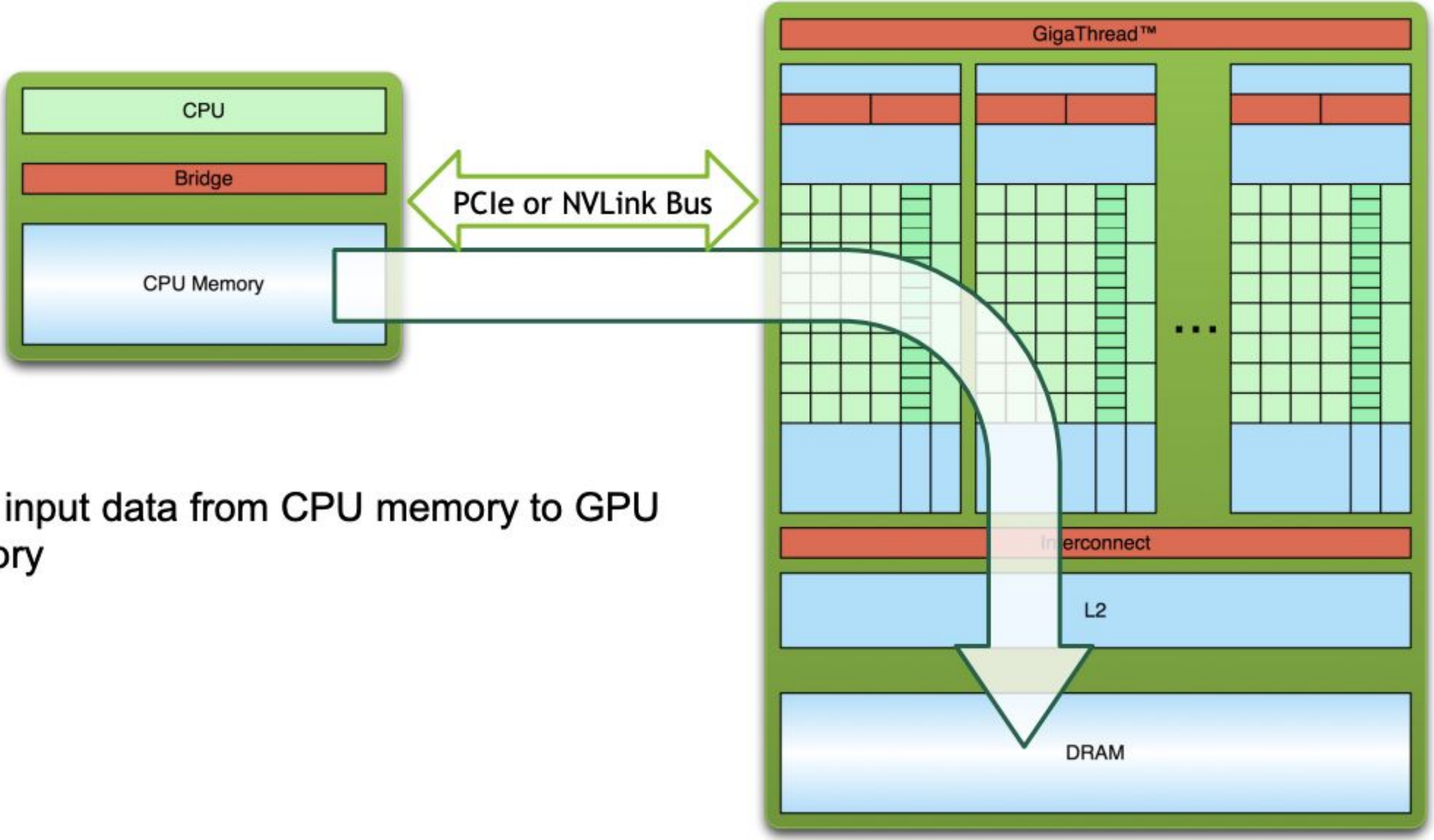
Crystal GPU Database

By Devesh

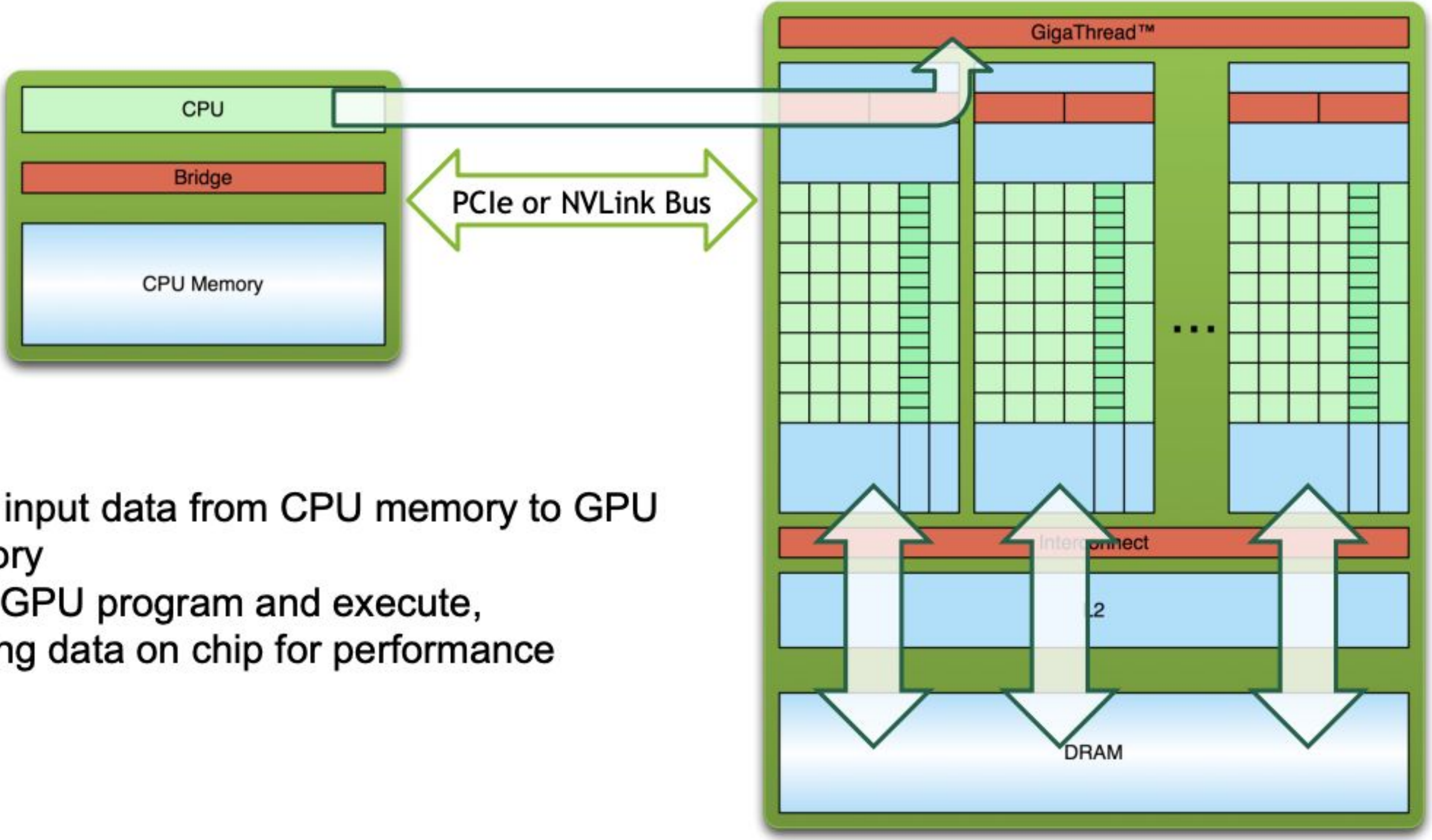
Intro to GPUS

SIMPLE PROCESSING FLOW



1. Copy input data from CPU memory to GPU memory

