
NVIDIA® TESLA™
Case study: CFD
Dr. Graham Pullan
University of Cambridge
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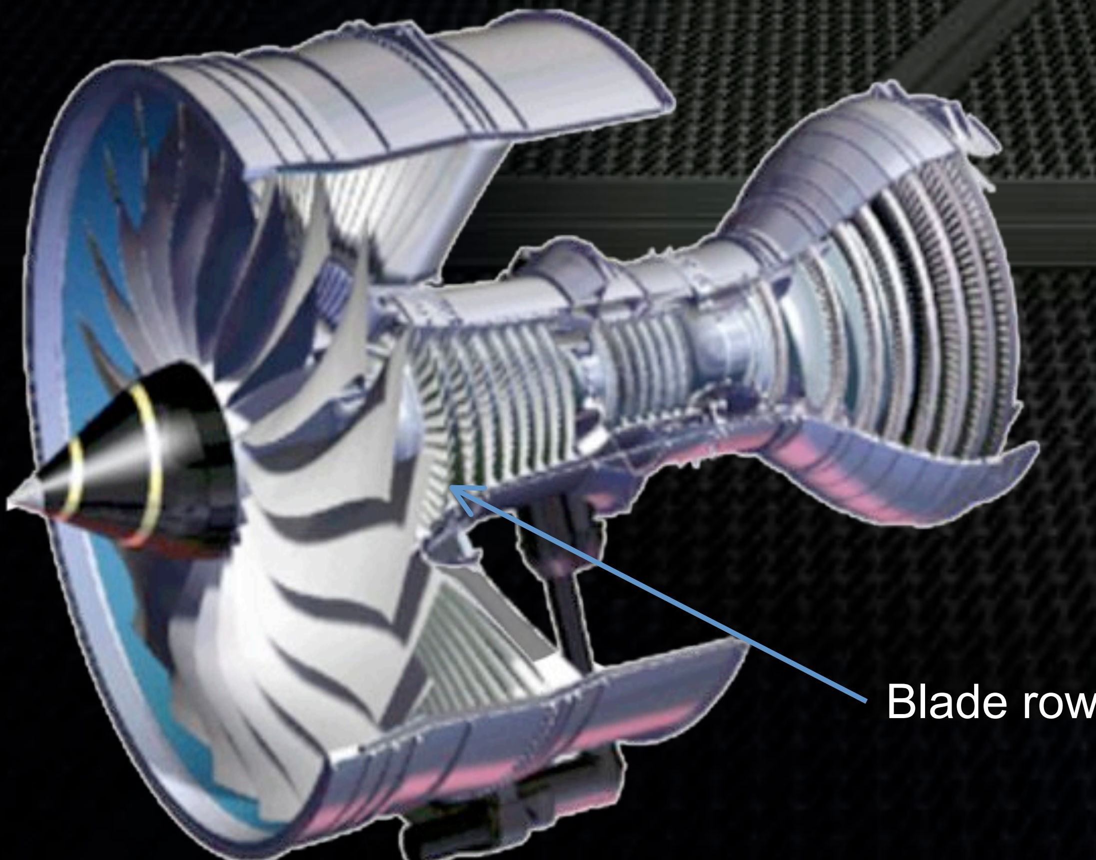
Outline

