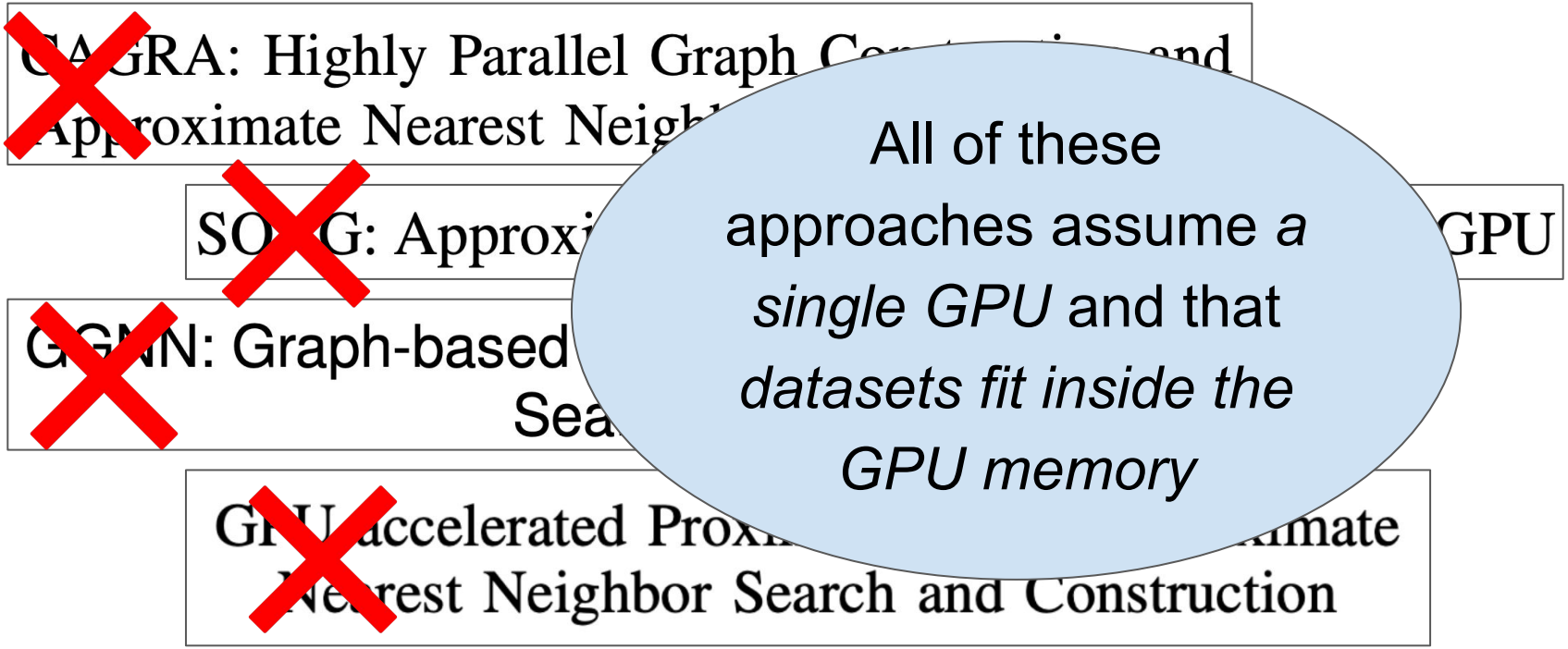
CAGRA: Highly Parallel Graph Construction and Approximate Nearest Neighbor Search for GPUs

SONG: Approximate Nearest Neighbor Search on GPU

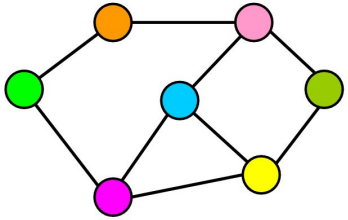
GGNN: Graph-based GPU Nearest Neighbor Search

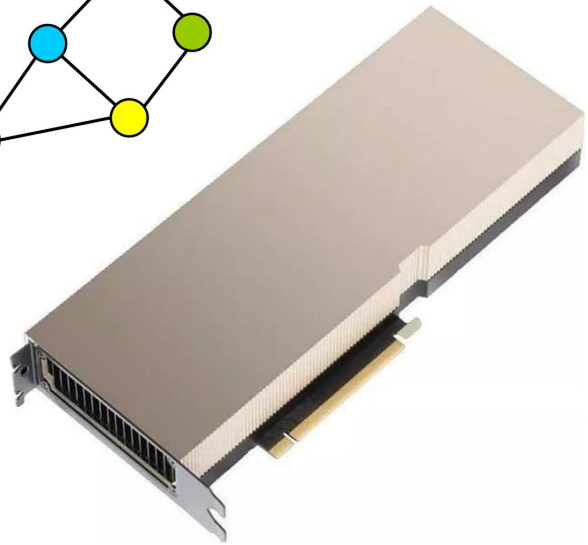
GPU-accelerated Proximity Graph Approximate Nearest Neighbor Search and Construction

# SOTA?


GANNS: GRA: Highly Parallel Graph
Approximate Nearest Neigh
SONG: Approxi
GPU
GGNN: Graph-based
Sea
GPU-accelerated Proxi
imate
Nearest Neighbor Search and Construction
All of these approaches assume *a single GPU* and that *datasets fit inside the GPU memory*