SIMPLE PROCESSING FLOW



1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance

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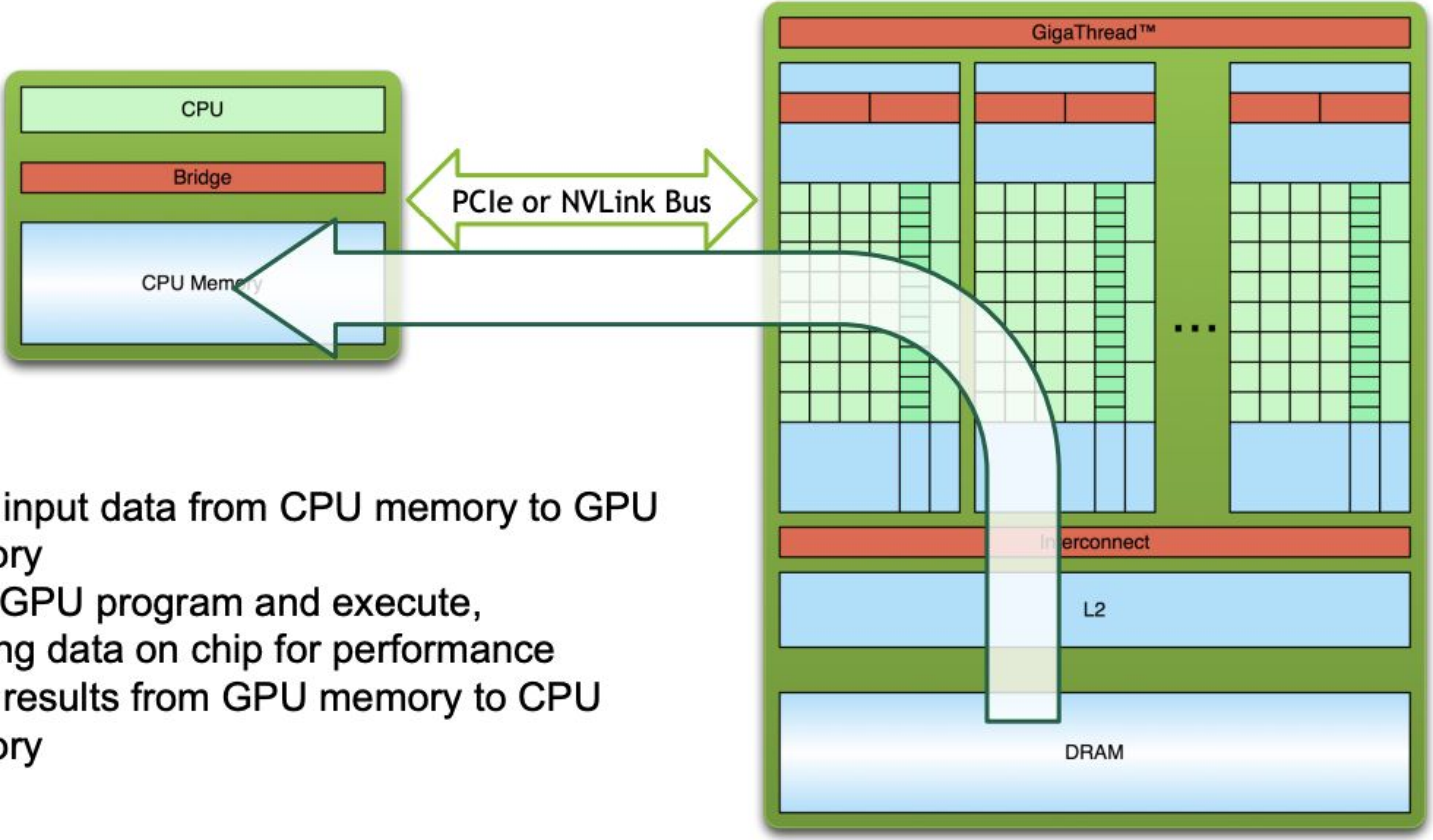
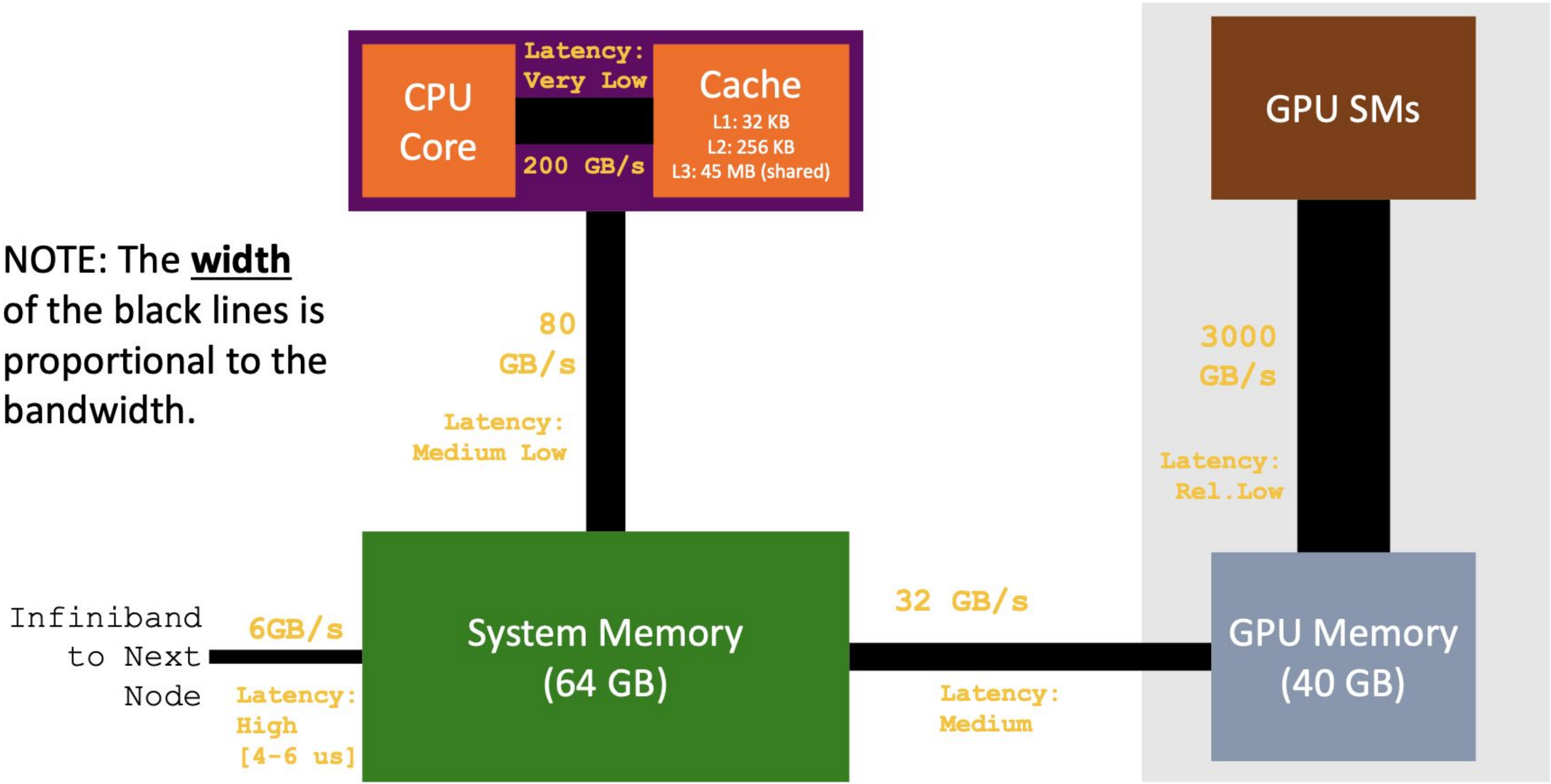