- CFD (for turbomachinery)
- A good fit for GPUs?
- Implementation
- Results

Turbomachinery

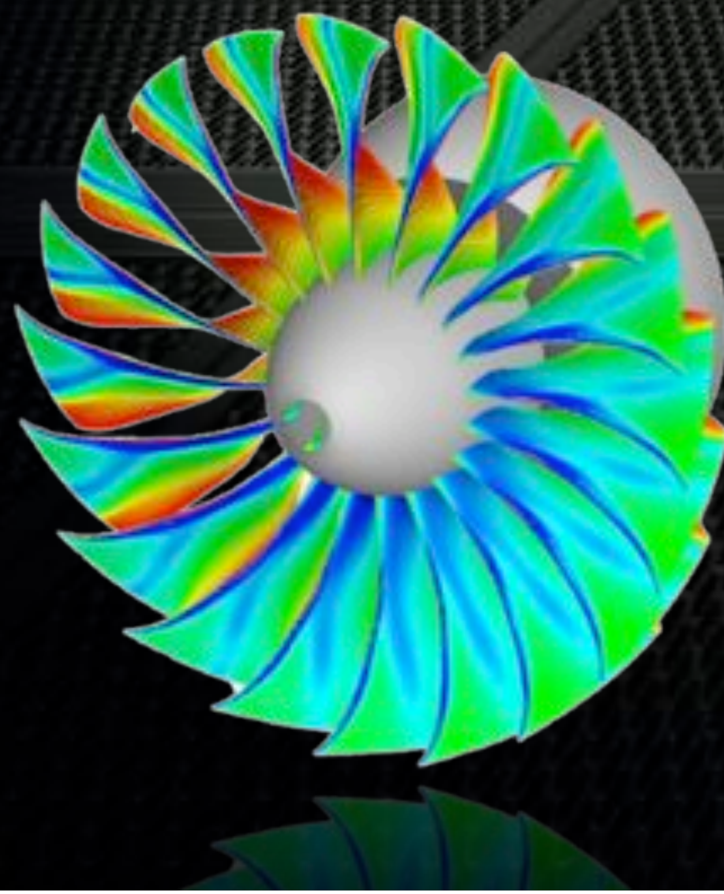


Thousands of blades

Arranged in rows

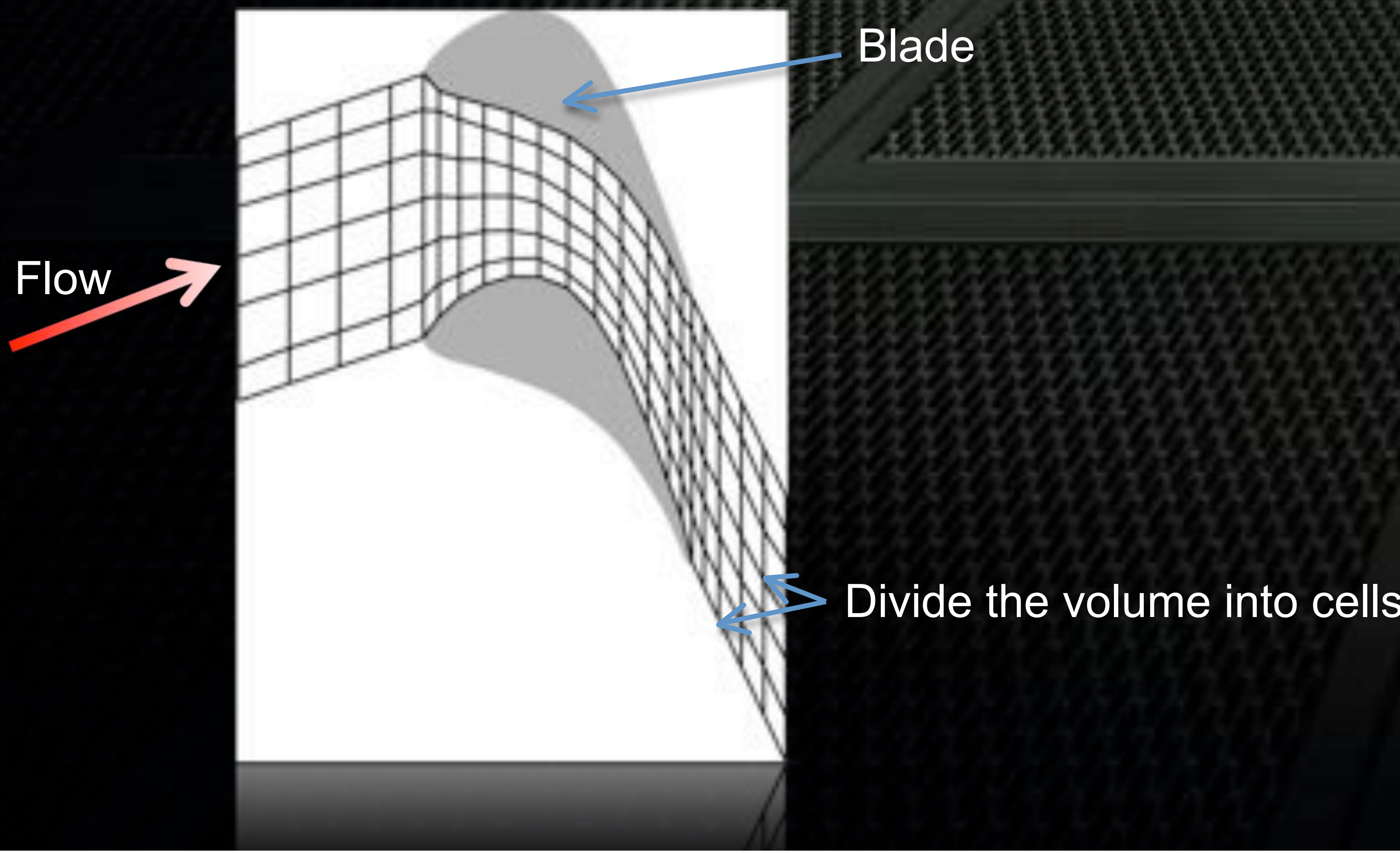
Each blade row has a bespoke blade profile designed with CFD