# Limits of SOTA





NVIDIA H100 80GB

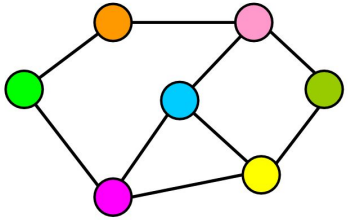
5M OpenAI Large Embeddings

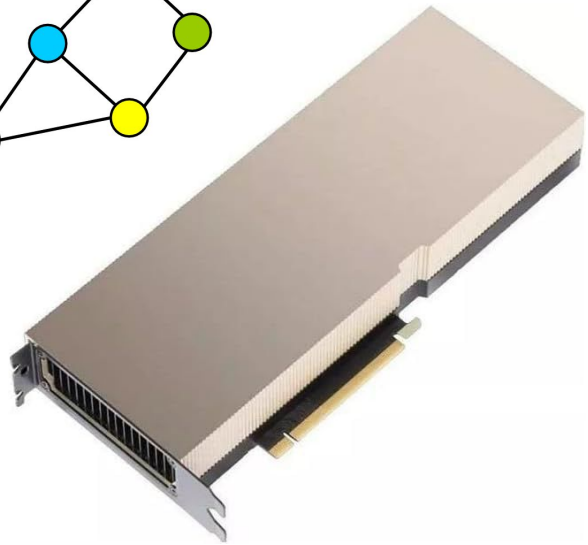
10M OpenAI Small Embeddings

200M DEEP 1B Embeddings

Source: Google Images

# Limits of SOTA





NVIDIA H100 80GB

5M OpenAI Large Embeddings

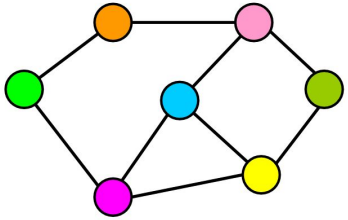
10M OpenAI Small Embeddings

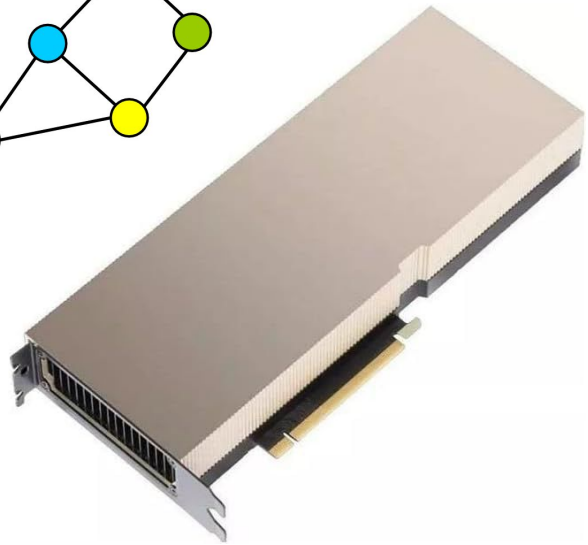
200M DEEP 1B Embeddings

**What about 1B vectors ?**

Source: Google Images

# Limits of SOTA





NVIDIA H100 80GB

5M OpenAI Large Embeddings

10M OpenAI Small Embeddings

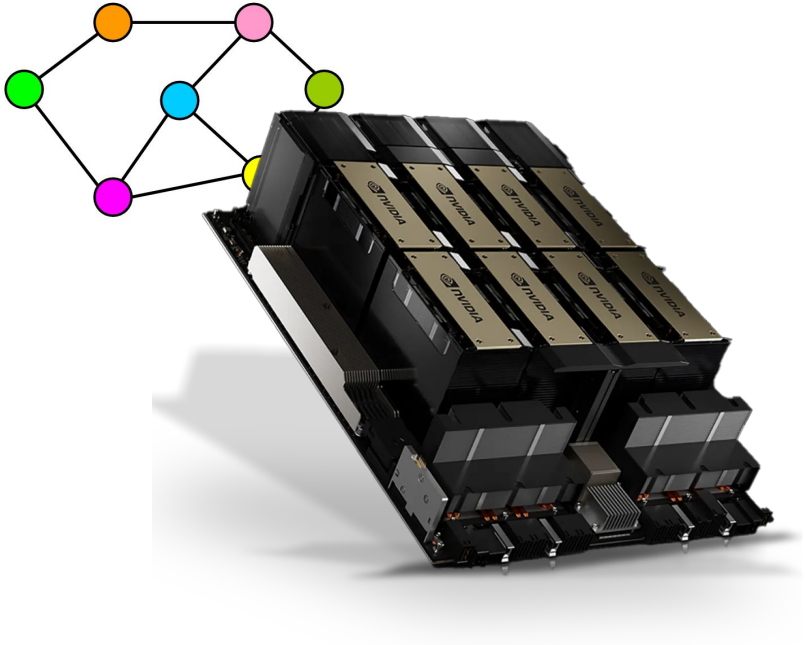
200M DEEP 1B Embeddings

**What about 1B vectors ?**

PQ hurts accuracy and requires reranking

Source: Google Images

# Limits of SOTA



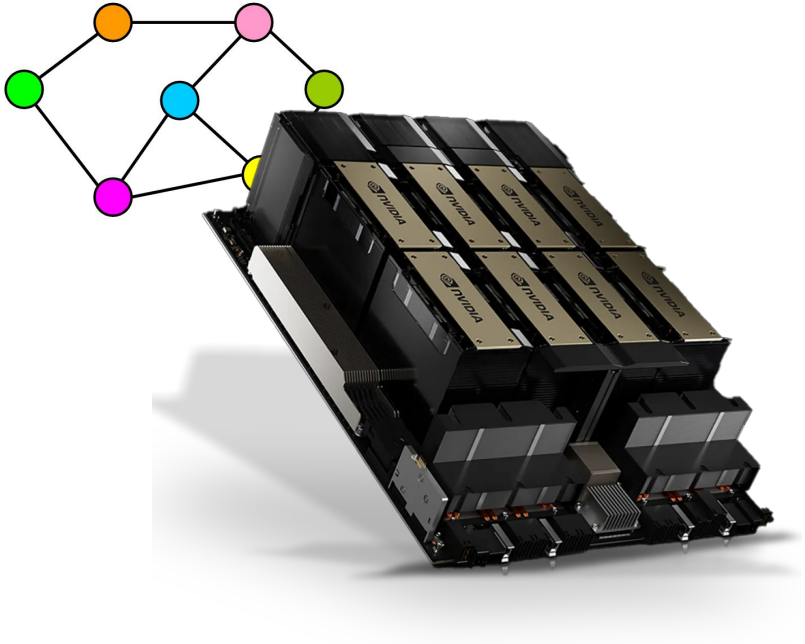
DGX H100 SXM 640GB

Running Graph-based algorithms on multiple GPUs is a huge inter-gpu **coordination** and **communication** overhead !

**Poor scalability :(**

Source: Google Images

# Limits of SOTA



DGX H100 SXM 640GB

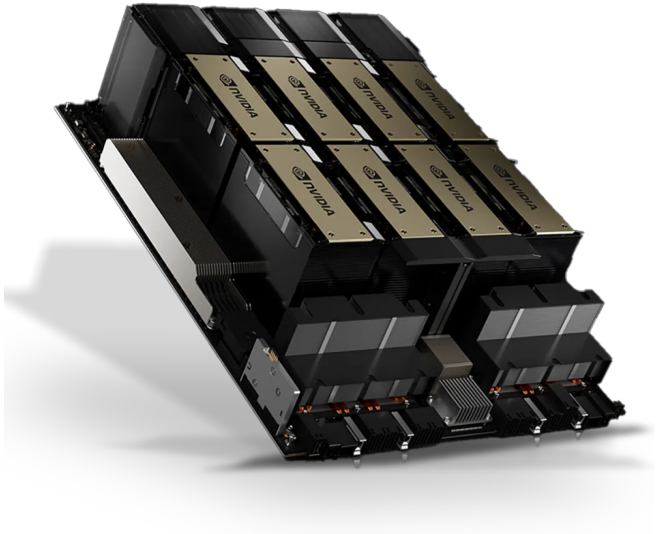
Running Graph-based algorithms on multiple GPUs is a huge inter-gpu **coordination** and **communication** overhead !