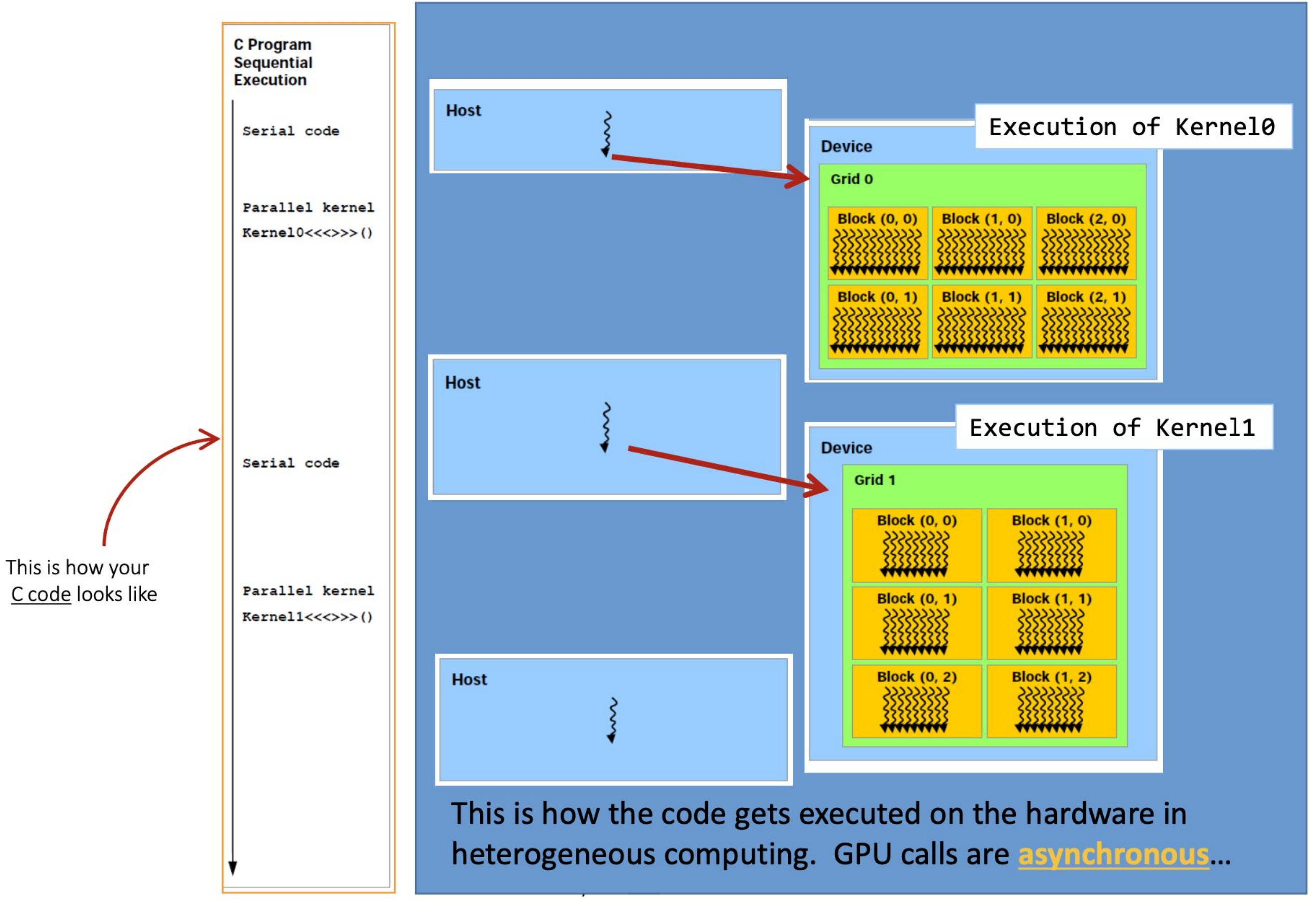
1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance
3. Copy results from GPU memory to CPU memory

Latencies, Bandwidths, and Limits

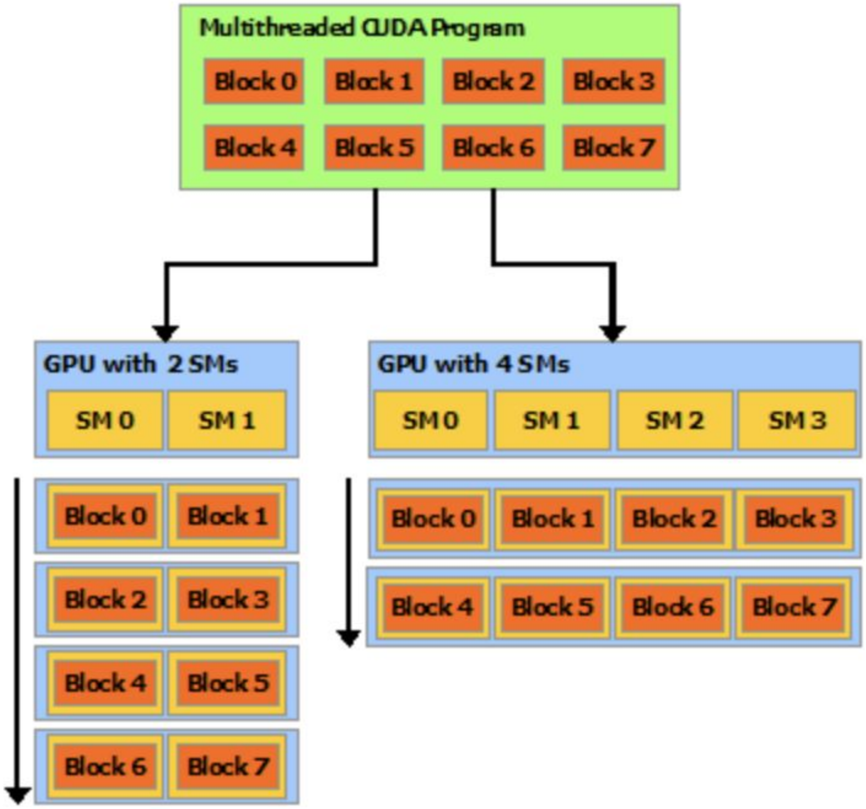
NOTE: The **width** of the black lines is proportional to the bandwidth.