CFD of a jet engine fan

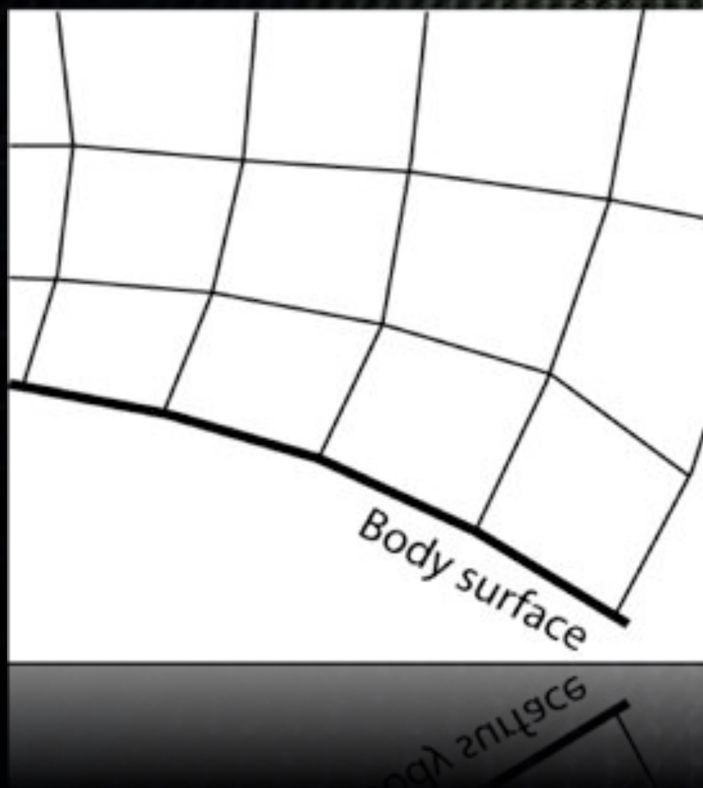


Blades coloured by pressure

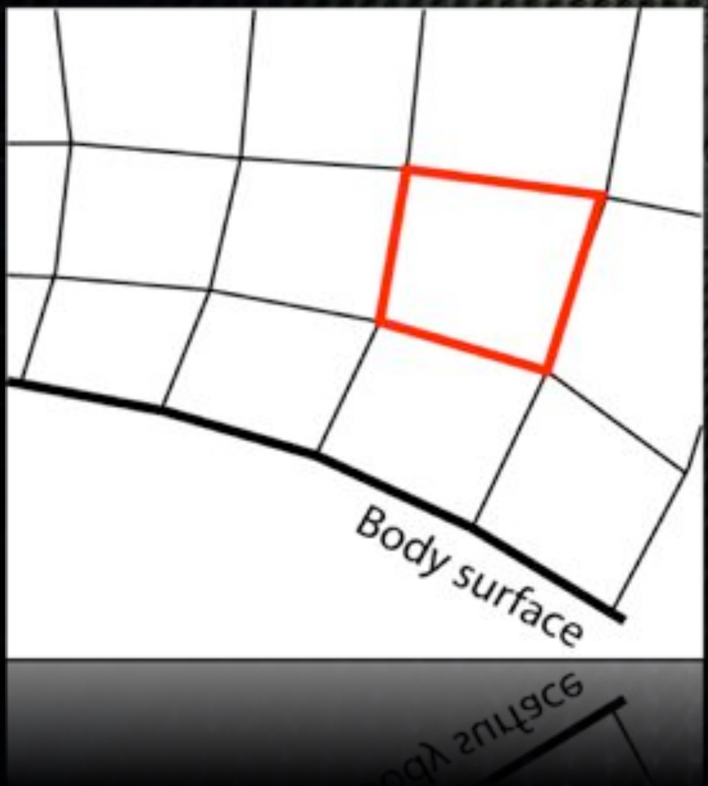
Introduction to CFD



Governing equations for each cell



Governing equations for each cell

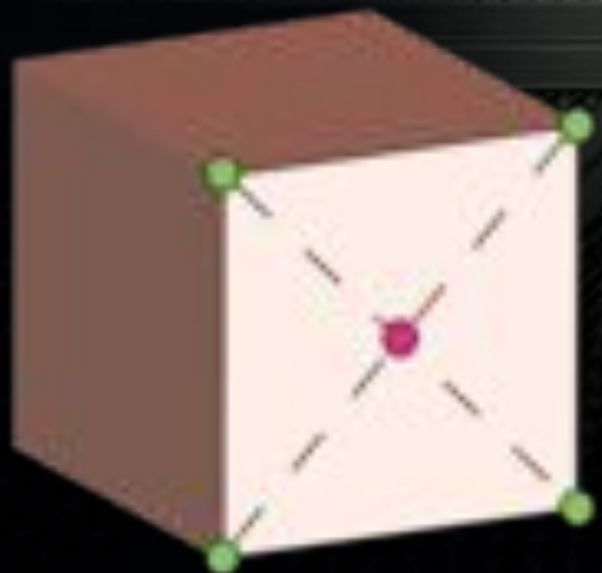


Conserve:

- Mass
- Momentum
- Energy

Example: mass conservation

- Evaluate mass fluxes on each face

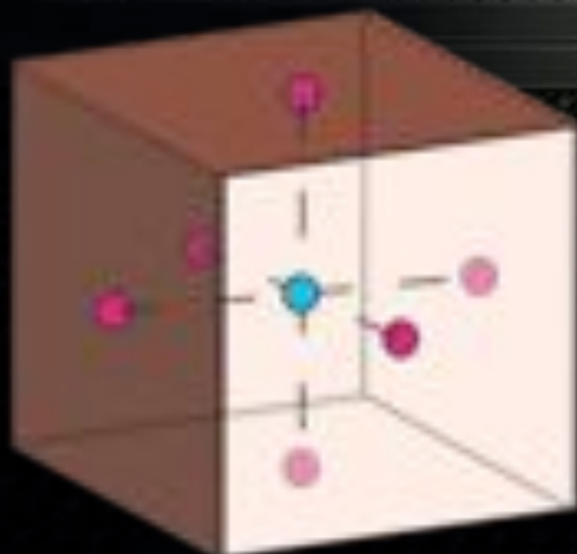


$$F_{mass} = \frac{A}{4}\sum \rho V_n$$

Example: mass conservation

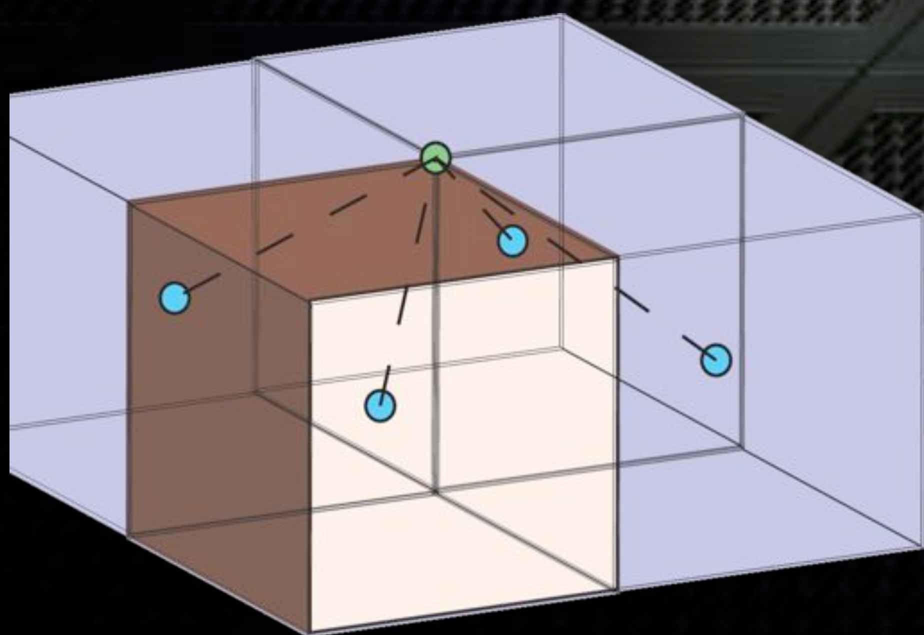
- Sum fluxes on faces to find density change in cell

$$\Delta\rho_{cell} = \frac{\Delta t}{\Delta vol}\sum F_{mass}$$



Example: mass conservation

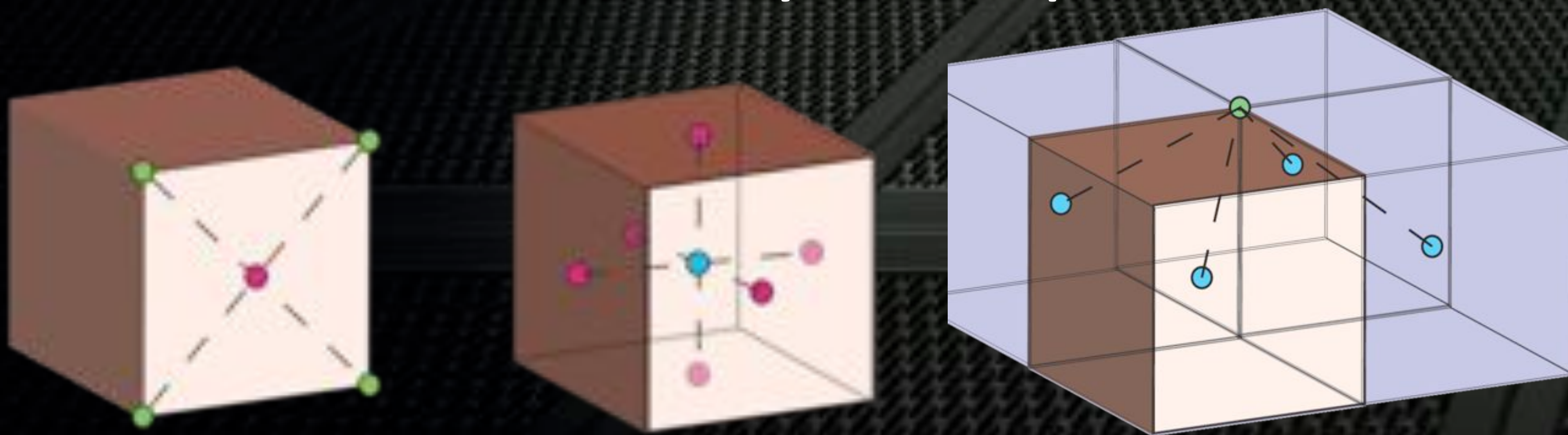
- Update density



$$\Delta\rho_{node} = \frac{1}{8}\sum\Delta\rho_{cell}$$

(only 4 of 8 surrounding cells shown)

