

Warp divergence

Lecture 3: control flow and synchronisation

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Threads are executed in warps of 32, with all threads in the warp executing the same instruction at the same time.

What happens if different threads in a warp need to do different things?

```
if (x<0.0)
    z = x-2.0;
else
    z = sqrt(x);
```

This is called *warp divergence* – CUDA will generate correct code to handle this, but to understand the performance you need to understand what CUDA does with it

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Warp divergence

This is not a new problem.

Old CRAY vector supercomputers had a logical merge vector instruction

```
z = p ? x : y;
```

which stored the relevant element of the input vectors x, y depending on the logical vector p , equivalent to

```
for(i=0; i<I; i++) {
    if (p[i]) z[i] = x[i];
    else     z[i] = y[i];
}
```

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Warp divergence

Similarly, NVIDIA GPUs have *predicated* instructions which are carried out only if a logical flag is true.

```
p: a = b + c; // computed only if p is true
```

In the previous example, all threads compute the logical predicate and two predicated instructions

```
p = (x<0.0);
p: z = x-2.0; // single instruction
!p: z = sqrt(x);
```

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Warp divergence

Note that:

- `sqrt(x)` would usually produce a NaN when $x < 0$, but it's not really executed when $x < 0$ so there's no problem
- all threads execute both conditional branches, so execution cost is sum of both branches
⇒ potentially large loss of performance

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Warp divergence

If the branches are big, `nvcc` compiler inserts code to check if all threads in the warp take the same branch (*warp voting*) and then branches accordingly.

```
p = ...  
  
if (any(p)) {  
p:    ...  
p:    ...  
}  
  
if (any(!p)) {  
!p:   ...  
!p:   ...  
}
```

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Warp divergence

Another example:

```
if (n >= 0)  
    z = x[n];  
else  
    z = 0;
```

- `x[n]` is only read here if $n \geq 0$
- don't have to worry about illegal memory accesses when n is negative

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Warp divergence

Note:

- doesn't matter what is happening with other warps – each warp is treated separately
- if each warp only goes one way that's very efficient
- warp voting costs a few instructions, so for very simple branches the compiler just uses predication without voting

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Warp divergence

In some cases, can determine at compile time that all threads in the warp must go the same way

e.g. if `case` is a run-time argument

```
if (case==1)
  z = x*x;
else
  z = x+2.3;
```

In this case, there's no need to vote

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Warp divergence

Another example: processing a long list of elements where, depending on run-time values, a few require very expensive processing

GPU implementation:

- first process list to build two sub-lists of “simple” and “expensive” elements
- then process two sub-lists separately

Note: none of this is new – this is what we did more than 30 years ago on CRAY and Thinking Machines systems.

What's important is to understand hardware behaviour and design your algorithms / implementation accordingly

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Warp divergence

Warp divergence can lead to a big loss of parallel efficiency – one of the first things I look out for in a new application.

In worst case, effectively lose factor $32\times$ in performance if one thread needs expensive branch, while rest do nothing

Typical example: PDE application with boundary conditions

- if boundary conditions are cheap, loop over all nodes and branch as needed for boundary conditions
- if boundary conditions are expensive, use two kernels: first for interior points, second for boundary points

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Synchronisation

Already introduced `__syncthreads()`; which forms a barrier – all threads wait until every one has reached this point.

When writing conditional code, must be careful to make sure that all threads do reach the `__syncthreads()`;

Otherwise, can end up in *deadlock*

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Typical application

```
// load in data to shared memory
...
...
...

// synchronisation to ensure this has finished

__syncthreads();

// now do computation using shared data
...
...
...
```

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Warp voting

There are similar *warp voting* instructions which operate at the level of a warp:

- `int __all(predicate)`
returns non-zero (true) if all predicates in warp are true
- `int __any(predicate)`
returns non-zero (true) if any predicate is true
- `unsigned int __ballot(predicate)`
sets n^{th} bit based on n^{th} predicate

Again, I've never used these

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Synchronisation

There are other synchronisation instructions which are similar but have extra capabilities:

- `int __syncthreads_count(predicate)`
counts how many predicates are true
- `int __syncthreads_and(predicate)`
returns non-zero (true) if all predicates are true
- `int __syncthreads_or(predicate)`
returns non-zero (true) if any predicate is true