It's all about threads



Executing the blocks



Memory Hierarchy

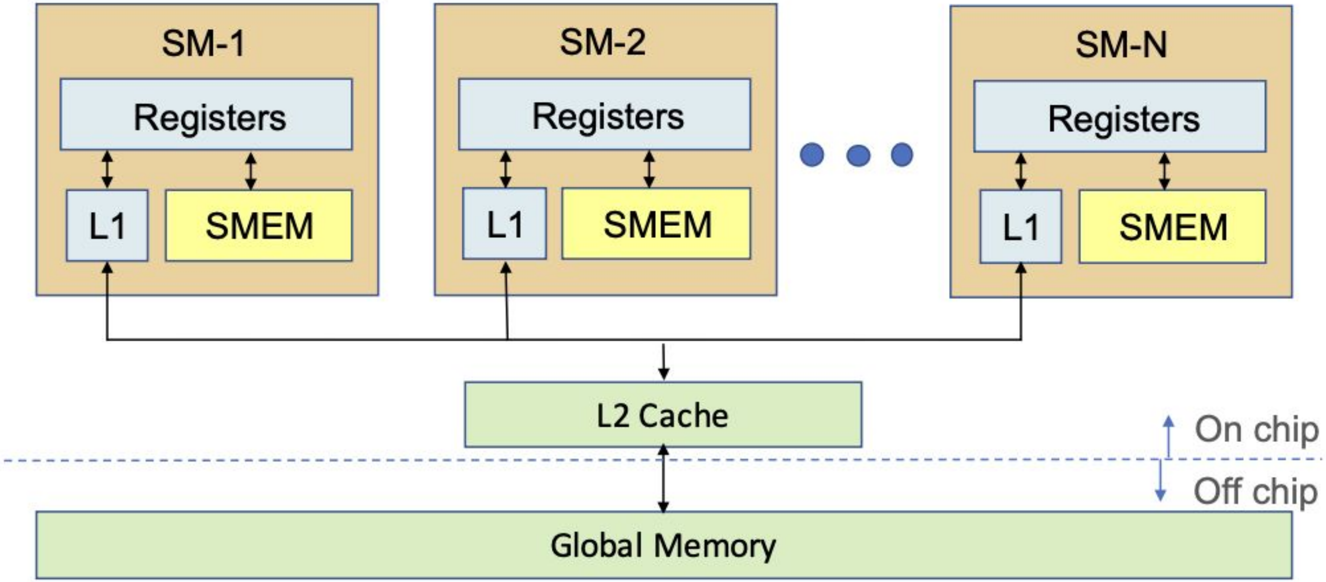
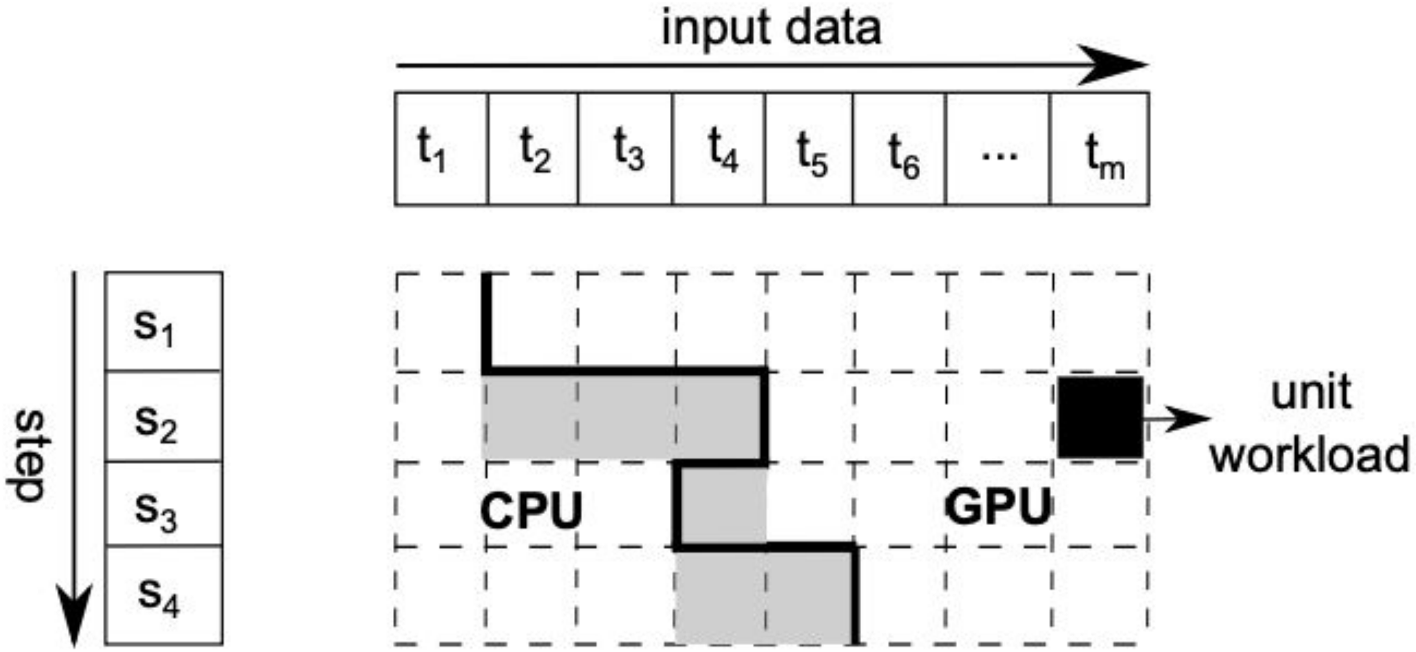


