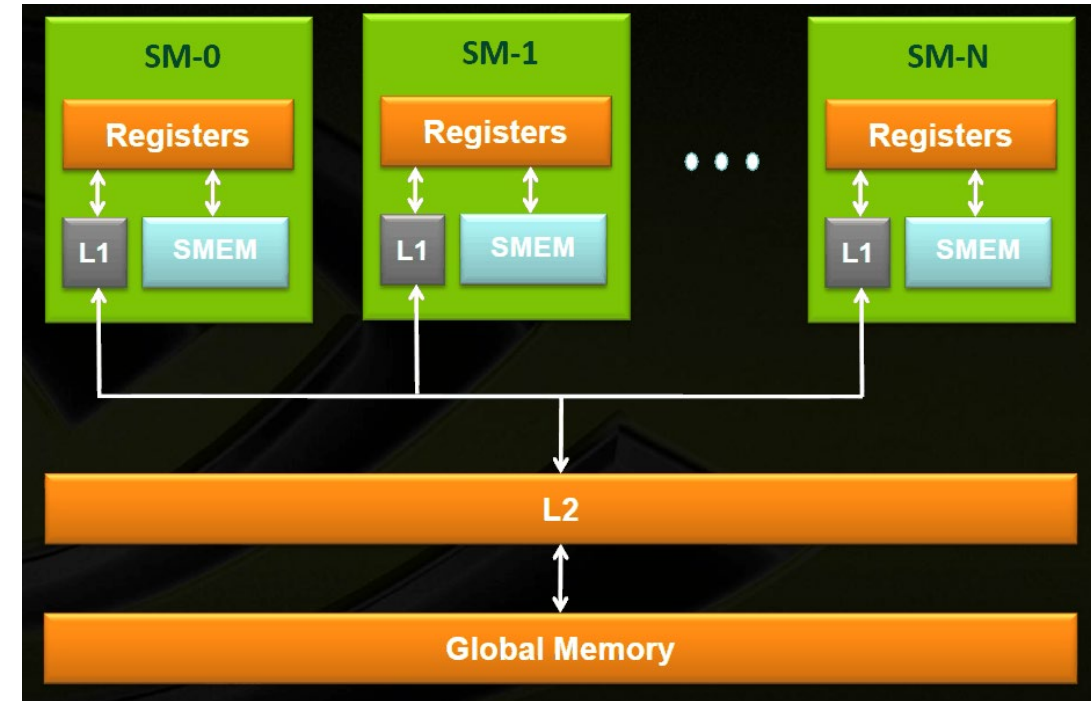


GPU memory hierarchy

- Global memory
 - Accessible by all threads and the CPU –
- L2 cache
 - Accessible by all threads
- L1 cache
 - Accessible by all threads within an SM.
 - (Hardware Cache)
- Shared memory
 - Accessible by all threads inside the block
 - **Programmable** (Software cache)
 - Allows for threads to communicate and share data between one another
- Registers
 - Per thread (lifetime is the thread lifetime)



Why shared memory:

- Shared memory is a **small, fast memory** located on-chip (inside the GPU).
- Lower latency (25 cycles vs 33 to 300 cycles).
- **Data reuse:** If multiple threads need the same data, loading it once into shared memory minimizes **global memory traffic**.
- It is shared among all threads within the **same block**, allowing them to **exchange data** without accessing global memory.

