GPU Computing: Advanced Memory

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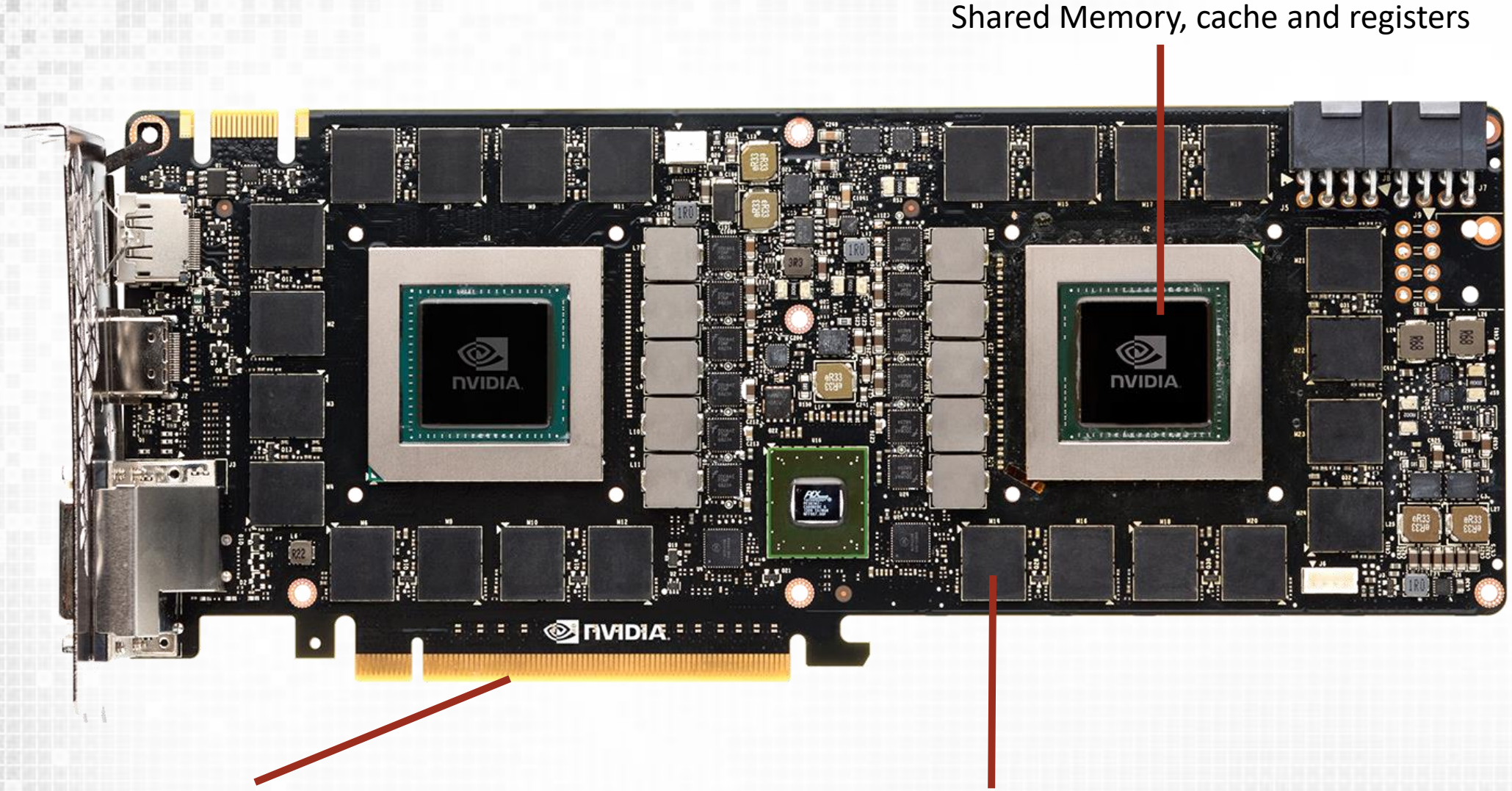
