

# **GPU Programming with CUDA**

# What is CUDA?

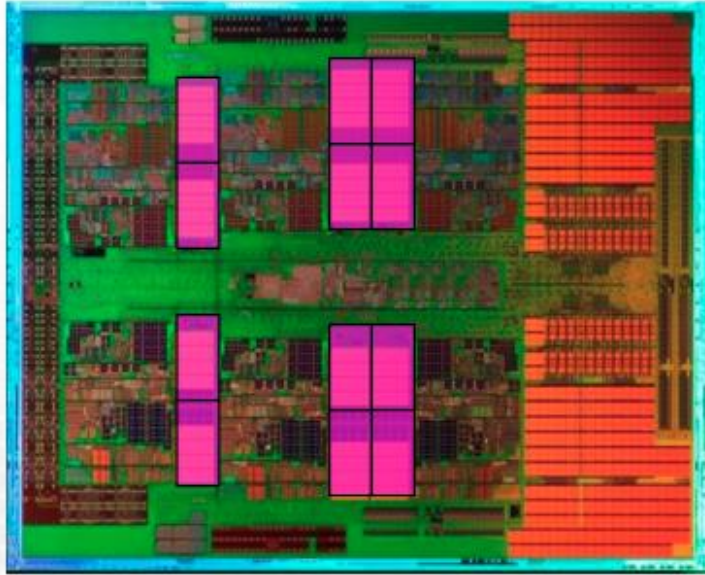
In November 2006, NVIDIA introduced CUDA, a general purpose parallel computing platform and programming model that leverages the parallel compute engine in NVIDIA GPUs.

Environment available in:

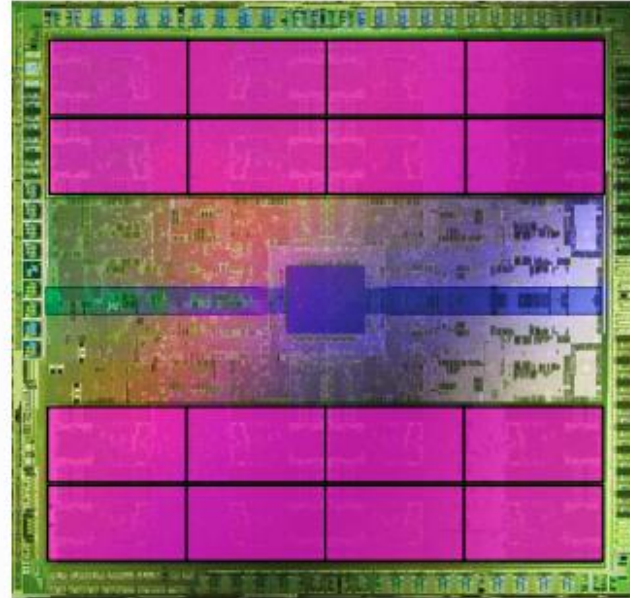
- C
- C++
- Fortran
- Python, Java wrappers