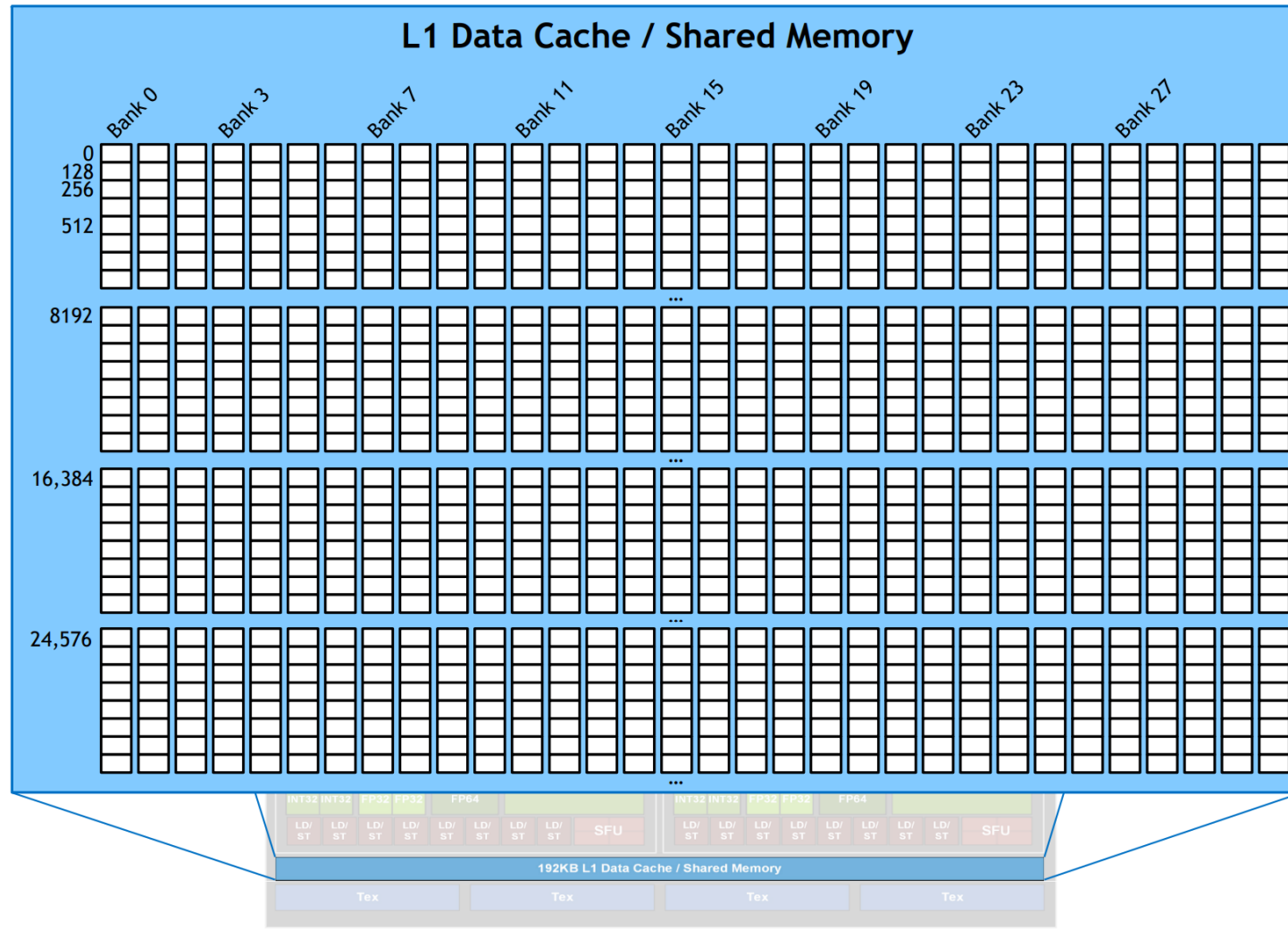
```
__shared__ float tileA[32][32];  
__shared__ float tileB[32][32];
```

slow
- Managed by software code.
- Thus, reduce the memory bottlenecks.

The shared memory size in the ampere architecture:

