GPU Databases—The New Modality of Data Analytics

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Outline

GPU hardware trend

Demo of Camelot

GPU database optimizations

- Tile-based execution **(SIGMOD 2020)**
- Data Compression **(SIGMOD 2022)**
- Heterogeneous CPU-GPU DBMS **(VLDB 2022)**
- Accelerating UDF on GPUs **(DaMoN@SIGMOD 2023)**
- Multi-GPU database (on-going)

GPU for SQL Data Analytics

GPU target applications:

- ➢ There are many, many threads
- ➢ Threads perform very similar operations
- ➢ Threads have simple control flow
- ➢ Threads are mostly independent (minimal synchronization)

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What about SQL data analytics???

GPU for SQL Data Analytics

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- ➢There are many, many threads ✓
- ➢Threads perform very similar operations ✓
- ➢Threads have simple control flow ✓
- ➢Threads are mostly independent (minimal synchronization) ✓

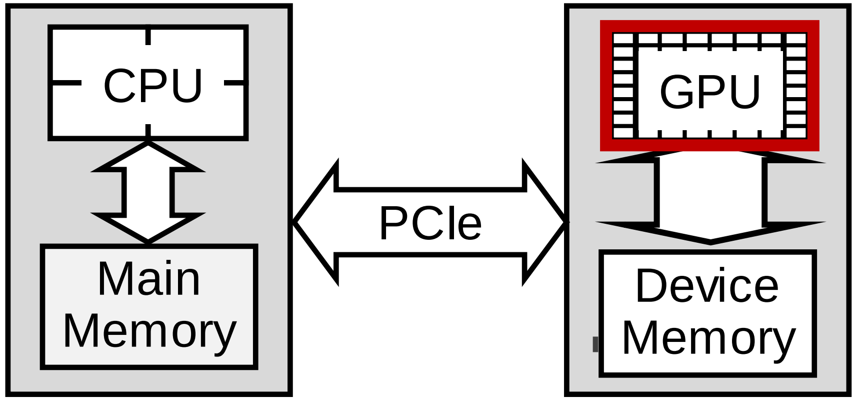
What about SQL data analytics???

GPU is very suitable for SQL data analytics

Running SQL analytics on GPUs can give 10–25x speedup over CPU [1]

[1] Anil Shanbhag, Samuel Madden, Xiangyao Yu, *A Study of the Fundamental Performance Characteristics of GPUs and CPUs for Database Analytics*, **SIGMOD 2020**

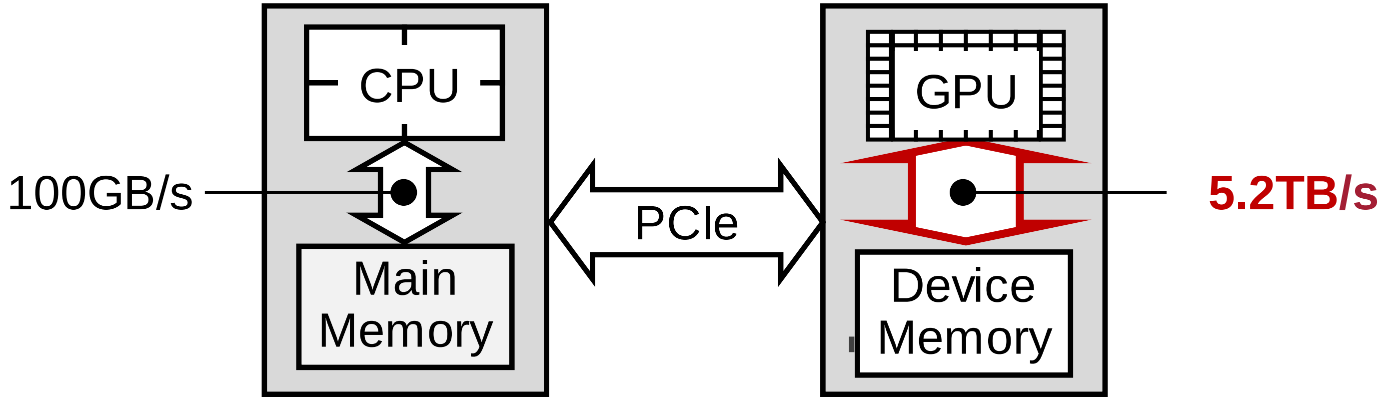
Advantages of GPU for Data Analytics



Advantage 1: **Higher computation power**

- GPU has massive parallelism using SIMT model

Advantages of GPU for Data Analytics

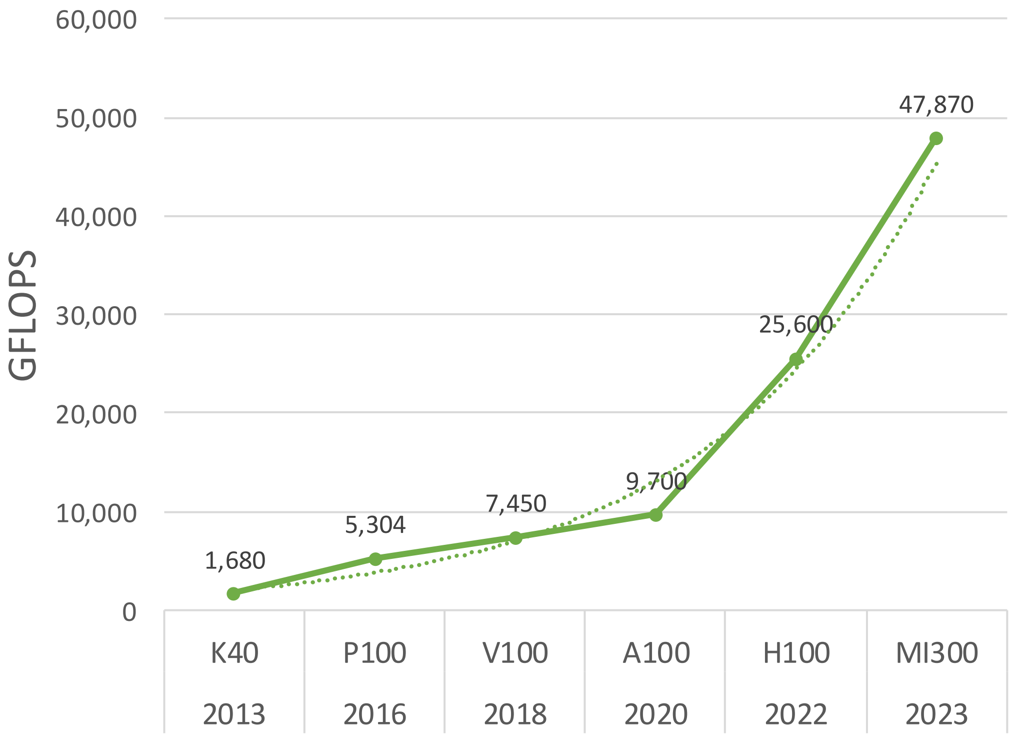


Advantage 1: **Higher computation power**

Advantage 2: **Higher memory bandwidth**

- GPU memory bandwidth is an order-of-magnitude higher than CPU.

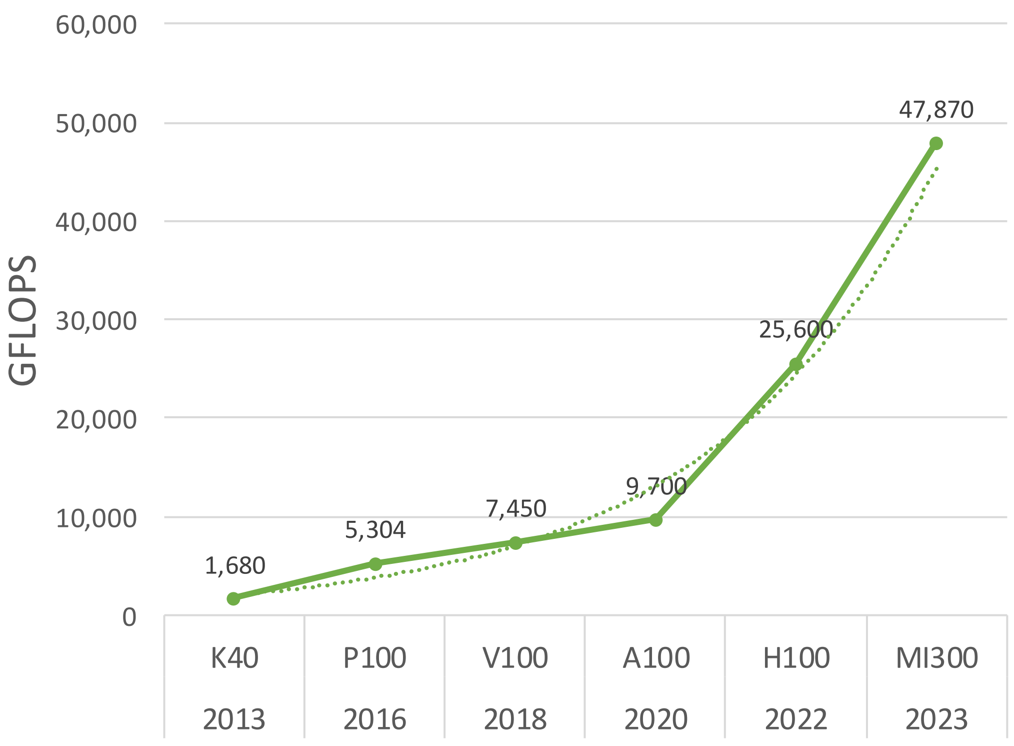
GPU Trend



(a) GPU Peak Performance

GPU **peak performance increase by 5x** from 2020 to 2023**.**

GPU Trend



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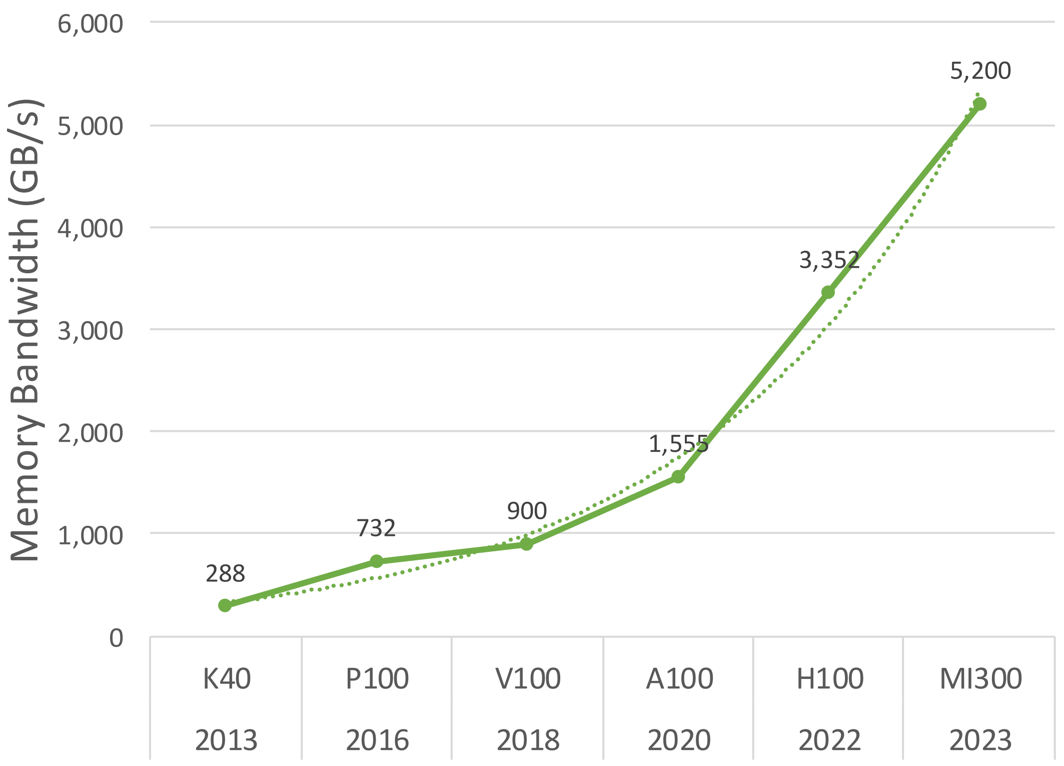
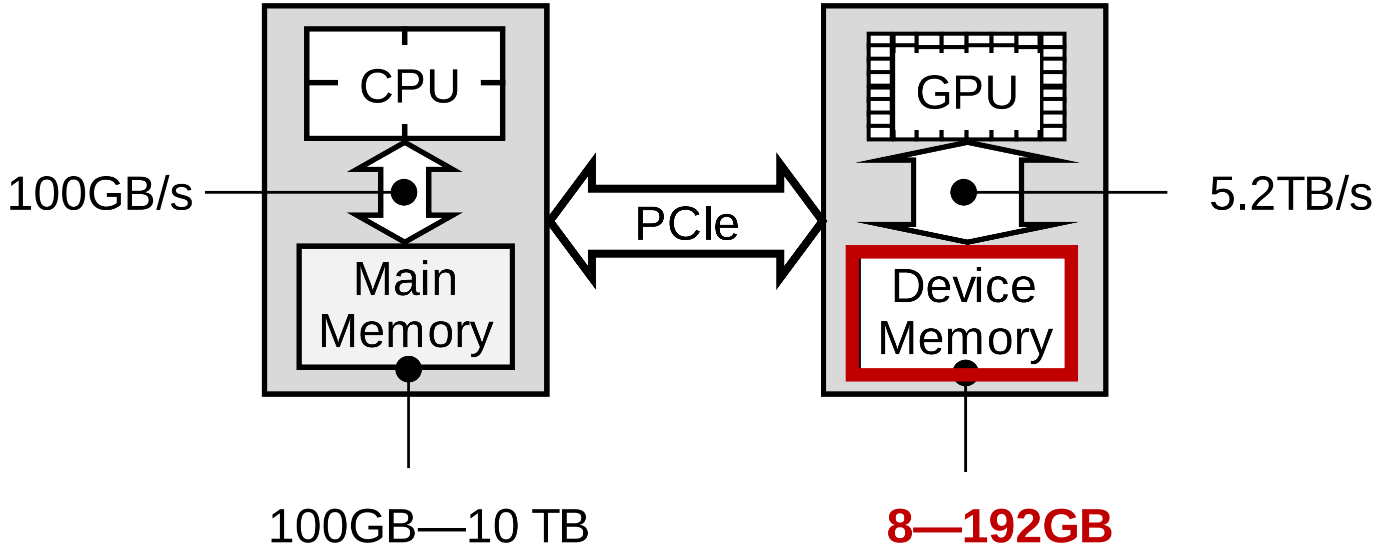


(b) GPU Memory Bandwidth

GPU **peak performance increase by 5x** from 2020 to 2023.

GPU **memory bandwidth increase by 3.5x** from 2020 to 2023.