# A closer look at CPU & GPU

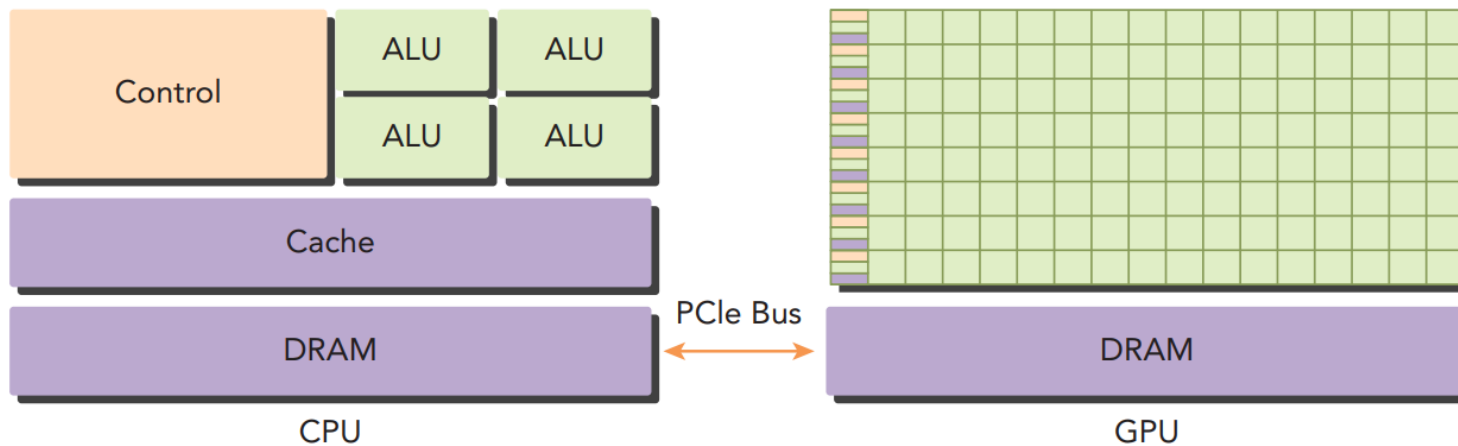
*CPU*



*GPU*



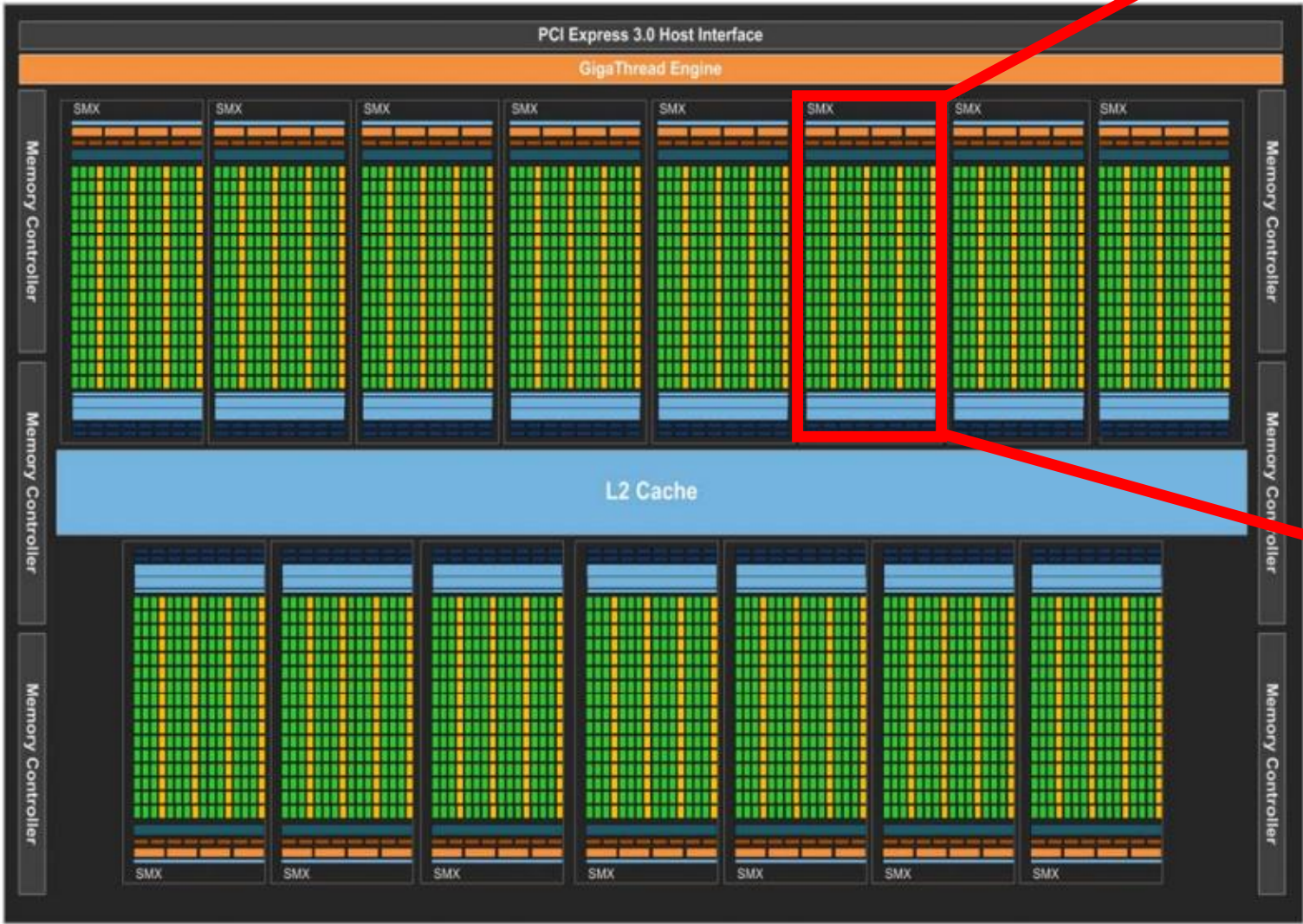
 = compute unit (core or multiprocessor)



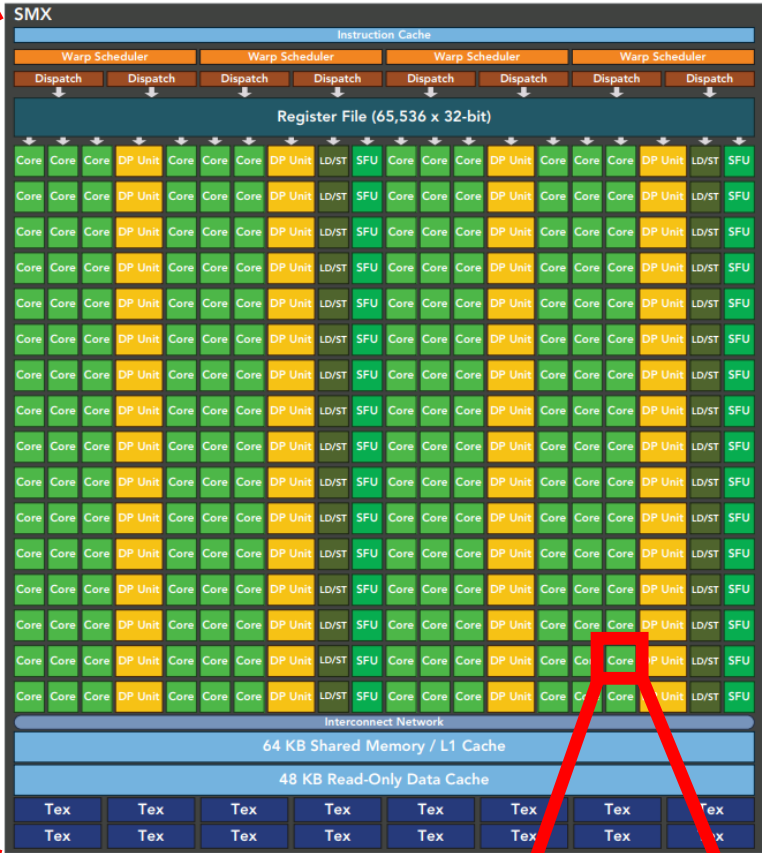
- **A CPU core**, relatively heavy-weight, is designed for very complex control logic, seeking to optimize the execution of sequential programs
- **A GPU core**, relatively light-weight, is optimized for data-parallel tasks with simpler control logic, focusing on the throughput of parallel programs

# A closer look at GPU: a multi-multi-core machine

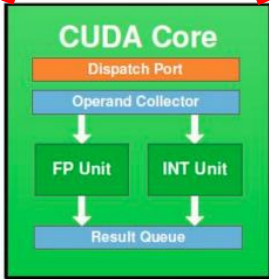
GPU: An array of *Streaming Multiprocessors (SM)*