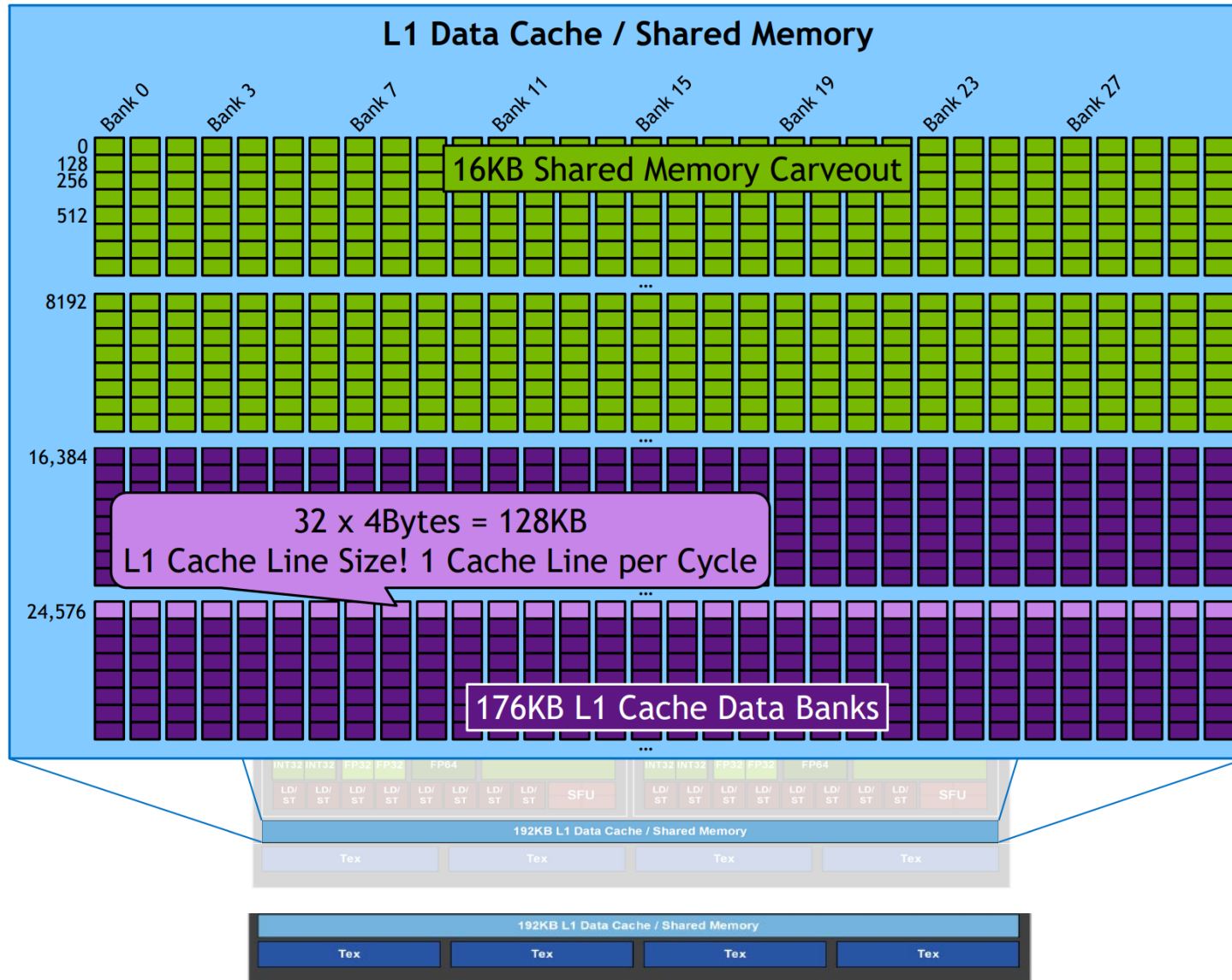
- Shared memory and L1 cache are built with 1 physical unit with a fixed total size.
- This means their sizes are configurable.
- Example, in A100 GPU their physical unit size is 192KB.
- Shared memory can be configured with specific sizes (0,8,16,32,64,100,132,164) KB.
- For example, if we choose 100 KB for the shared memory, then the l1 size will be 92 KB.
- The compiler manipulates this according to the application usage of shared memory.

The shared memory architecture:



- Shared memory is divided into cache lines with a size of 128 Byte.
- Each cache line consists of 32 banks.
- The bank size is 4 bytes.
- **4Byte data access per bank per cycle.**
- This means, once cache line can be read per cycle.