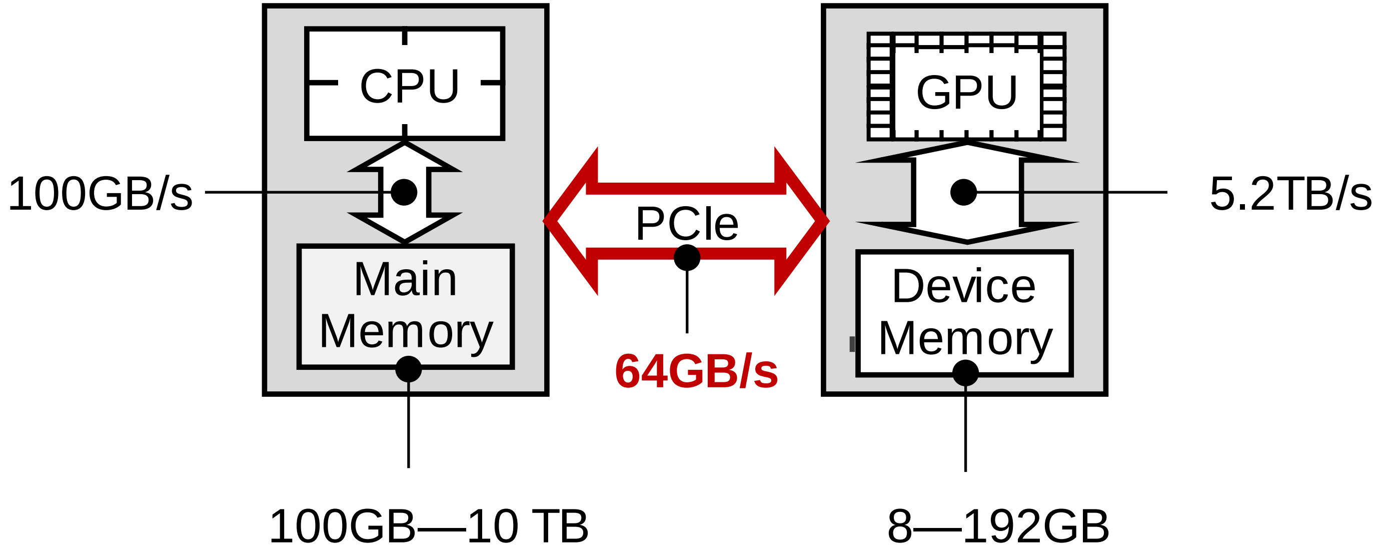
Challenges of GPU for Data Analytics



Challenge 1: **Limited memory capacity**

- Some data sets do not fit in GPU memory

Challenges of GPU for Data Analytics

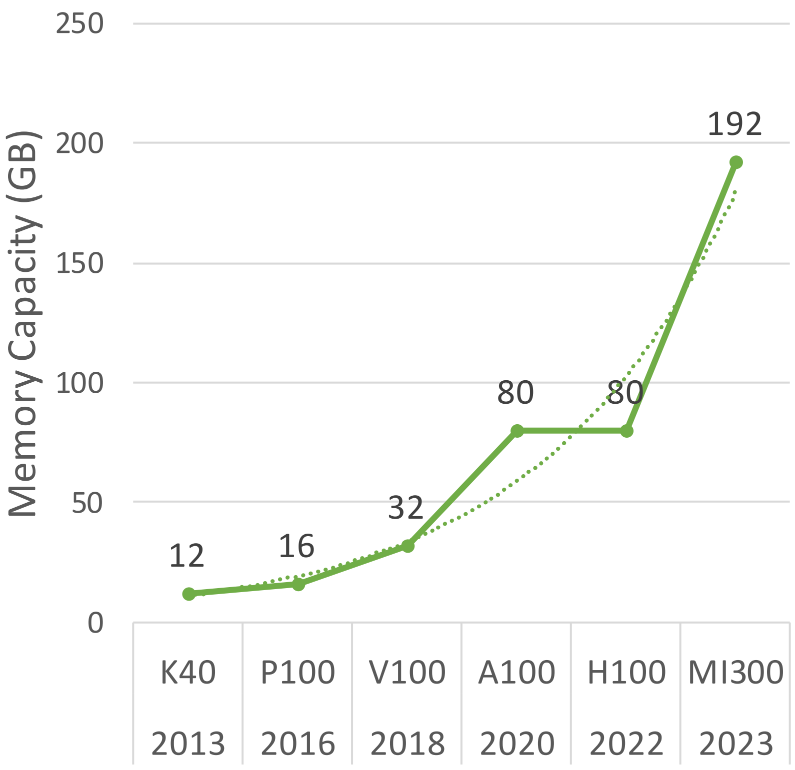


Challenge 1: **Limited memory capacity**

Challenge 2: **Limited interconnect bandwidth**

- Transferring data from CPU can be expensive

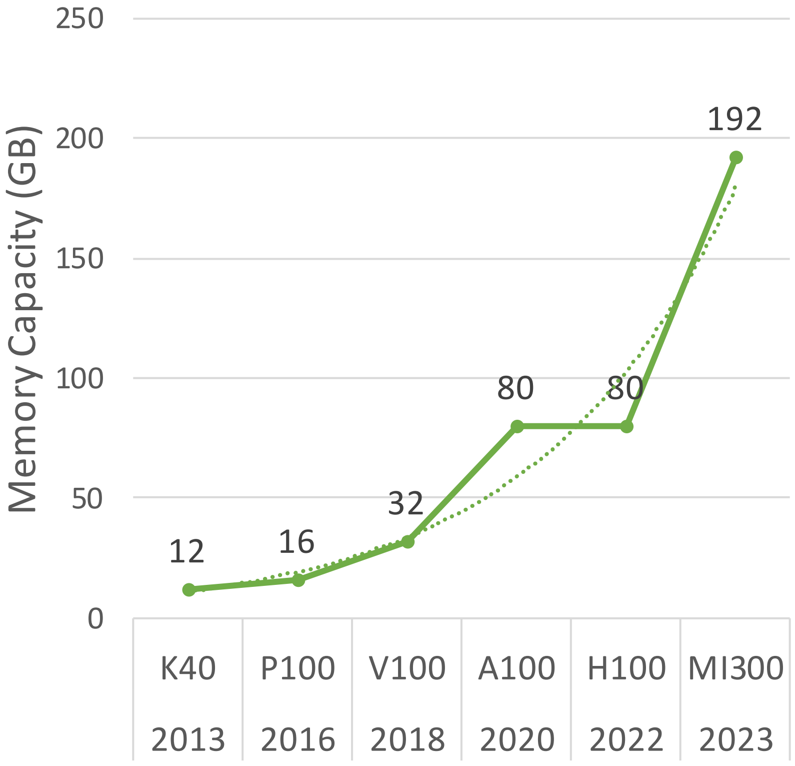
GPU Trend



(a) GPU Memory Capacity

GPU **memory capacity increase by 6x** in the last 5 years**.**

GPU Trend



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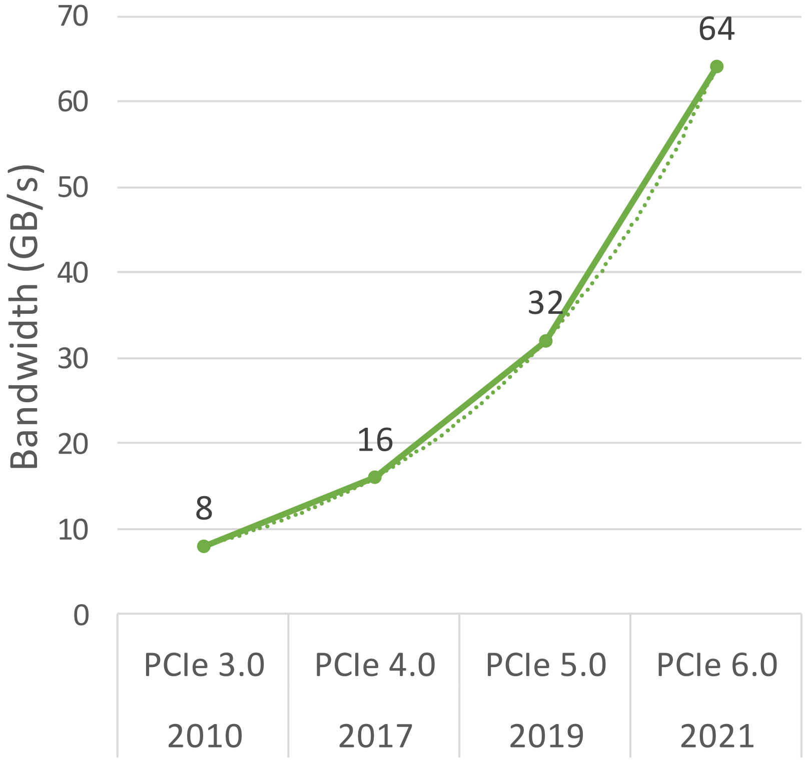

(b) PCIe Bandwidth

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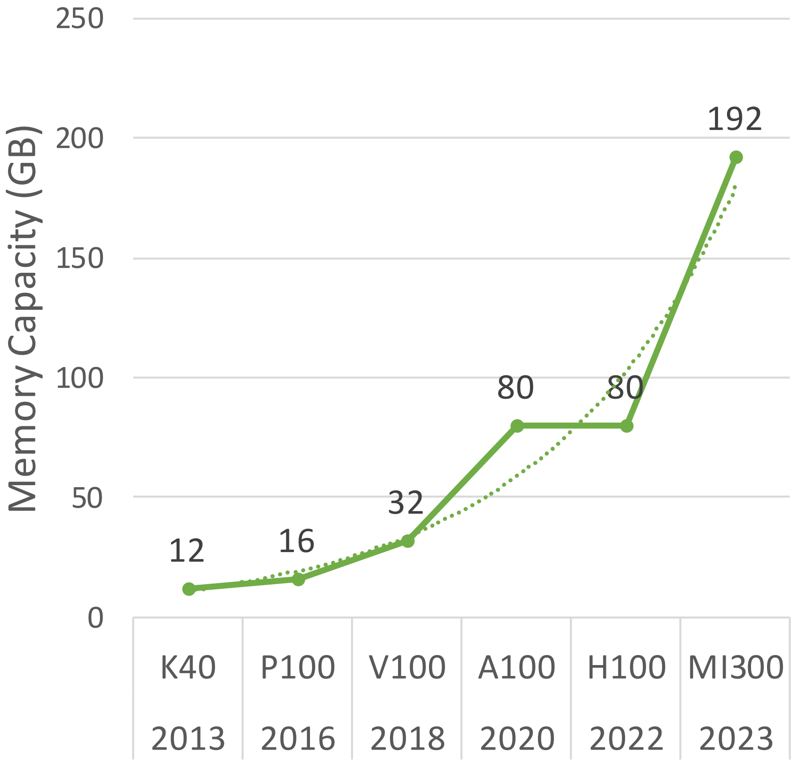
PCIe **increase by 2x** every two years.

GPU Trend



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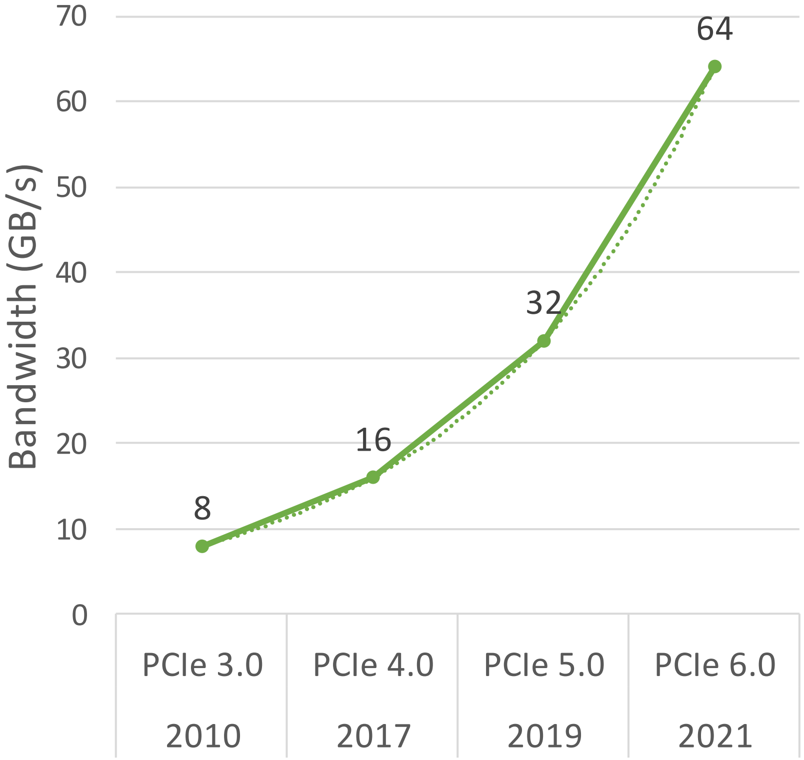

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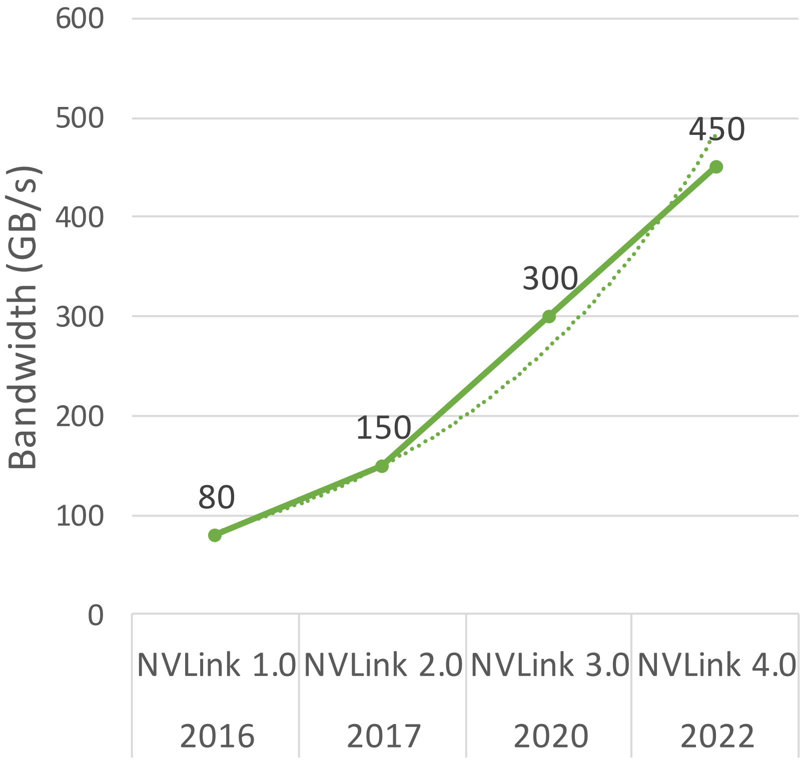
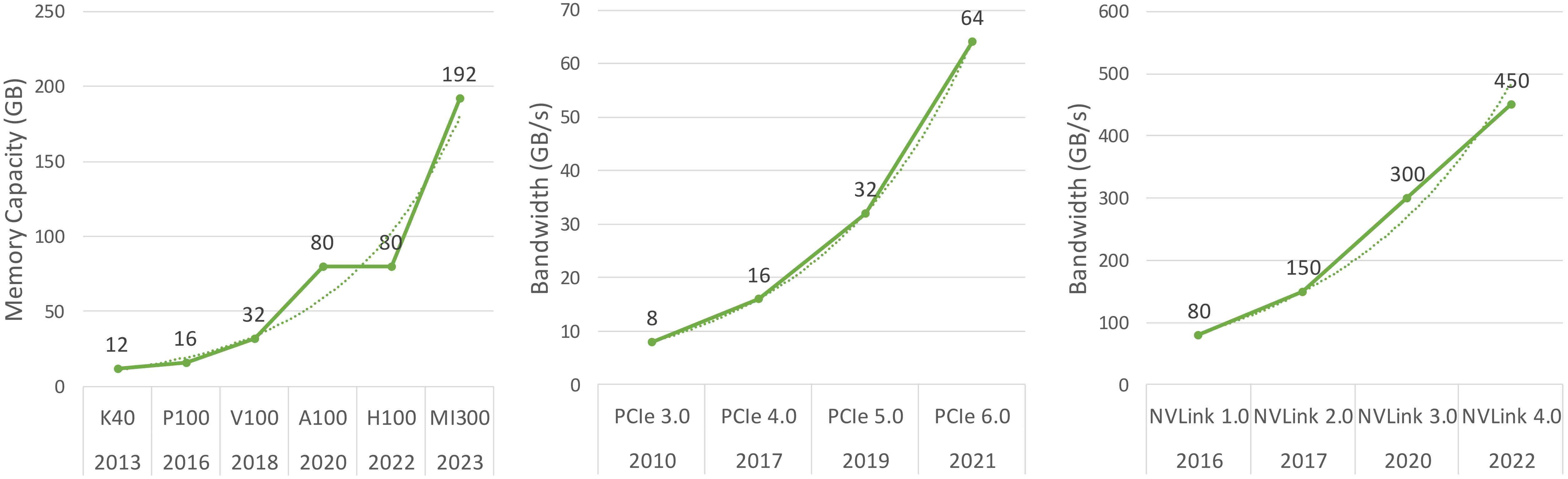


(c) NVLink Bandwidth

GPU **memory capacity increase by 6x** in the last 5 years**.**
PCIe **increase by 2x** every two years.
NVLink Bandwidth **increase by 3x in 5 years.**

GPU Trend



(a) GPU Memory Capacity **(b) PCIe Bandwidth** **(c) NVLink Bandwidth**

GPU **memory capacity increase by 6x** in the last 5 years**.**

PCIe **increase by 2x** every two years.

NVLink Bandwidth **increase by 3x in 5 years.**

NVLink C2C (2022) connect NVIDIA GPU and NVIDIA CPU **(450 GB/s).**

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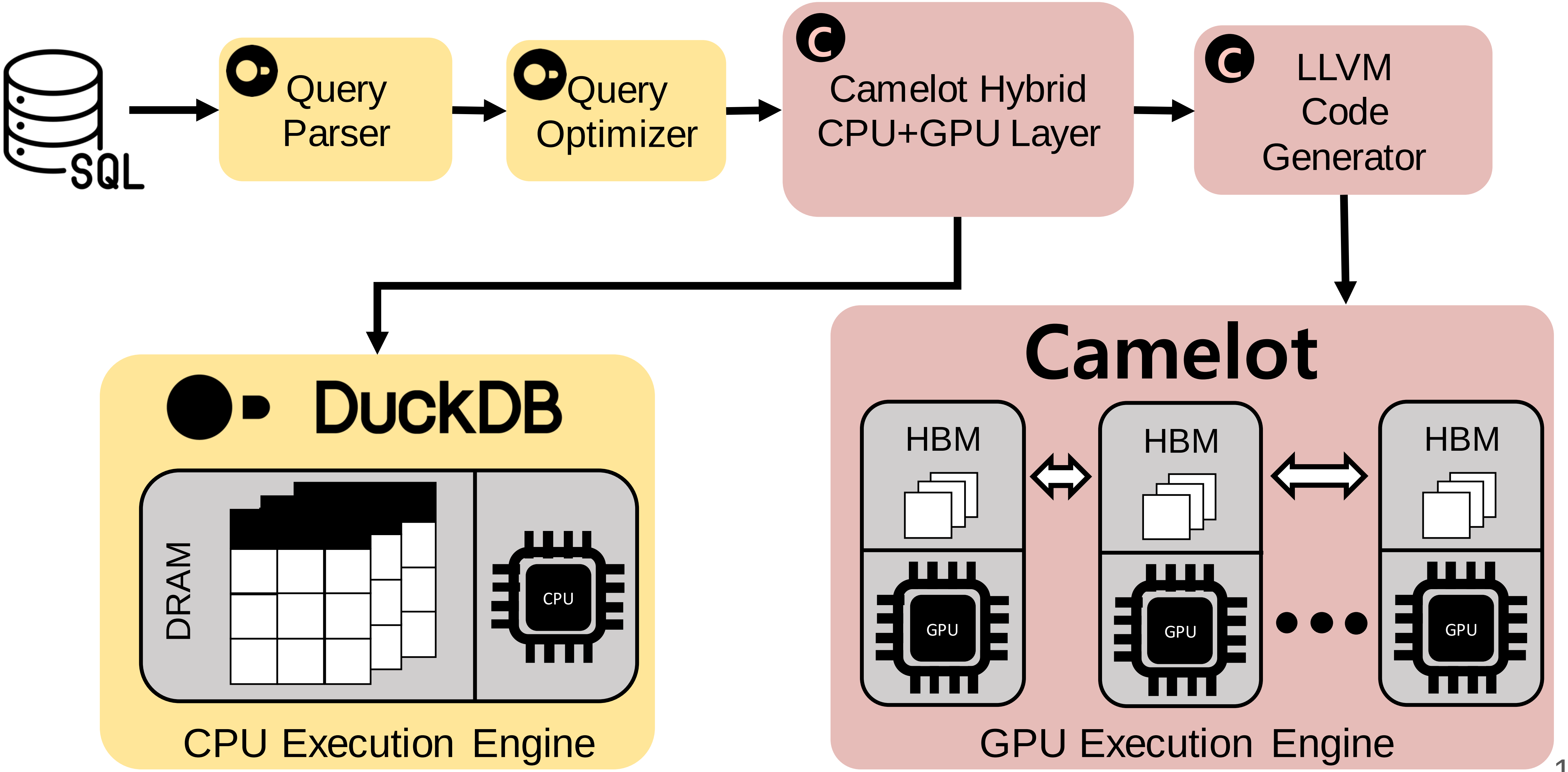
Camelot v0.1 → Demo!



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GPU Database Optimizations

Thrust 1: Enabling **Large-Scale** Data Analytics on GPUs

- Crystal: tile-based execution **(SIGMOD 2020[1])**
- Data Compression **(SIGMOD 2022[2])**
- Heterogeneous CPU-GPU DBMS **(VLDB 2022[3])**
- Multi-GPU DBMS (ongoing)

Thrust 2: Enhancing the **Practicality** of GPU Databases

- Accelerating UDF on GPUs **(DaMoN@SIGMOD 2023[4])**
- Code Generation for GPU DBMS (ongoing)

[1] Anil Shanbhag, Samuel Madden, Xiangyao Yu. *A Study of the Fundamental Performance Characteristics of GPUs and CPUs for Database Analytics*, **SIGMOD 2022**
[2] Anil Shanbhag*, Bobbi Yogatama*, Xiangyao Yu, and Samuel Madden. *Tile-based Lightweight Integer Compression in GPU*, **SIGMOD 2022**
[3] Bobbi Yogatama, Weiwei Gong, Xiangyao Yu. *Orchestrating data placement and query execution in heterogeneous CPU-GPU DBMS*, **VLDB 2022**
[4] Bobbi Yogatama et al. *Accelerating User-Defined Aggregate Functions with Block-wide Execution and JIT Compilation on GPUs*, **DaMoN@SIGMOD 2023**