*Streaming Multiprocessor (SM)*



- Less Scheduling units than cores
- Cores multiples of 32
- Scheduling of cores/ threads in groups of 32 (warps)



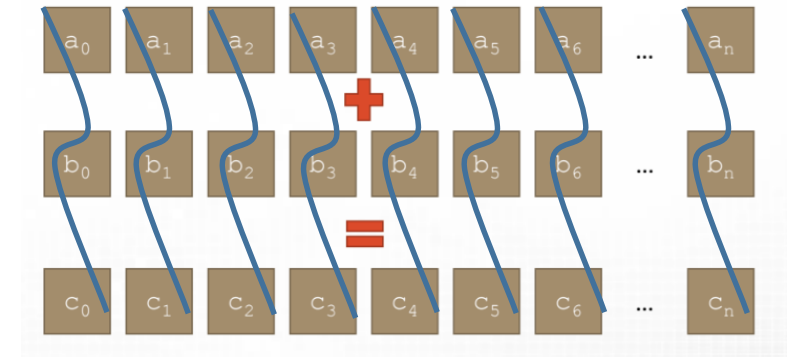
# First GPU program

Kernel is the code that is called by the **host** (CPU) and executed by the **device** (GPU)

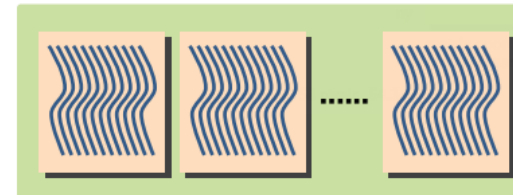
```
int main()
{
    ...

    //Kernel invocation (grid of blocks of threads)
    VecAdd<<<Blocks,ThreadsPerBlock>>>(A,B,C);

    ...
}
```

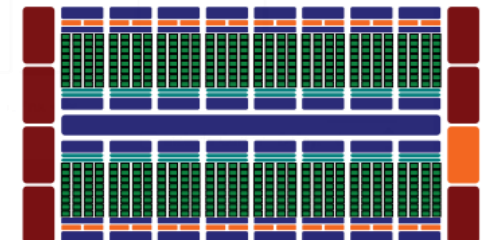
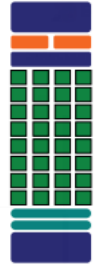
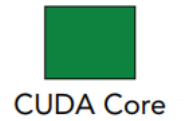


## Software



Grid

## Hardware



Device



# First GPU program

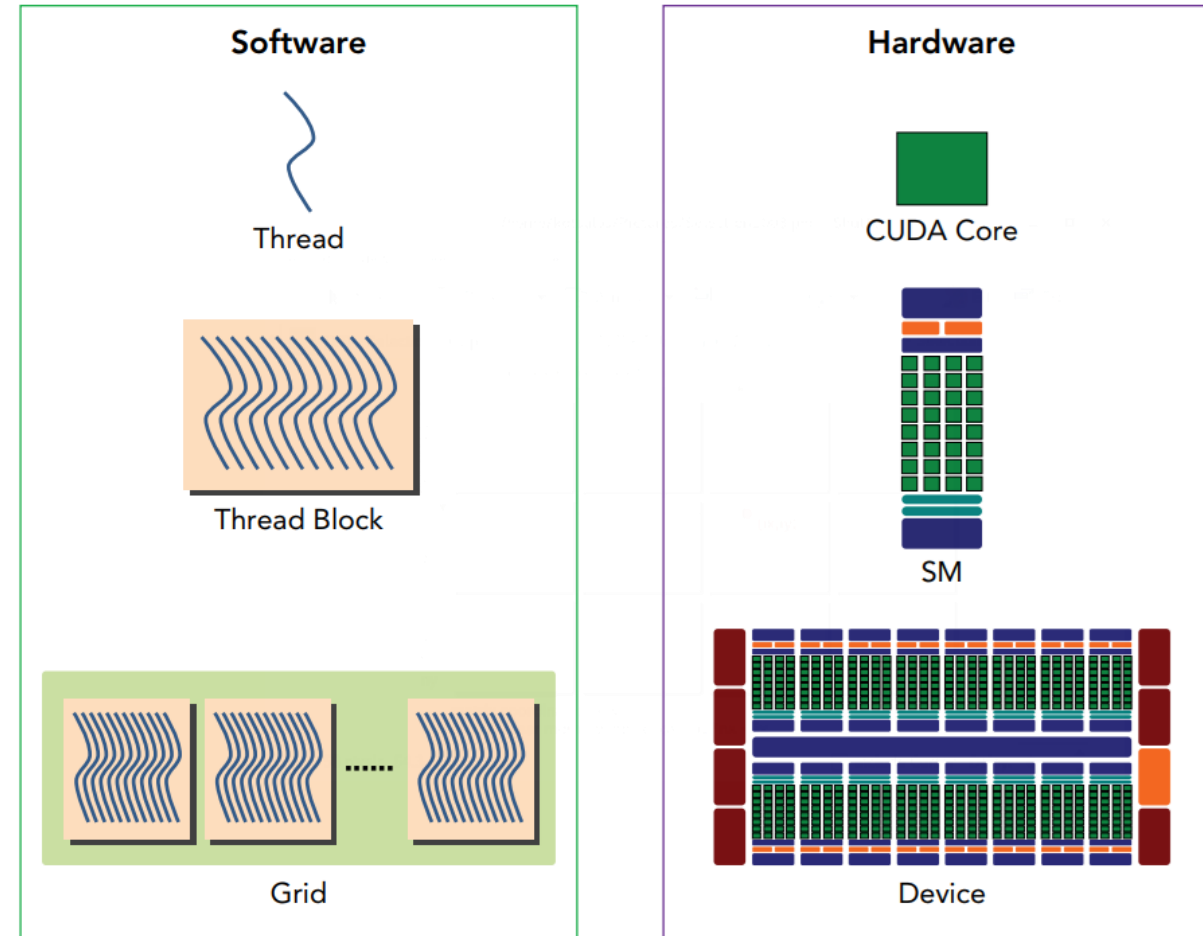
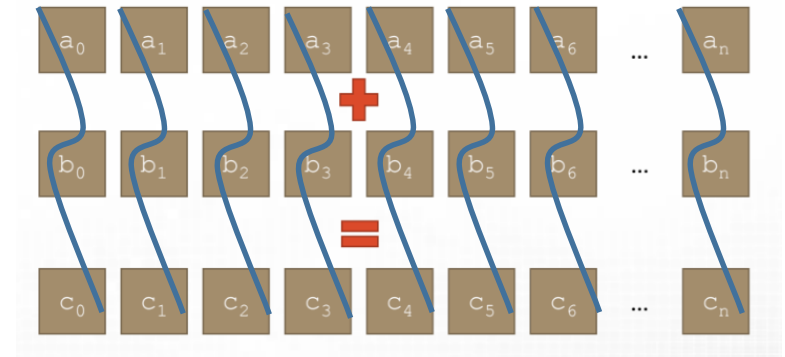
Kernel is the code that is called by the **host** (CPU) and executed by the **device** (GPU)

```
int main()
{
    ...

    //Kernel invocation (grid of blocks of threads)
    VecAdd<<<Blocks, ThreadsPerBlock>>>>(A, B, C);

    ...
}
```