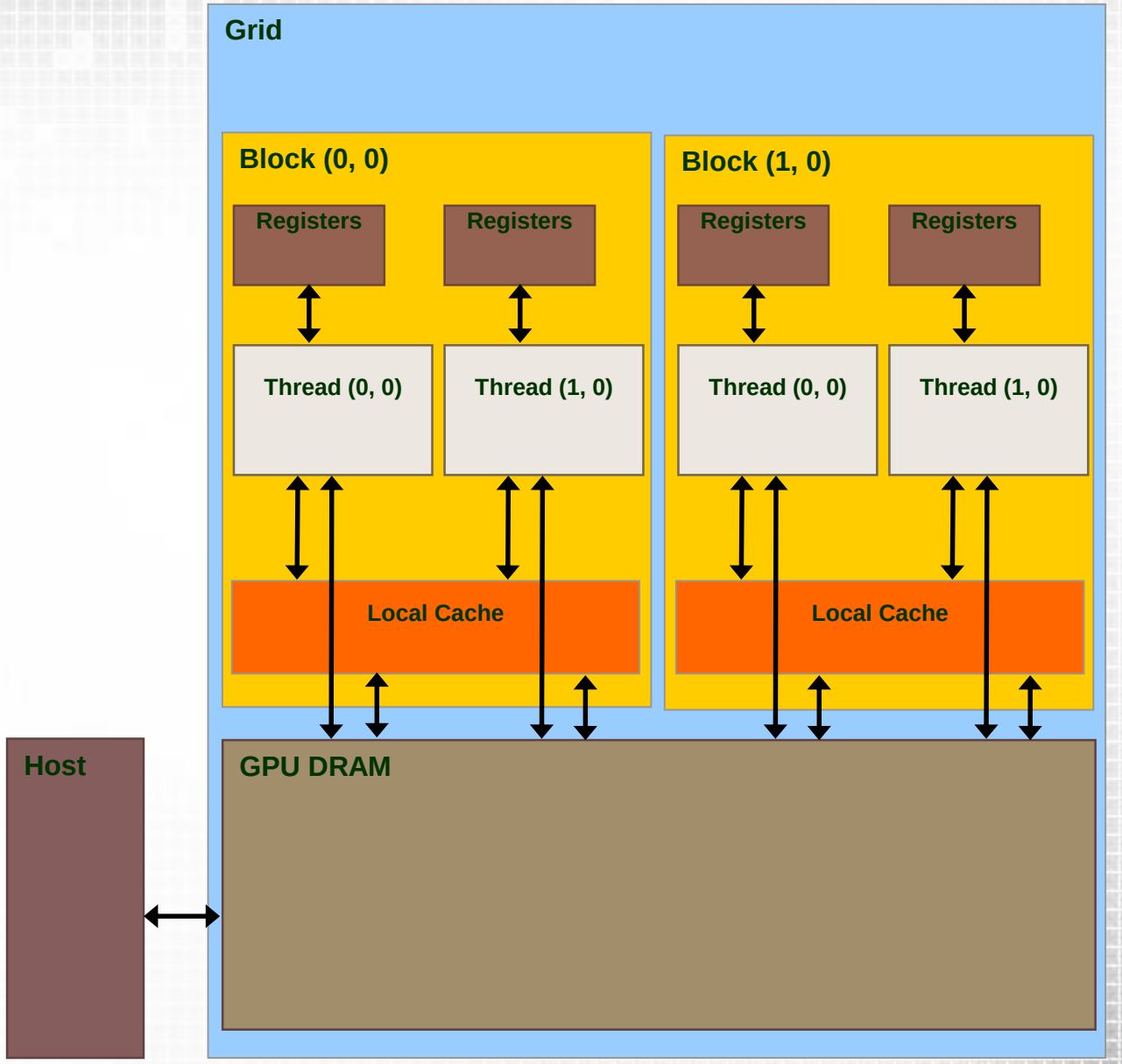
- Memory Hierarchy Overview
- Constant and Read-only Cache Memory
- Shared Memory