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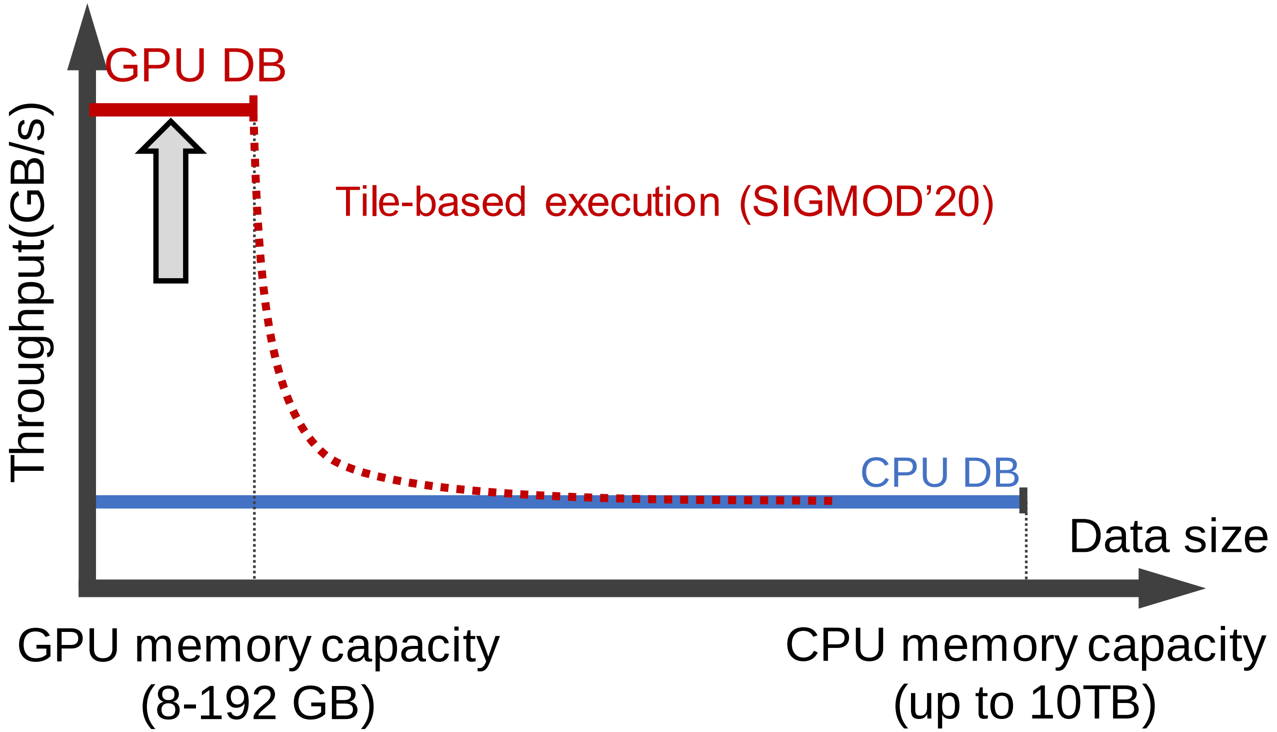
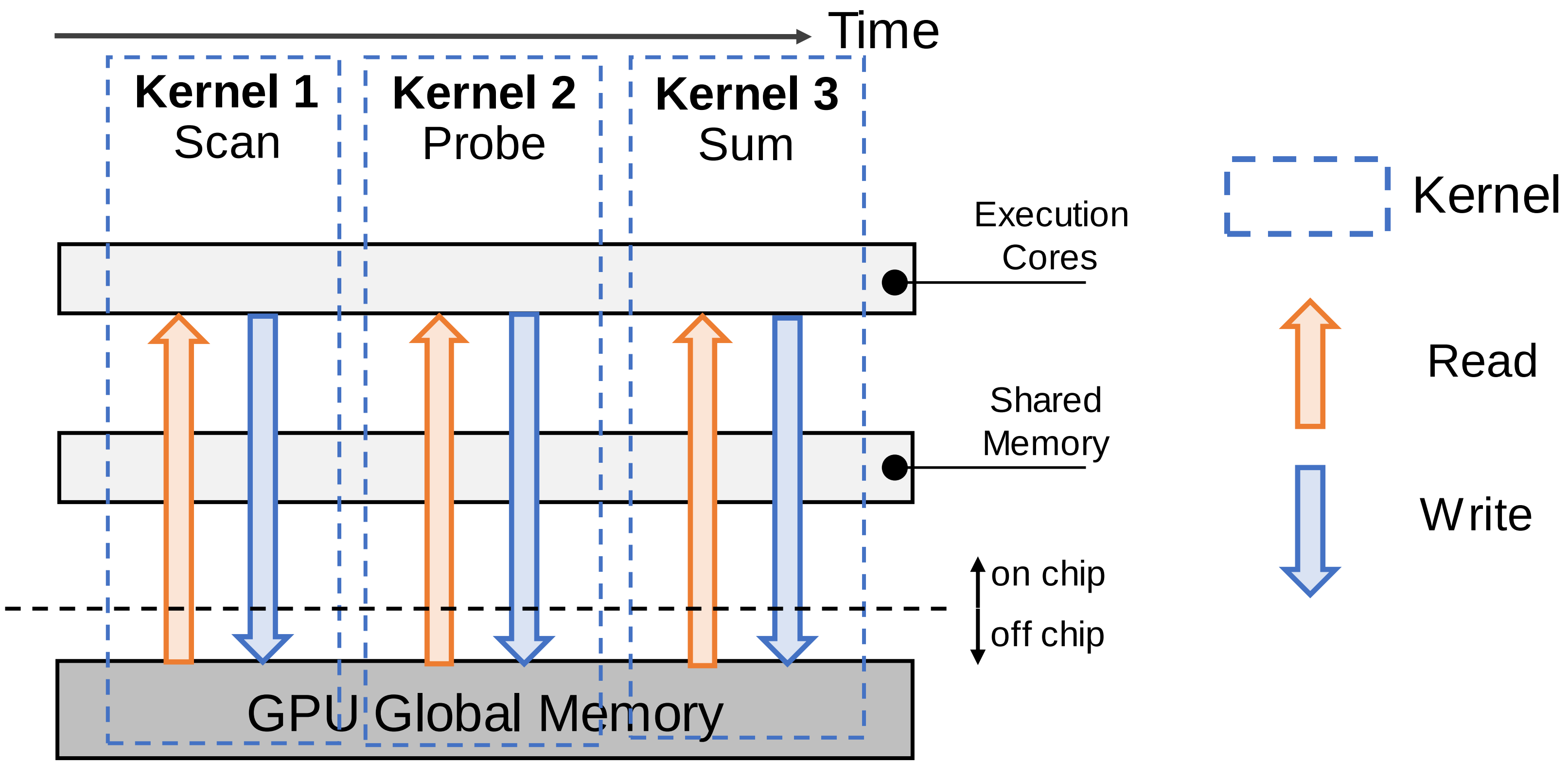


Crystal Library: Tile-Based Execution Model

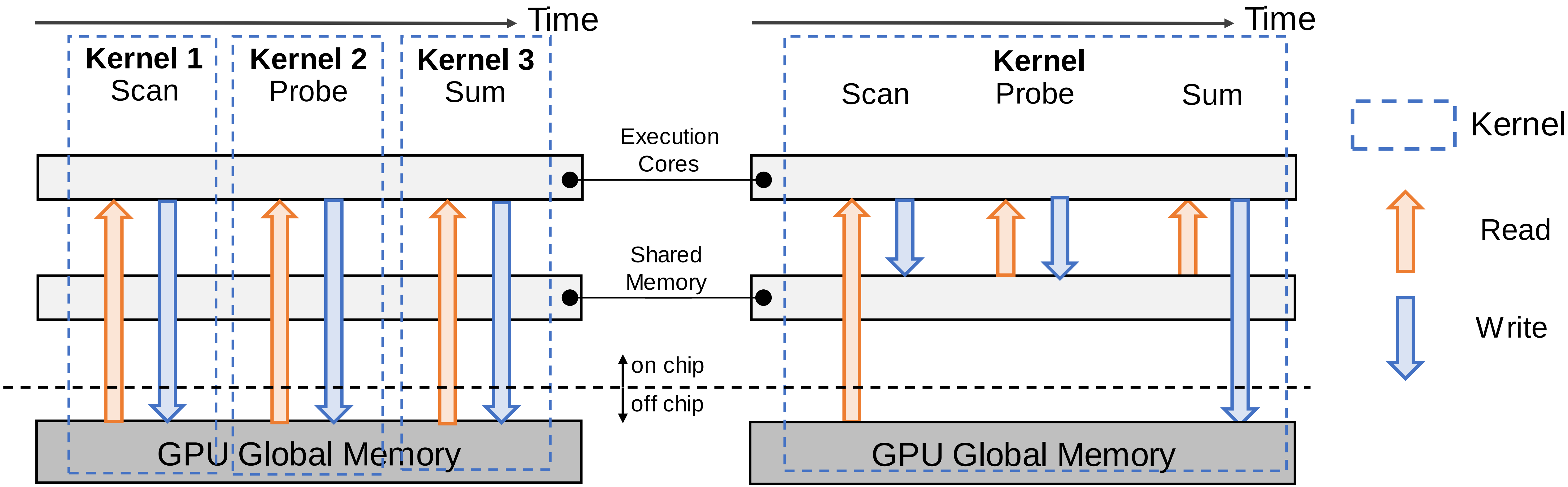
Problem: Conventional execution model incurs excessive memory traffic for reading/writing intermediate results



(a) Conventional execution model

Crystal Library: Tile-Based Execution Model

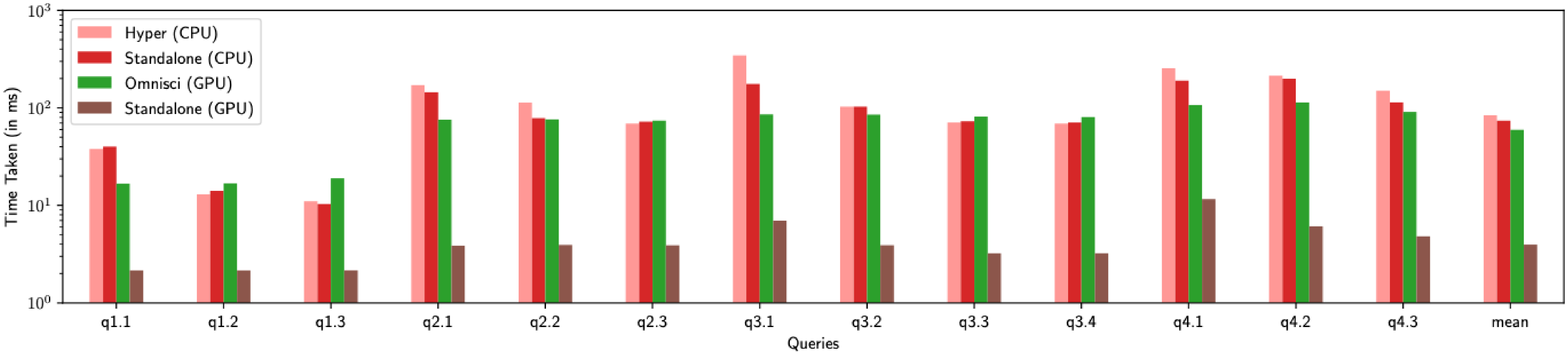
Key Idea: Partition data into small tiles and store intermediate results in the shared memory (~10x faster)



(a) Conventional execution model

(b) Tile-based execution model

Experimental Results



With Crystal, GPU is on average **25X** faster than CPU running Star-Schema Benchmark (SSB).

Hardware: NVIDIA V100 GPU. Intel i7-6900 CPU (8 cores)
Benchmark: Star Schema Benchmark (SF = 20).

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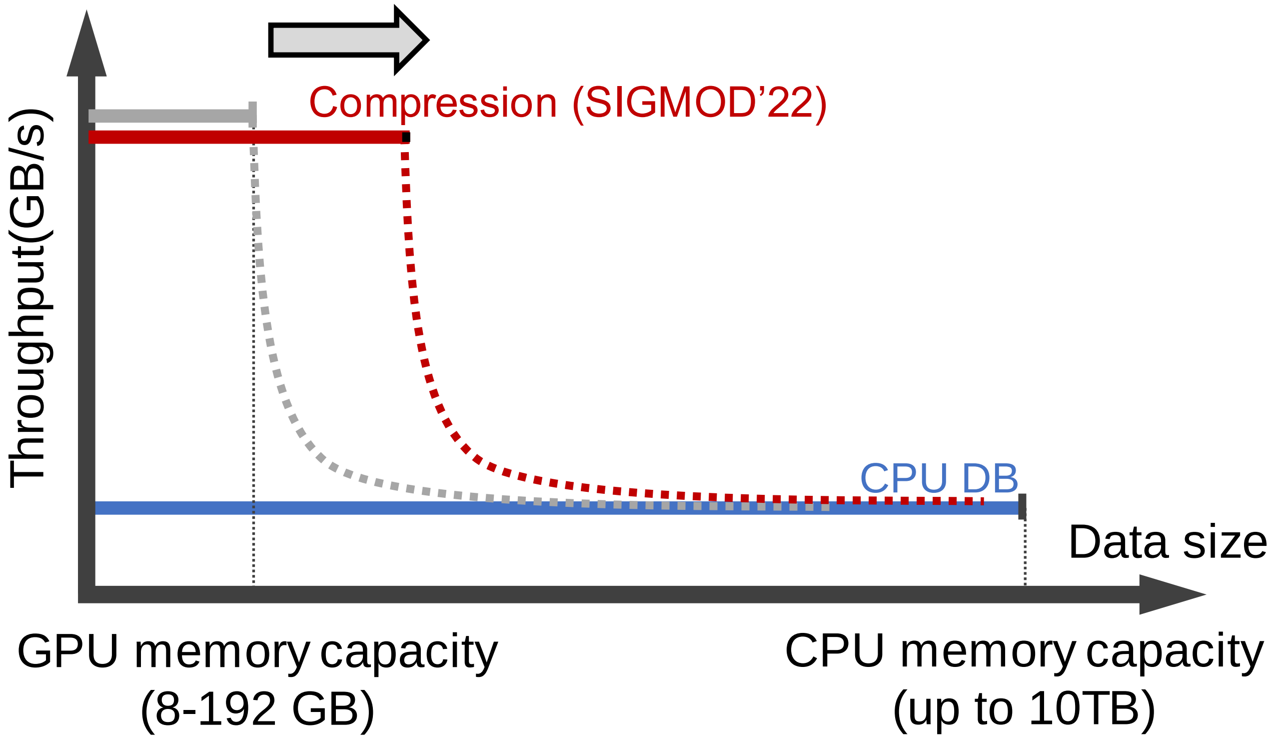
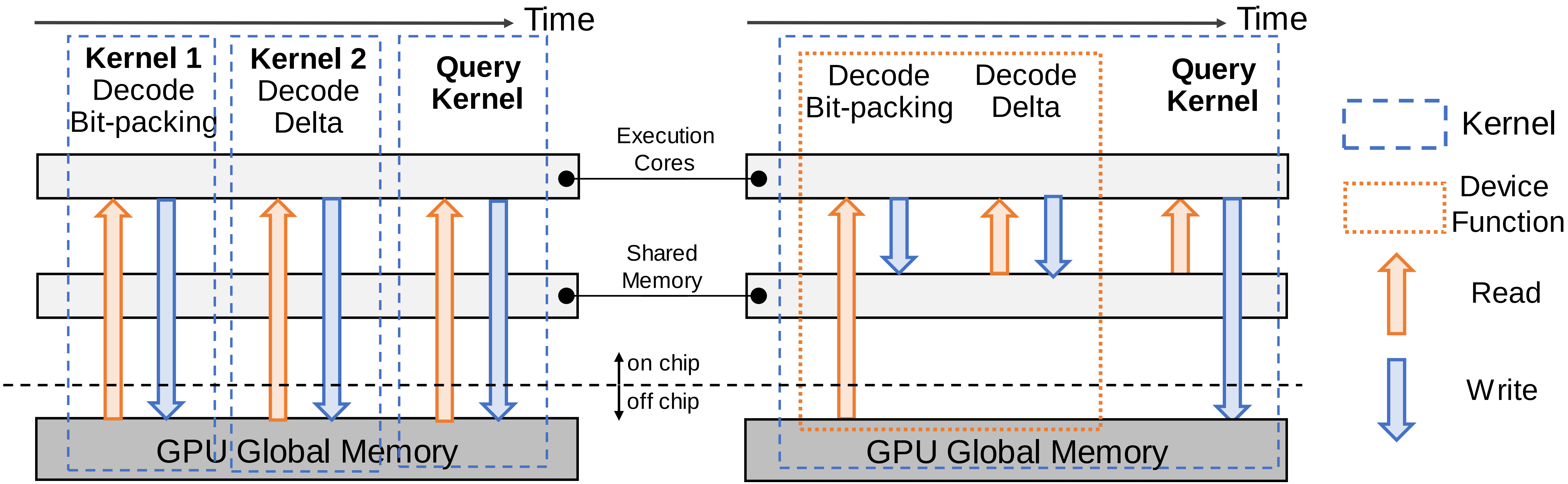


Idea 1: Tile-Based Decompression

Tile-based execution to keep intermediate results in shared memory



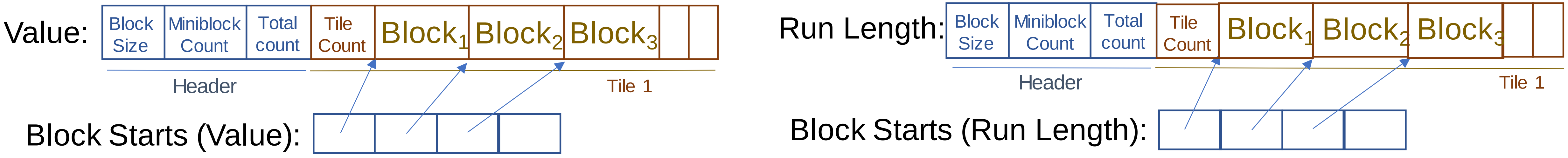
(a) Conventional decompression model

(b) Tile-based decompression model

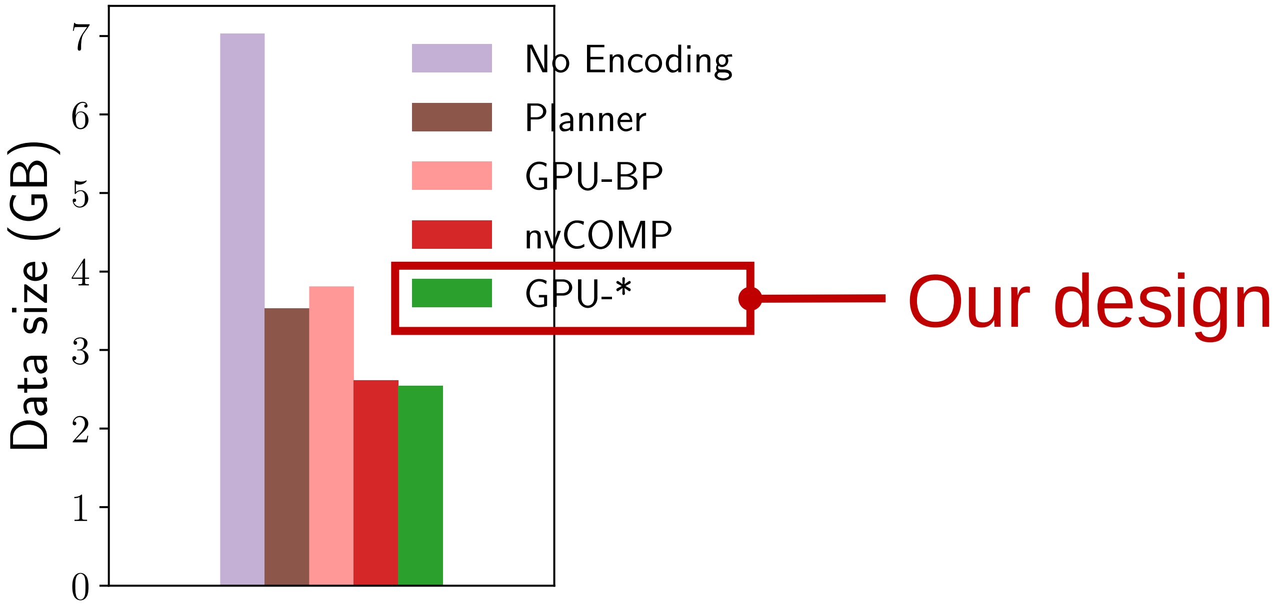
Idea 2: GPU-Optimized Compression Format

Compact data format that can **fully saturates GPU memory bandwidth** during decompression

- **GPU-FOR**: Frame of Reference + **Bit-Packing**
- **GPU-DFOR**: **Delta encoding** + Frame of Reference + **Bit-Packing**
- **GPU-RFOR**: **Run-length encoding** + Frame of Reference + **Bit-Packing**



GPU Data Compression – Evaluation



(a) Compressed data size

Compression rate comparable to the best-previous scheme (i.e. nvCOMP)

Hardware: NVIDIA V100 GPU.
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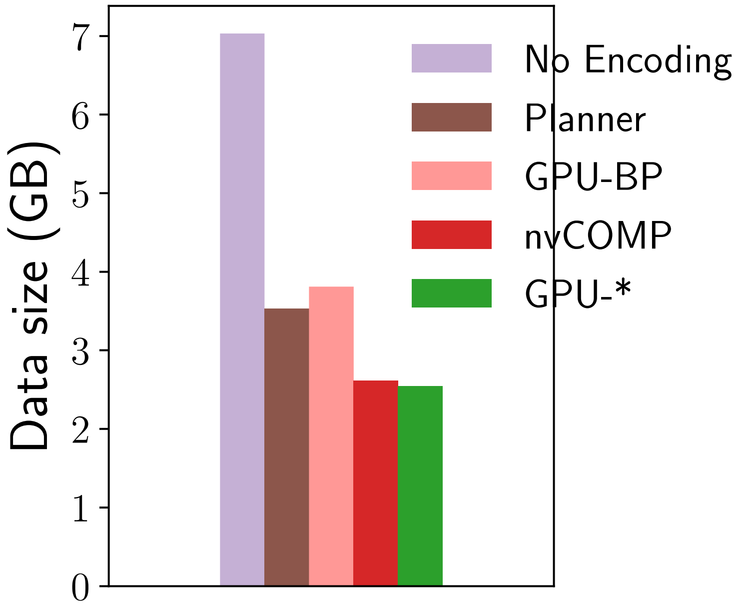