- To maximize performance, we need to fully utilize GPU resources
- Every CUDA core, every Streaming Multiprocessor should be in use
- The kernel acts like a for-loop, whose contents are executed by each thread (CUDA core)
- The goal is to create as many blocks/ threads as possible (even if we exceed the resources) so as to hide latency with computations. A GPU may have 192 CUDA cores but we should create more threads than the available so as, when one thread waits for a memory access, it is replaced by one that does actual computations

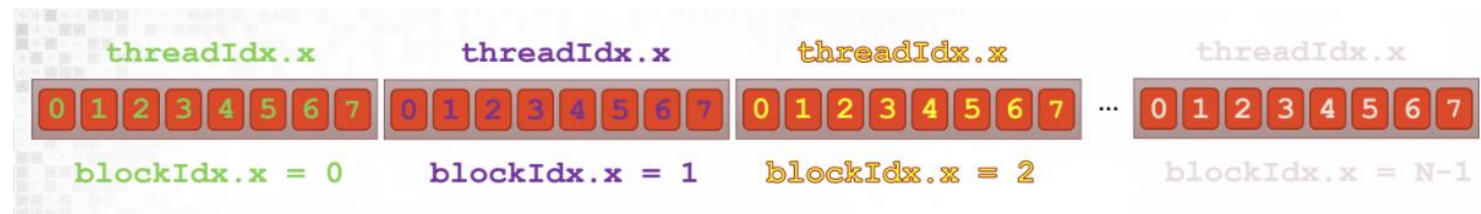
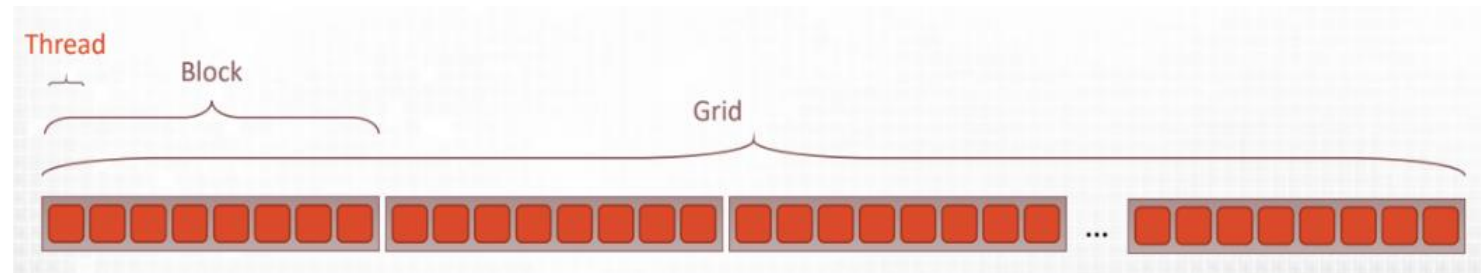
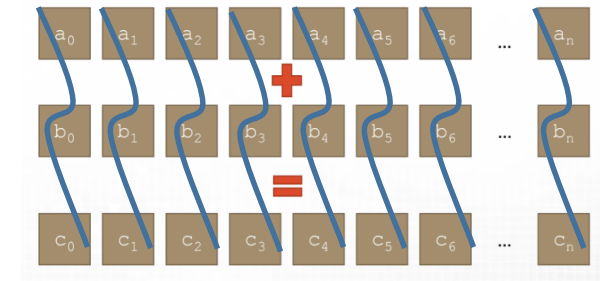