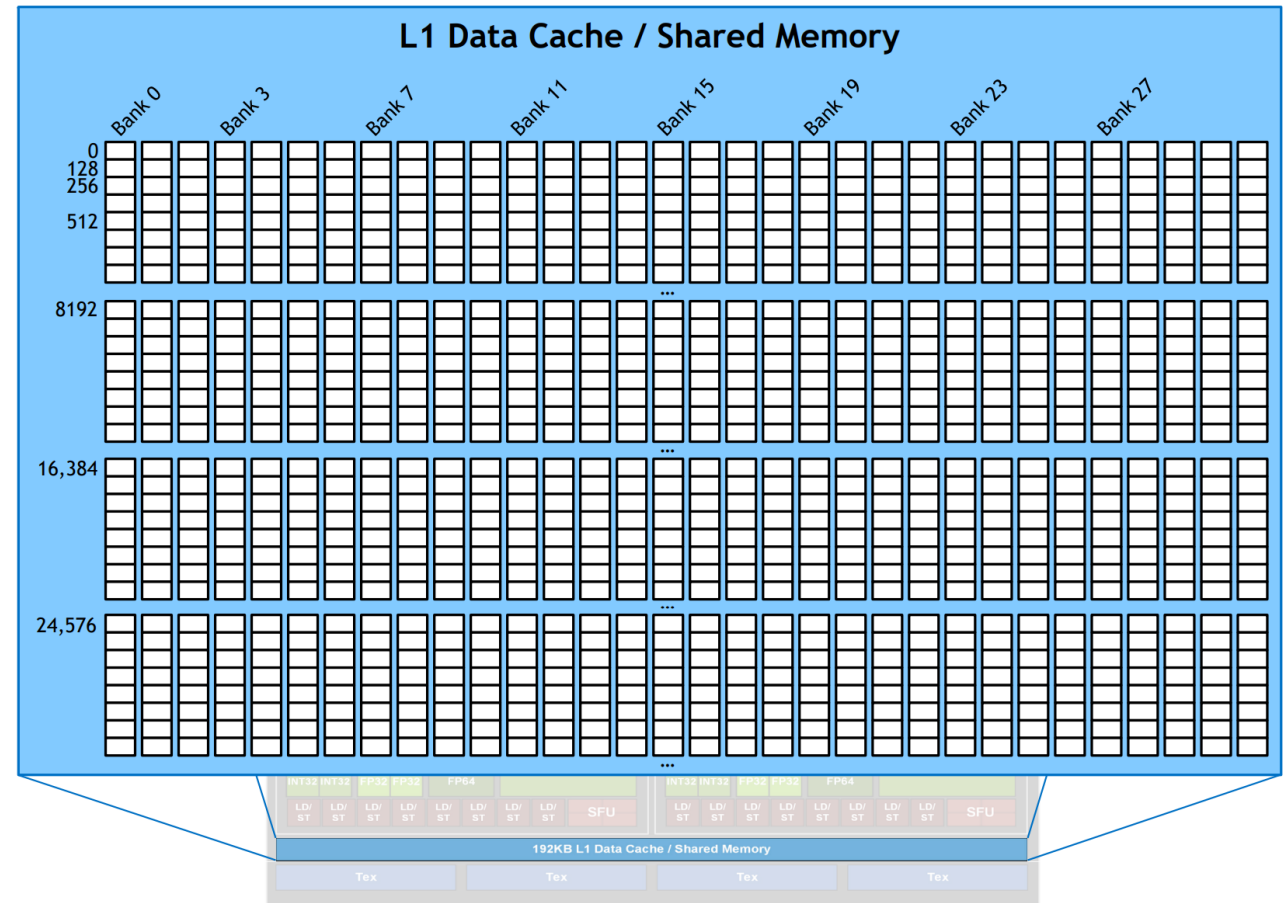
The shared memory architecture:



- The figure shows physical unit itself.