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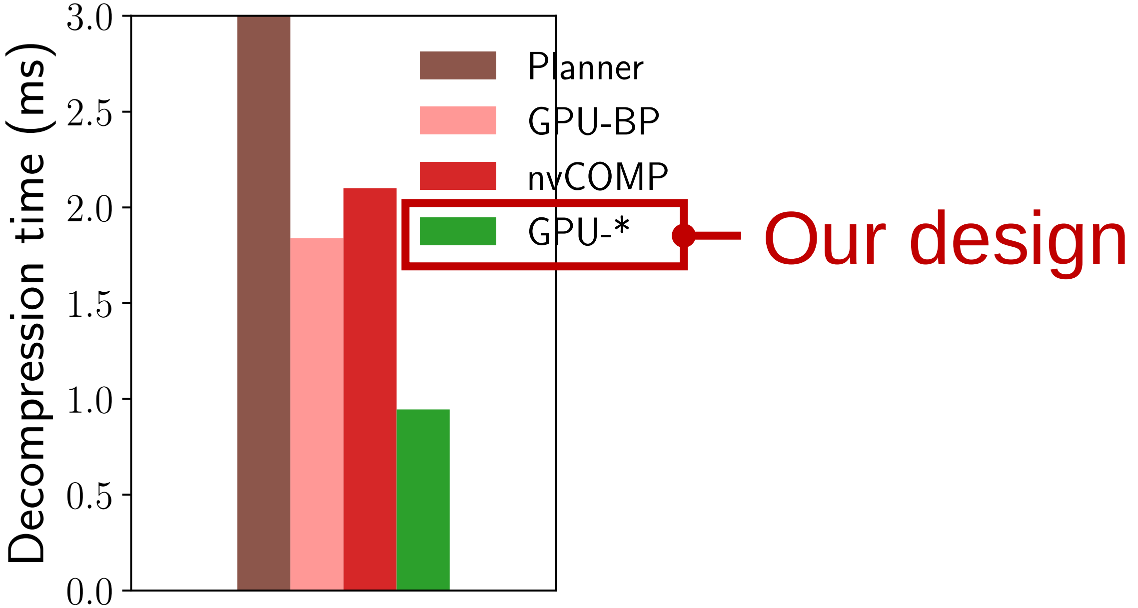

(b) Decompression time

Compression rate comparable to the best-previous scheme (i.e. nvCOMP)

Decompression time is 2.2x faster than the best-previous scheme

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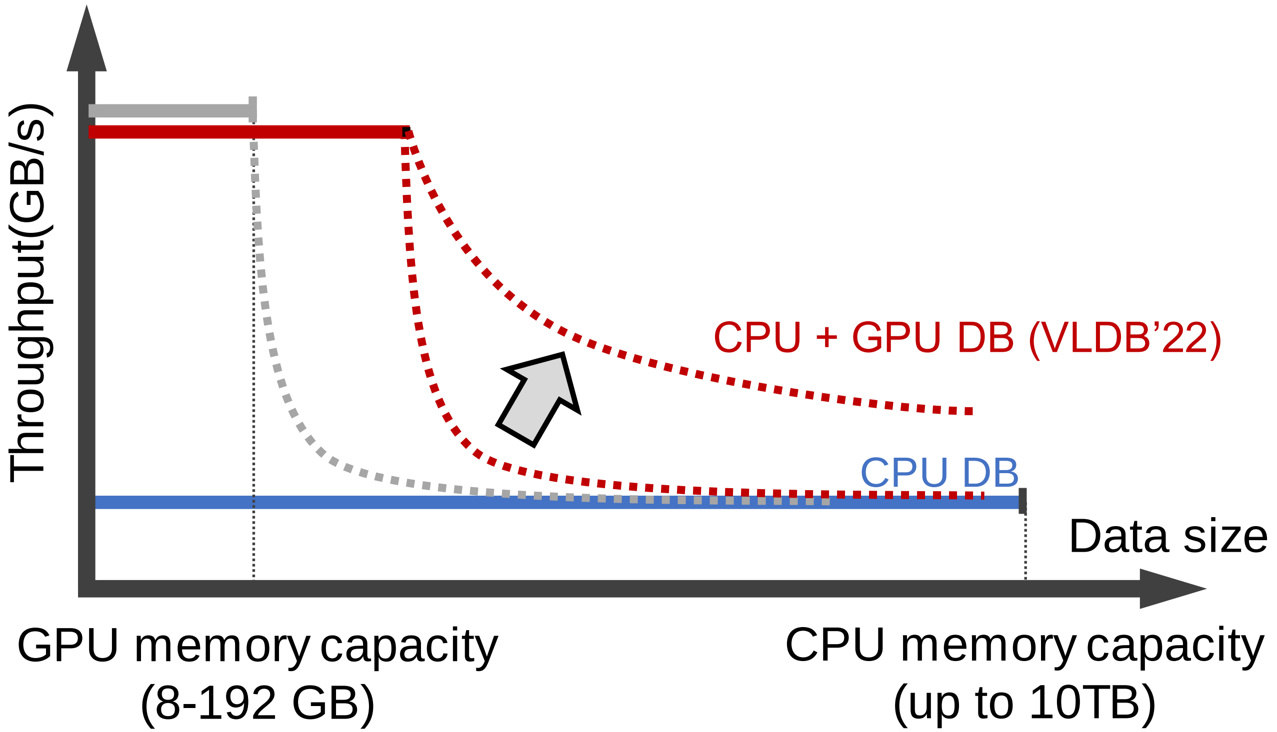

Challenges in Heterogeneous CPU-GPU Model

We aim to answer the **existing challenges** in heterogeneous CPU-GPU DBMS:

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We treat data placement as a **caching problem** → the complete data set resides in CPU memory and a mirrored subset of data is **cached** in GPU.

Key design decision: **cache replacement policy**?

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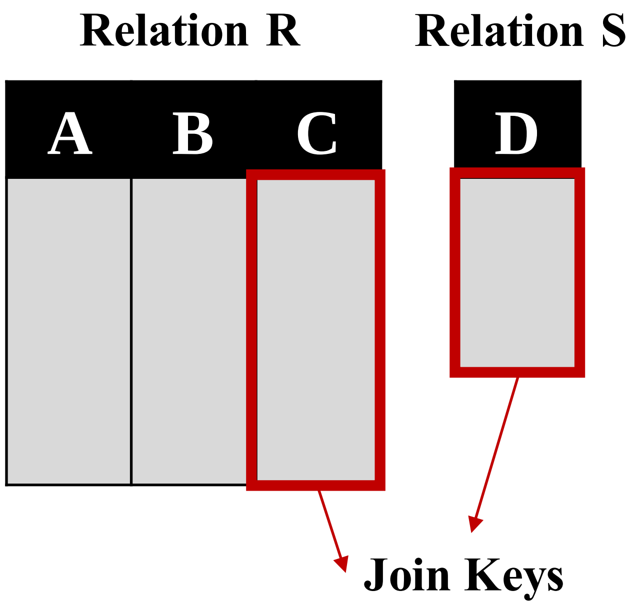

Data Placement

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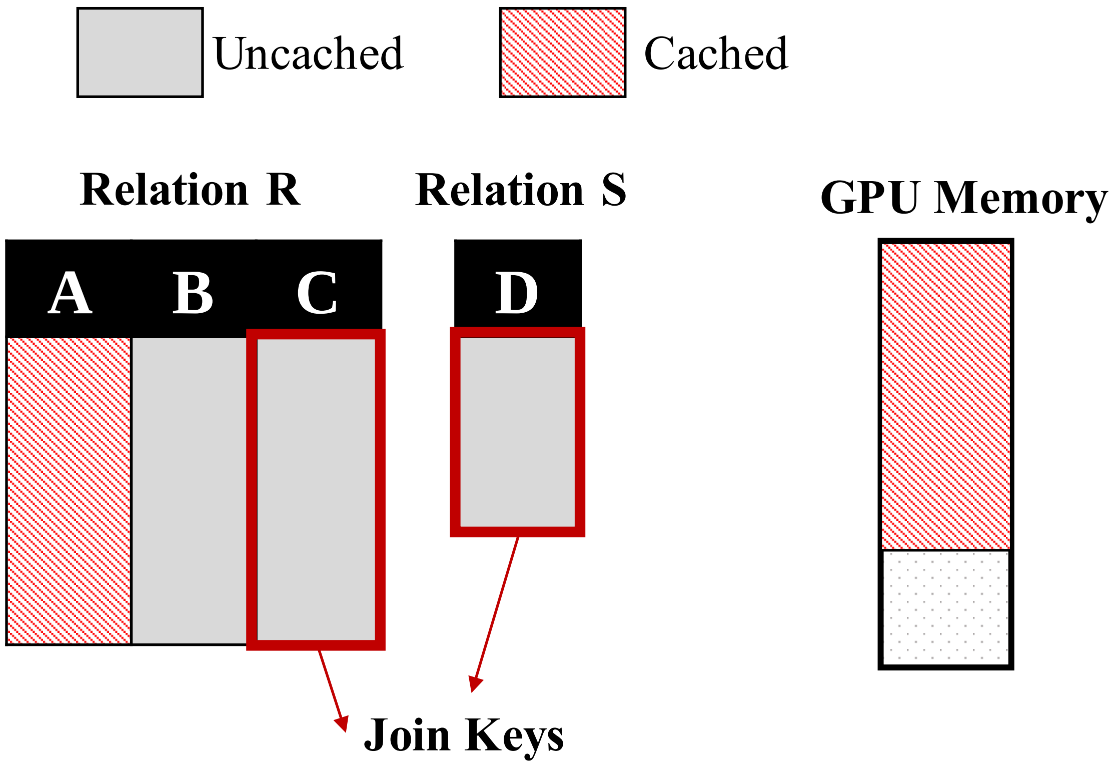
Previous works did a **column-granularity frequency-based/timestamp-based** policy.



(a) Coarse-grained caching (LFU/LRU)[2]

[2] Sebastian Breß, Henning Funke, and Jens Teubner. *Robust Query Processing in Co-Processor-Accelerated Databases*, **SIGMOD 2016.**

Data Placement

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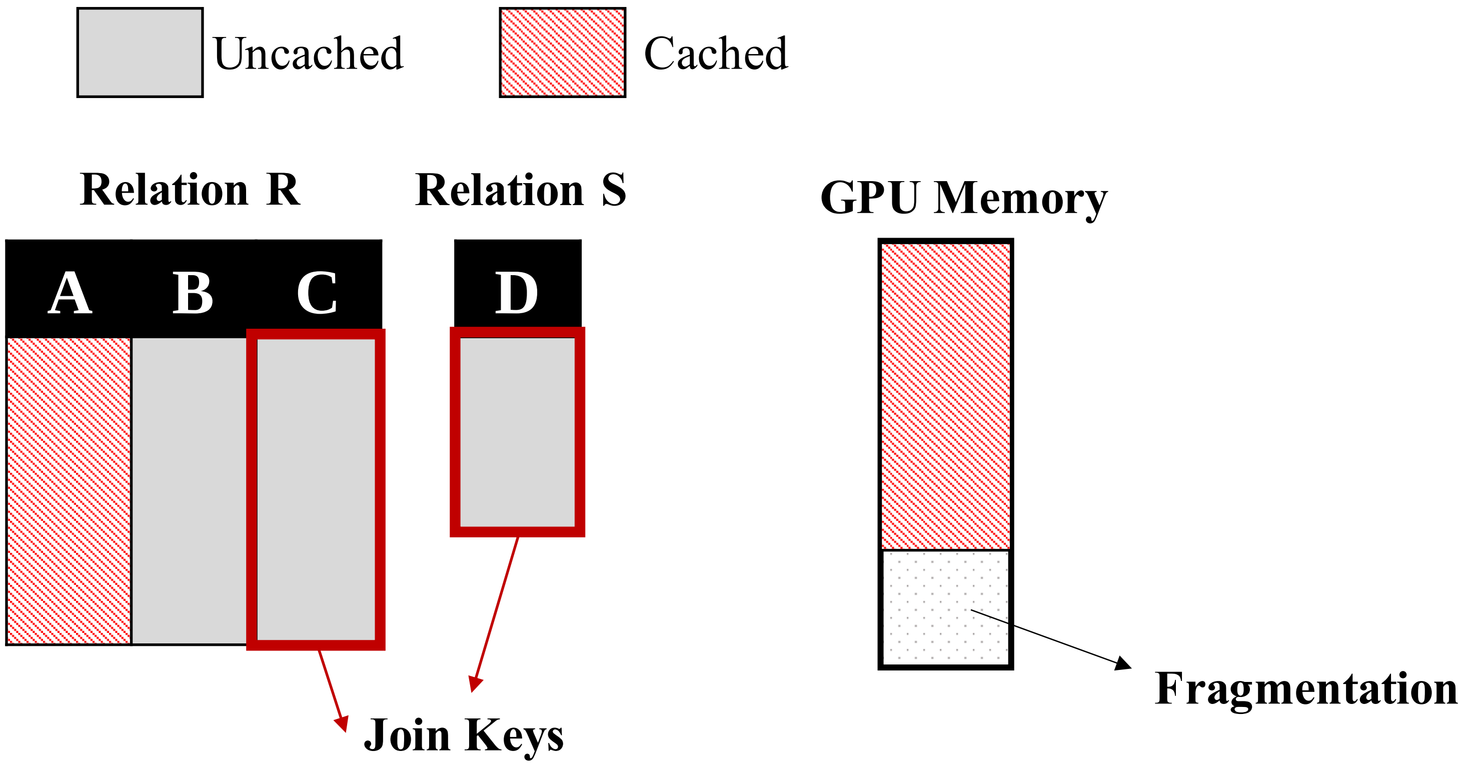
Limitation: Fragmentation



(a) Coarse-grained caching (LFU/LRU)

Data Placement

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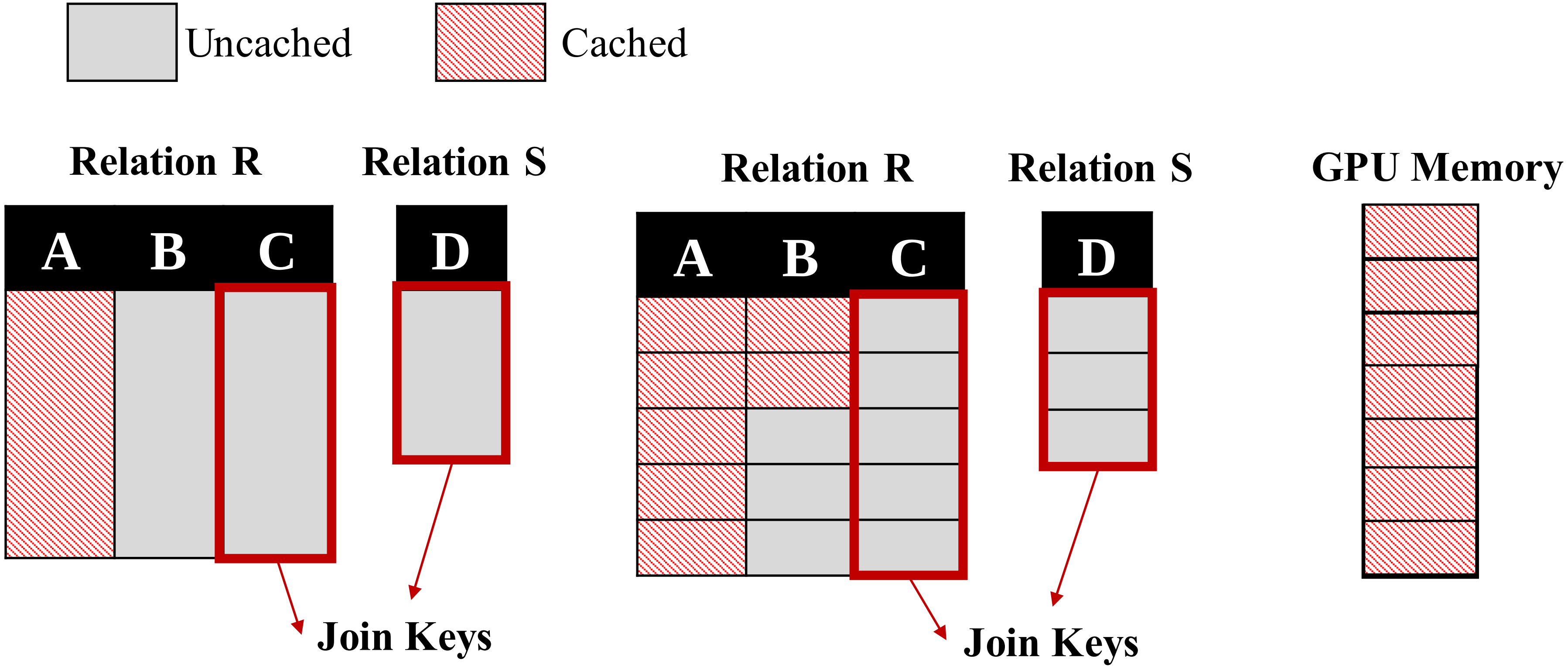
A sub-column (segment) **fine-grained** policy can improve caching efficiency.



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[3] Todd Mostak. *An Overview of MapD (Massively Parallel Database)*.

Data Placement

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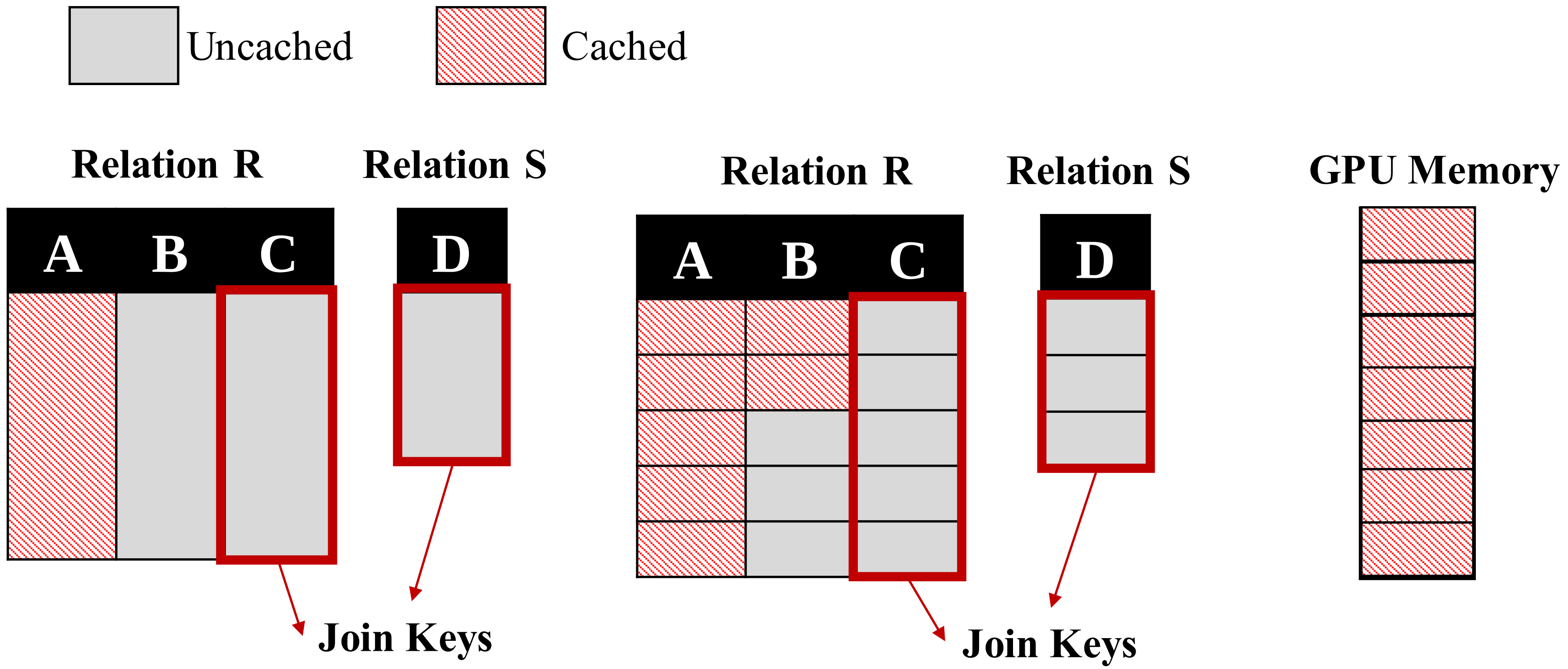
Limitation: unaware of **query semantic**.