Similarity of steps



Each step uses data from surrounding nodes – “stencil” operation

Similarity of equations

- For each equation (5 in all):
  - Set relevant flux (mass, momentum, energy)
  - Sum fluxes
  - Update nodes
  - (plus smoothing – also stencil
    boundary conditions – not stencil)

CPU run times (x86 machines)

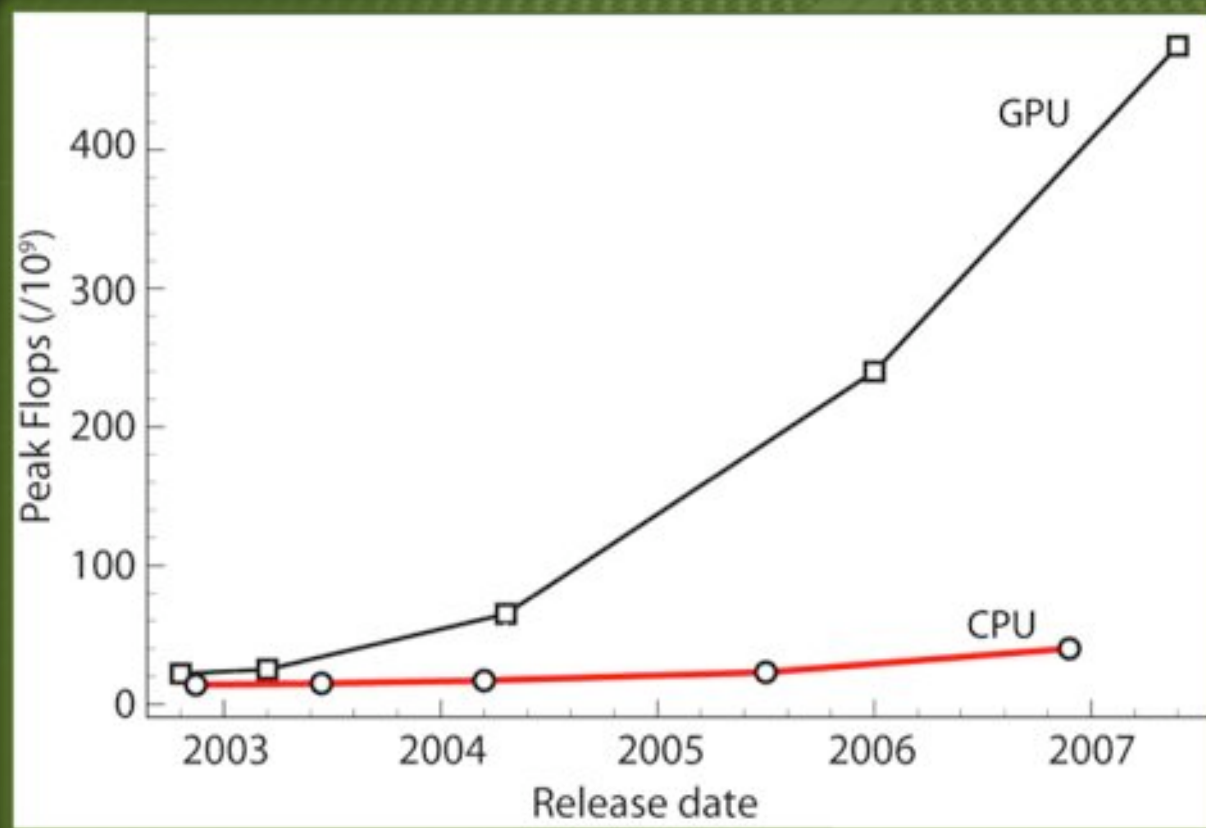
Steady approximation – one blade per row

1 blade	0.5 Mcells	1 CPU hour
1 stage (2 blades)	1.0 Mcells	3 CPU hours
1 component (5 stages)	5.0 Mcells	20 CPU hours