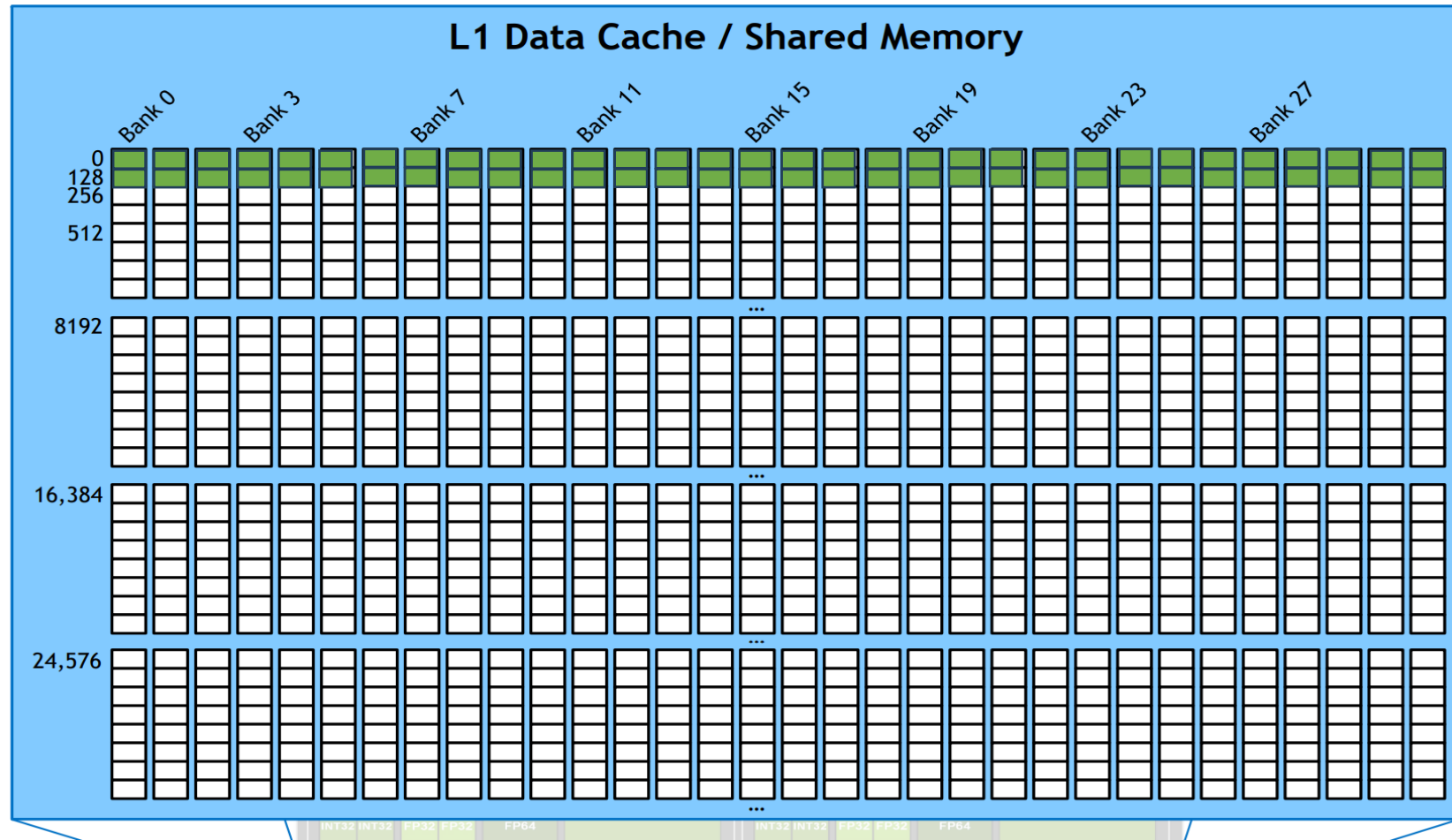
The shared memory architecture:

- Try to minimize the number of conflicts as much as you can.
- Use the shared memory for re-using data as much as you can.
- We will apply the shared memory optimizations on the vector reduction application.