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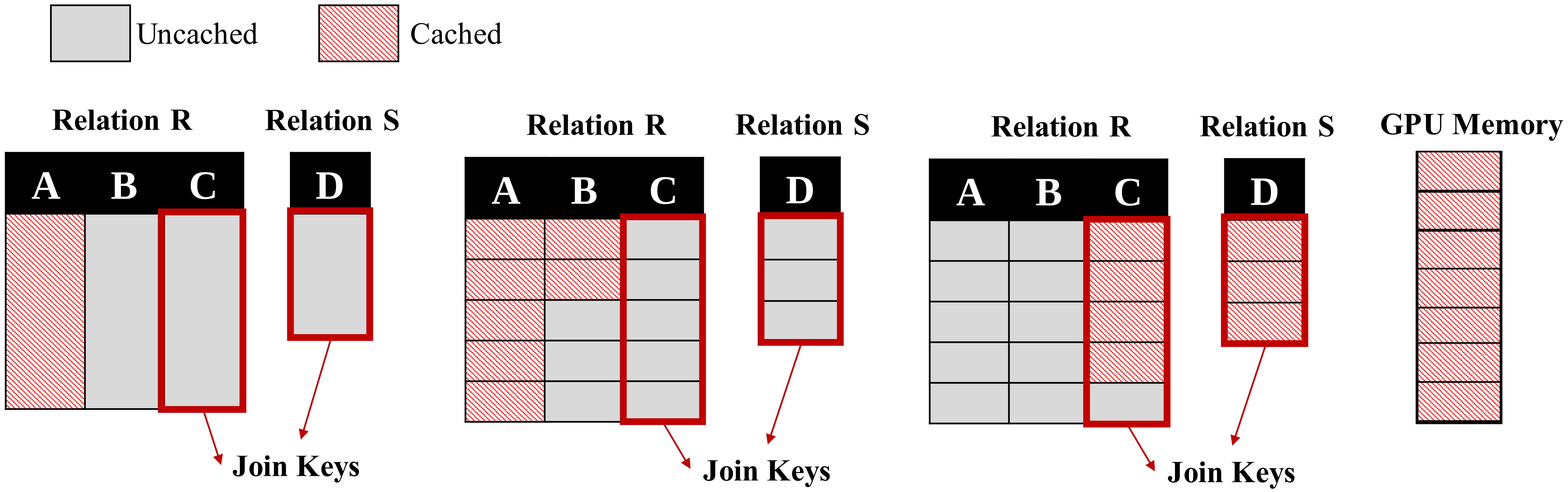
Semantic-aware replacement leads to better performance.



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Semantic-Aware Fine-Grained Caching

Extend conventional LFU with **weighted frequency counters.**

Weight reflects the potential **benefits of caching the segments** and is derived using cost model.

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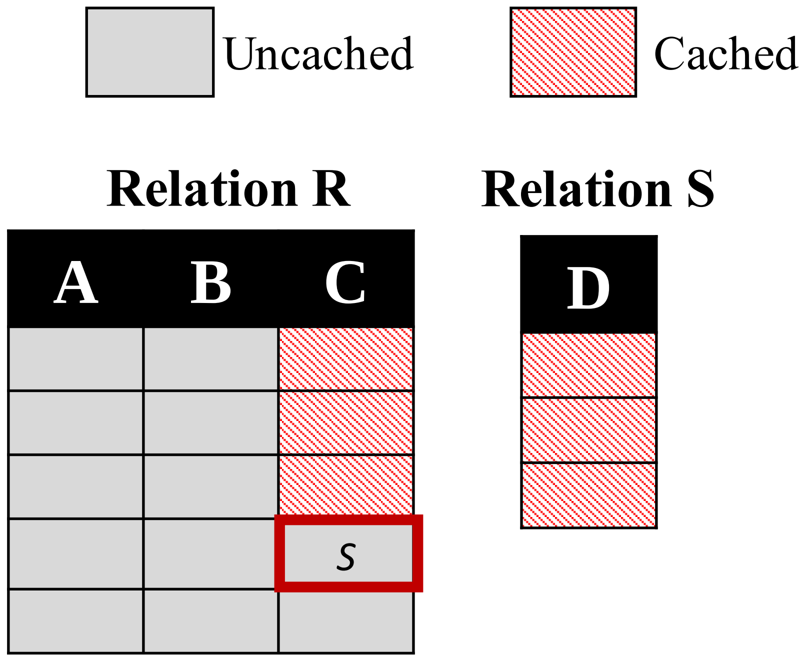

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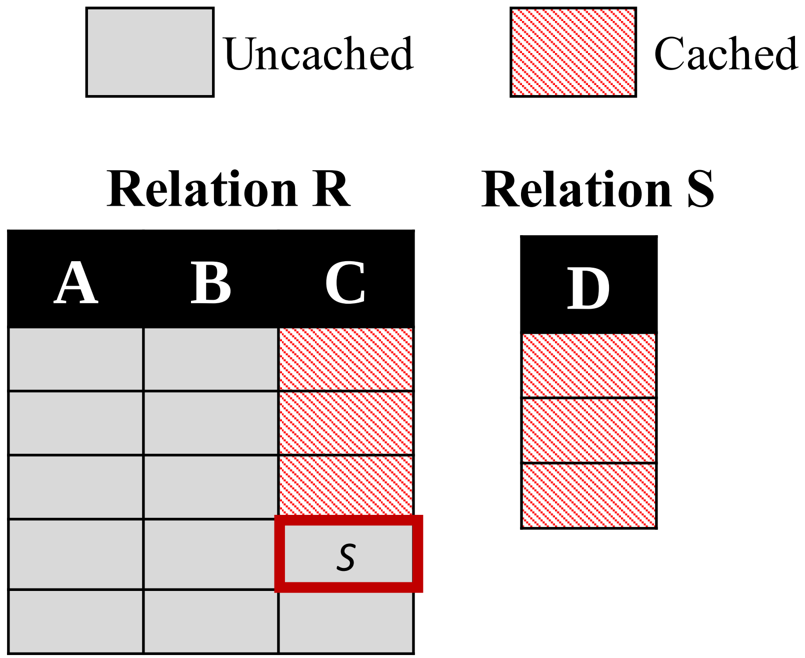

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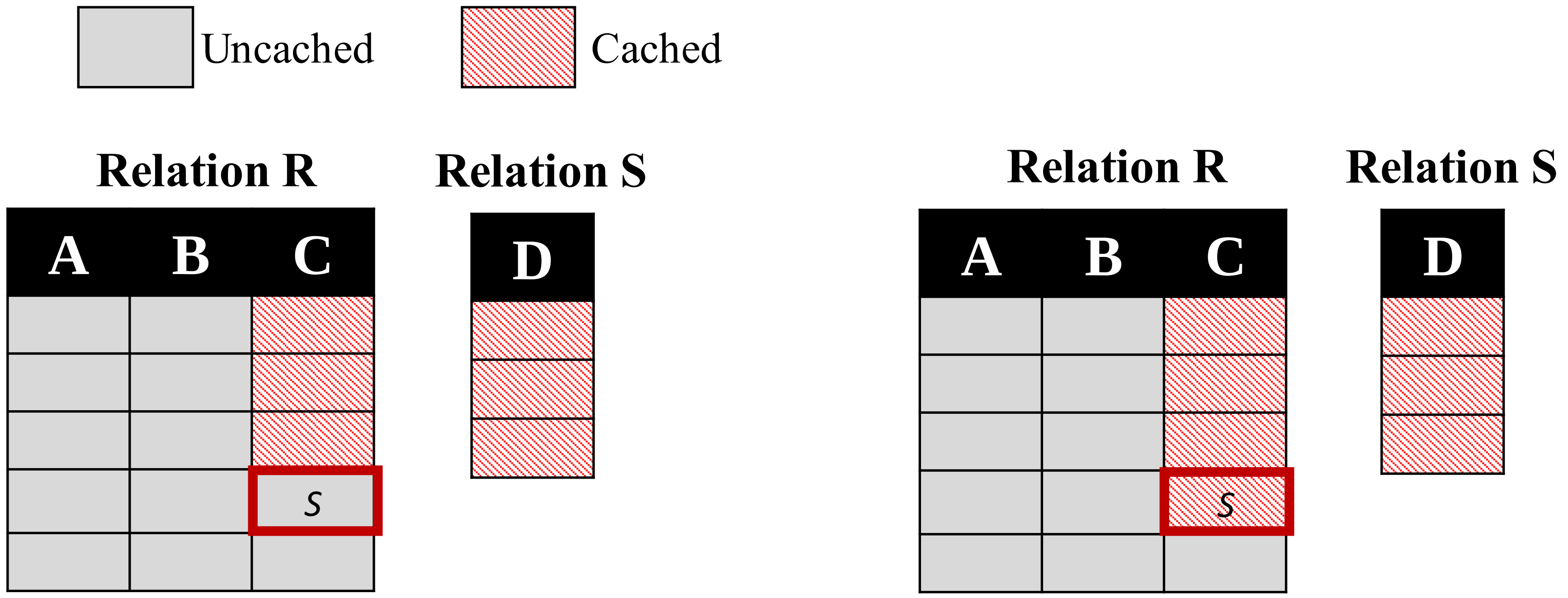

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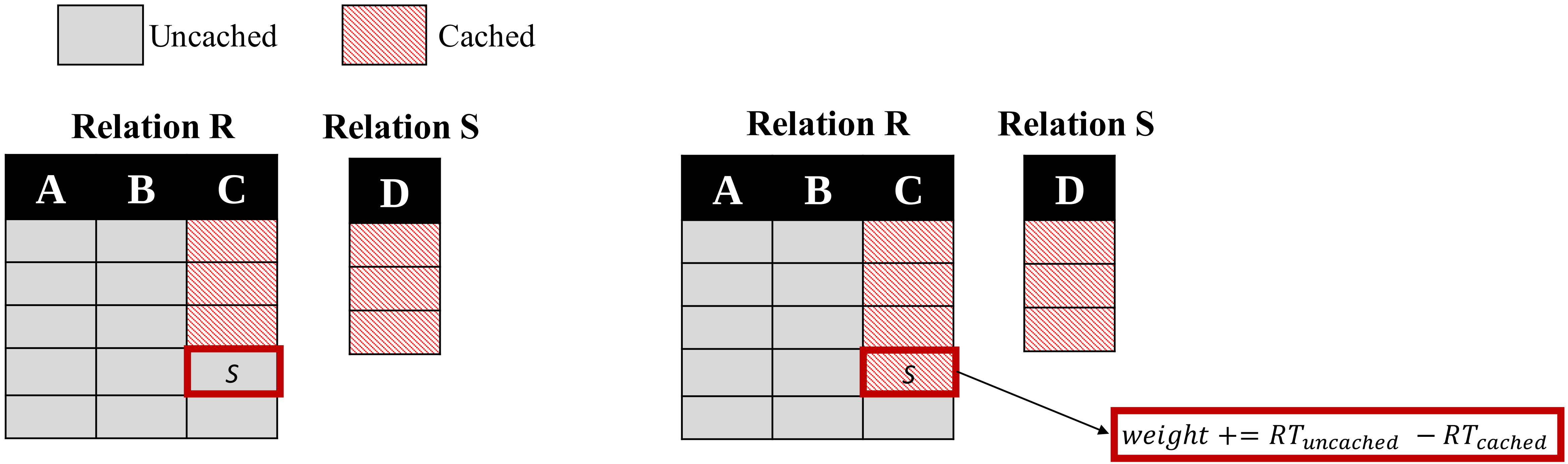

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Heterogeneous Query Execution

Challenges:

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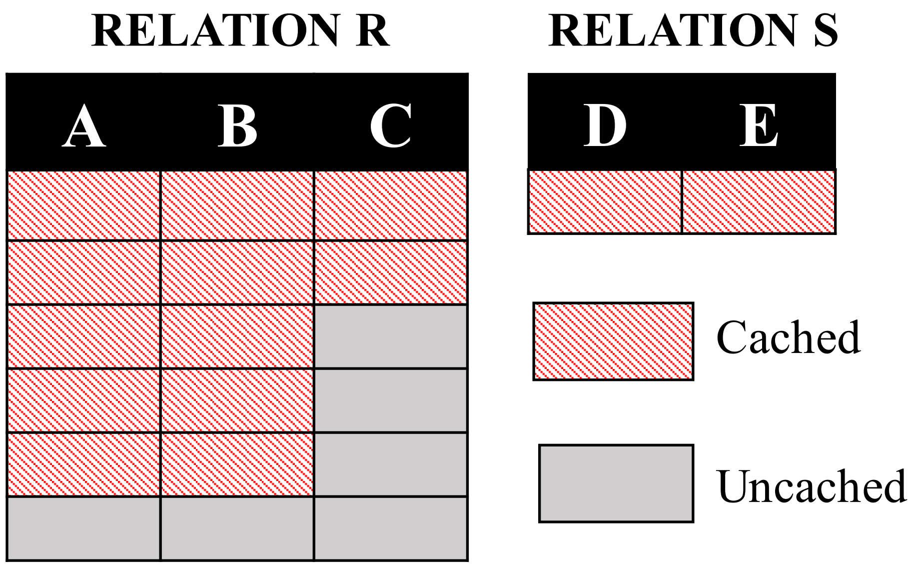
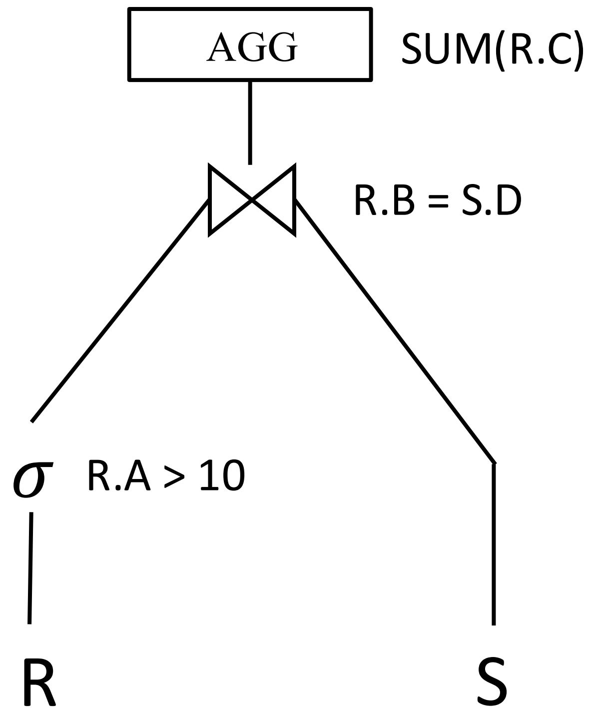
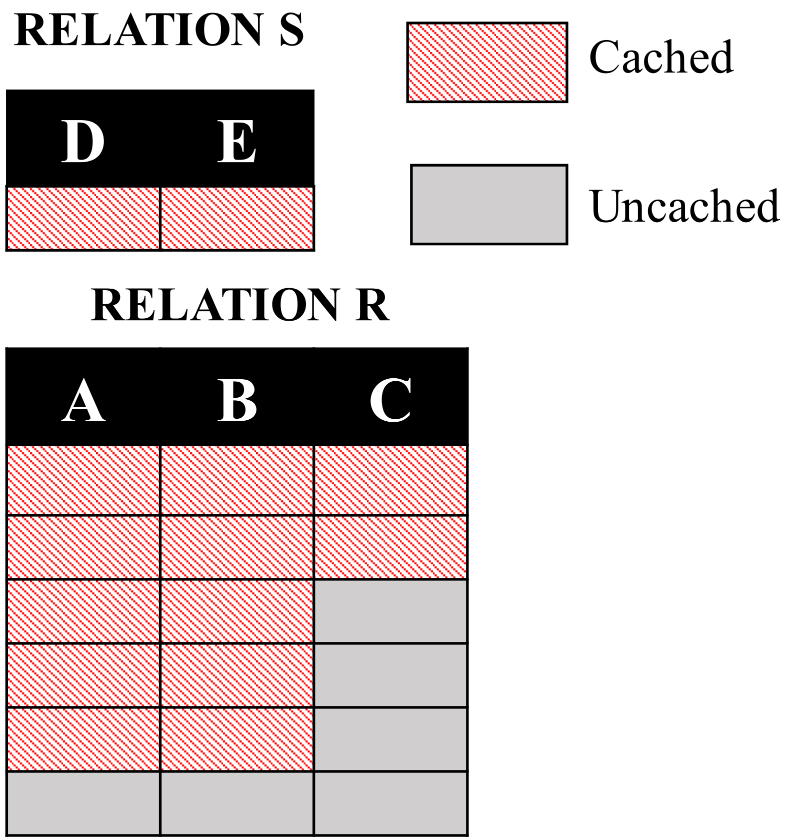
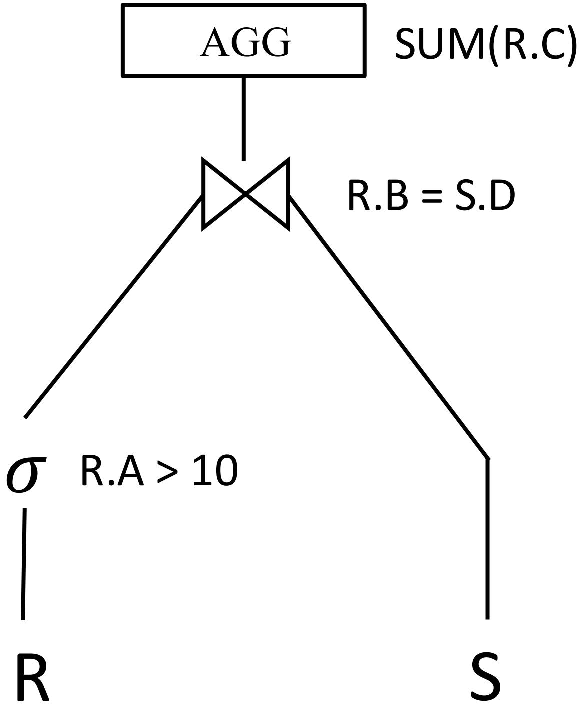
Solution: Introduce segment-level query execution