Unsteady approximation – all blades in row

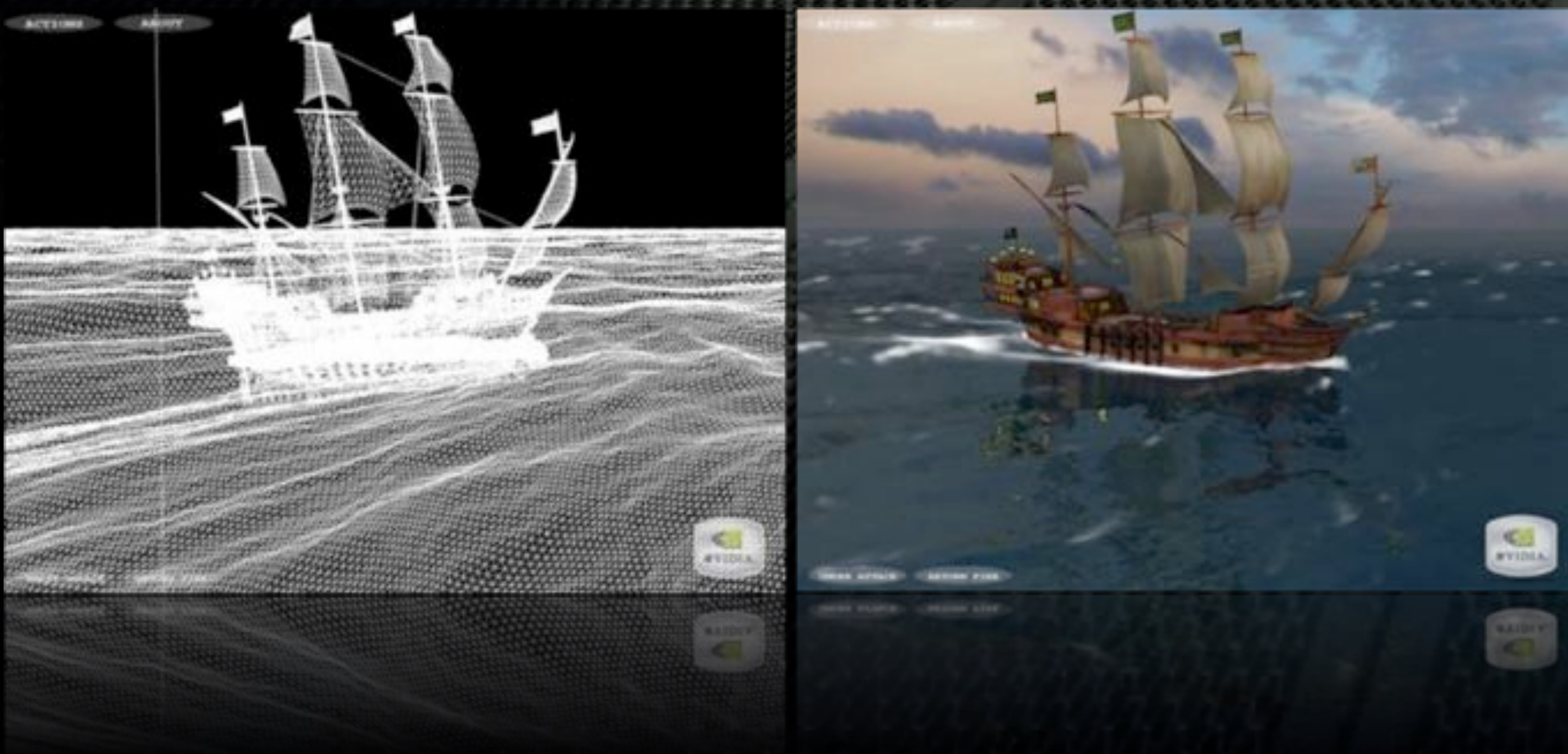
1 component (1000 blades)	500 Mcells	0.1 M CPU hours
Engine (4000 blades)	2 Gcells	1 M CPU hours

Peak FLOPs



GPU
CPU
Peak Flops (/10^9)
0
100
200
300
400
2003
2004
2005
2006
2007
Release date

The purpose of GPUs



Graphics and scientific computing

GPUs are designed to apply the
same ***shading function***
to many ***pixels*** simultaneously

Graphics and scientific computing

GPUs are designed to apply the

same *function*

to many *data* simultaneously

Are GPUs a good fit for CFD?

- Our CFD code is:
  - SIMD (same functions applied to all cells in domain)
  - Single precision
  - Large datasets (c 10M nodes) fit on one 4GB Tesla card
    - (bandwith on card is high c 102 GB/s
      much slower to/from card c 8 GB/s
      and steps in CFD are "memory bound")

CUDA

- Programming GPUs without the graphics abstraction
- Scalar variables (not graphics-type 4-vectors!)
- Extensions to C (not graphics APIs, eg OPENGL)

CUDA

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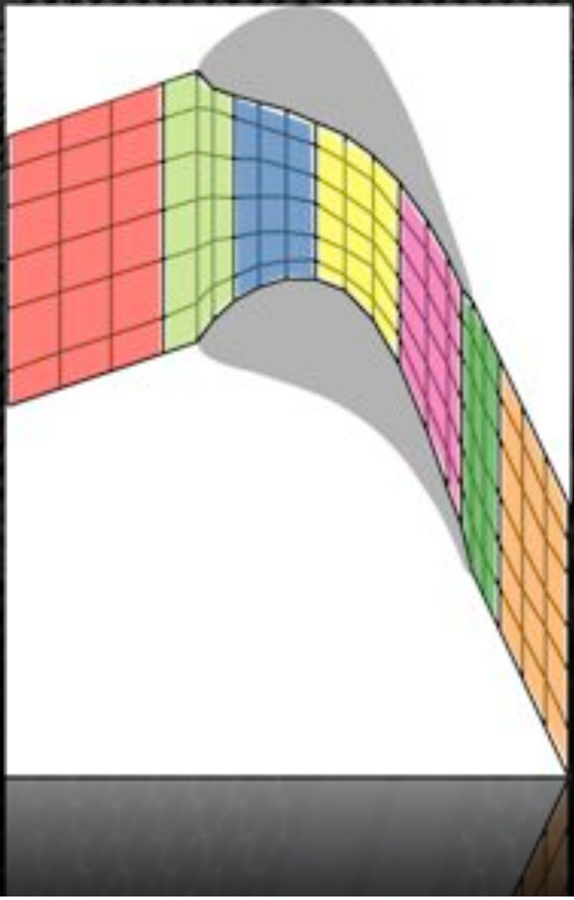
- Scalar variables (not graphics-type 4-vectors!)
- Extensions to C (not graphics APIs, eg OPENGL)

- BUT – porting 15,000 lines of existing FORTRAN CFD code to CUDA still a lengthy task

Overall strategy

- Divide up domain
  - each sub-domain to a thread block
  - update nodes in sub-domain with most efficient stencil operation we can come up with!
  - update sub-domain boundaries (MPI if needed)



SBLOCK – stencil framework

- SBLOCK framework for stencil operations on structured grids:
  - Source-to-source compiler
    - Takes in high level kernel definitions
    - Produces optimised kernels in C or CUDA
- Allows new stencils to be implemented quickly
- Allows new stencil optimisation strategies to be deployed on all stencils (without typos!)

SBLOCK


Kernel definition
CUDA template
C template
GPU Kernel
CPU Kernel

Example SBLOCK definition

```
kind = "stencil"
bpin = ["a"]
bpout = ["b”]
lookup = ((1,0, 0), (0, 0, 0), (1,0, 0), (0, 1,0),
          (0, 1, 0), (0, 0, 1), (0, 0, 1))

calc = {"lvalue": "b",
        "rvalue": """sf1*a[0][0][0] +
                     sfd6*(a[1][0][0] + a[1][0][0] +
                          a[0][1][0] + a[0][1][0] +
                          a[0][0][1] + a[0][0][1])"""}
```

C implementation

```
void smooth(float sf, float *a, float *b)
{
   for (k=0; k < nk; k++) {
    for (j=0; j < nj; j++) {
      for (i=0; i < ni; i++) {
// compute indices i000, im100, etc (not shown) //
        b[i000] = sf1*a[i000] +
                    sfd6*(a[im100] + a[ip100] +
                             a[i0m10] + a[i0p10]
                        + a[i00m1] + a[i00p1]);
      }
    }
  }
}
```

CUDA strategy (after Datta et al.)