Figure 1: GPU Memory Hierarchy

Or as the Mythbusters explained

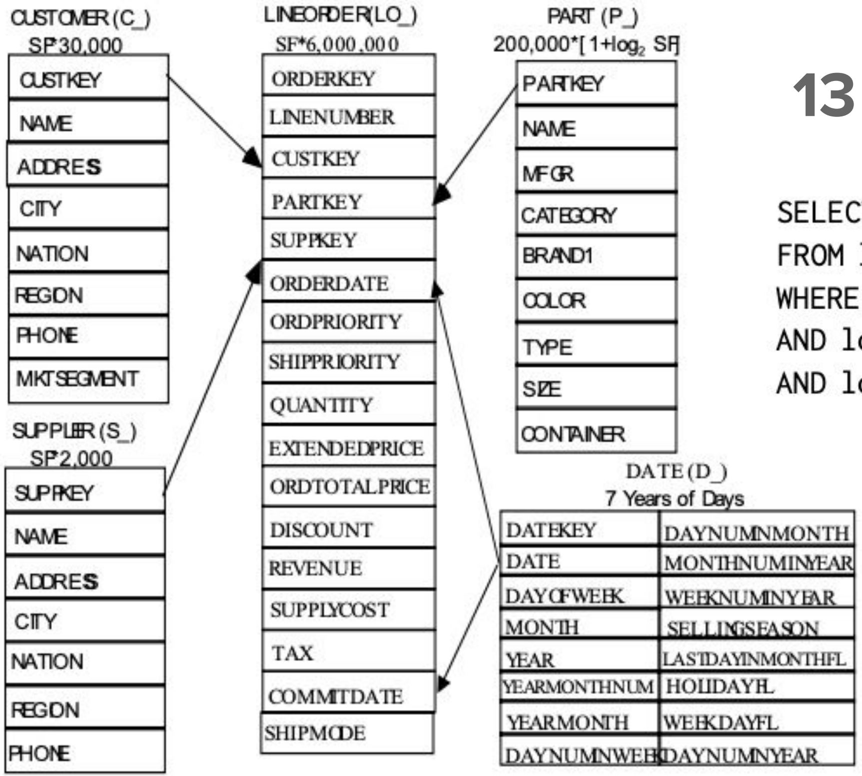
Previous Works

GPU as a Co Processor



Data resides in CPU memory and is moved to the GPU during query execution

SSB Benchmark

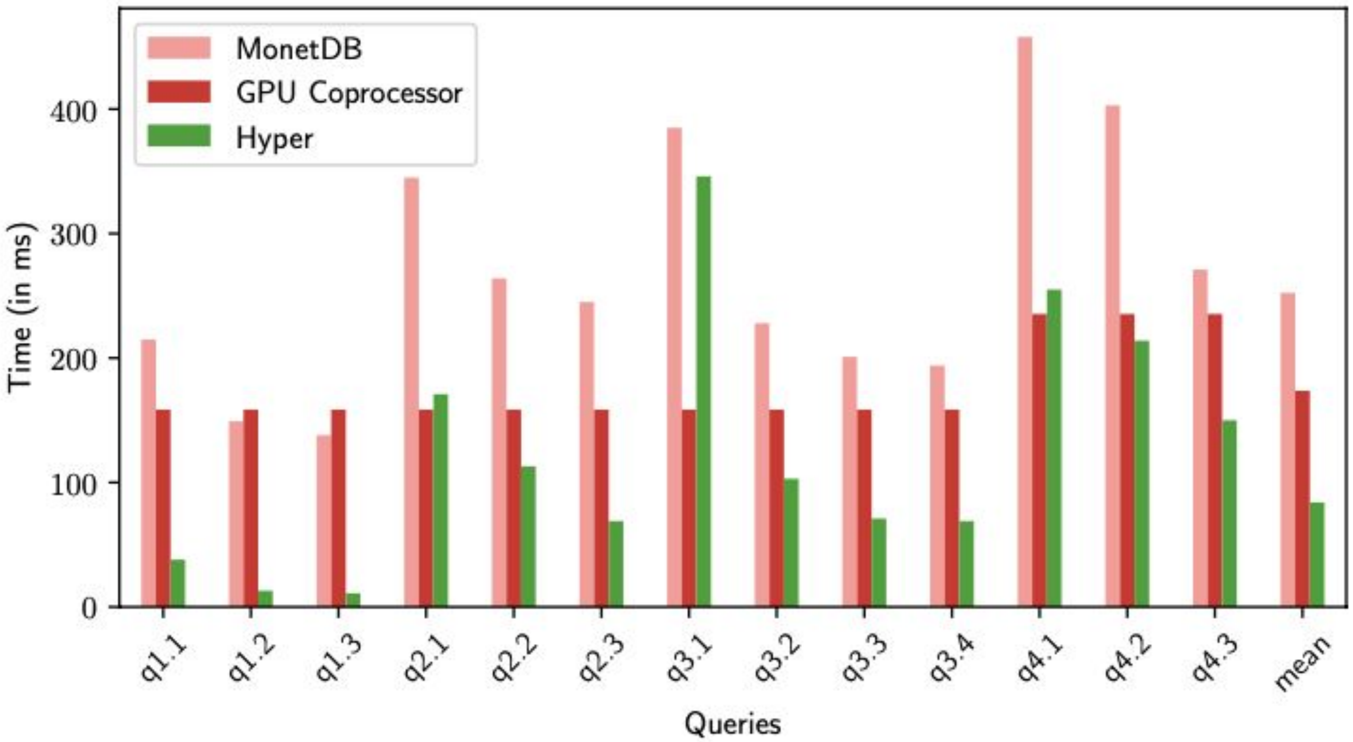


13 different queries like this

```
SELECT SUM(lo_extendedprice * lo_discount) AS revenue
FROM lineorder
WHERE lo_quantity < 25
AND lo_orderdate >= 19930101 AND lo_orderdate <= 19940101
AND lo_discount >= 1 AND lo_discount <= 3;
```

Using SF = 20

Comparison against other OLAP databases



On average GPU co processing is 1.4x times slower than Hyper

Crystal

Solution

Store the working set in the GPU memory itself as done by

omnisci

kinetica

BLAZINGDB

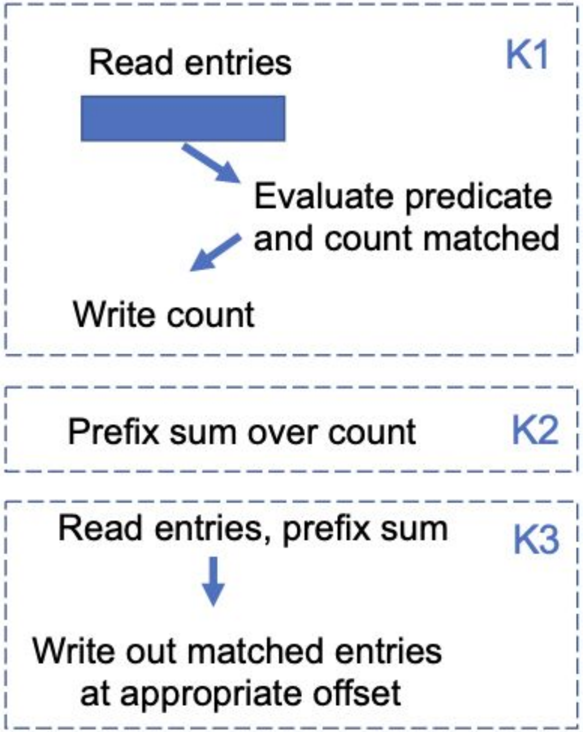
Crystal builds on these using a tile based execution model

Problem with current GPU approach

Motivating query

```
Q0: SELECT y FROM R WHERE y > v;
```

How current systems do it



"Each thread strides through the dataset and determines number of matching rows"

If 100 total threads then
Thread 0 checks rows 0, 100, 200, …
Thread 1 checks rows 1, 101, 201, …

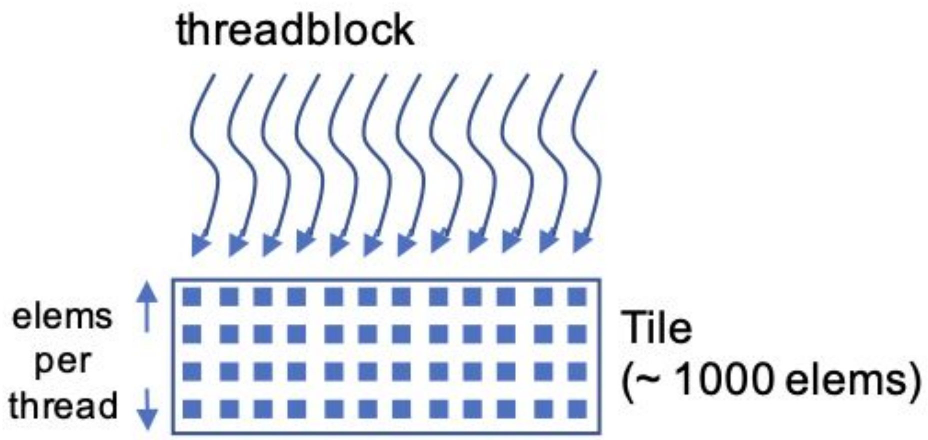
Example count arr: [1, 3, 4, 2, 5]