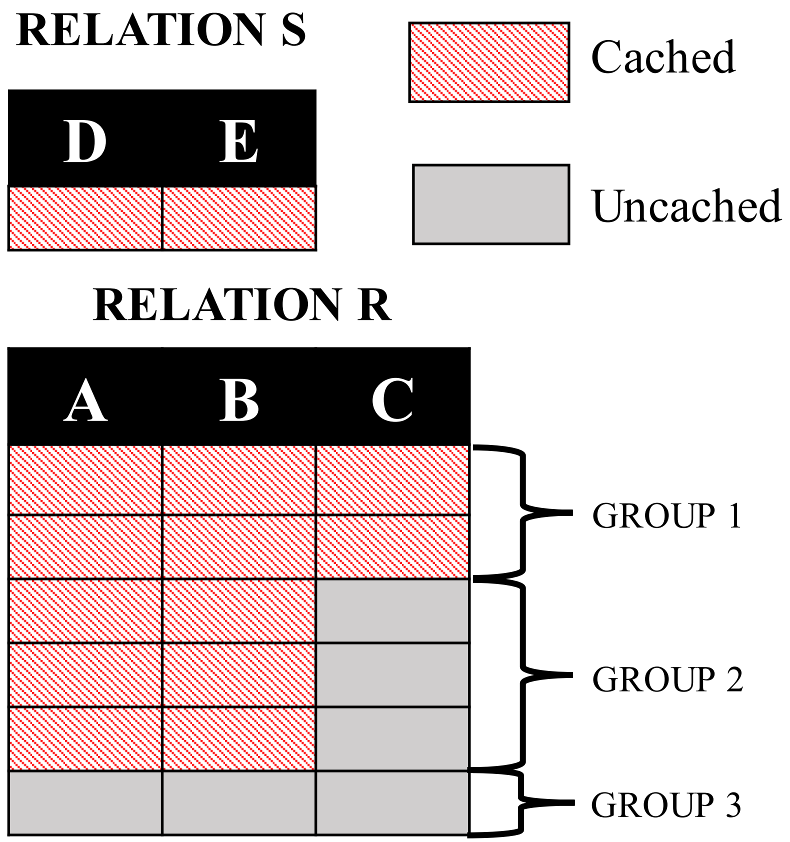
Segment-level Query Execution

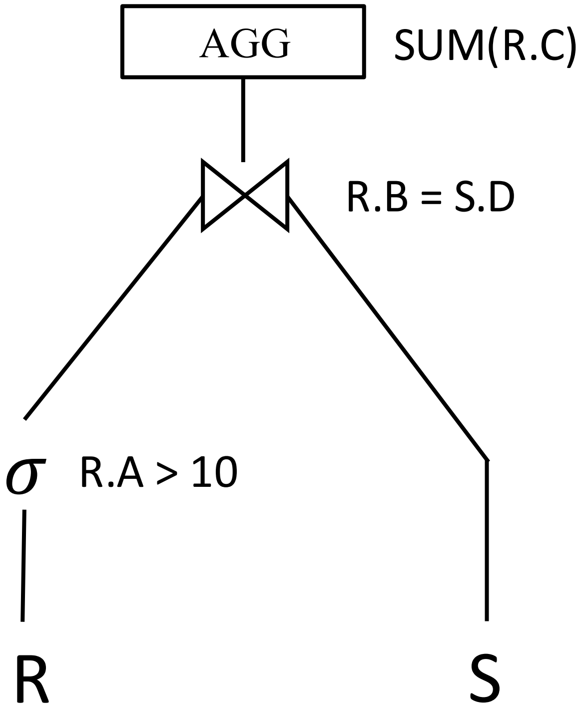




Segment-level Query Execution

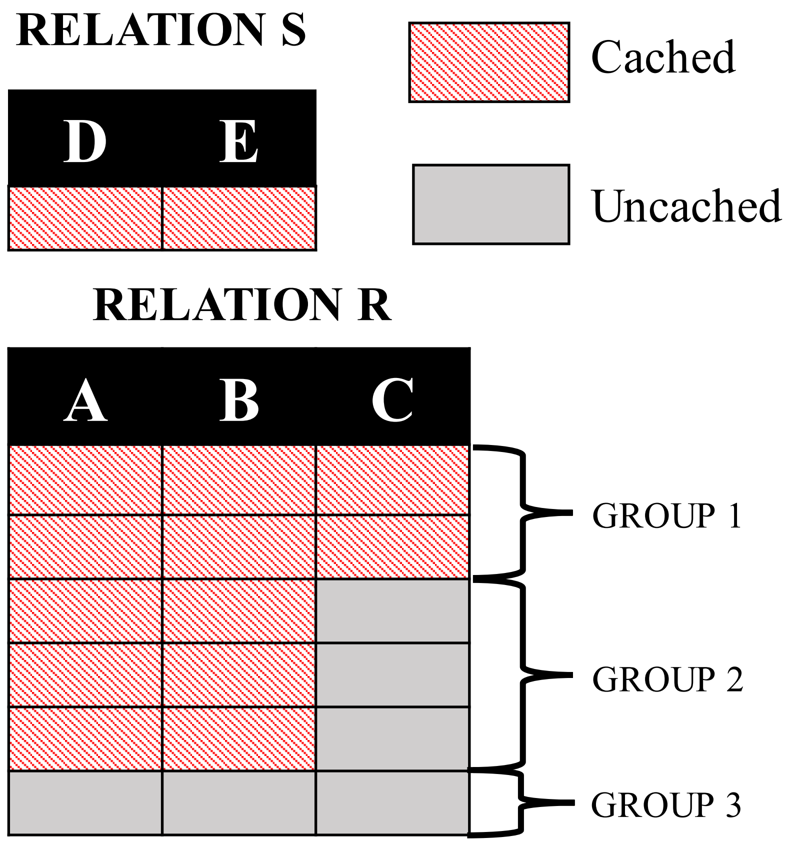
Group segments with the same execution plan into **segment groups.**

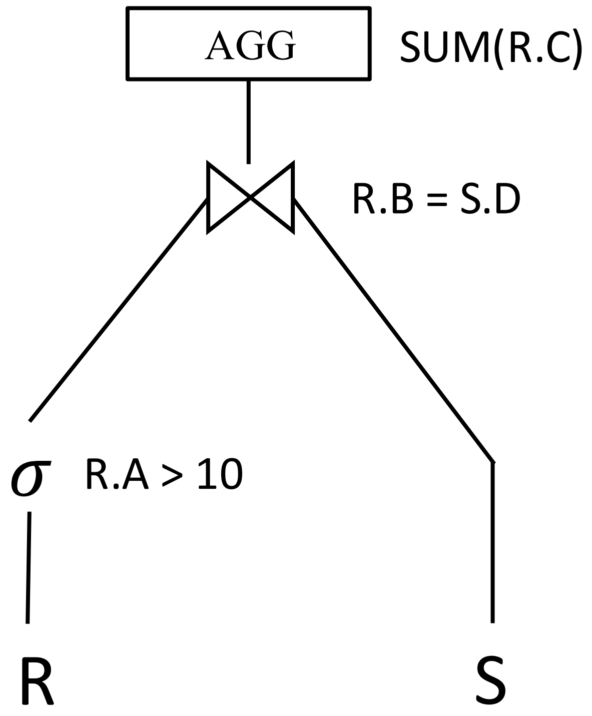




Segment-level Query Execution

Group segments with the same execution plan into **segment groups.**
Execute segment groups **in parallel** following ***data-driven operator placement***[2] → execute operators in GPU only if all input segments reside in GPU.





[2] Sebastian Breß, Henning Funke, and Jens Teubner. *Robust Query Processing in Co-Processor-Accelerated Databases*, **SIGMOD 2016.**

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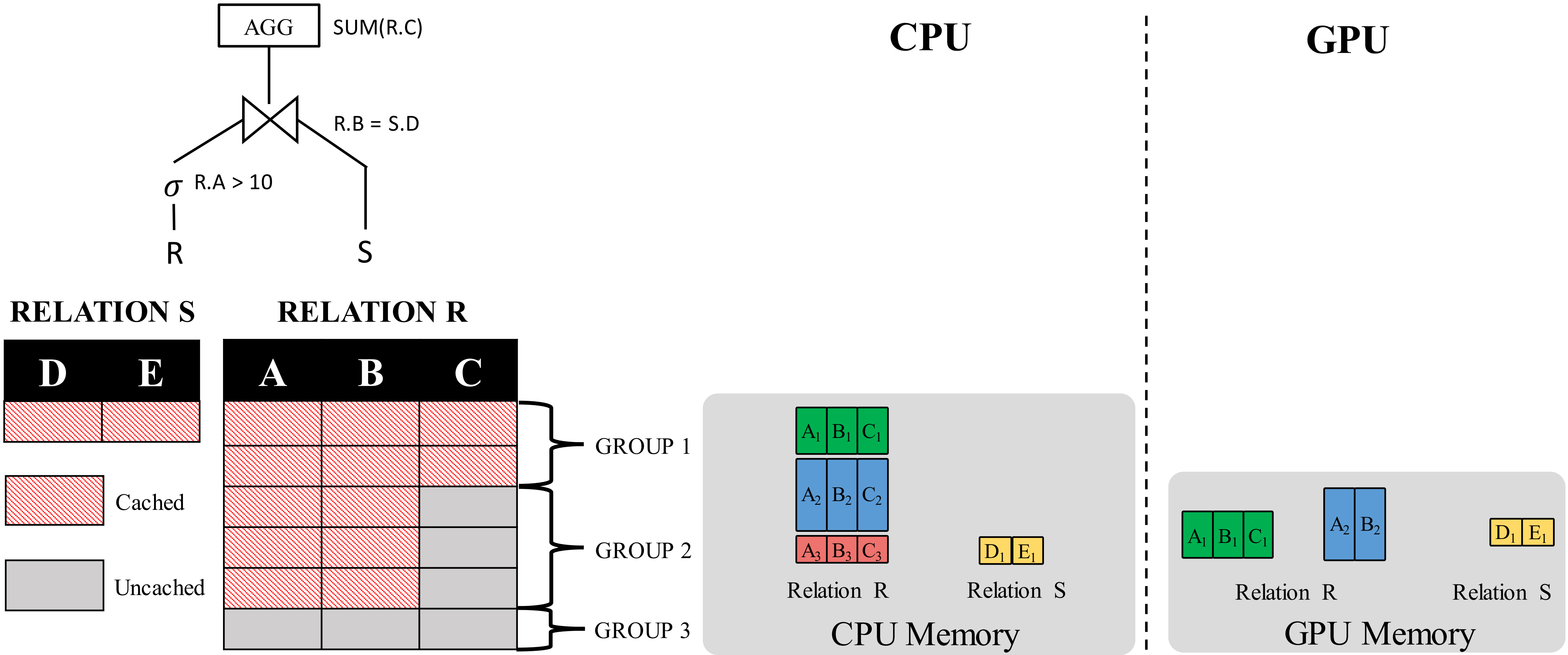

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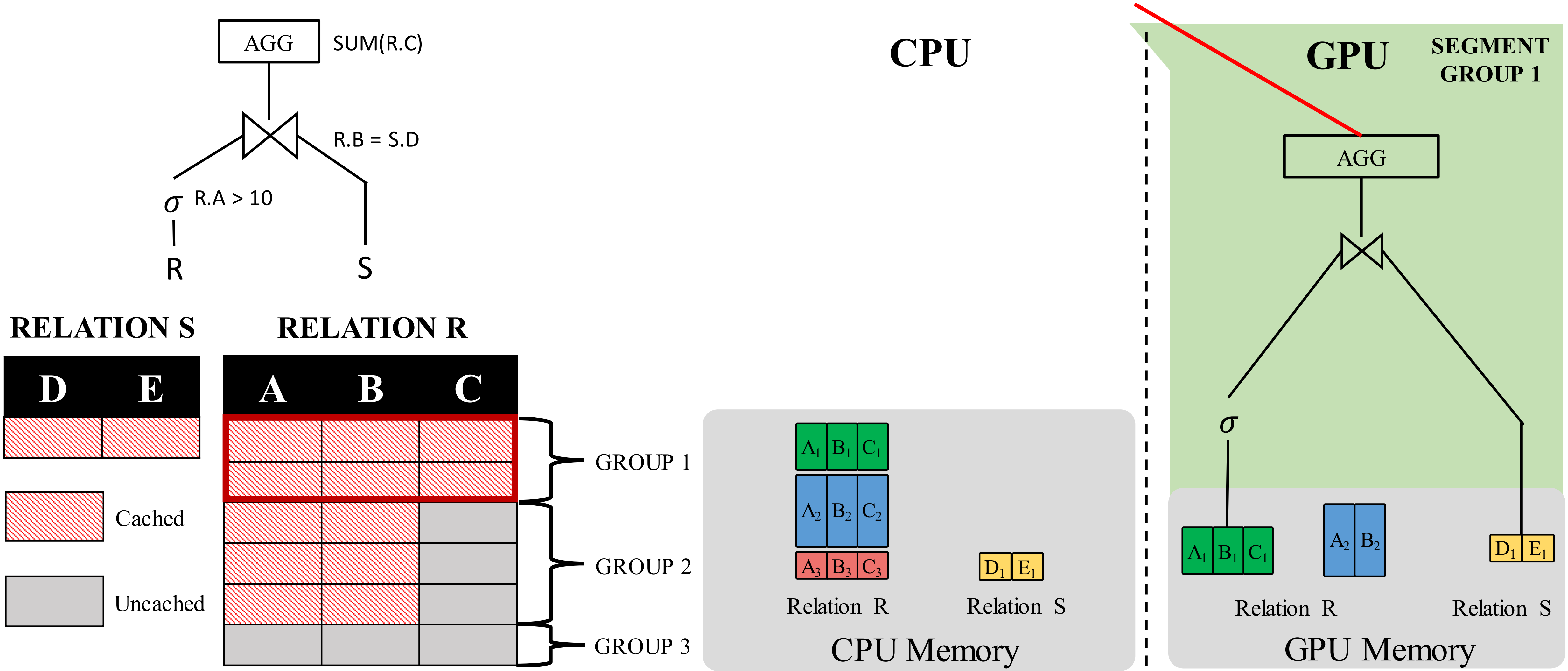

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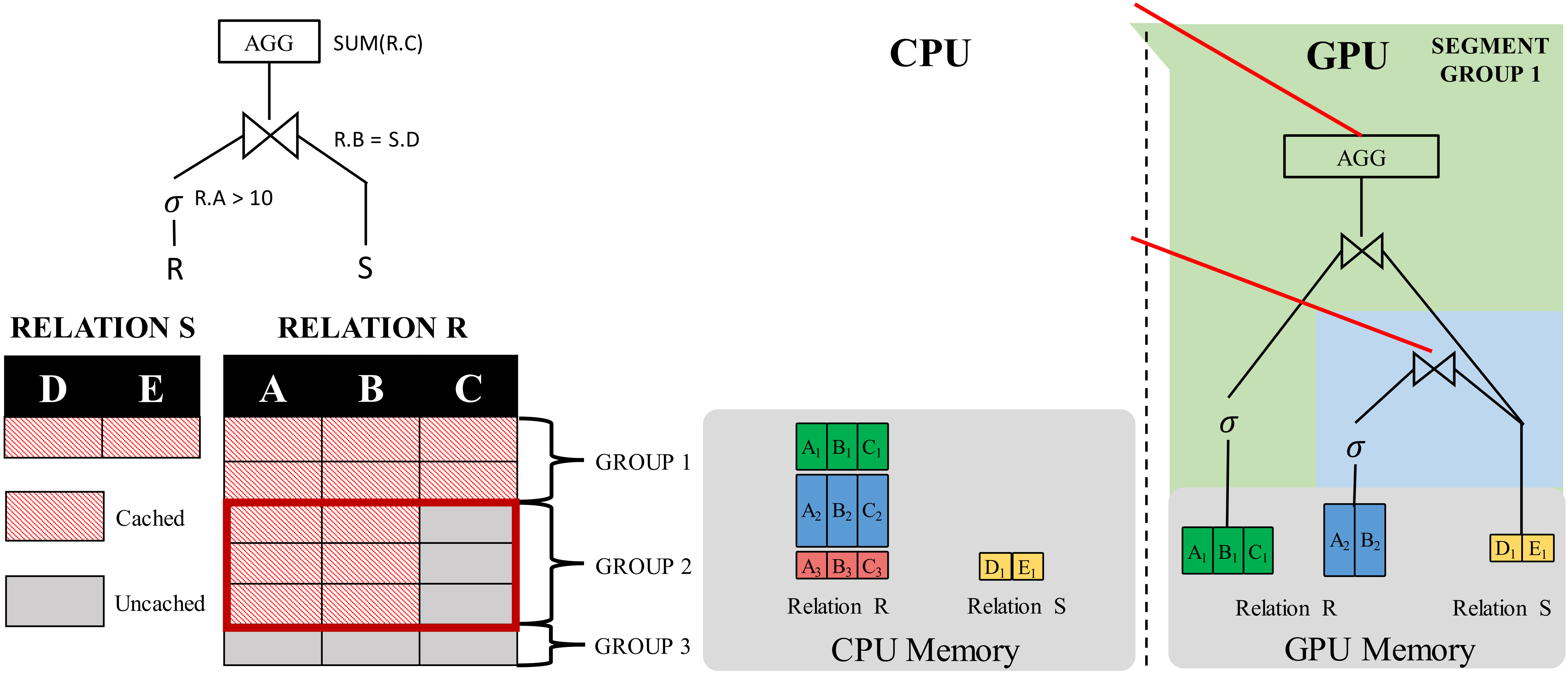

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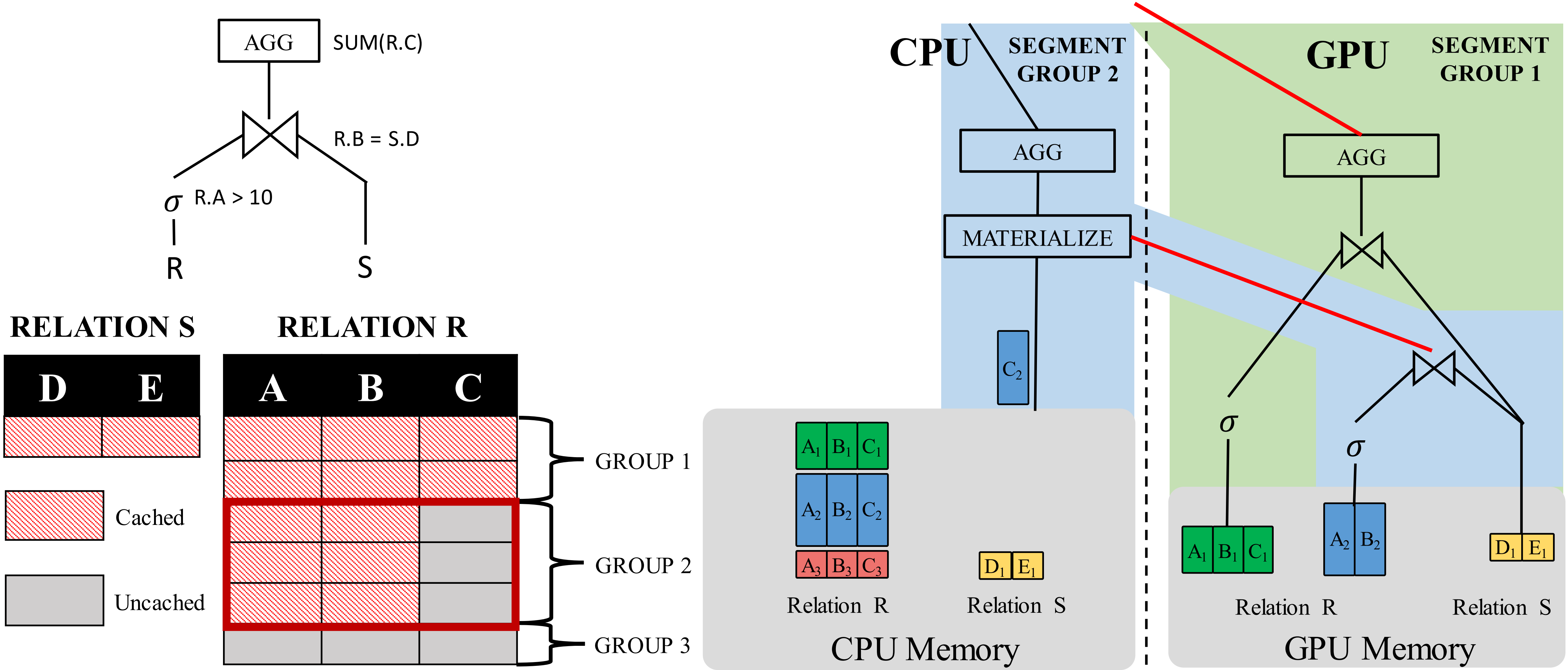