- Each thread in a block reads sub-domain data from global device memory to SM shared memory (coalesced reads for maximum bandwidth)
- Synch threads
- Update nodes in sub-domain using shared memory and output result back to global memory

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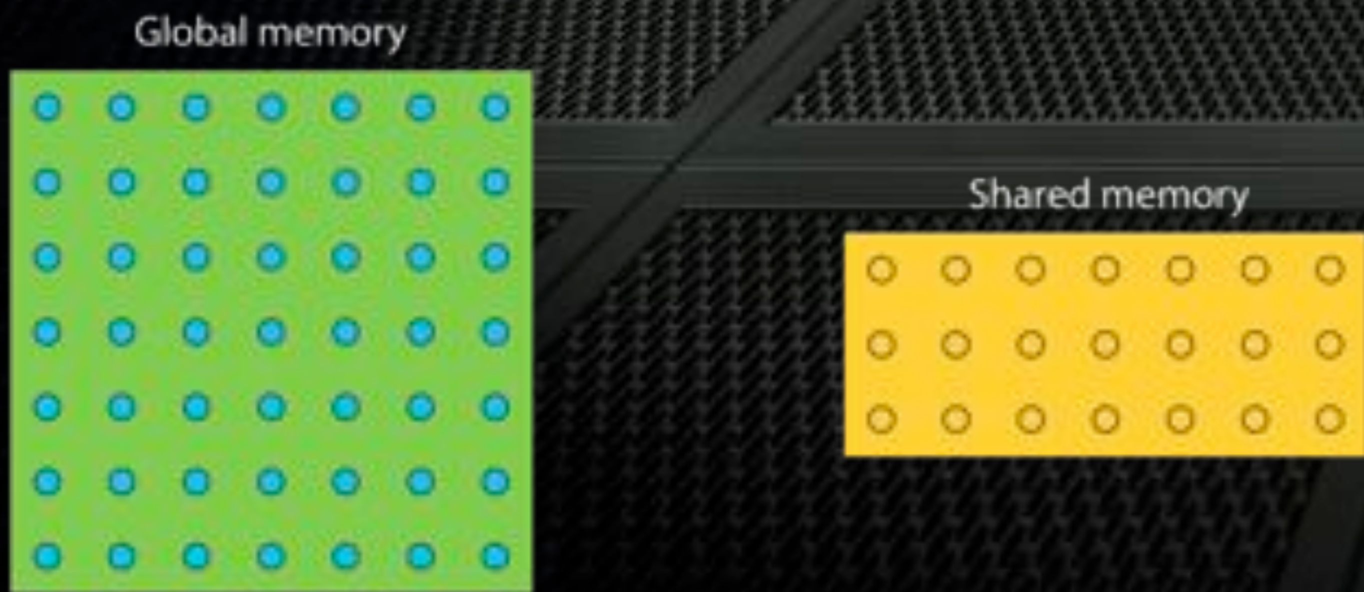
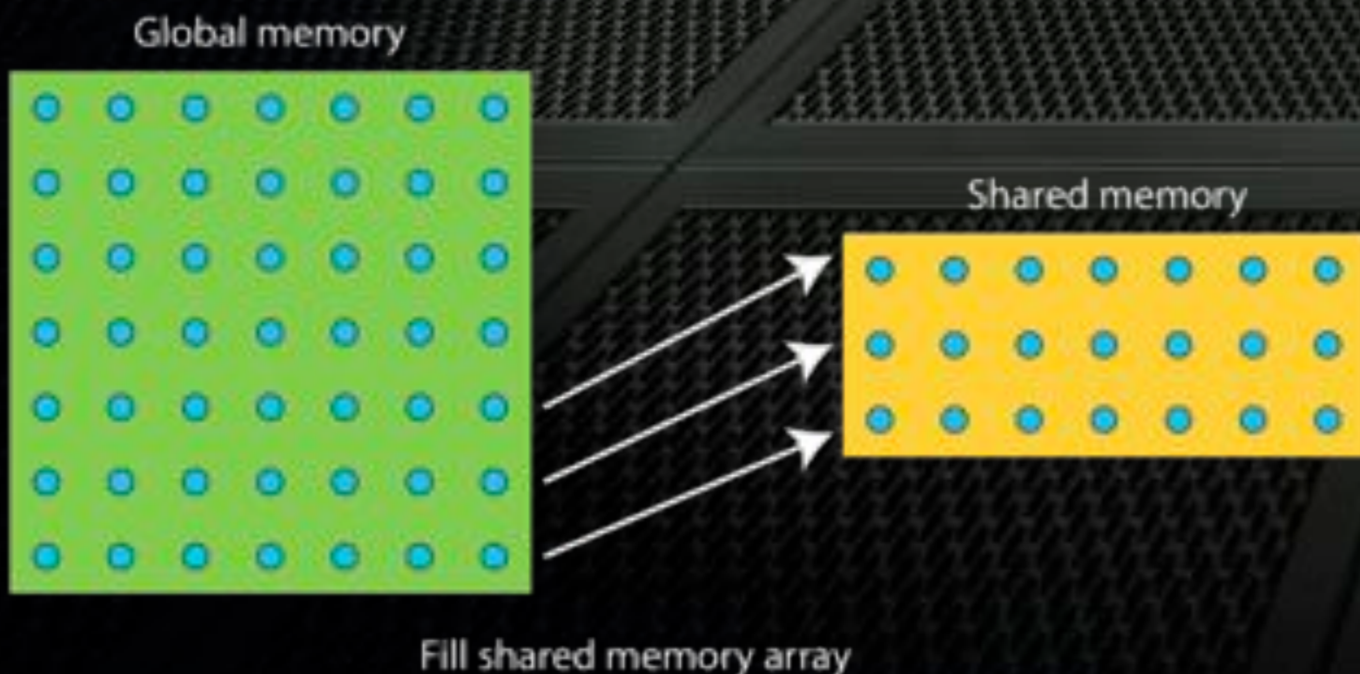
- Each thread in a block reads sub-domain data from global device memory to SM shared memory (coalesced reads for maximum bandwidth)
- Synch threads
- Update nodes in sub-domain using shared memory and output result back to global memory
- But shared memory and max threads per block are limited, so best plan is to march through sub-domain plane-by-plane…