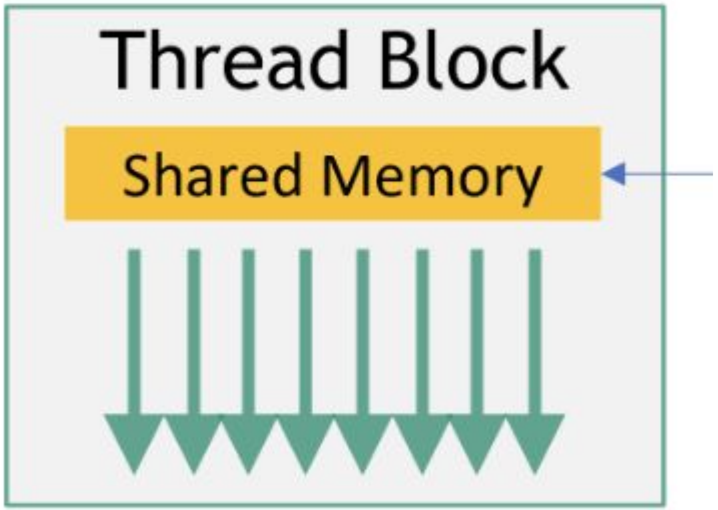
Prefix sum: [0, 1, 4, 8, 10, 15]

Thread 0 will write result in indices [0, 1)
Thread 1 will write result in indices [1, 4)
Thread 2 will write result in [4, 8)
…

Problem: Requires 3 kernels and 2 iterations over the dataset

Introducing Tile Based Execution Model

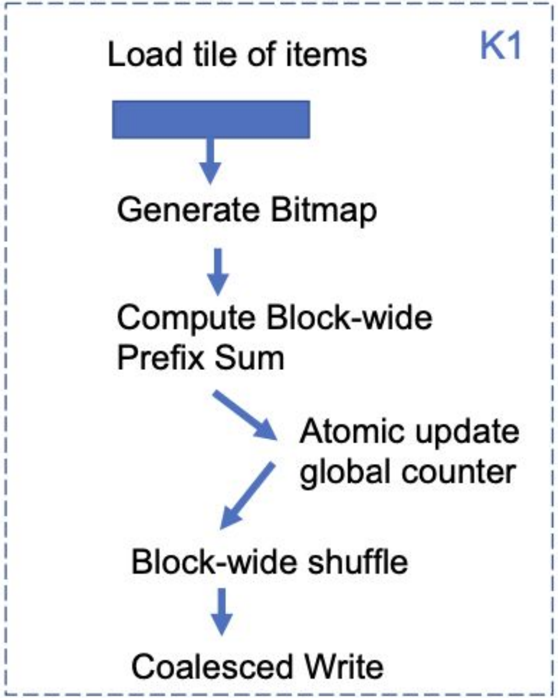




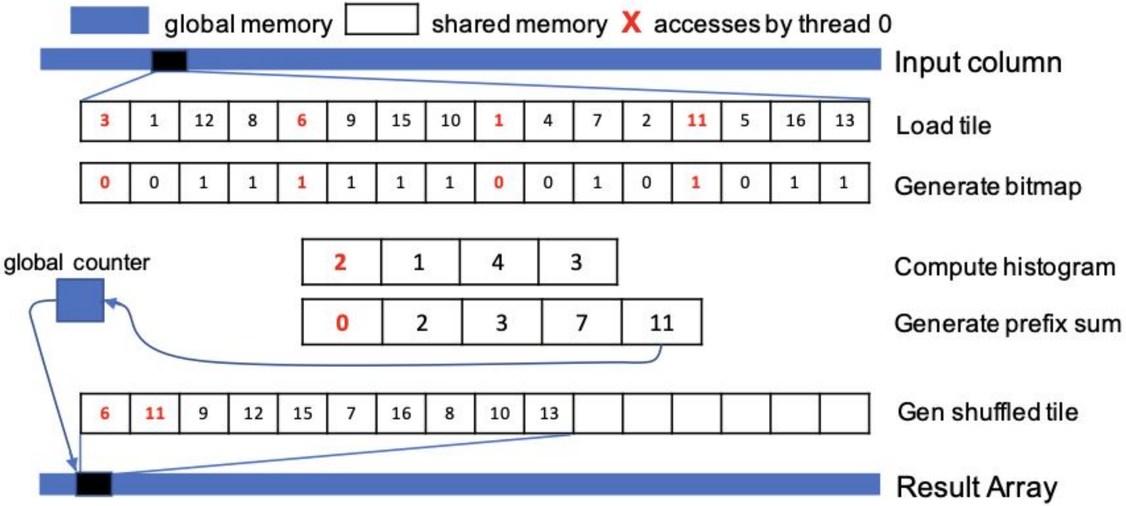
Tiles rather than threads are basic units of execution

Load all of tile's data into shared memory once and reuse it

Going back to the example



(b) With Tile-based processing



SELECT Y FROM R WHERE Y > 5

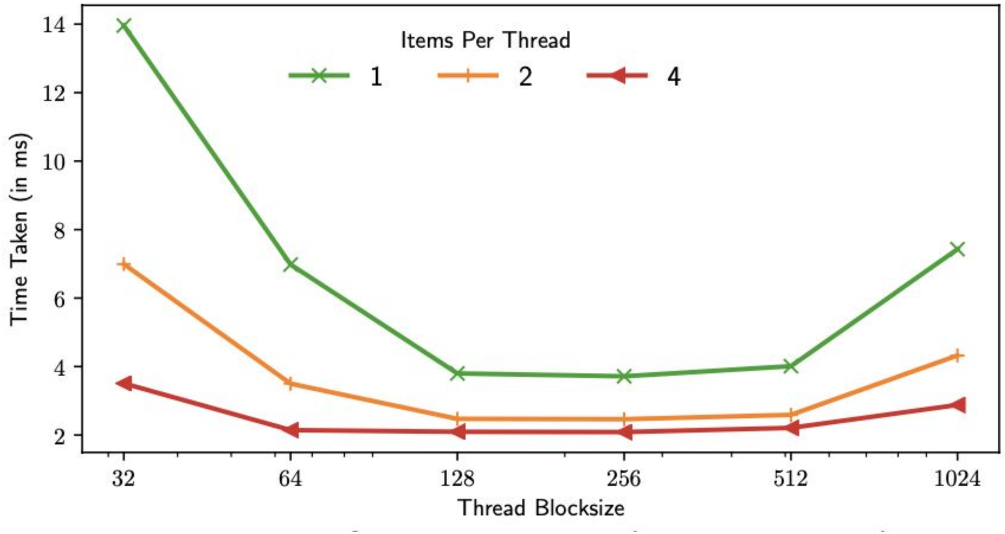
Converting this to code

Primitive	Description
`BlockLoad`	Copies a tile of items from global memory to shared memory. Uses vector instructions to load full tiles.
`BlockLoadSel`	Selectively load a tile of items from global memory to shared memory based on a bitmap.
`BlockStore`	Copies a tile of items in shared memory to device memory.
`BlockPred`	Applies a predicate to a tile of items and stores the result in a bitmap array.
`BlockScan`	Co-operatively computes prefix sum across the block. Also returns sum of all entries.
`BlockShuffle`	Uses the thread offsets along with a bitmap to locally rearrange a tile to create a contiguous array of matched entries.
`BlockLookup`	Returns matching entries from a hash table for a tile of keys.
`BlockAggregate`	Uses hierarchical reduction to compute local aggregate for a tile of items.