**Poor scalability :(**

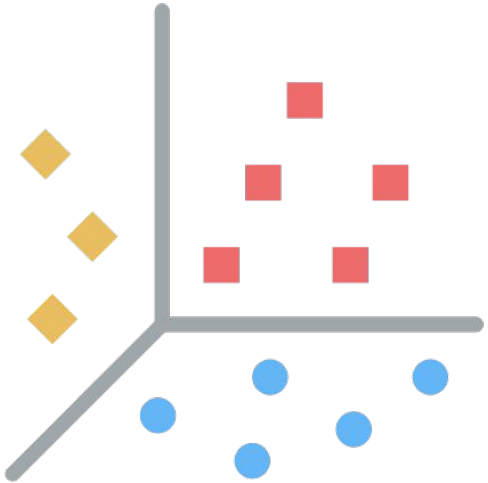
Low GPU utilization

Source: Google Images

# Billion-Scale Searches



DGX H100 SXM 640GB

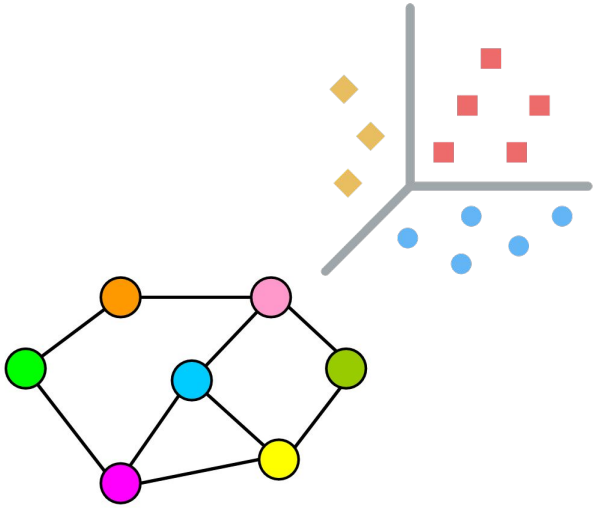


Cluster-based

Source: Google Images

# Billion-Scale Searches

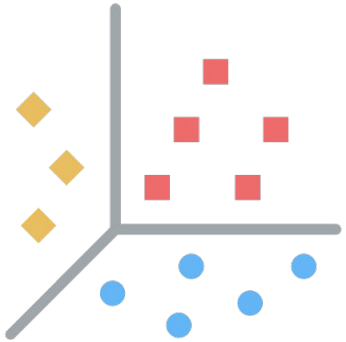

Multi-Core CPU + DRAM + GPU

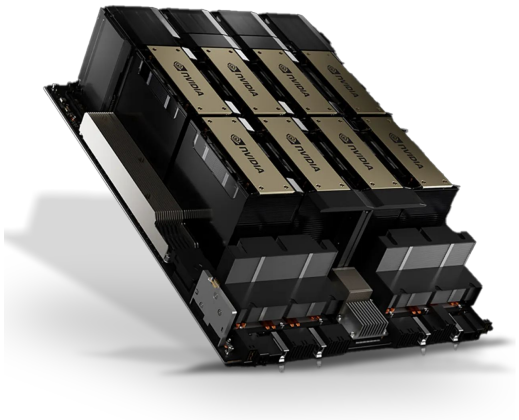


Hybrid Graph + Cluster Index

Source: Google Images

# Billion-Scale Searches





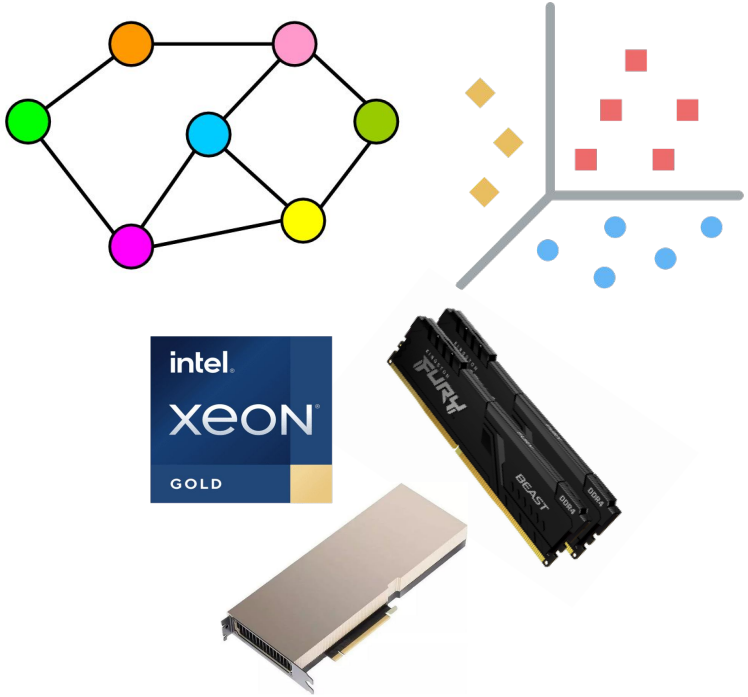
Highly parallel algorithm and Massively parallel hardware; Good scalability

Faster interconnect and higher bandwidth memory helps

Performance at a very very high cost
Each DGX is ~**$300,000**

Source: Google Images

# Billion-Scale Searches



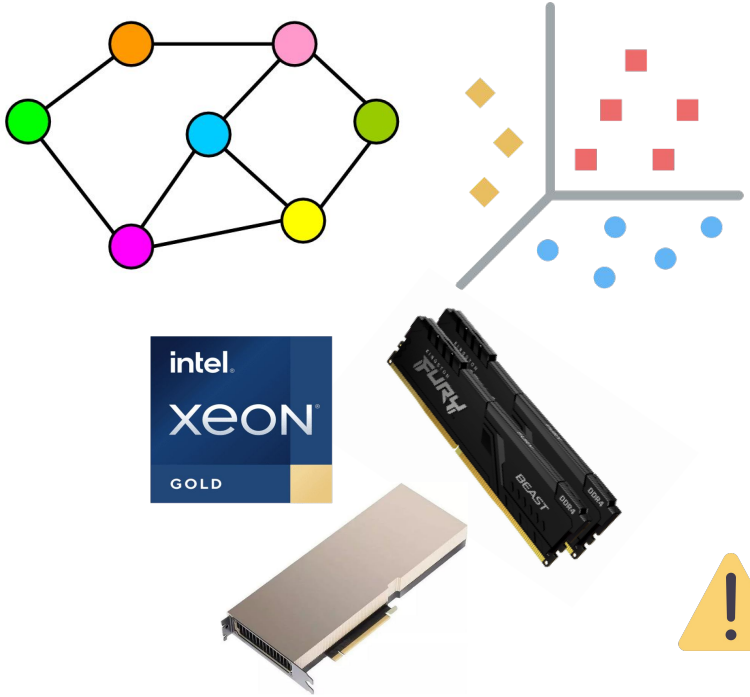

Use Hybrid Graph + Cluster based algorithms. HNSW-IVF-PQ ?

Let the CPU and GPU do at what they are really good at

Sapphire Rapids CPU + H100 GPU + 512 GB DDR5 memory < $50,000

Source: Google Images

# Billion-Scale Searches




Use Hybrid Graph + Cluster based algorithms. HNSW-IVF-PQ ?

Let the CPU and GPU do at what they are really good at

Sapphire Rapids CPU + H100 GPU + 512 GB DDR5 memory < $50,000

**Unified Virtual Memory (UVM)**

Source: Google Images

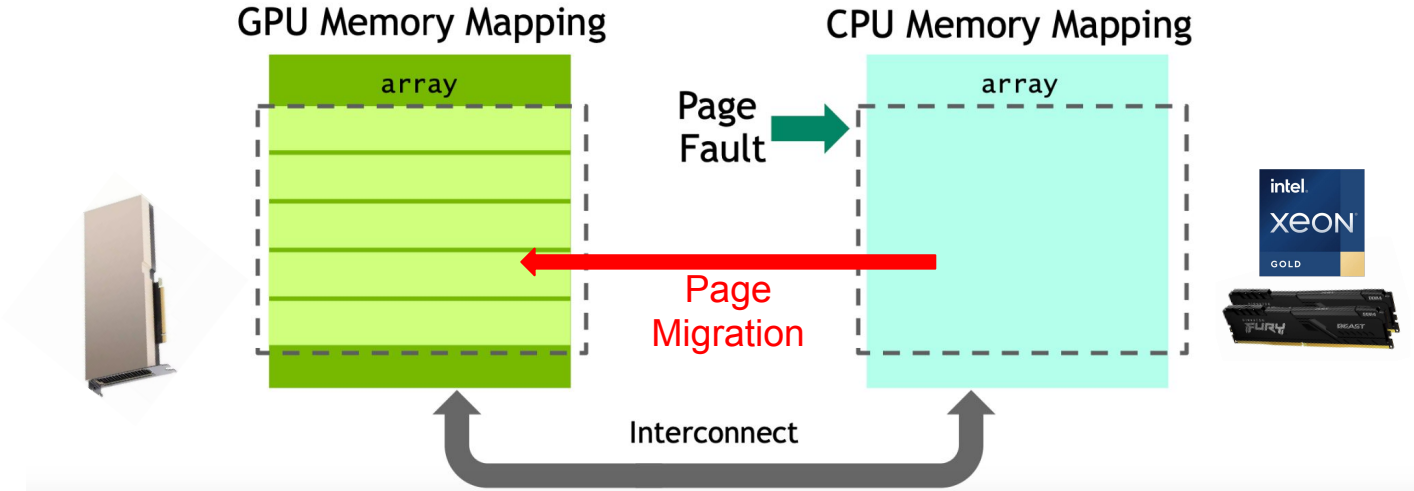
# CUDA Unified Virtual Memory

GPU Code

```
__global__
void setValue(char *ptr, int index, char val)
{
  ptr[index] = val;
}
```