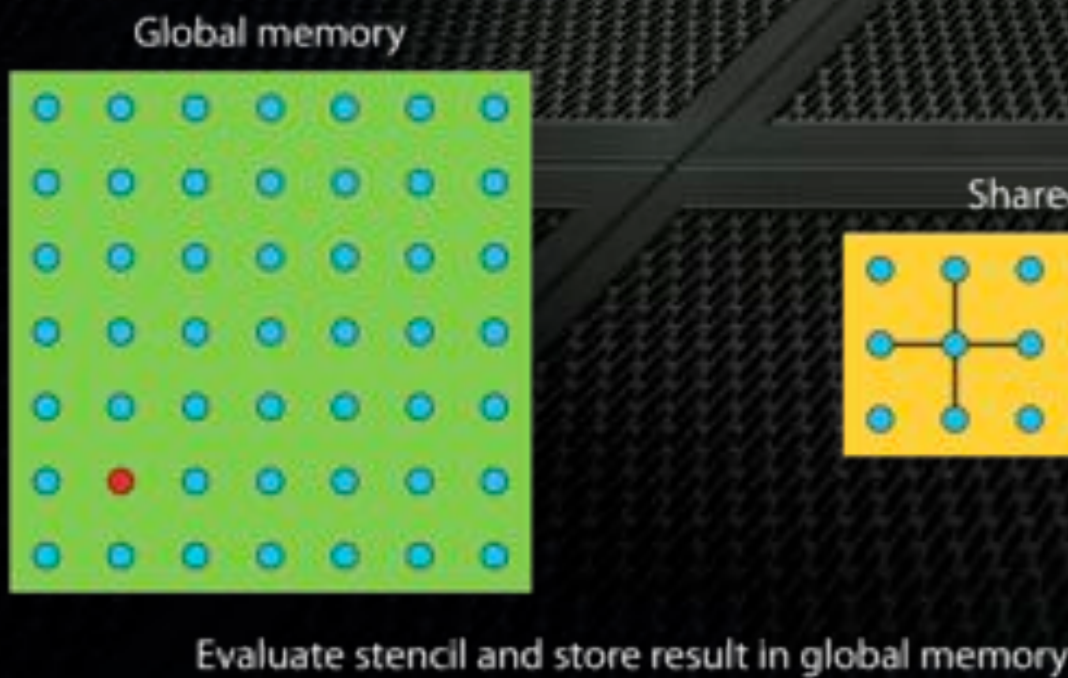
CUDA strategy

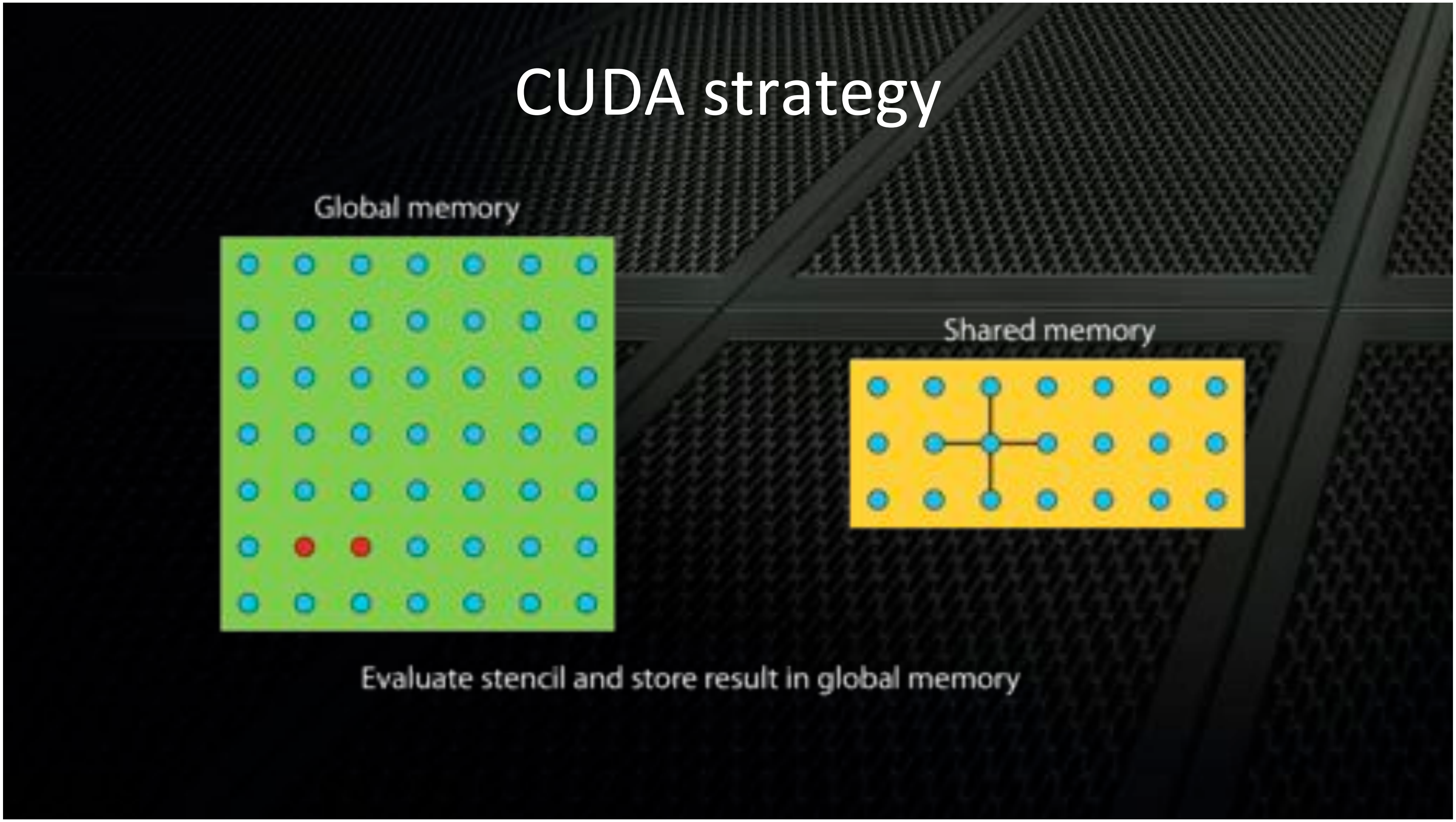


CUDA strategy

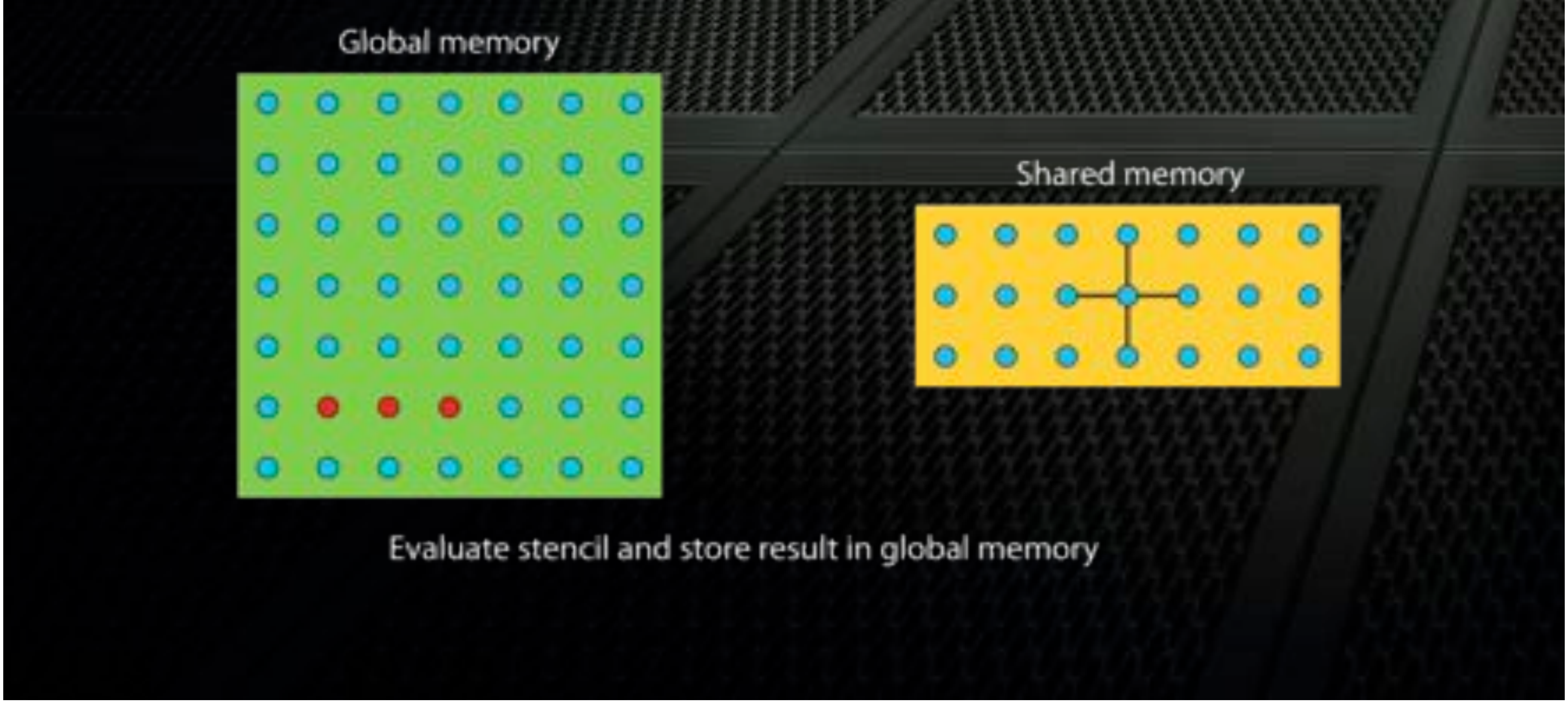