# First GPU program

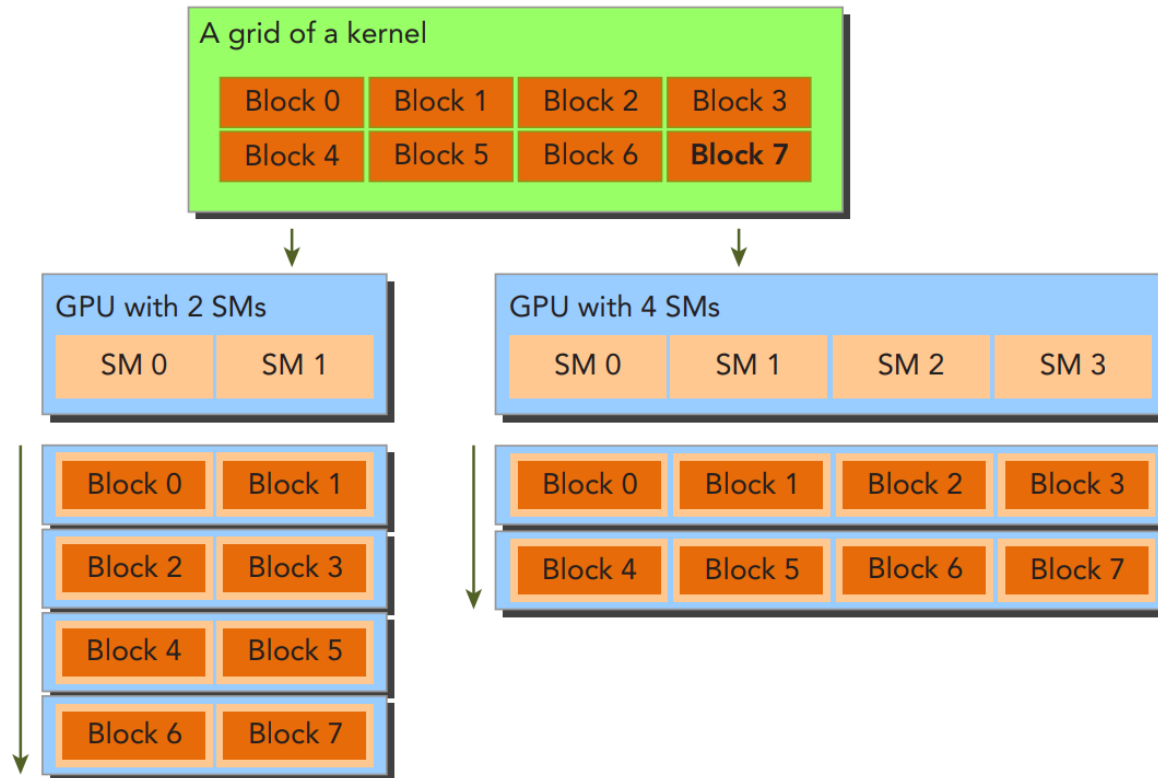
```
VecAdd<<<Blocks,ThreadsPerBlock>>>(A,B,C);

...

// Kernel definition - Executed by every thread
__global__ void VecAdd(float* A, float* B, float* C)
{
    // threadIdx, blockDim, blockIdx: CUDA built-in vars
    int i = threadIdx.x + blockDim.x * blockIdx.x;
    if (i < N) // Size of vectors
        C[i] = A[i] + B[i];
}
```



# Scheduling

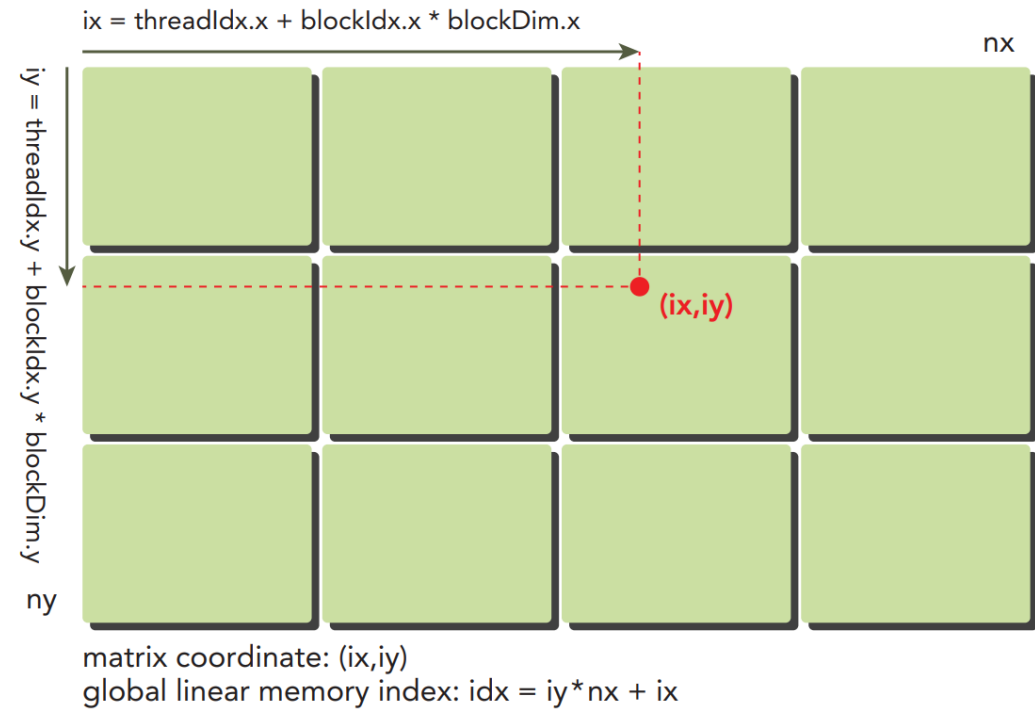
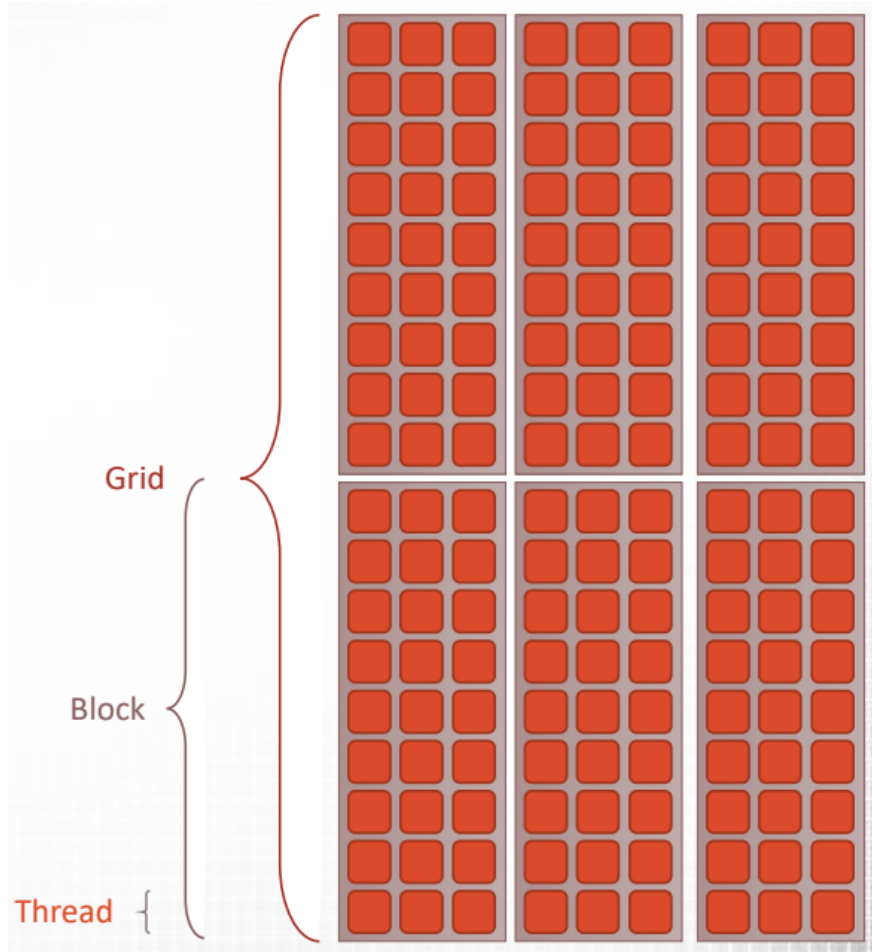