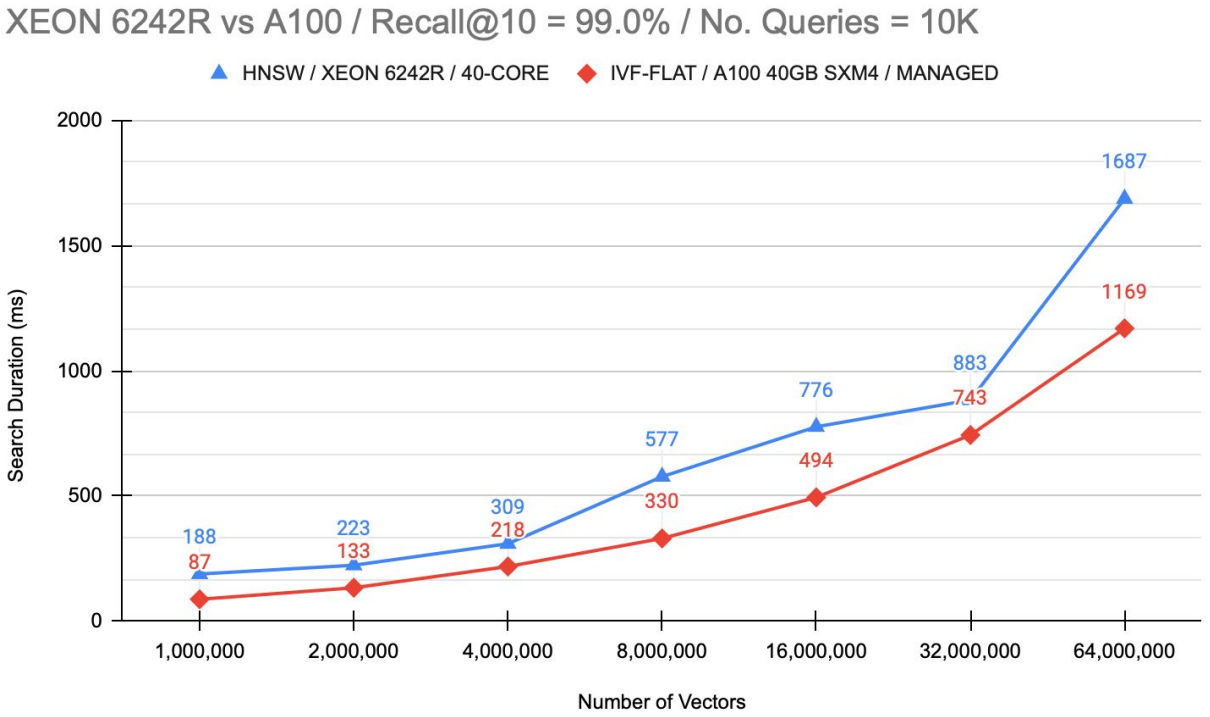
CPU Code

```
cudaMallocManaged(&array, size);
memset(array, size);
setValue<<<...>>>(array, size/2, 5);
```

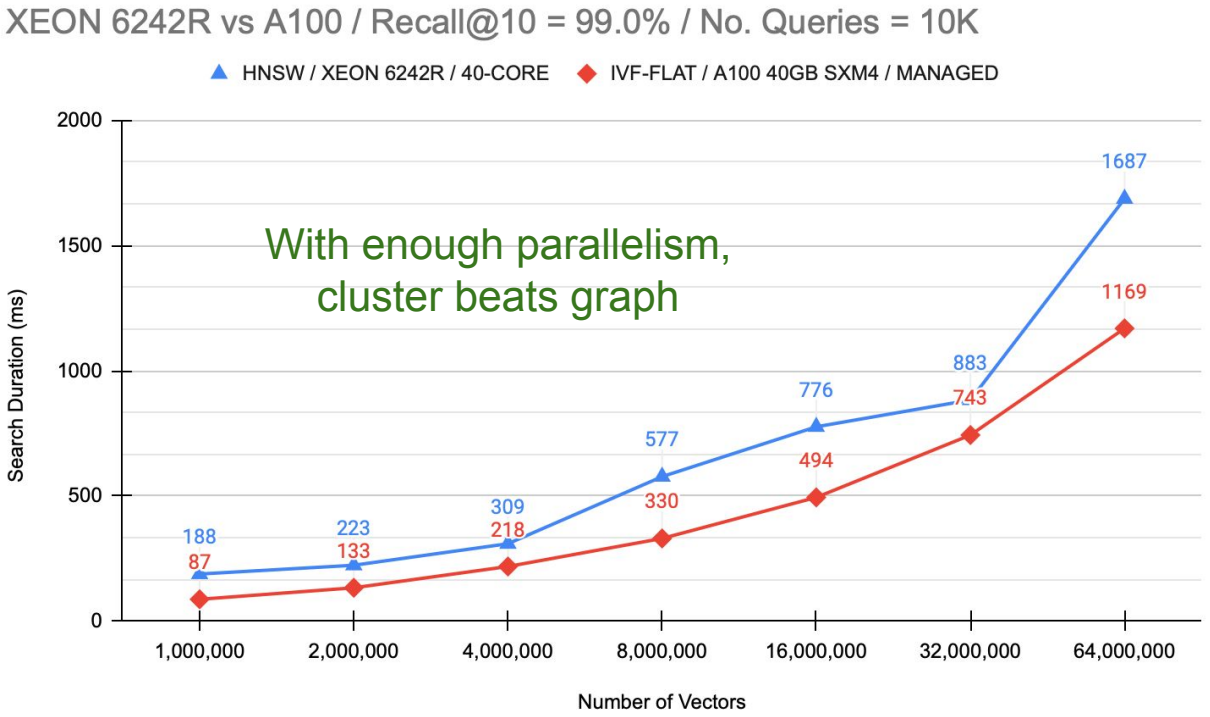



Source: https://www.olcf.ornl.gov/wp-content/uploads/2019/06/06_Managed_Memory.pdf

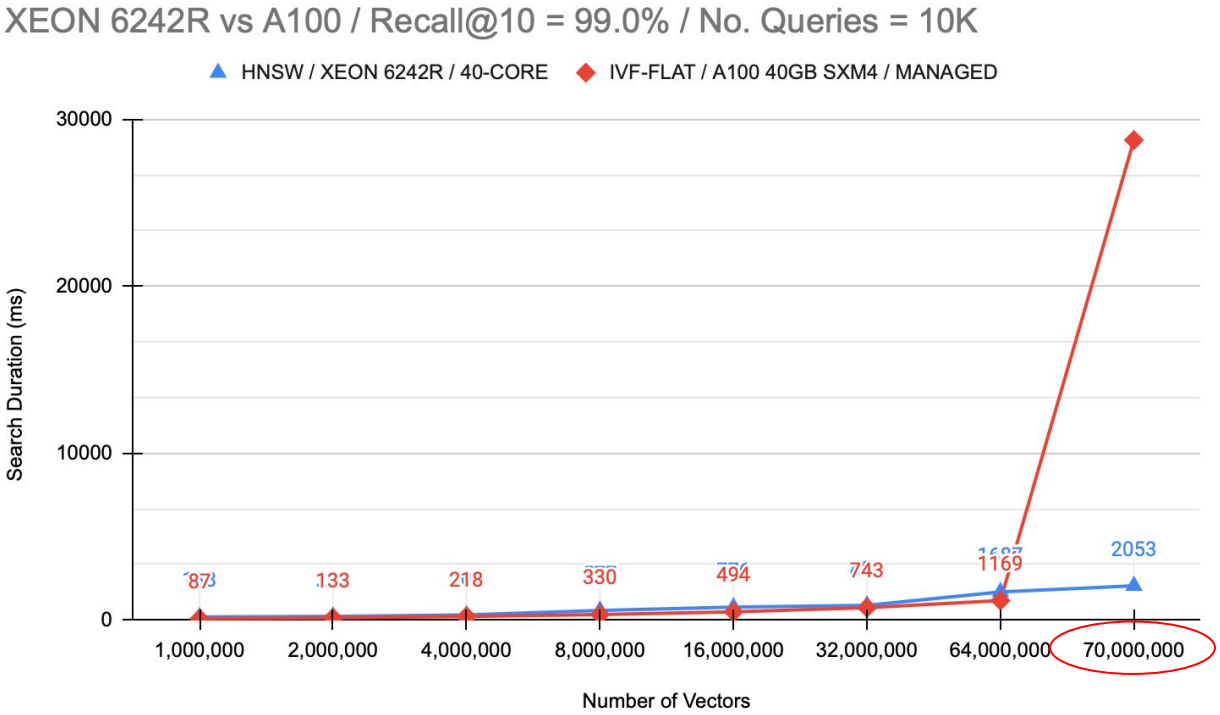
# CPU (Graph) vs. GPU (Cluster)