Crystal provides primitives for each of these steps

Tuning some key parameters

- Thread Block Size: Number of threads per thread block
- Items per thread: Number of rows each thread will process



- R has 2^29 rows
- Selectivity factor: 0.5

Projection Queries

$$\text{Q1: SELECT } ax_1 + bx_2 \text{ FROM R;}$$

$$\text{Q2: SELECT } \sigma(ax_1 + bx_2) \text{ FROM R;}$$

Note: Q2 is performing a sigmoid operation

Will Crystal against

- CPU based multi threaded implementation
- CPU-Opt: CPU + Non temporal writes (write out cache line to main memory) + SIMD optimizations
- Modeling: Calculating expected runtimes given hardware specifications

How does modeling work

For query $\texttt{SELECT } ax_1 + bx_2 \texttt{ FROM R;}$

$$runtime = \boxed{\frac{2 \times 4 \times N}{B_r}} + \boxed{\frac{4 \times N}{B_w}}$$

Time to load both columns

Time to write result back

- N = # of rows
- Br = Read bandwidth
- Bw = Write bandwidth

Projection Performance

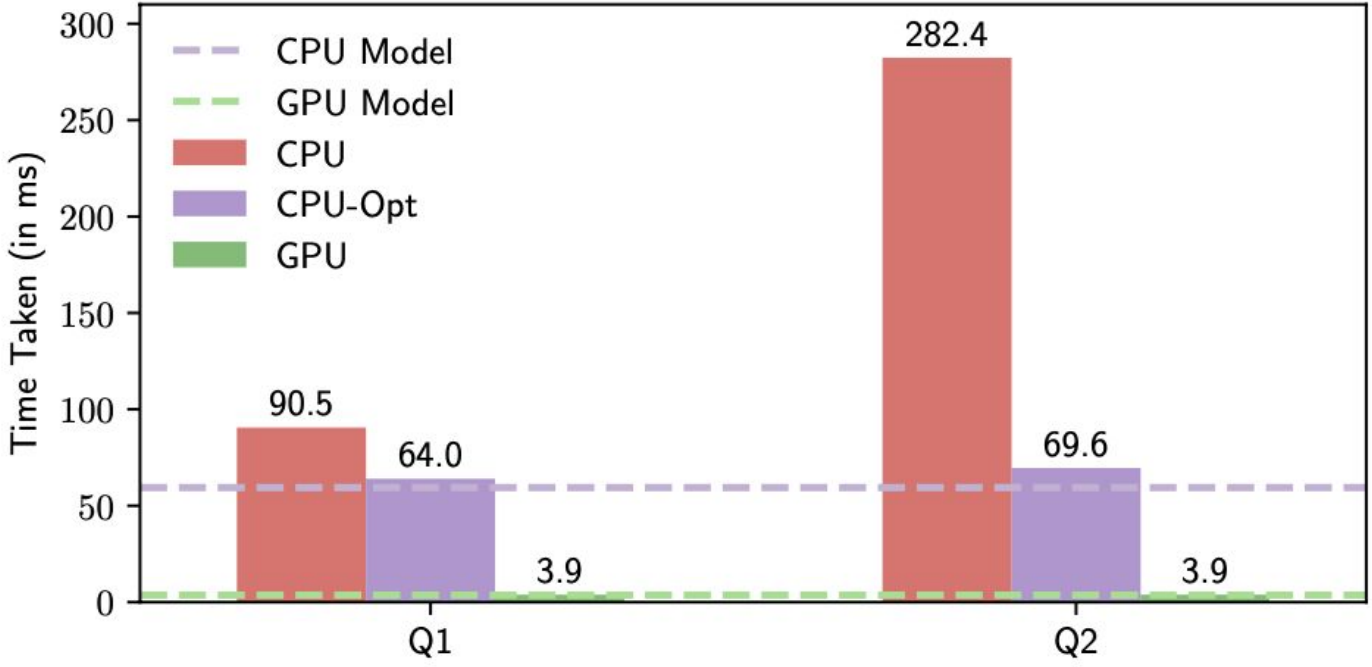


Table with 2^29 rows

Selection

```
Q3: SELECT y FROM R WHERE y < v;
```

Two possible approaches:

```
for each y in R:
  if y > v:
    output[i++] = v
```

(a) With branching

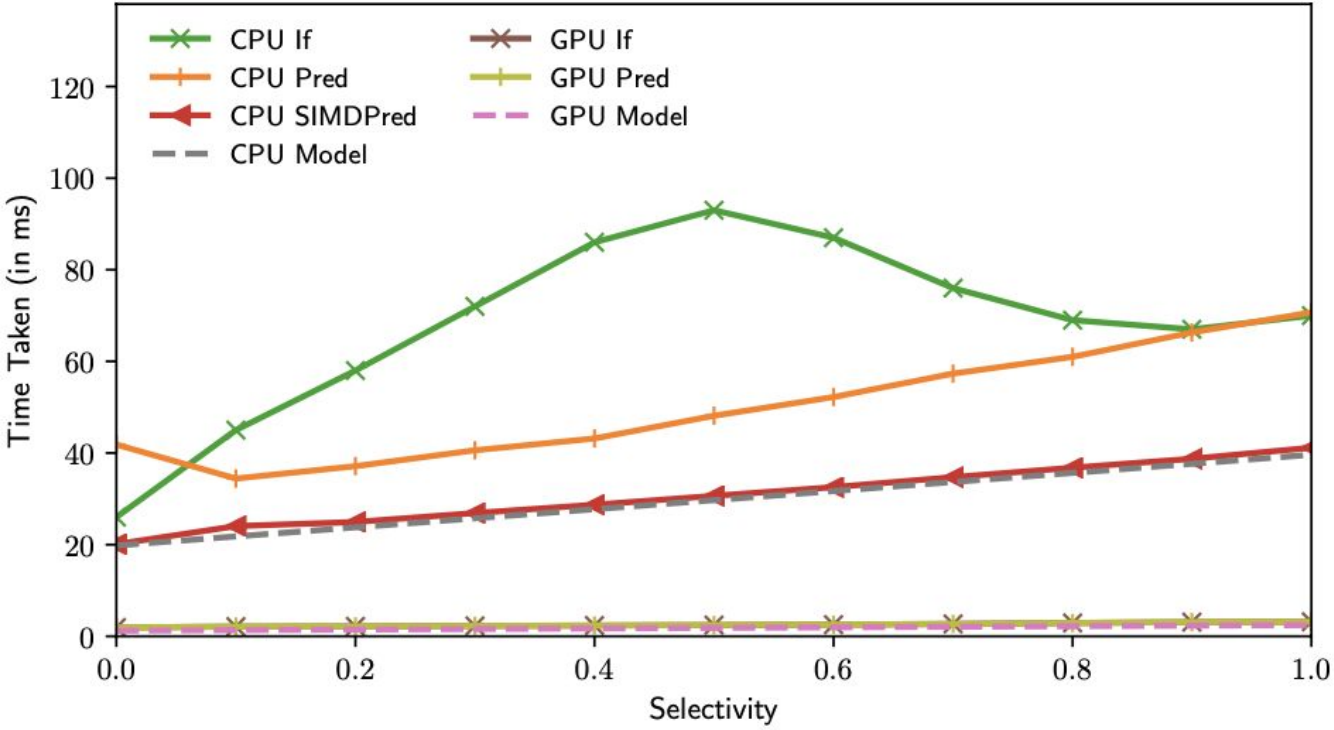
GPU IF

```
for each y in R:
  output[i] = y
  i += (y > v)
```