- CUDA will do the scheduling in the background given the available resources
- Remember to create more blocks/ threads than the available (SMs/CUDA cores) to hide latency

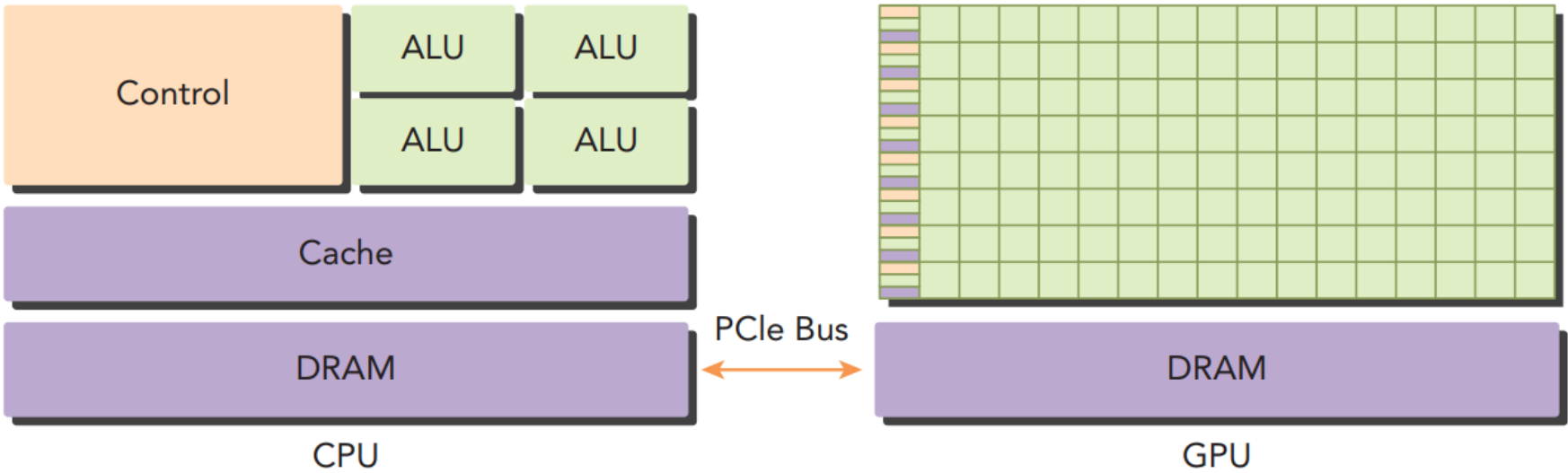




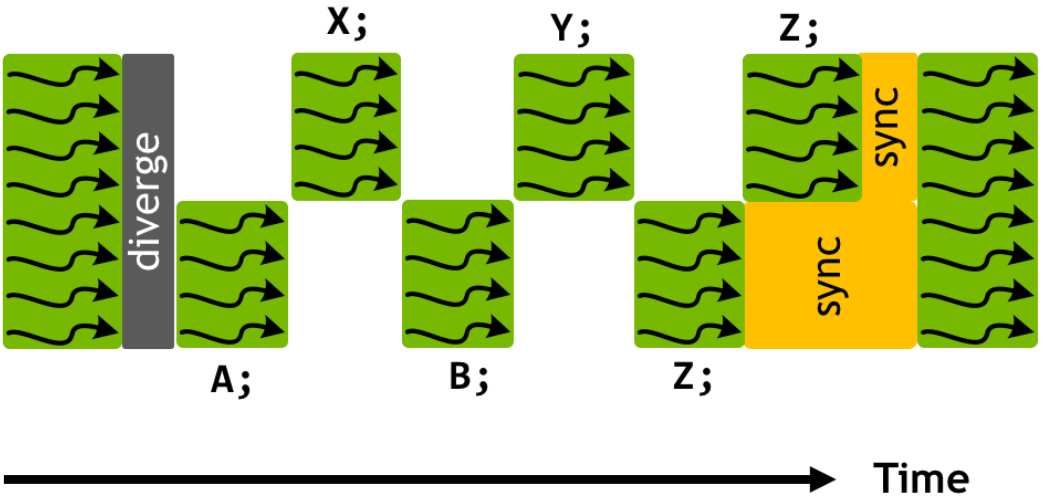
# 2D Blocks



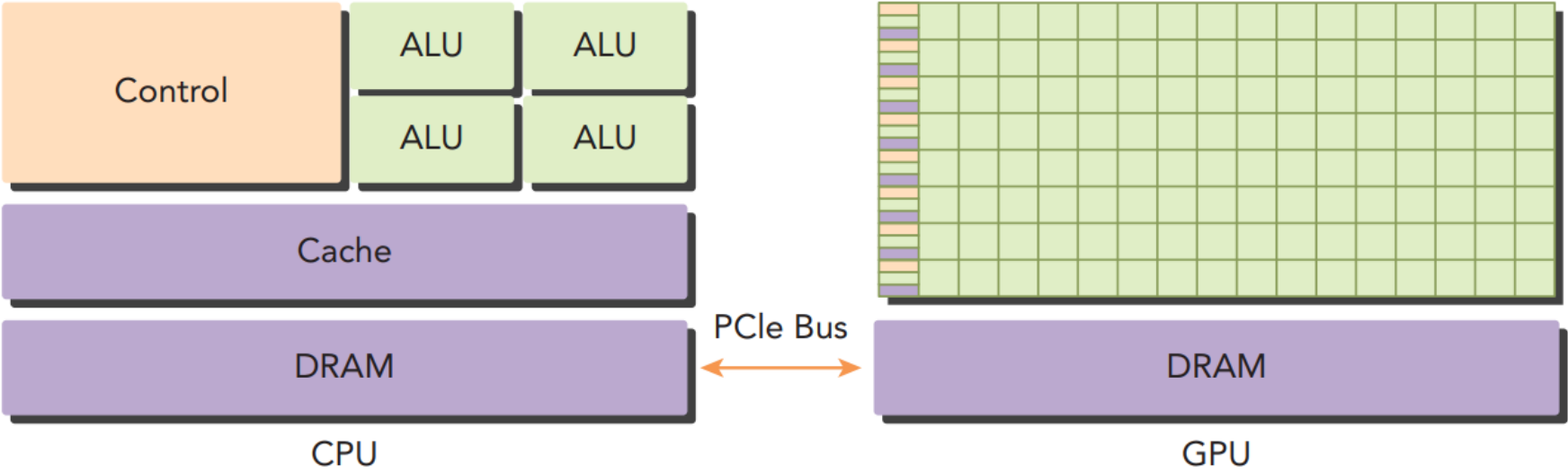
# Branch Divergence in GPU



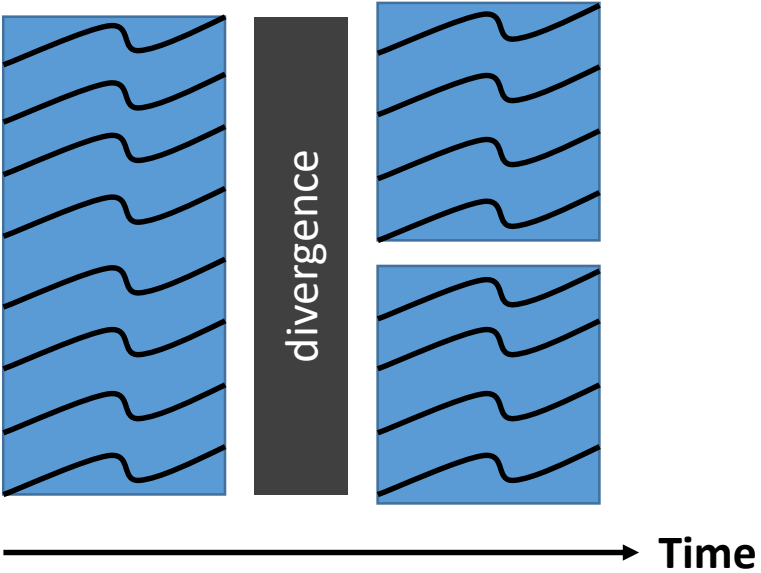
```
if (threadIdx.x < 4) {  
    A;  
    B;  
} else {  
    X;  
    Y;  
}  
Z;  
__syncwarp();
```



# Branch Divergence in CPU



```
if (threadIdx.x < 4) {  
    A;  
    B;  
} else {  
    X;  
    Y;  
}  
Z;  
__syncwarp()
```