GPU Memory (GTX Titan Z)



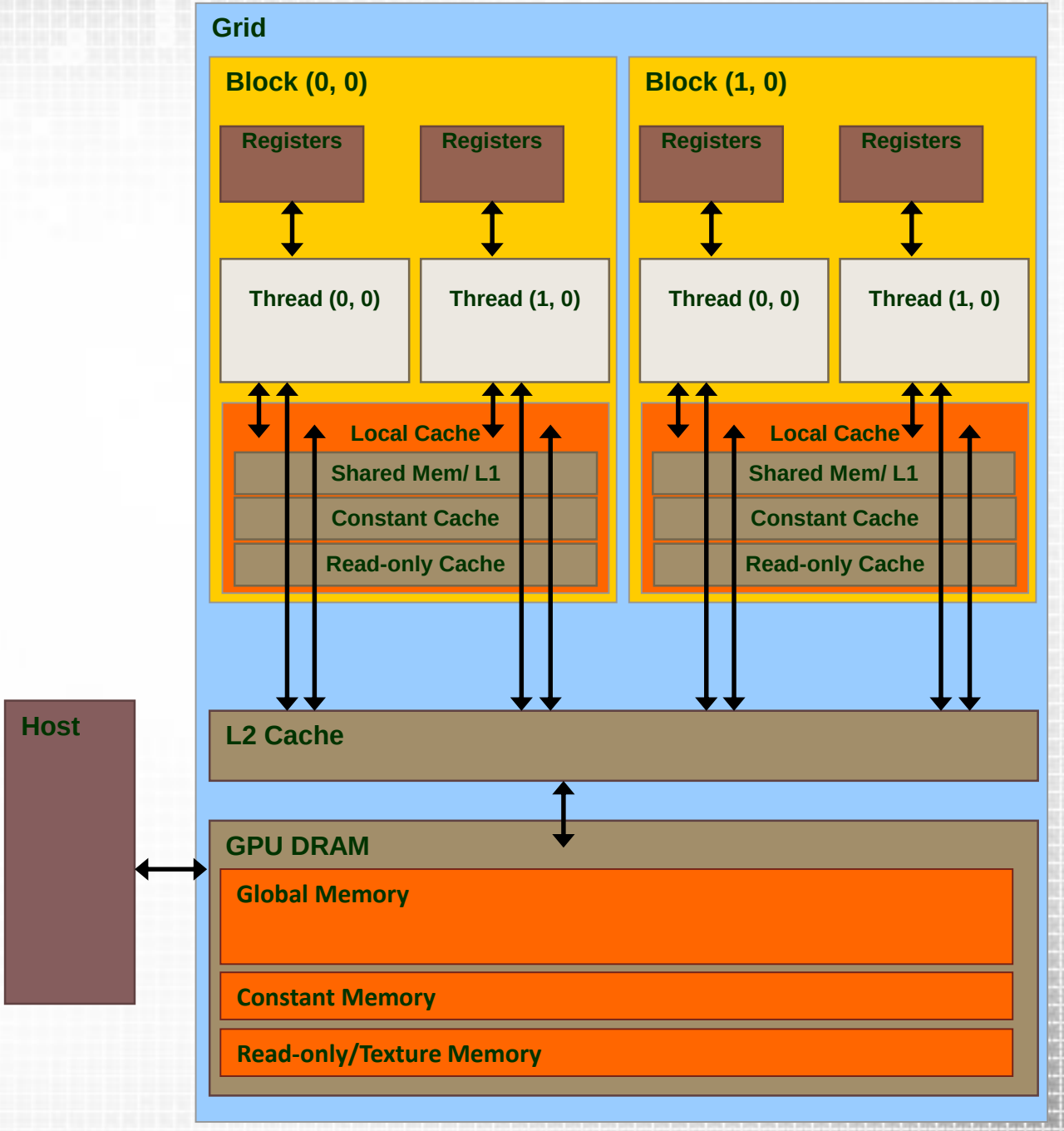
Simple Memory View

- Threads have access to;
  - **Registers**
    - Read/Write **per thread**
  - **Local memory**
    - Read/Write **per thread**
  - **Local Cache**
    - Read/Write **per block**
  - **Main DRAM Memory**
    - Read/Write **per grid**



Kepler Memory View

- Each Thread has access to
  - **Registers**
    - Read/Write per thread
  - **Local memory**
    - Read/Write per thread
    - Does not physically exist (reserved area in global memory)
    - Cached in L1
    - Overspill for registers
  - Main DRAM Memory via cache
    - Global Memory
      - Via **L2 cache** and configurable per block **Shared Memory / L1 cache**
    - Constant Memory
      - Via **L2 cache** and per **block Constant cache**
    - Read-only/Texture Memory
      - Via **L2 cache** and per block **Read-only cache**



Memory Latencies

- What is the cost of accessing each area of memory?
  - On chip caches are MUCH lower latency

	Cost (cycles)
Register	1
Global	200-800
Shared memory	~1
L1	1
Constant	~1 (if cached)
Read-only	1 if cached (same as global if not)

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Constant Memory

- Constant Memory
  - Stored in the device's global memory
  - Read through the per SM constant cache
  - Set at runtime
  - When using correctly only 1/16 of the traffic compared to global loads
- When to use it?
  - When small amounts of data are **read only**
  - When values are **broadcast** to threads in a half warp (of 16 threads)
  - Very fast when cache hit
  - Very slow when no cache hit
- How to use
  - Must be **statically** defined as a symbol using `__constant__` qualifier
  - Value must be copied using **cudaMemcpytoSymbol**.