I've not used these, and don't currently see a need for them

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Atomic operations

Occasionally, an application needs threads to update a counter in shared memory.

```
__shared__ int count;

...

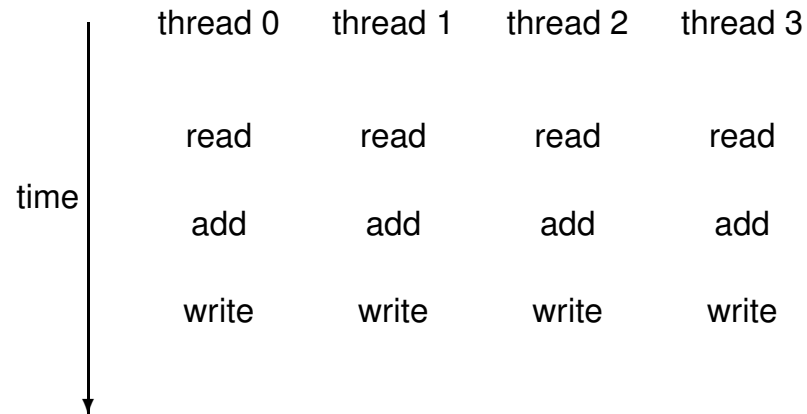
if ( ... ) count++;
```

In this case, there is a problem if two (or more) threads try to do it at the same time

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Atomic operations

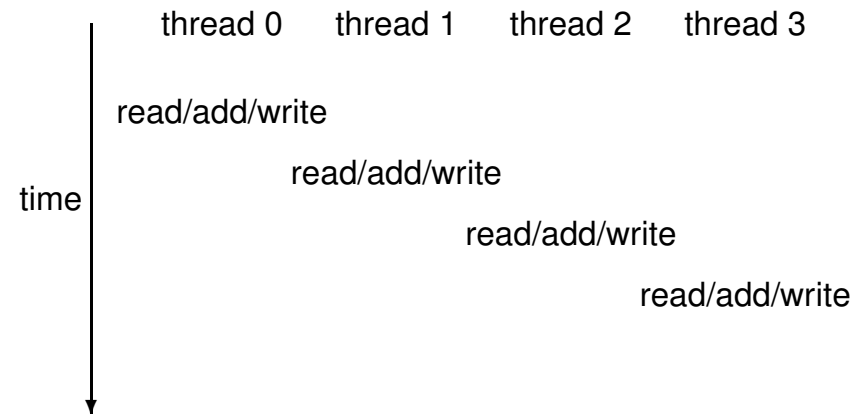
Using standard instructions, multiple threads in the same warp will only update it once.



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Atomic operations

With atomic instructions, the read/add/write becomes a single operation, and they happen one after the other



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Atomic operations

Several different atomic operations are supported:

- addition / subtraction
`atomicAdd, atomicSub`
- minimum / maximum
`atomicMin, atomicMax`
- increment / decrement
`atomicInc, atomicDec`
- exchange / compare-and-swap
`atomicExch, atomicCAS`
- bitwise AND / OR / XOR
`atomicAnd, atomicOr, atomicXor`

Fast for variables in shared memory, only slightly slower for variables in device global memory (operations performed in L2 cache)

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Atomic operations

Compare-and-swap:

```
int atomicCAS(int* address, int compare, int val);
```

- if `compare` equals `old` value stored at `address` then `val` is stored instead
- in either case, routine returns the value of `old`
- seems a bizarre routine at first sight, but can be very useful for atomic locks

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Global atomic lock

```
// global variable: 0 unlocked, 1 locked
__device__ int lock=0;

__global__ void kernel(...) {
    ...

    if (threadIdx.x==0) {
        // set lock
        do {} while(atomicCAS(&lock,0,1));

        ...

        // free lock
        lock = 0;
    }
}
```

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Global atomic lock

Problem: when a thread writes data to device memory the order of completion is not guaranteed, so global writes may not have completed by the time the lock is unlocked

```
__global__ void kernel(...) {
    ...

    if (threadIdx.x==0) {
        do {} while(atomicCAS(&lock,0,1));
        ...
        __threadfence(); // wait for writes to finish

        // free lock
        lock = 0;
    }
}
```

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__threadfence

- `__threadfence_block();`
wait until all global and shared memory writes are visible to
 - all threads in block
- `__threadfence();`
wait until all global and shared memory writes are visible to
 - all threads in block
 - all threads, for global data

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Summary

- lots of esoteric capabilities – don't worry about most of them
- essential to understand warp divergence – can have a very big impact on performance
- `__syncthreads()` is vital – will see another use of it in next lecture
- the rest can be ignored until you have a critical need – then read the documentation carefully and look for relevant NVIDIA sample codes

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Key reading

CUDA Programming Guide:

- Section 5.4.2: control flow and predicates
- Section 5.4.3: synchronization
- Appendix B.5: `__threadfence()` and variants
- Appendix B.6: `__syncthreads()` and variants
- Appendix B.14: atomic functions
- Appendix B.19: warp voting

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2D Laplace solver

Jacobi iteration to solve discrete Laplace equation on a uniform grid:

```
for (int j=0; j<J; j++) {
    for (int i=0; i<I; i++) {

        id = i + j*I;    // 1D memory location

        if (i==0 || i==I-1 || j==0 || j==J-1)
            u2[id] = u1[id];
        else
            u2[id] = 0.25*( u1[id-1] + u1[id+1]
                           + u1[id-I] + u1[id+I] );
    }
}
```

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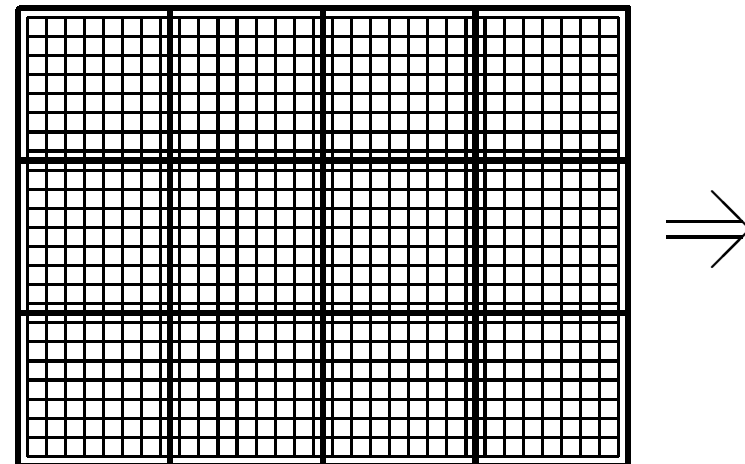
2D Laplace solver

How do we tackle this with CUDA?

- each thread responsible for one grid point
- each block of threads responsible for a block of the grid
- conceptually very similar to data partitioning in MPI distributed-memory implementations, but much simpler
- (also similar to blocking techniques to squeeze the best cache performance out of CPUs)
- great example of usefulness of 2D blocks and 2D “grid”s

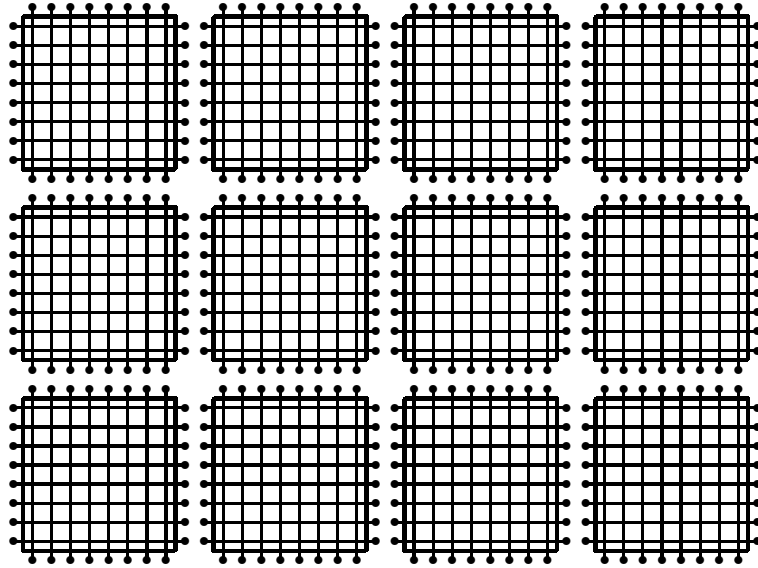
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2D Laplace solver



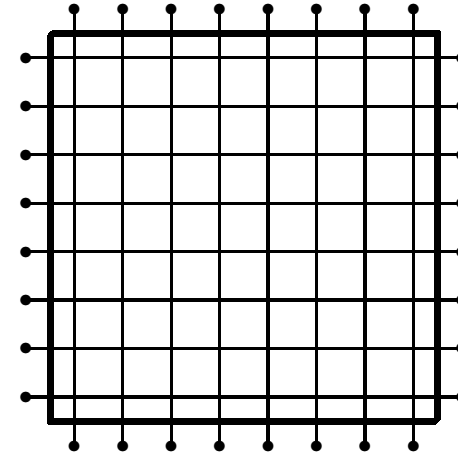
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2D Laplace solver