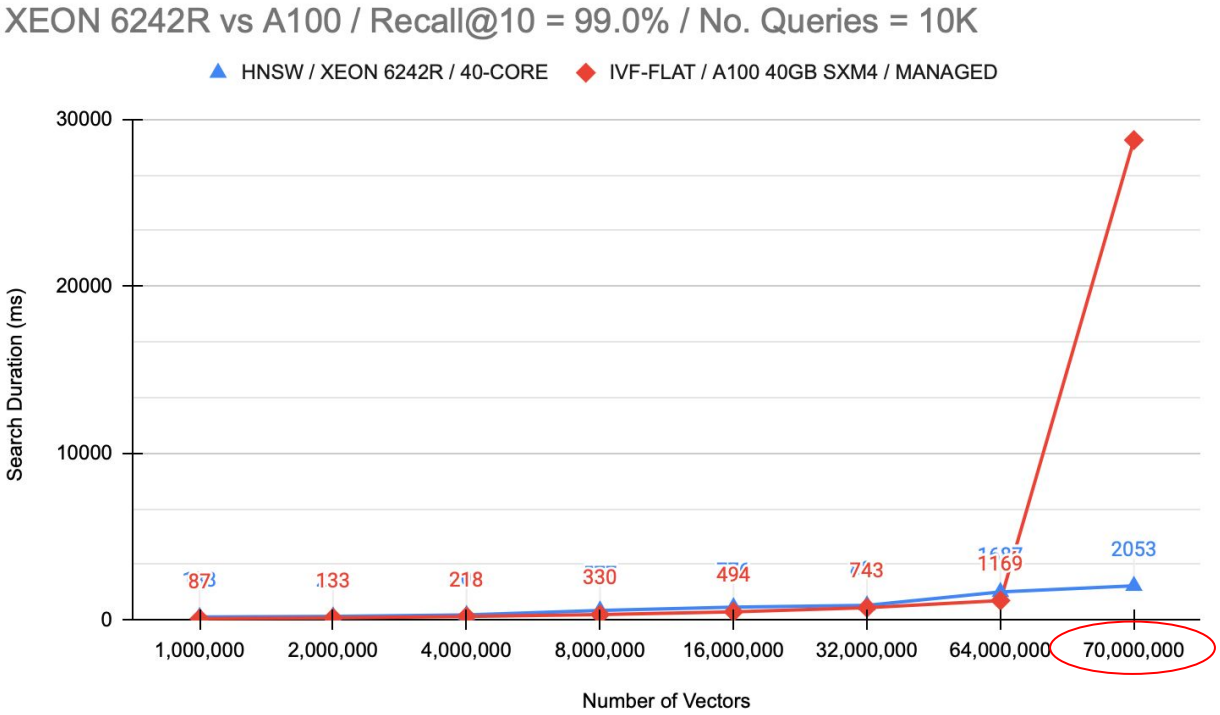
# CPU (Graph) vs. GPU (Cluster)