Constant Memory Broadcast

- …. When values are **broadcast** to threads in a half warp (groups of 16 threads)

```
__constant__ int my_const[16];

__global__ void vectorAdd() {
int i = blockIdx.x;

int value = my_const[i % 16];
}
```

```
__constant__ int my_const[16];

__global__ void vectorAdd() {
int i = blockIdx.x * blockDim.x + threadIdx.x;

int value = my_const[i % 16];
}
```

Which is good use of constant memory?

Constant Memory Broadcast

- …. When values are **broadcast** to threads in a half warp (groups of 16 threads)

```
__constant__ int my_const[16];

__global__ void constant_test() {
int i = blockIdx.x;

int value = my_const[i % 16];
}
```

```
__constant__ int my_const[16];

__global__ void constant_test() {
int i = blockIdx.x * blockDim.x + threadIdx.x;

int value = my_const[i % 16];
}
```

Which is good use of constant memory?

- Best possible use of constant memory
- Every thread in half warp reads the same
  - Index based on `blockIdx`
- No serialisation
  - 1 read request for every thread!
- Other threads in the block will also hit cache

- Worst possible use of constant memory
- Every thread in half warp reads different value
  - Index based on `threadIdx`
- Each access will be serialised
  - 16 different read requests!
- Other threads in the block will likely miss the cache

Read-only Memory

- Useful where threads have good coherence
  - Encourages the compiler to use L2 Read-only cache
- Indicates to the compiler that the data is read-only
  - Using the `const` and `__restrict__` qualifiers
- Not the same as `__constant__` memory
  - Does not require broadcast reading

```
#define N 1024

__global__ void kernel(float const* __restrict__ buffer) {
  int i = blockIdx.x * blockDim.x + threadIdx.x;
  float x = buffer[i];
}


int main() {
  float *buffer;
  cudaMalloc(&buffer, N*sizeof(float));
  kernel << <grid, block >> >(buffer);
  cudaFree(buffer);
}
```

- ❑Memory Hierarchy Overview
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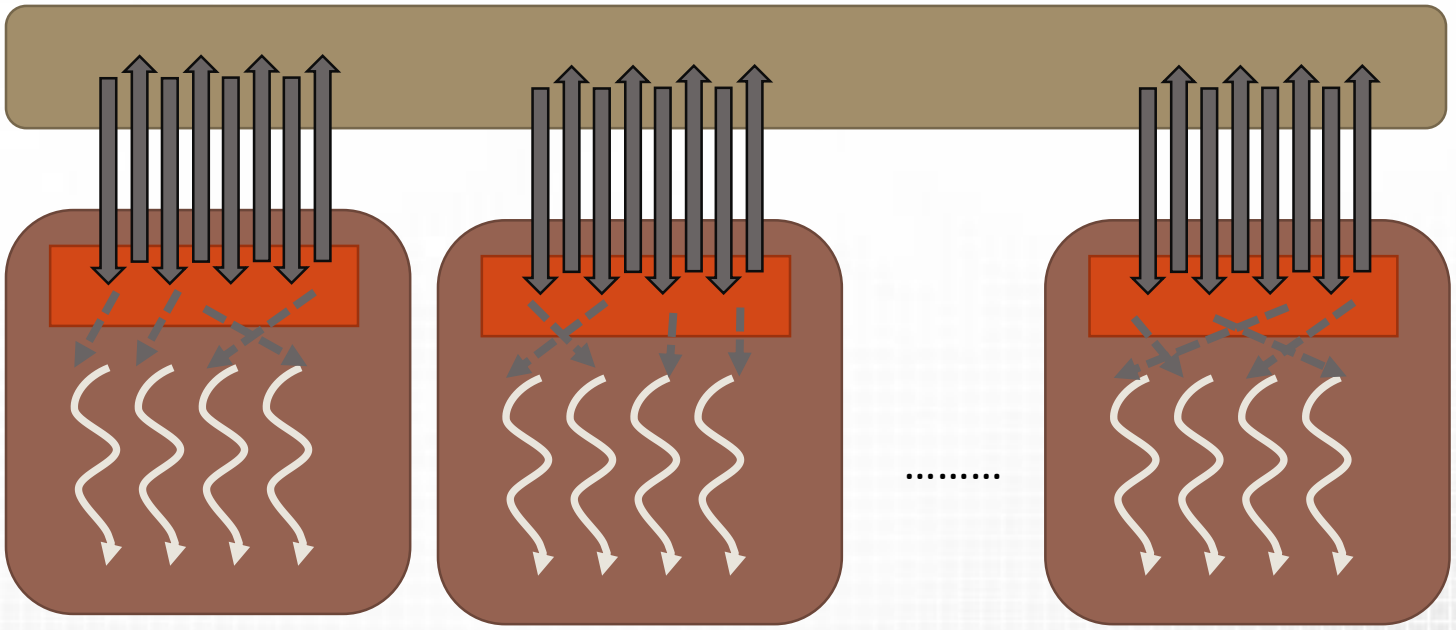
- ❑Shared Memory