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2D Laplace solver



Each block of threads processes one of these grid blocks, reading in old values and computing new values

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2D Laplace solver

```
__global__ void lap(int I, int J,
    const float* __restrict__ u1,
    float* __restrict__ u2) {

    int i = threadIdx.x + blockIdx.x*blockDim.x;
    int j = threadIdx.y + blockIdx.y*blockDim.y;
    int id = i + j*I;

    if (i==0 || i==I-1 || j==0 || j==J-1) {
        u2[id] = u1[id]; // Dirichlet b.c.'s
    }
    else {
        u2[id] = 0.25 * ( u1[id-1] + u1[id+1]
            + u1[id-I] + u1[id+I] );
    }
}
```

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2D Laplace solver

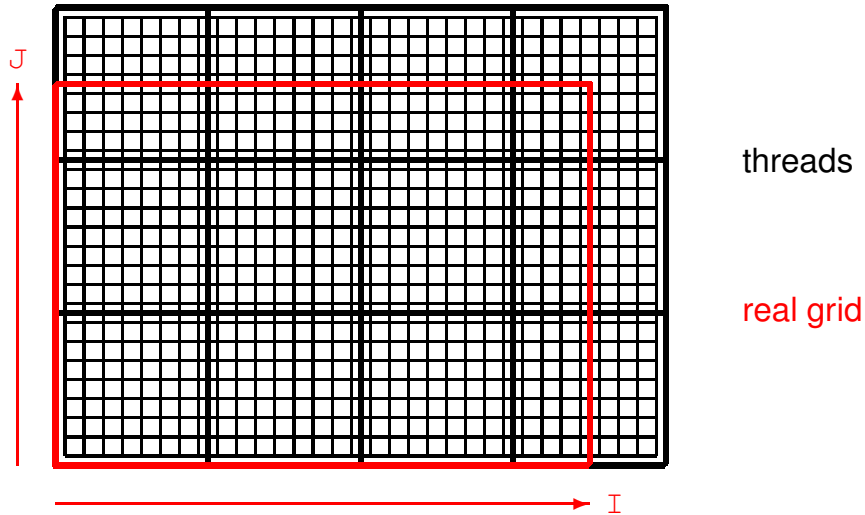
Assumptions:

- I is a multiple of blockDim.x
- J is a multiple of blockDim.y
- hence grid breaks up perfectly into blocks

Can remove these assumptions by testing whether i, j are within grid

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2D Laplace solver



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2D Laplace solver

```
__global__ void lap(int I, int J,
                    const float* __restrict__ u1,
                    float* __restrict__ u2) {

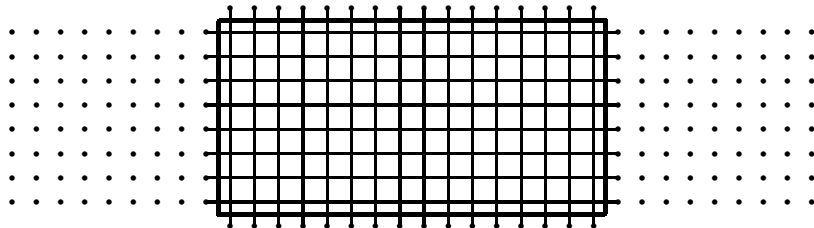
    int i = threadIdx.x + blockIdx.x*blockDim.x;
    int j = threadIdx.y + blockIdx.y*blockDim.y;
    int id = i + j*I;

    if (i==0 || i==I-1 || j==0 || j==J-1) {
        u2[id] = u1[id]; // Dirichlet b.c.'s
    }
    else if (i<I && j<J) {
        u2[id] = 0.25f * ( u1[id-1] + u1[id+1]
                          + u1[id-I] + u1[id+I] );
    }
}
```

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2D Laplace solver

How does cache function in this application?



- if block size is a multiple of 32 in x -direction, then interior corresponds to set of complete cache lines
- “halo” points above and below are full cache lines too
- “halo” points on side are the problem – each one requires the loading of an entire cache line
- optimal block shape has aspect ratio of roughly 32:1 (or 8:1 if cache line is 32 bytes)

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3D Laplace solver

- practical 3
- each thread does an entire line in z -direction
- x, y dimensions cut up into blocks in the same way as 2D application
- `laplace3d.cu` and `laplace3d_kernel.cu` follow same approach described above
- this used to give the fastest implementation, but a new version uses 3D thread blocks, with each thread responsible for just 1 grid point
- the new version has lots more integer operations, but is still faster, perhaps due to many more active threads – in either case the application is probably bandwidth-limited

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