# CPU (Graph) vs. GPU (Cluster)

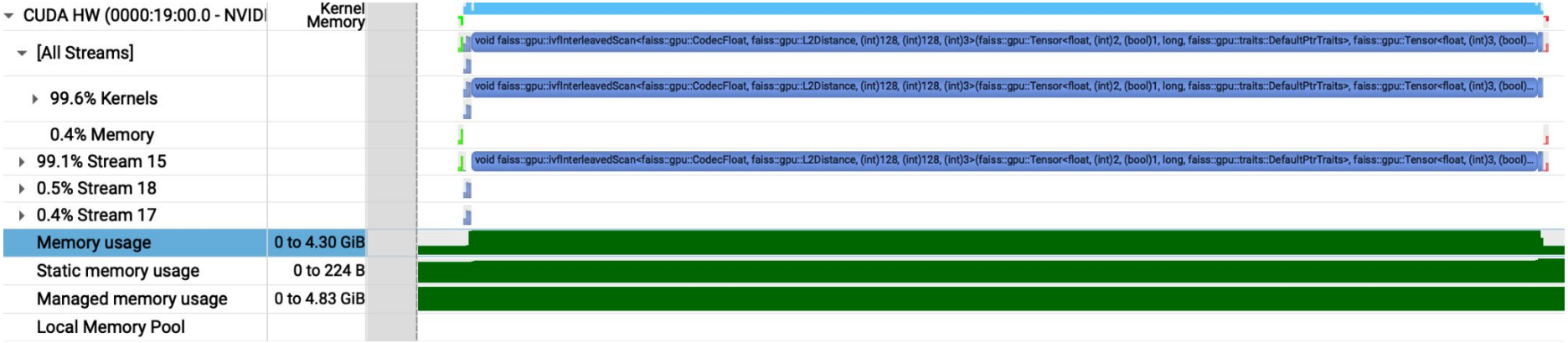


# CPU (Graph) vs. GPU (Cluster)



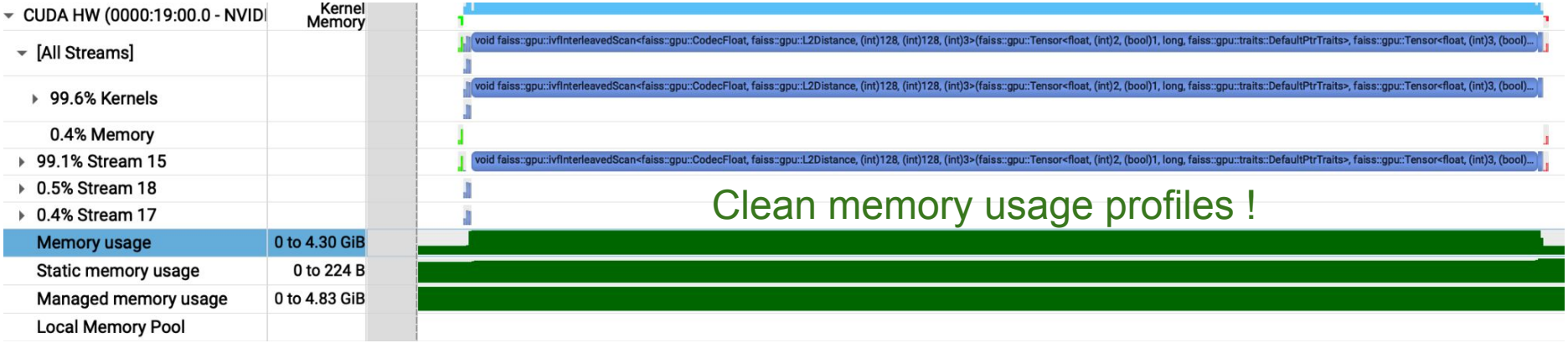

When dataset does not fit, exponential slow down in GPU

# Profiling UVM



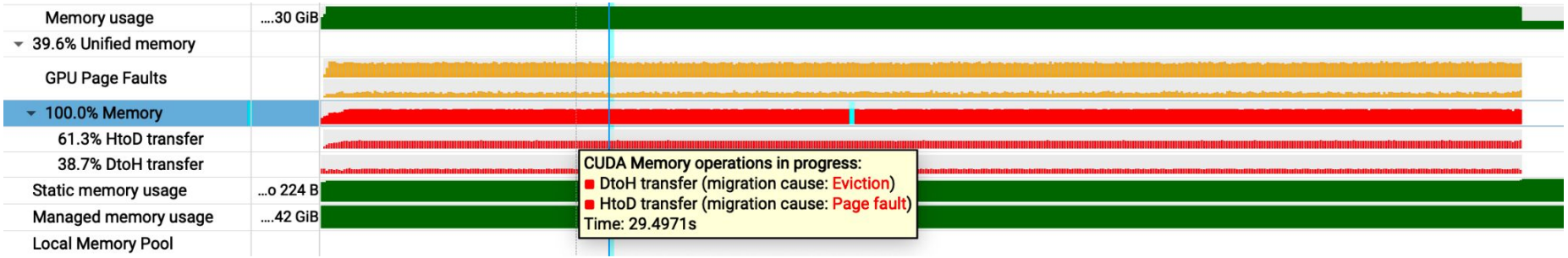

*nsys* profile when the dataset **fits** entirely in the GPU memory

# Profiling UVM



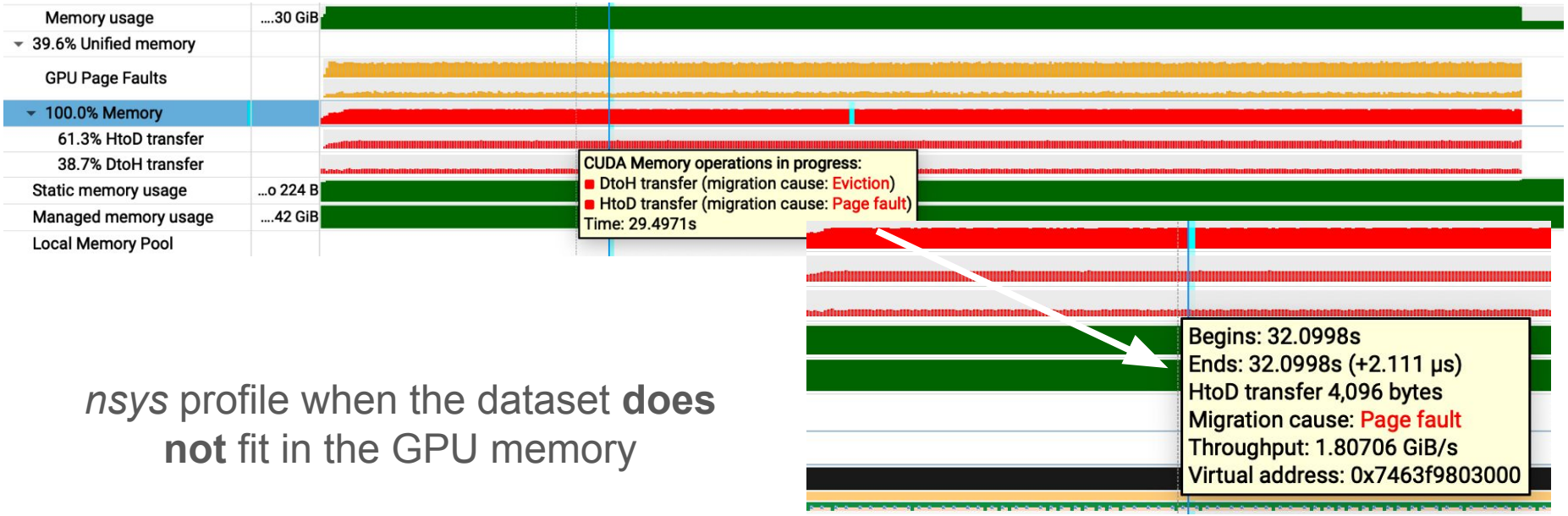

*nsys* profile when the dataset **fits** entirely in the GPU memory

# Profiling UVM




*nsys* profile when the dataset **does not** fit in the GPU memory

# Profiling UVM




*nsys* profile when the dataset **does not** fit in the GPU memory

# Memory Management Modes in CUDA

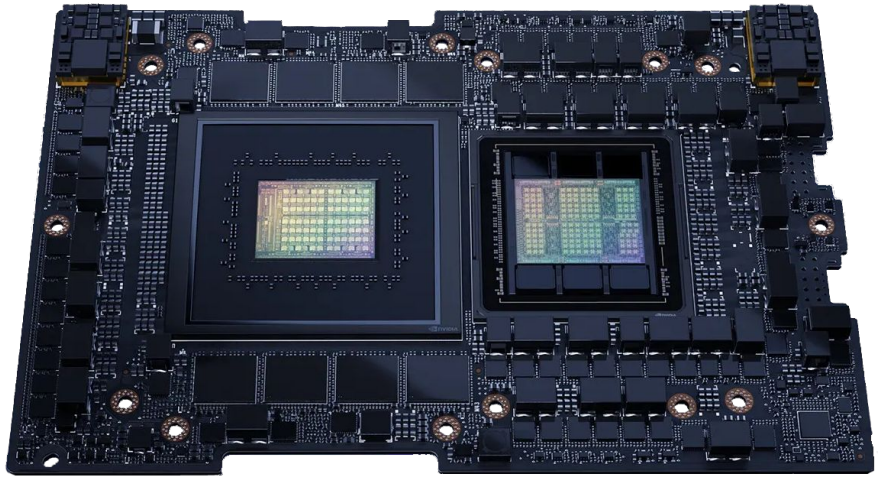
CRSS

| | cuda + pool | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **no. of vectors** | **cuda** | **async** | **managed** | **managed_pool** | **prefetch** | **prefetch_pool** | **n-probe** | RECALL@10 = 99.0% |
| 1,000,000 | 357 | 361 | 410 | 402 | 369 | 361 | 135 | No. of Queries = 10,000 |
| 2,000,000 | 468 | 465 | 536 | 521 | 476 | 464 | 140 | |
| 4,000,000 | 621 | 619 | 718 | 704 | 629 | 617 | 145 | |
| 8,000,000 | 848 | 839 | 979 | 961 | 861 | 858 | 150 | |
| 10,000,000 | 957 | 956 | 1111 | 1082 | 974 | 968 | 155 | |
| 11,000,000 | 992 | 1011 | 1162 | 1132 | 1015 | 1009 | 155 | |
| 12,000,000 | 0 | 0 | 1287 | 1312 | 2067 | 6109 | 155 | |
| 14,000,000 | 0 | 0 | 2545 | 2582 | 1566 | 2408 | 160 | |
| 16,000,000 | 0 | 0 | 2782 | 2230 | 2461 | 2166 | 160 | |
| 18,000,000 | 0 | 0 | 3094 | 2757 | 2864 | 2737 | 160 | |

In **prefetch**, we try to prefetch every pointer allocated through **cudaMallocManaged**