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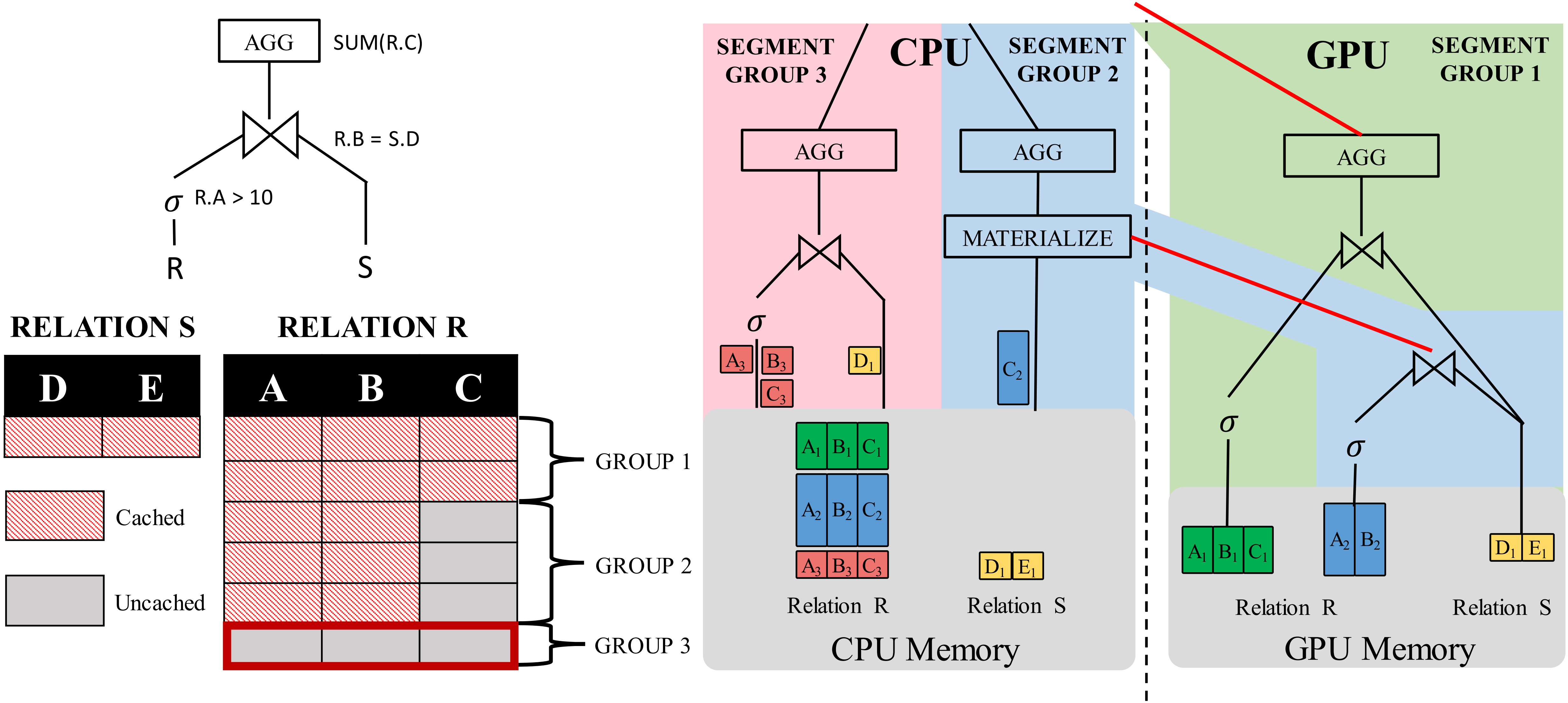
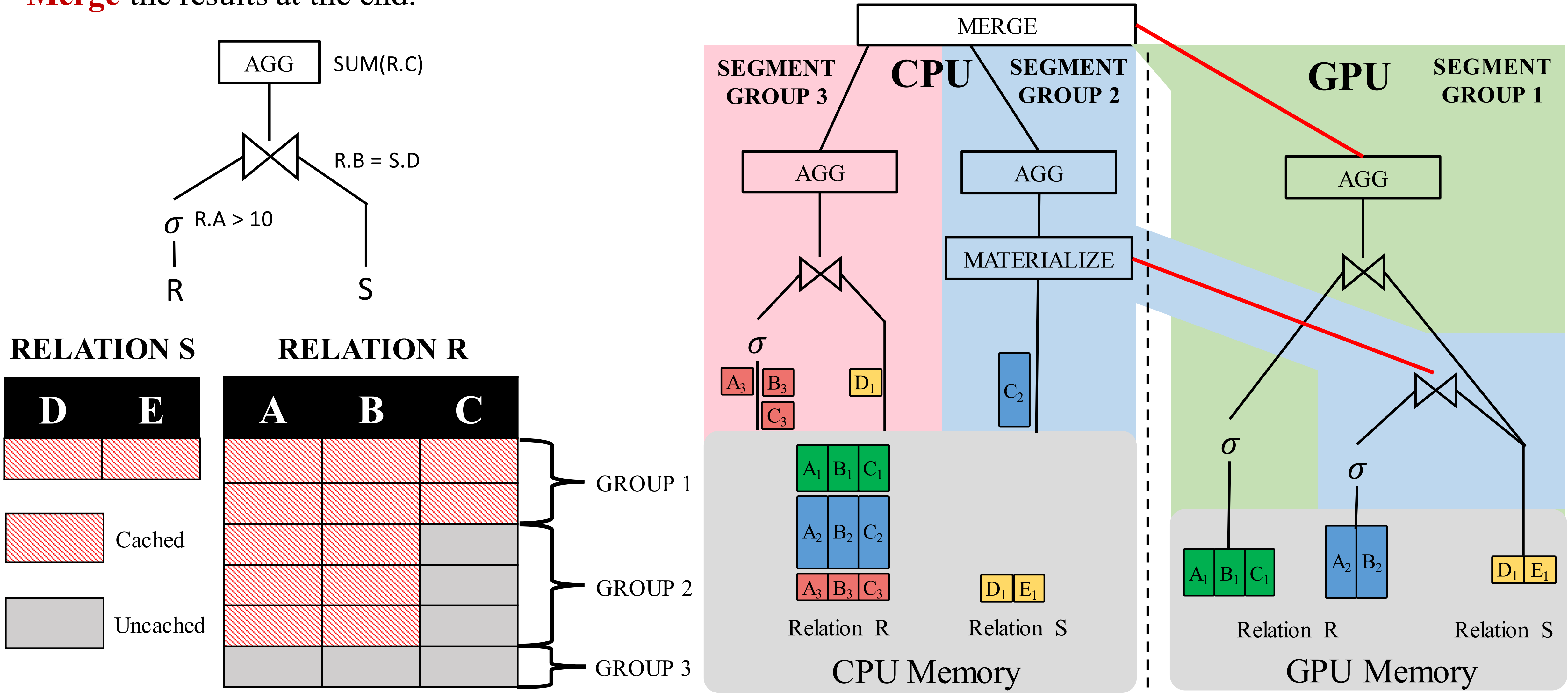


Segment-level Query Execution

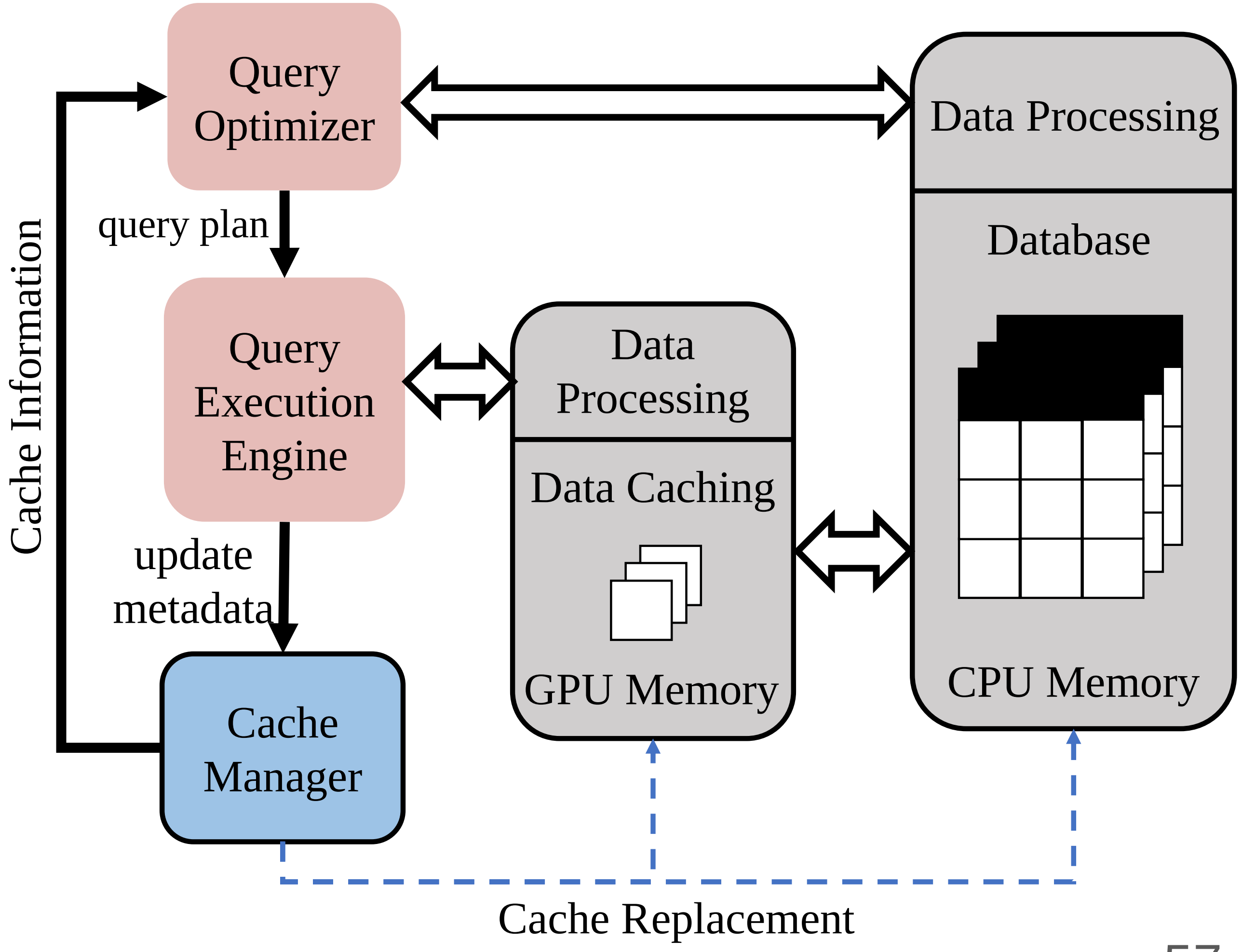
Group segments with the same execution plan into **segment groups.**
Execute segment groups **in parallel** following ***data-driven operator placement.***
Merge the results at the end.



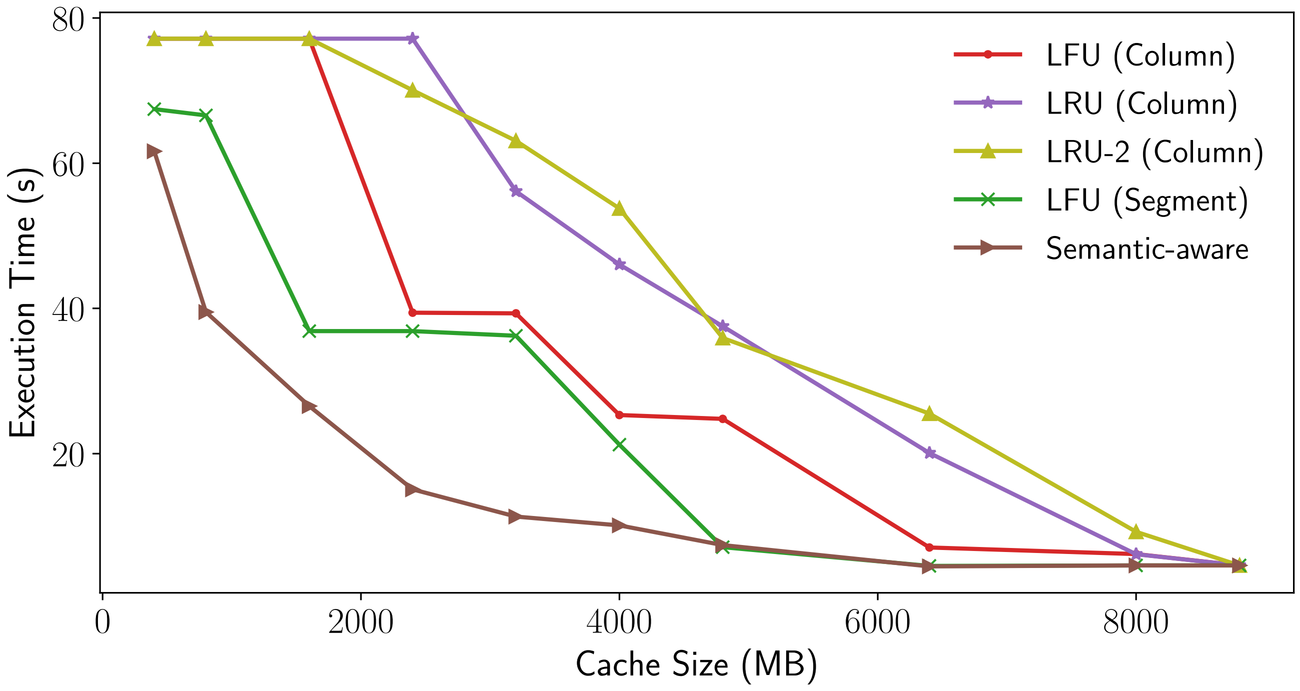
Mordred: A Hybrid CPU-GPU DBMS

Three components:

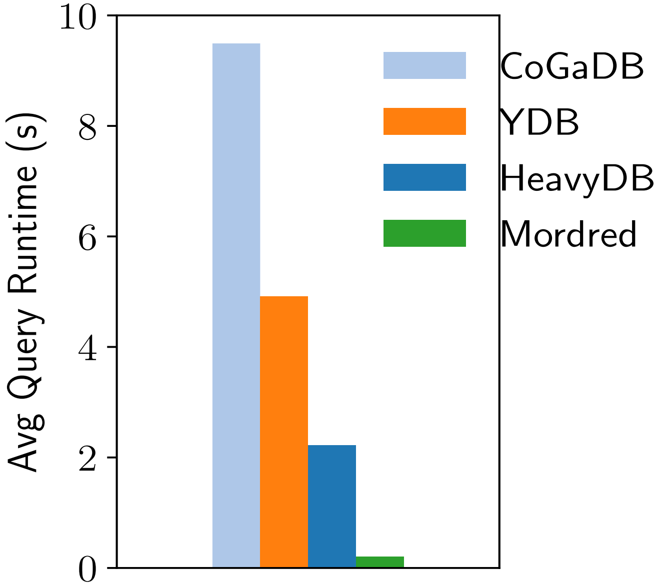
- **Cache Manager**
  - Semantic-Aware Caching Policy
- **Query Optimizer**
  - Data-driven Operator Placement
- **Query Execution Engine**
  - Segment-level Query Execution
  - Tile-based Execution Model
  - Late Materialization
  - Segment Skipping



Hybrid CPU-GPU DBMS – Evaluation



(a) Comparison of Different Data Placement Policies



(b) End-to-end Performance

Semantic-aware caching outperforms the best prior policy **by up to 3x.**

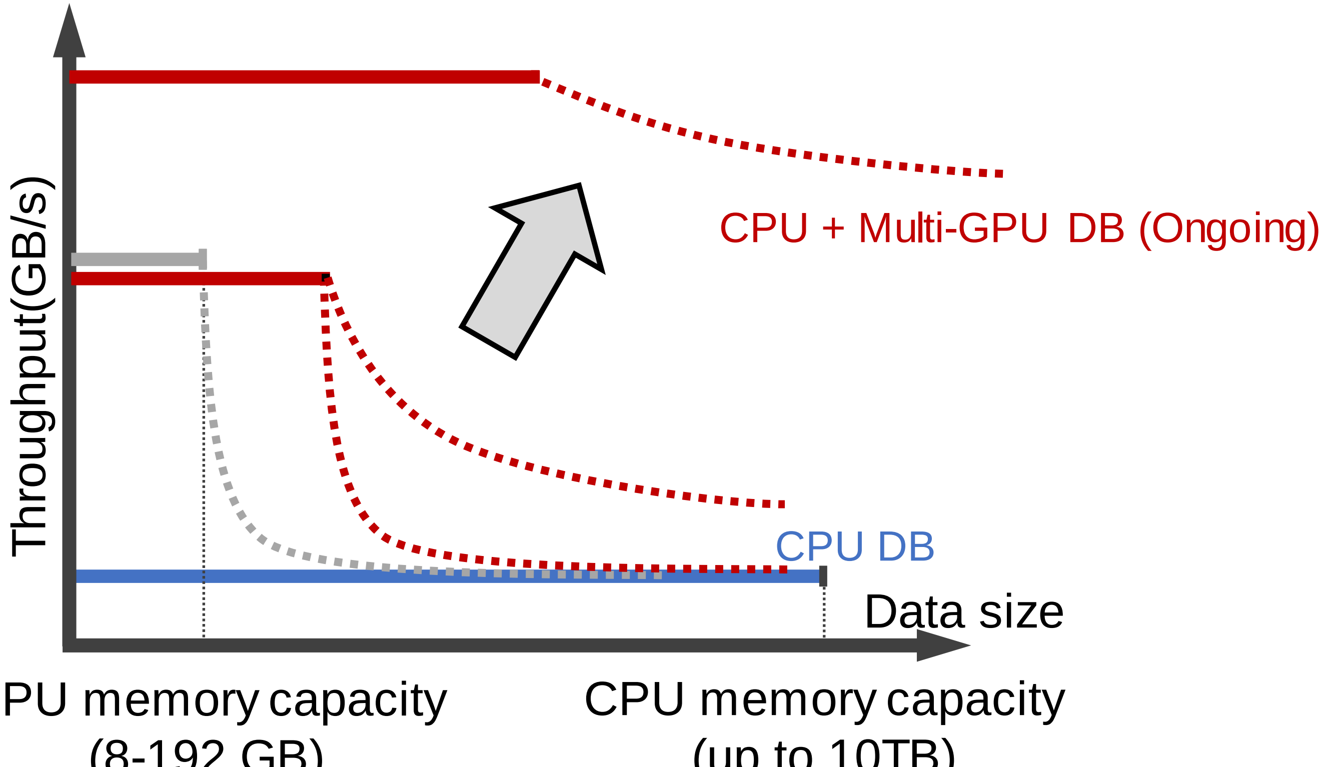
Mordred is 11x faster than the best existing GPU DBMS.

Hardware: NVIDIA V100 GPU. Intel Xeon Platinum CPU (24 Cores).
Benchmark: Star Schema Benchmark: (1) SF = 40 → Figure a, (2) SF = 160 → Figure b.