Shared Memory

- Its just another Cache, right?
  - User configurable
  - Requires manually loading and synchronising data
- Performance
  - Shared memory is very fast
  - Bandwidth > 1 TB/s
  - Latency ~10 cycles
- Block level computations
  - Allows data to be shared between threads in the same block
  - User configurable cache at the thread block level
  - Still no broader synchronisation beyond the level of thread blocks

Block Local Computation

- Partition data into groups that fit into shared memory
- Load subset of data into shared memory
- Perform computation on the subset
- Copy subset back to global memory



A Case for Shared Memory

```
__global__ void sum3_kernel(int *c, int *a)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;
    int left, right;

    //load value at i-1
    left = 0;
    if (i > 0)
      left = a[i - 1];

    //load value at i+1
    right = 0;
    if (i < (N - 1))
      right = a[i + 1];

    c[i] = left + a[i] + right; //sum three values
}
```

A Case for Shared Memory

```
__global__ void sum3_kernel(int *c, int *a)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;
    int left, right;

    //load value at i-1
    left = 0;
    if (i > 0)
      left = a[i - 1];

    //load value at i+1
    right = 0;
    if (i < (N - 1))
      right = a[i + 1];

    c[i] = left + a[i] + right; //sum three values
}
```

- Thread-local computation
- Bandwidth limited
  - Requires three loads per thread (at index `i-1`, `i`, and `i+1`)
- Wouldn't it be nice if we could load each value only once!

CUDA Shared memory

- Shared memory between threads in the same block can be defined using `__shared__`
- Shared variables are only accessible from within device functions
  - Not addressable in host code
- Must be careful to avoid race conditions
  - Multiple threads writing to the same shared memory variable
    - Results in undefined behaviour
  - Typically access shared memory using `threadIdx`
  - Thread level synchronisation is available through `__syncthreads()`
    - Ensures data is ready for access

```
__shared__ int s_data[BLOCK_SIZE];
```

Example

```
__global__ void sum3_kernel(int *c, int *a)
{
  __shared__ int s_data[BLOCK_SIZE];

  int i = blockIdx.x*blockDim.x + threadIdx.x;
  int left, right;

  s_data[threadIdx.x] = a[i];
  __syncthreads();

  //load value at i-1
  left = 0;
  if (i > 0){
    if (threadIdx.x > 0)
      left = s_data[threadIdx.x - 1];
    else
      left = a[i - 1];
  }

  //load value at i+1
  right = 0;
  if (i < (N - 1)){
    if (threadIdx.x <(BLOCK_SIZE-1))
      right = s_data[threadIdx.x + 1];
    else
      right = a[i + 1];
  }

  c[i] = left + s_data[threadIdx.x] + right; //sum
}
```

- Allocate a shared array
  - One integer element per thread
- Each thread loads a single item to shared memory
- Call `__syncthreads` to ensure shared memory data is populated by all threads
- Check boundary conditions for the edge of the block
- Load all elements through shared memory

Problems with Shared memory

- Shared memory is accessed in banks
  - A bank conflict occurs when two threads request addresses from the same bank
- In the example we saw the introduction of boundary conditions
  - Global loads still present at boundaries
  - We have introduced divergence in the code (remember the SIMD model)
  - This is even more prevalent in 2D examples where we *tile* data into shared memory

```
//boundary condition
left = 0;
if (i > 0){
  if (threadIdx.x > 0)
    left = s_data[threadIdx.x - 1];
  else
    left = a[i - 1];
}
```

Summary

- The CUDA Memory Hierarchy varies between hardware generations
- Utilisation of local caches can have a big impact on the expected performance (1 cycle vs. 100s)
- Constant cache is good for small read only data accessed with a broadcast pattern
- Read-Only cache is for caching data read where access patterns are closely aligned in nearby threads
- Shared memory is user configurable cache, the moving of data and synchronisation are left to the user (you).