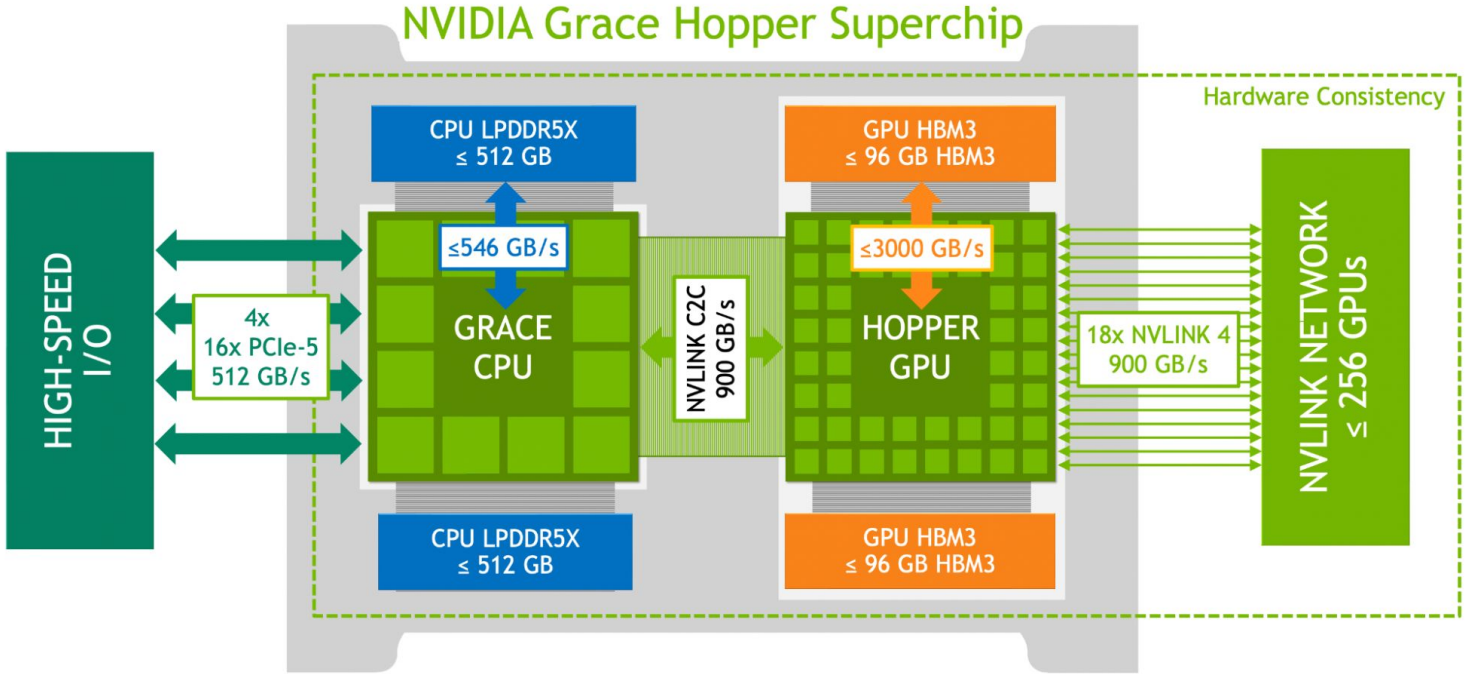
# NVIDIA Grace Hopper Superchip

- **Grace CPU**
  - 72 ArmV9 Neoverse v2 cores
  - LPDDR5X 480 GB ECC memory
- **Hopper GPU**
  - H100 Tensor Core NVL
  - 96 GB HBM3e
- **C2C-NVLink**
  - Cache-coherent
  - 900 GB/s total bandwidth