GPU Database Optimizations

Thrust 1: Enabling **Large-Scale** Data Analytics on GPUs

- ➢Tile-based execution (SIGMOD 2020[1])
- ➢Data Compression (SIGMOD 2022[2])
- ➢Heterogeneous CPU-GPU DBMS (VLDB 2022[3])
- ➢**Multi-GPU DBMS (ongoing)**



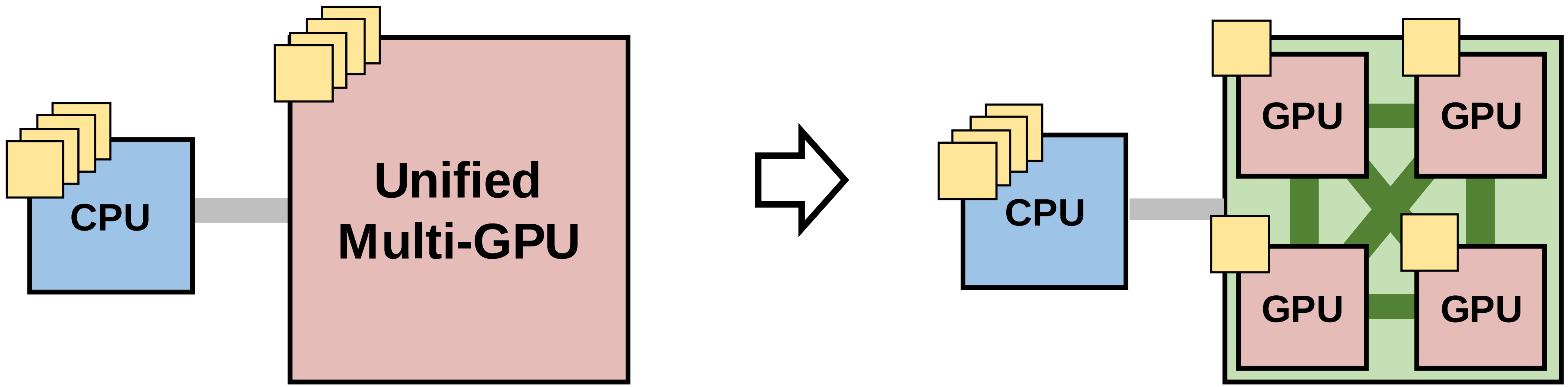
Heterogeneous CPU + Multi-GPU DBMS

Idea 1: Unified Multi-GPU Abstraction

- ➢Views multi-GPU as a single large monolithic GPU.

Idea 2: Capacity-aware Replication Policy

- ➢Intelligent replication policy to reduce data transfer between GPUs.



(a) Data Caching **(b) Data Partitioning/Replication**

Lancelot: A Hybrid CPU + Multi-GPU DBMS

Three components:

➢ **Cache Manager**
- Semantic-Aware Caching Policy
- Capacity-Aware Replication Policy

➢ **Query Optimizer**
- Data-driven Operator Placement

➢ **Query Execution Engine**
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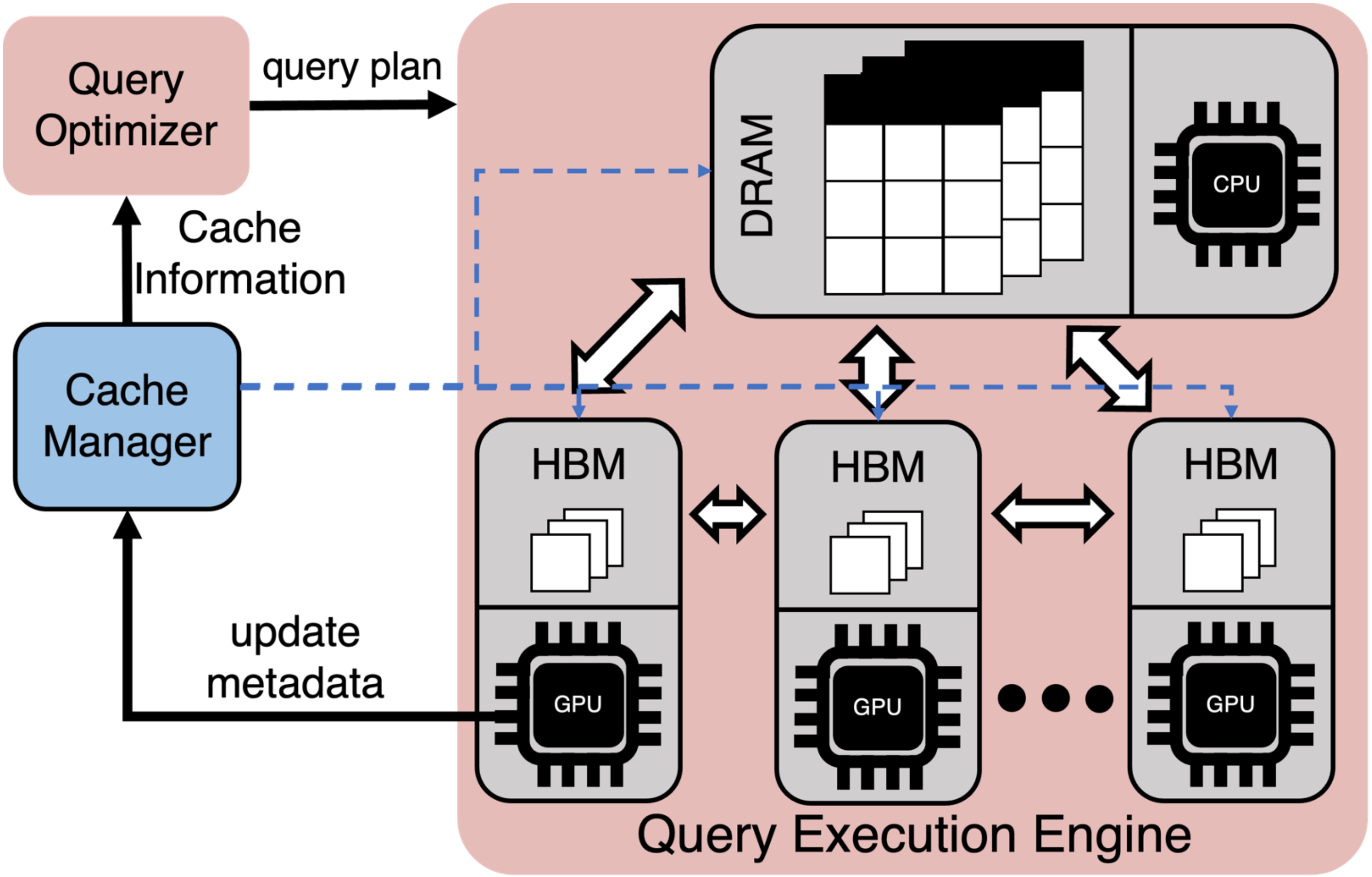
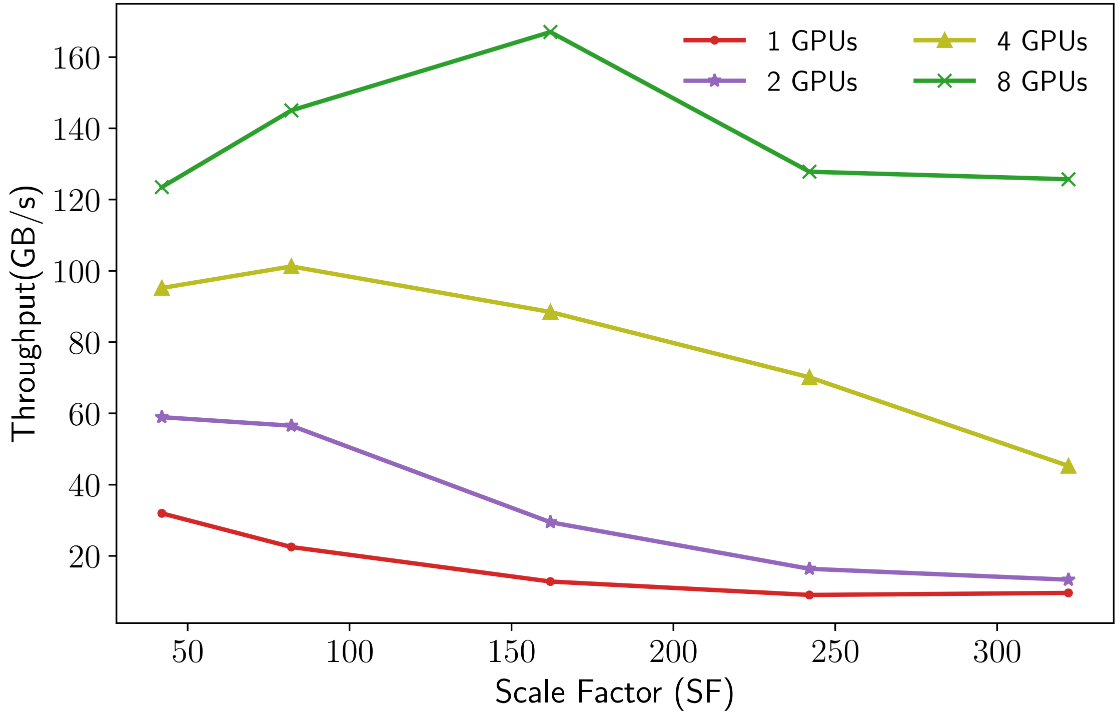
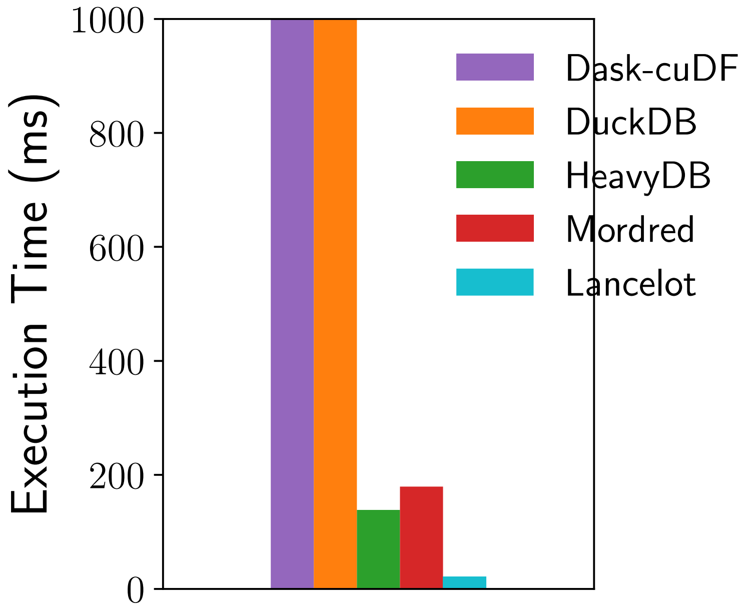


Multi-GPU DBMS – Evaluation



(a) Scaling to Multiple GPUs



(b) End-to-end Performance

Lancelot can scale Mordred to Multiple GPUs.

Lancelot is 7x faster than the best existing multi-GPU DBMS.

Hardware: NVIDIA V100 GPU. Intel Xeon Platinum CPU (104 Cores).
Benchmark: Star Schema Benchmark: SF = 160 (Figure b)

GPU Database Optimizations

Thrust 1: Enabling **Large-Scale** Data Analytics on GPUs

- Crystal: tile-based execution **(SIGMOD 2020[1])**
- Data Compression **(SIGMOD 2022[2])**
- Heterogeneous CPU-GPU DBMS **(VLDB 2022[3])**
- Multi-GPU DBMS (ongoing)

Thrust 2: Enhancing the Practicality of GPU Databases

- Accelerating UDF on GPUs **(DaMoN@SIGMOD 2023[4])**
- Code Generation for GPU DBMS (ongoing)

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Accelerating UDAF on GPUs

Challenge: UDAF Execution is slow on GPUs (sometimes even slower than CPU).

Accelerating UDAF on GPUs

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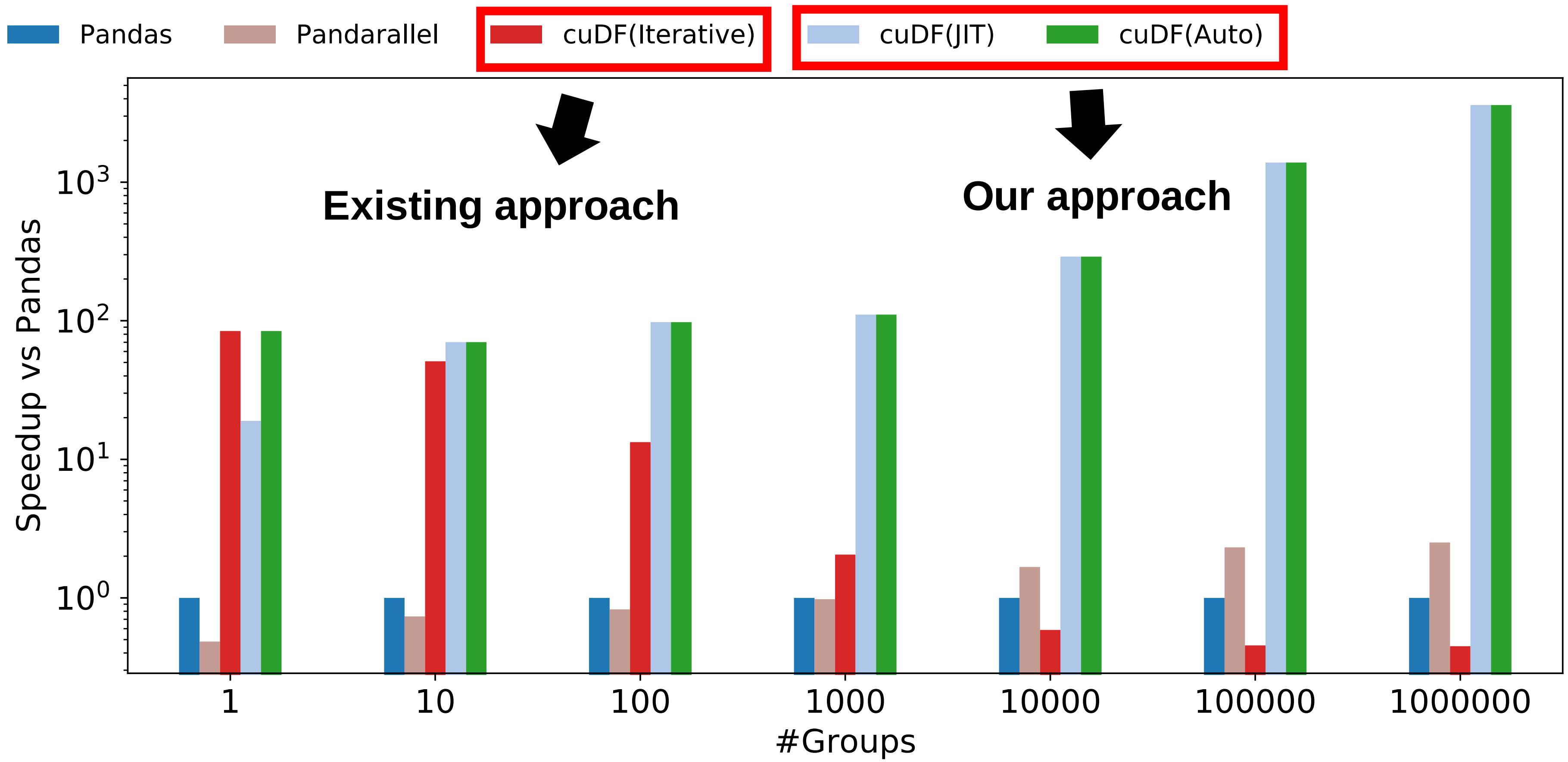
We **introduce a novel UDAF execution framework** with **Tile-based Execution and JIT Compilation.**



We are up to **8000×** faster against existing approach (on NVIDIA V100 GPU).

Fully integrated and released in **NVIDIA RAPIDS cuDF v23.02**[2].

Confronting Challenges in GPU DBMS

Goal: Solve these challenges with **two research thrusts**

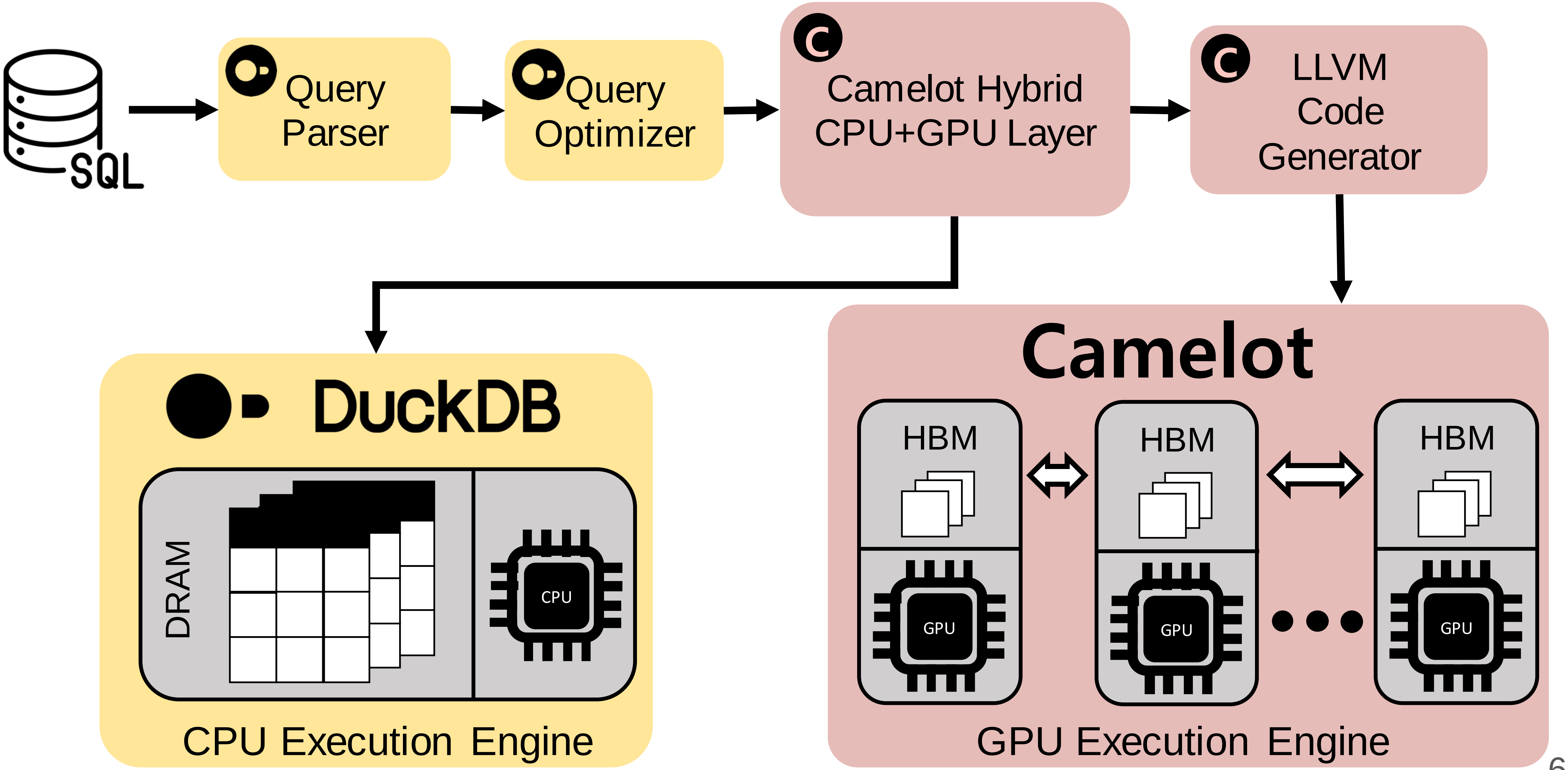
Thrust 1: Enabling **Large-Scale** Data Analytics on GPUs

- Data Compression (SIGMOD 2022[1])
- Heterogeneous CPU-GPU DBMS (VLDB 2022[2])
- Multi-GPU DBMS (ongoing)

Thrust 2: Enhancing the Practicality of GPU Databases

- **Accelerating UDF on GPUs (DaMoN@SIGMOD 2023[3])**
- **Code Generation for GPU DBMS (ongoing)**

Camelot v0.1


SQL
Query Parser
Query Optimizer
Camelot Hybrid CPU+GPU Layer
LLVM Code Generator
DuckDB
DRAM
CPU
CPU Execution Engine
Camelot
HBM
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GPU
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Conclusion

GPU is becoming the new modality of SQL analytics