# CUDA Memory Model

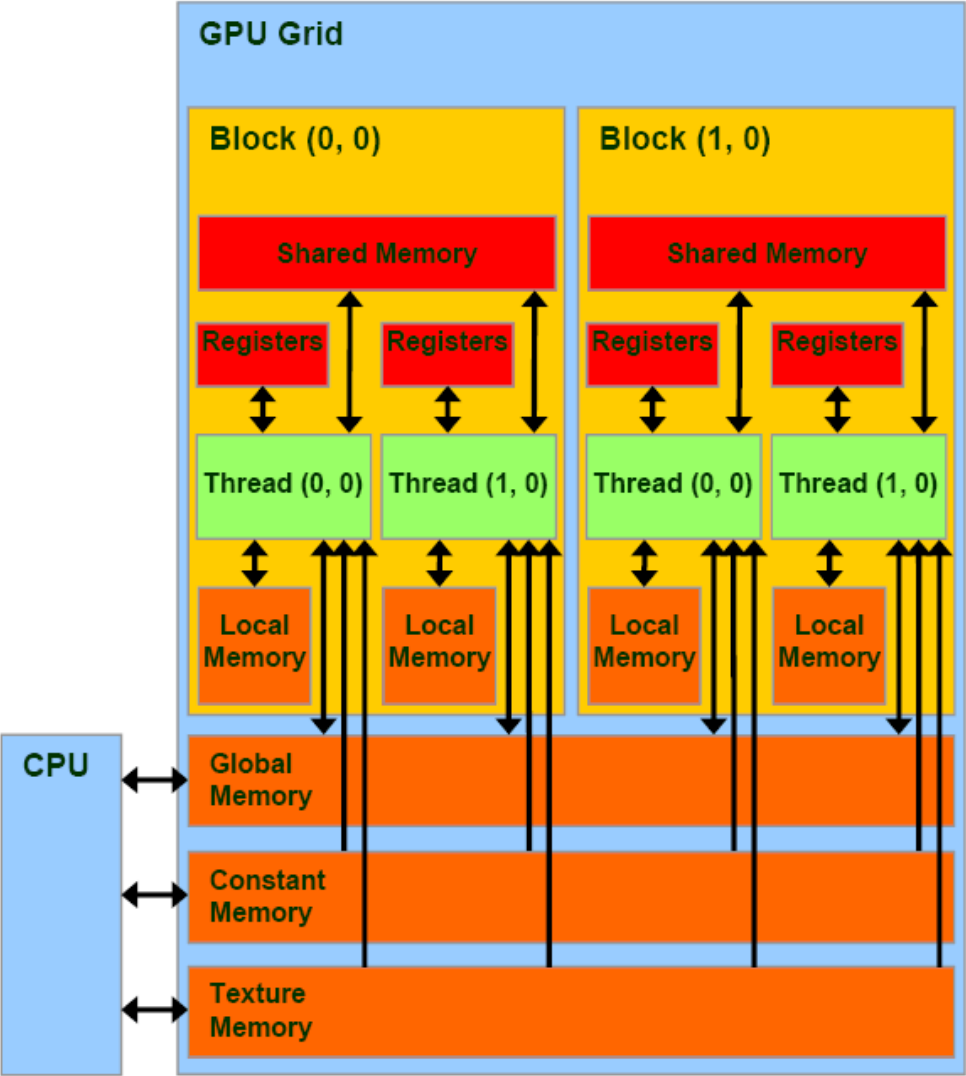


TABLE 4-2: Salient Features of Device Memory

MEMORY	ON/OFF CHIP	CACHED	ACCESS	SCOPE	LIFETIME
Register	On	n/a	R/W	1 thread	Thread
Local	Off	†	R/W	1 thread	Thread
Shared	On	n/a	R/W	All threads in block	Block
Global	Off	†	R/W	All threads + host	Host allocation
Constant	Off	Yes	R	All threads + host	Host allocation
Texture	Off	Yes	R	All threads + host	Host allocation

† Cached only on devices of compute capability 2.x

Off chip access is 100 times slower than on chip



# Memory Allocation in action

```
#define N 2048
#define THREADS_PER_BLOCK 128

__global__ void vectorAdd(float *a, float *b, float *c) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    c[i] = a[i] + b[i];
}

int main(void) {
    float *a, *b, *c;           // host copies of a, b, c
    float *d_a, *d_b, *d_c;     // device copies of a, b, c
    int size = N * sizeof(float);

    cudaMalloc((void **)&d_a, size);
    cudaMalloc((void **)&d_b, size);
    cudaMalloc((void **)&d_c, size);

    a = (float *)malloc(size); random_floats(a, N);
    b = (float *)malloc(size); random_floats(b, N);
    c = (float *)malloc(size);

    cudaMemcpy(d_a, a, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, b, size, cudaMemcpyHostToDevice);

    vectorAdd <<<N / THREADS_PER_BLOCK, THREADS_PER_BLOCK >>>(d_a, d_b, d_c);

    cudaMemcpy(c, d_c, size, cudaMemcpyDeviceToHost);

    free(a); free(b); free(c);
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

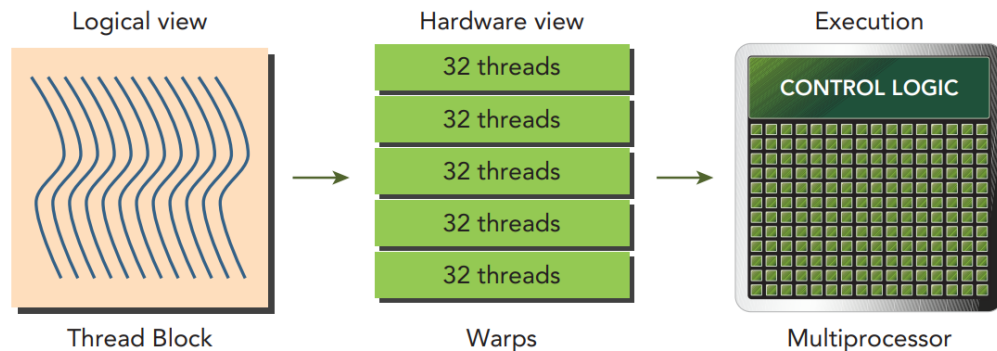
# Warps

- CUDA Cores multiple of 32
- The blocks of threads are further subdivided into warps (groups of 32 threads)
- Transparent to the user, but can be critical for the performance

The number 32\* is a magic number in CUDA programming. It comes from hardware and has a significant impact on the performance of software.

Conceptually, you can think of it as the granularity of work processed simultaneously in SIMD fashion by a SM. Optimizing your workloads to fit within the boundaries of a warp will generally lead to more efficient utilization of GPU compute resources.

\* The “32” may change in the future



## Streaming Multiprocessor (SM)



Depending on the number of warp schedulers and available CUDA cores, the warps can be executed concurrently

# Optimized Performance

- The threads of the warps should access memory that is contiguous (close in the memory space)
- Threads of the warps should execute the same path (avoid if-branches per warp). Divergence of threads of a warp lead to serialization which impacts performance. Different warps can take whichever branch they want