(b) With predication

GPU Pred

Selection Performance



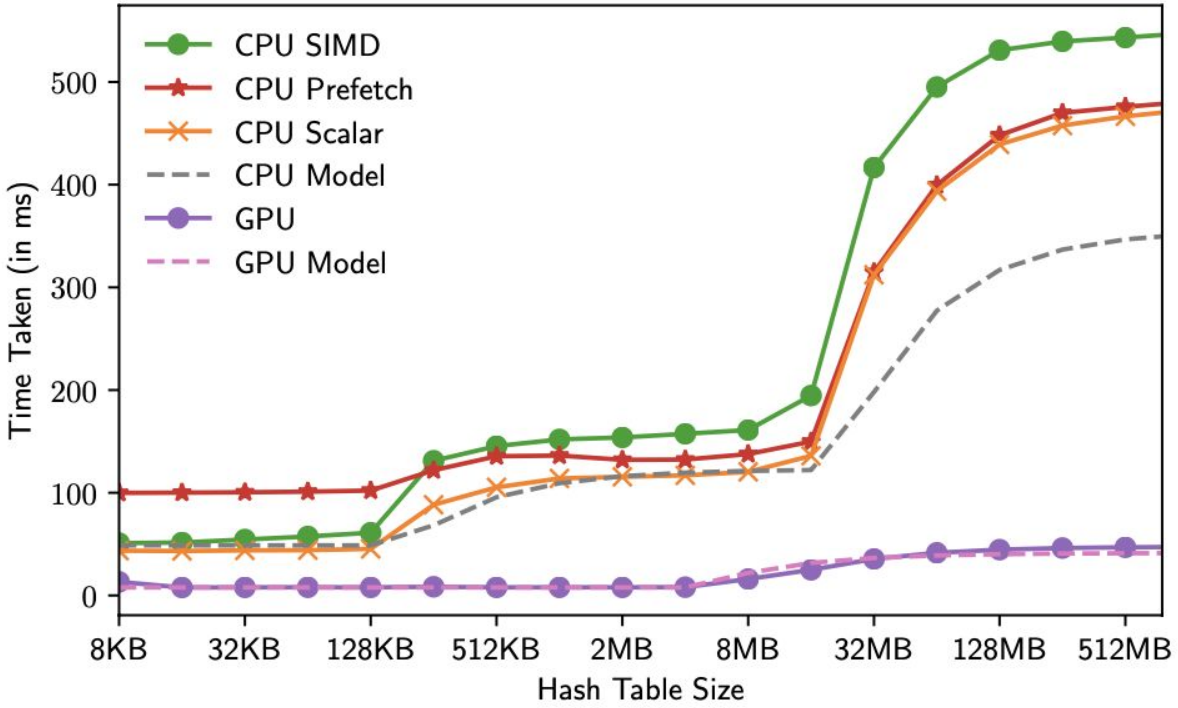
Hash Join

```
Q4: SELECT SUM(A.v + B.v) AS checksum
    FROM A,B WHERE A.k = B.k
```

Important points:

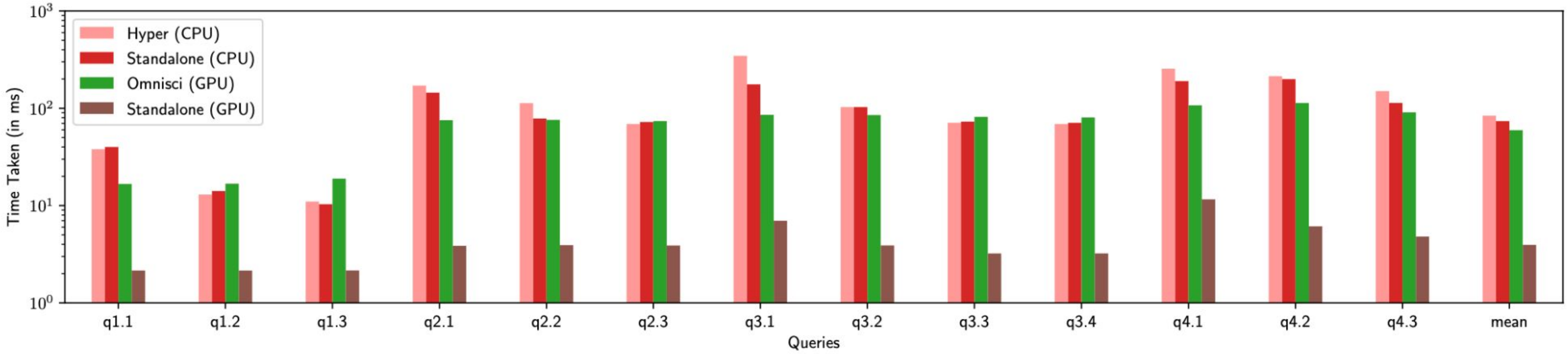
- Probe table: 256 million rows, 50% fill rate, linear probing
- Crystal approach:
    1. Load dating using BlockLoad
    2. Each thread finds matching entries and maintains a local sum
    3. Get overall sum using BlockAggergate

Hash Join Performance



Build hash table size

SSB Comparison



Takeaway: Crystal is around 25x than SOTA OLAP

The $$$ effect

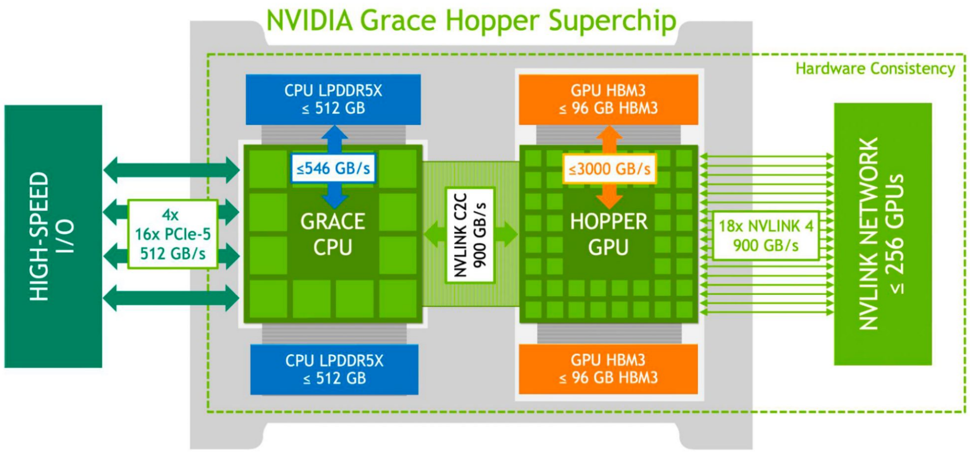
	Purchase Cost	Renting Cost
CPU	$2-5K	$0.504 per hour
GPU	$CPU + 8.5K	$3.06 per hour

GPUS are 6x more expensive but 25x faster

Limitations

Limited amount of GPU memory:

- Use multiple GPUs
- Bit compression to store more data



Only supports numeric formats

- Strings, Dates, etc..

Thoughts?