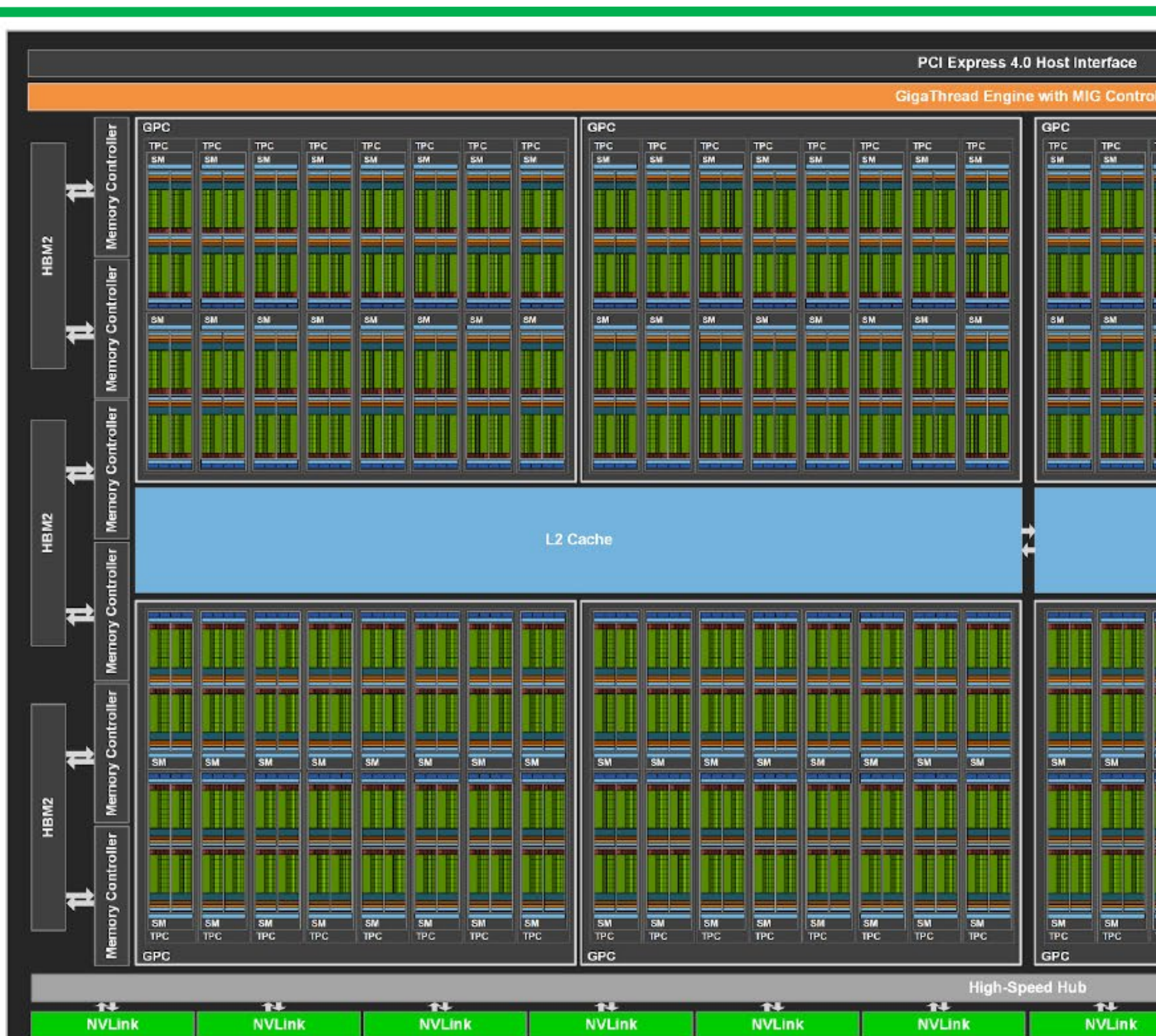


The shared memory architecture:

- Ex: how many conflicts if a warp is going to read a 32 double precision elements ?!
 - Double precision element size is 8 bytes.
 - Total size required is 8×32 threads = 256 Bytes.
 - We must have at least one conflict (because we can't read more than 128 Bytes per cycle).
 - If the elements are stored contiguously, we will have two accesses per column.
 - This provides at least 1 conflict.