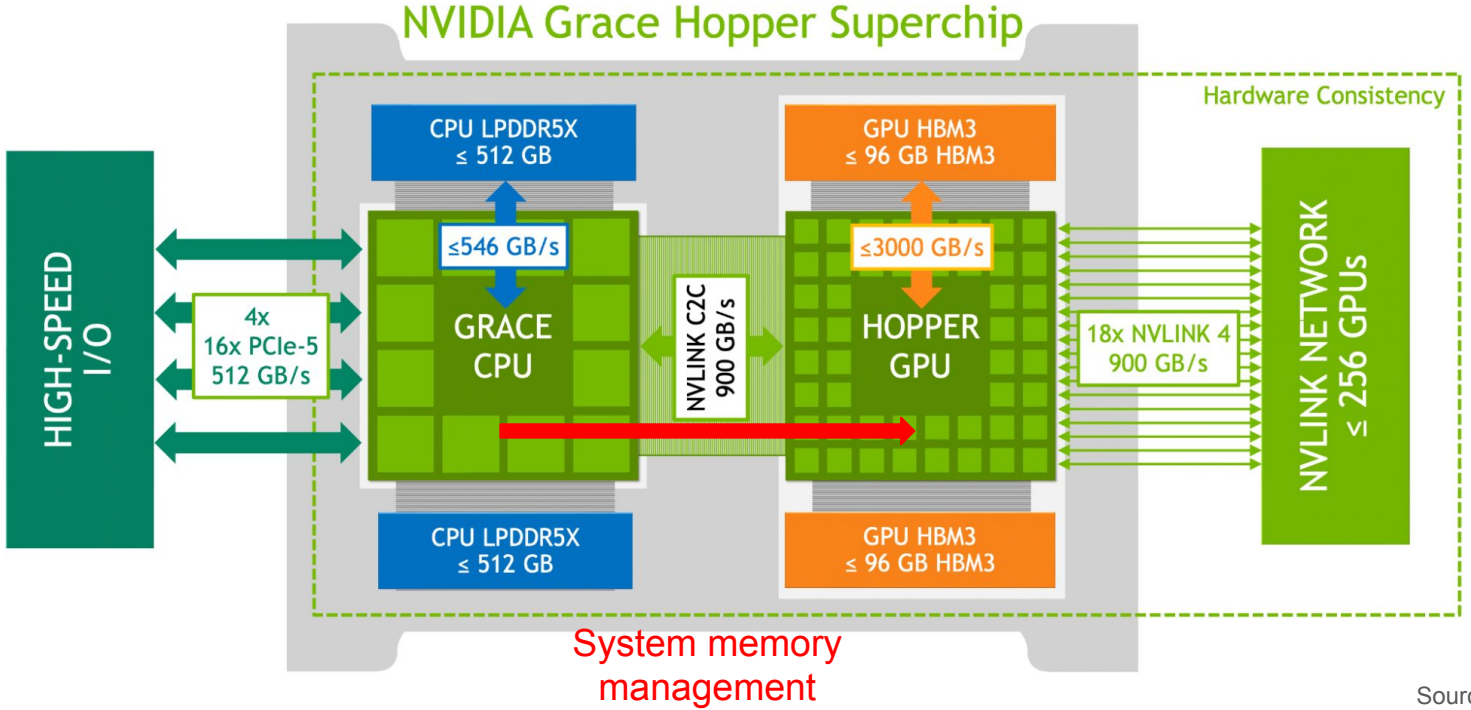
Source: Google Images

# Architecture of Grace Hopper



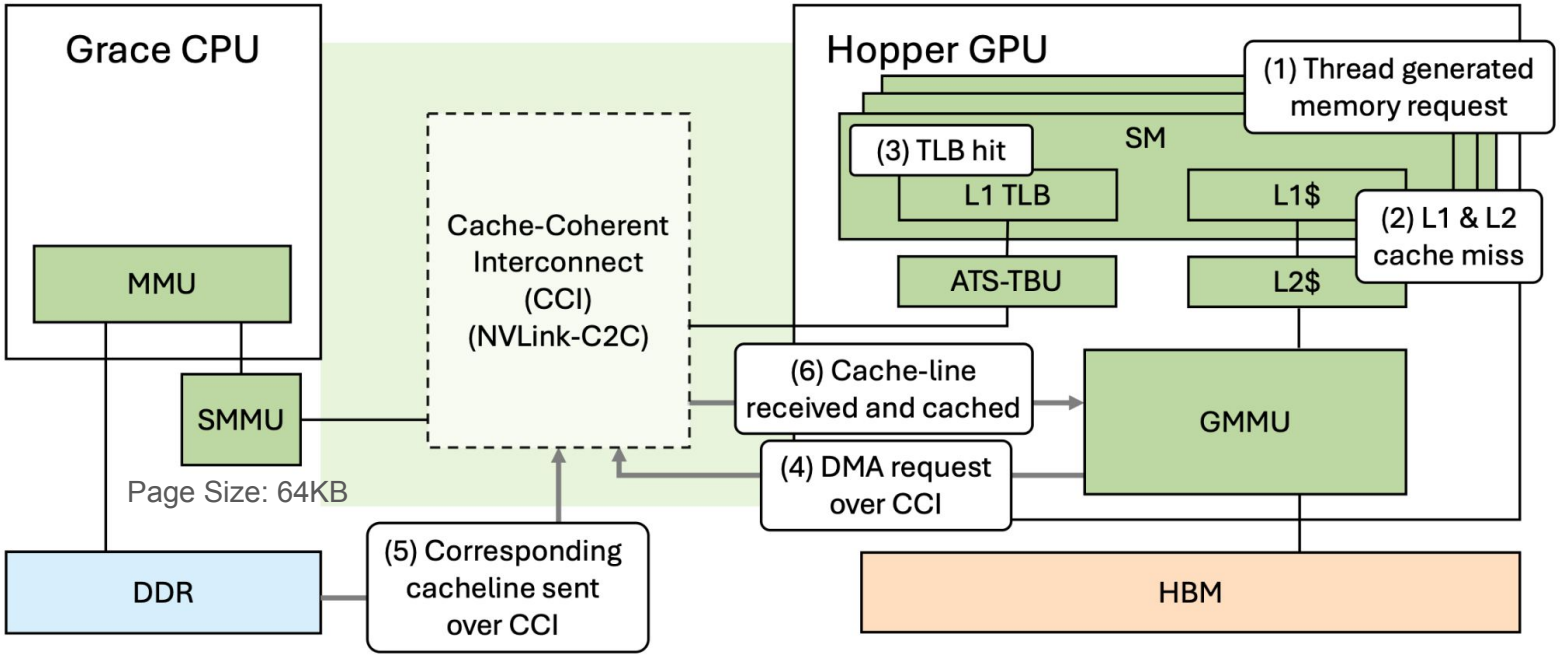

Source: Google Images

# Architecture of Grace Hopper



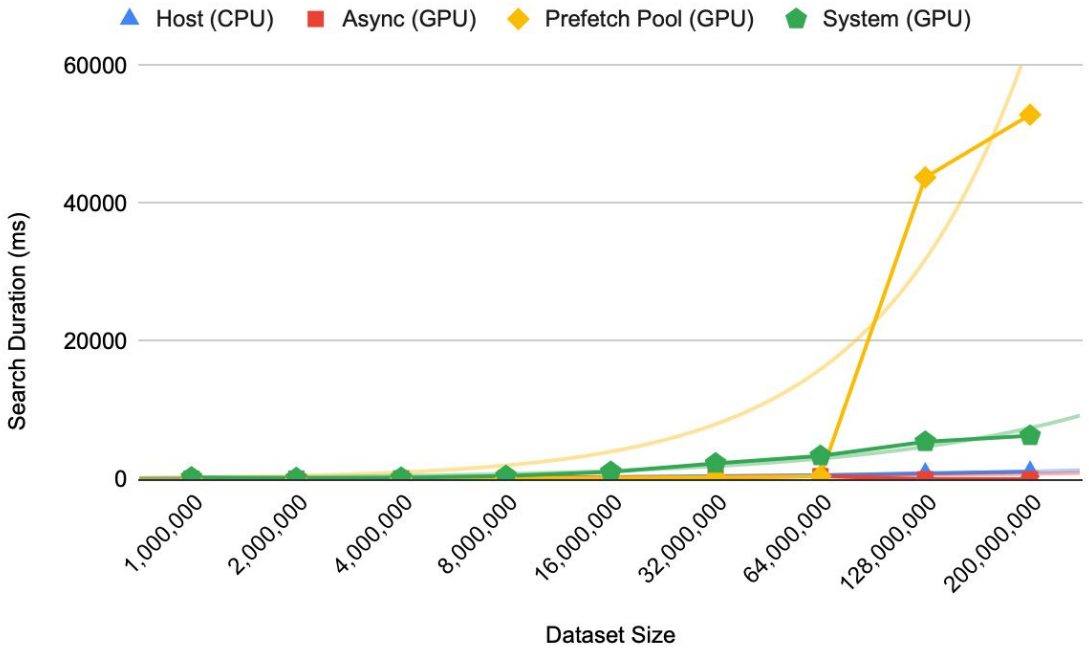

Source: Google Images

# System Memory in Grace Hopper

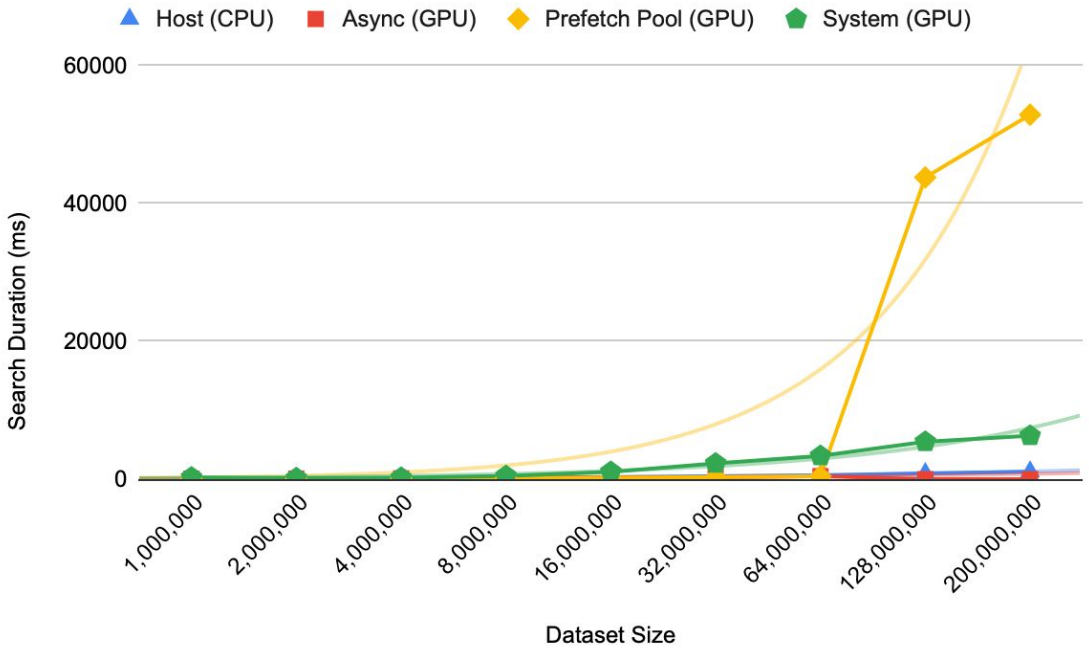



Source: https://arxiv.org/abs/2407.07850

# System Memory >> UVM



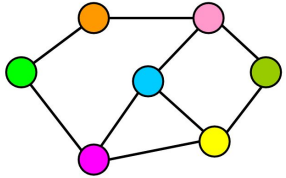
# System Memory >> UVM

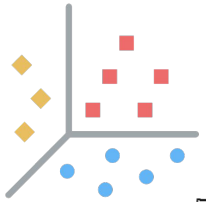



System memory in Grace Hopper scales much better than UVM :)

But system memory is slower in under-subscribed cases :(

# A CPU/GPU Hybrid ANNS System





$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

General Purpose Cores / Accelerators

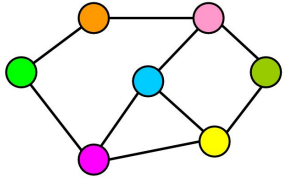
Use a Hybrid Index: Graph (HNSW) + Cluster (IVF)

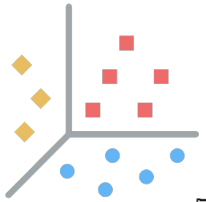
$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

CUDA Cores / Tensor Cores

Source: Google Images

# A CPU/GPU Hybrid ANNS System





$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$


General Purpose Cores / Accelerators

Store / traverse graph layers in CPU memory;

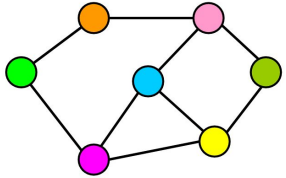
Store / process cluster layer in GPU memory

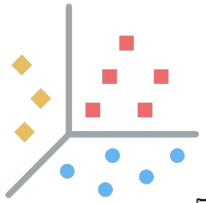
$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

CUDA Cores / Tensor Cores

Source: Google Images

# A CPU/GPU Hybrid ANNS System





$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$


General Purpose Cores / Accelerators

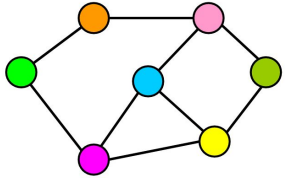
Perform heuristics based prefetching wherever possible

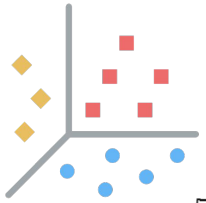
$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

CUDA Cores / Tensor Cores

Source: Google Images

# A CPU/GPU Hybrid ANNS System





$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

General Purpose Cores / Accelerators

**Inter Query Parallelism**:
GP cores, CUDA cores

**Intra Query Parallelism**:
Accelerators, Tensor Cores

CUDA Cores / Tensor Cores

Source: Google Images

# Ongoing Work

CRSS

Researching CPU/GPU collaborative vector search algorithms

Trying out heuristics based prefetching techniques to lessen the UM slowdown

Utilizing hardware accelerators on the CPU and GPU for accelerating distance calculation operations

# Thank You

Questions?

jayjeetc@ucsc.edu

https://jayjeetc.github.io

# Thank you to our sponsors!

CRSS