GPU hardware in general



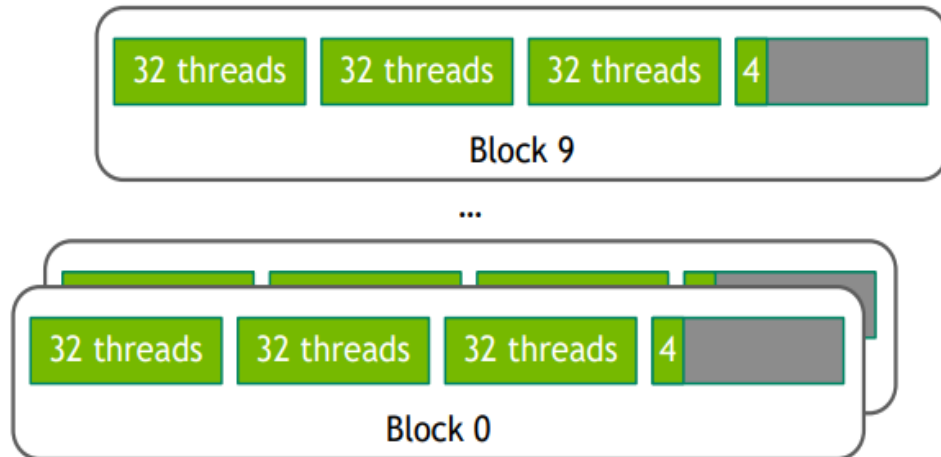
Important example

- In previous apps:
 - The number of elements = a Multiple of 32 value .
 - For example, 1024 elements per vector. (or 2048)
 - Minimum size of any cuda application is 1 warp (32 threads).
 - We can use 32 threads but assign an operation to only one.
 - But we can't use less than 32.
 - So, we have to use 32 or multiple of 32.
 - That make it easy to determine the number of warps (block size).

Important example

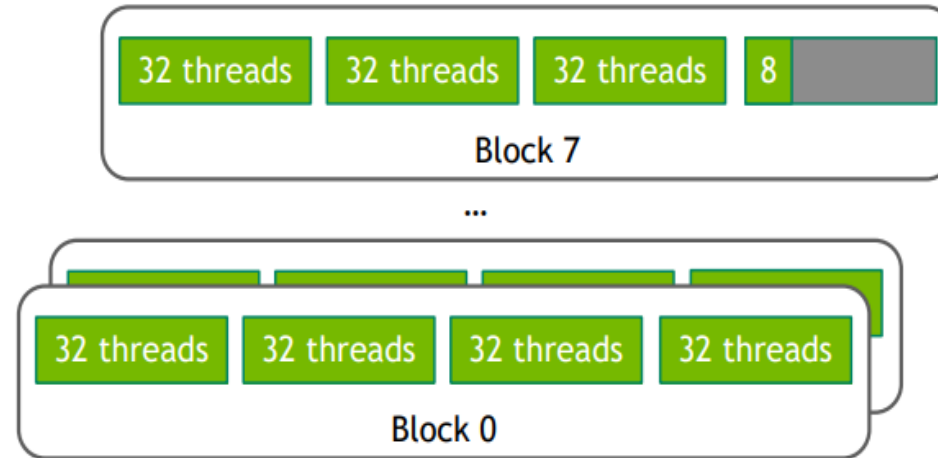
Question:

- What if the total elements are not equal to a multiple of 2 value ?
- Let's say we want to add two vectors of size $N = 1000$.
 - **Scenario #1:** 1-D grid of 10 1-D blocks of size 100.
 - **Scenario #2:** 1-D grid of 8 1-D blocks of size 128.
- Which option is better in terms of thread resource utilization?



Scenario #1:

3 full warps and 1 warp with 4 active threads per block
Average thread utilization = 78.125%



Scenario #2:

4 full warps per block, except last block
Average thread utilization = 97.656%