CUDA strategy

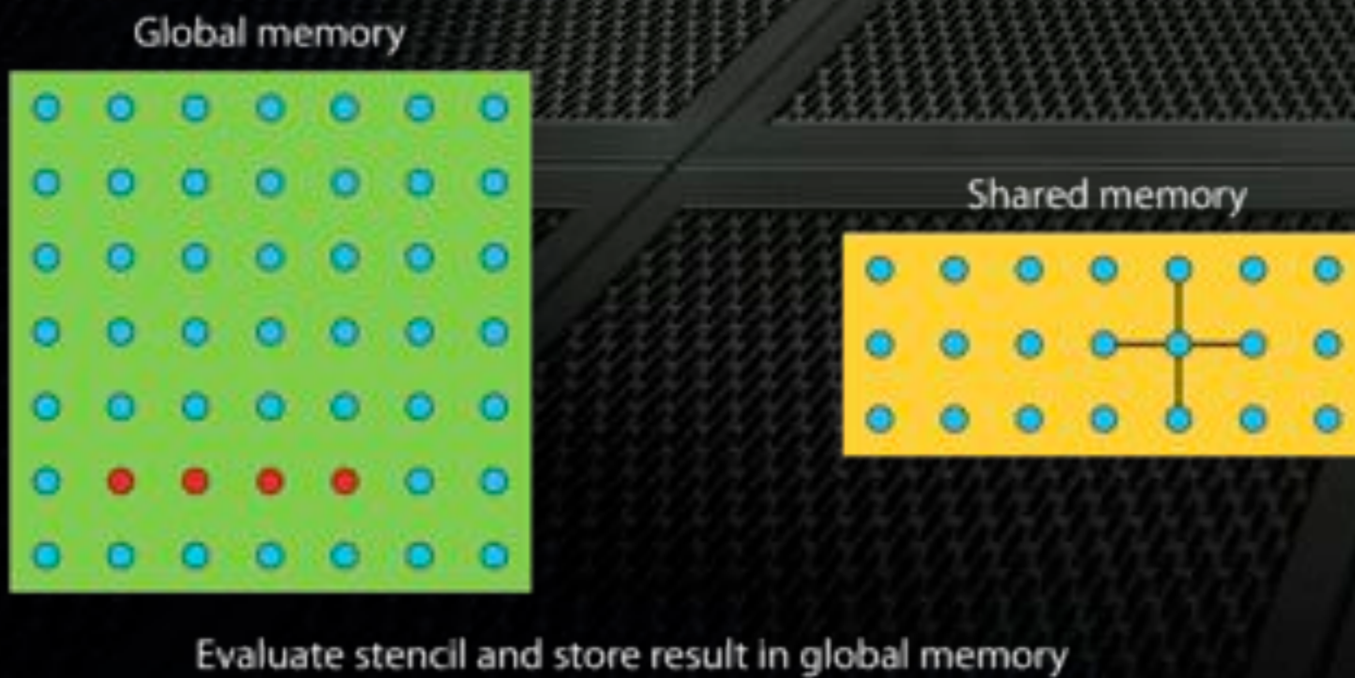



CUDA strategy
Global memory
Shared memory
Evaluate stencil and store result in global memory

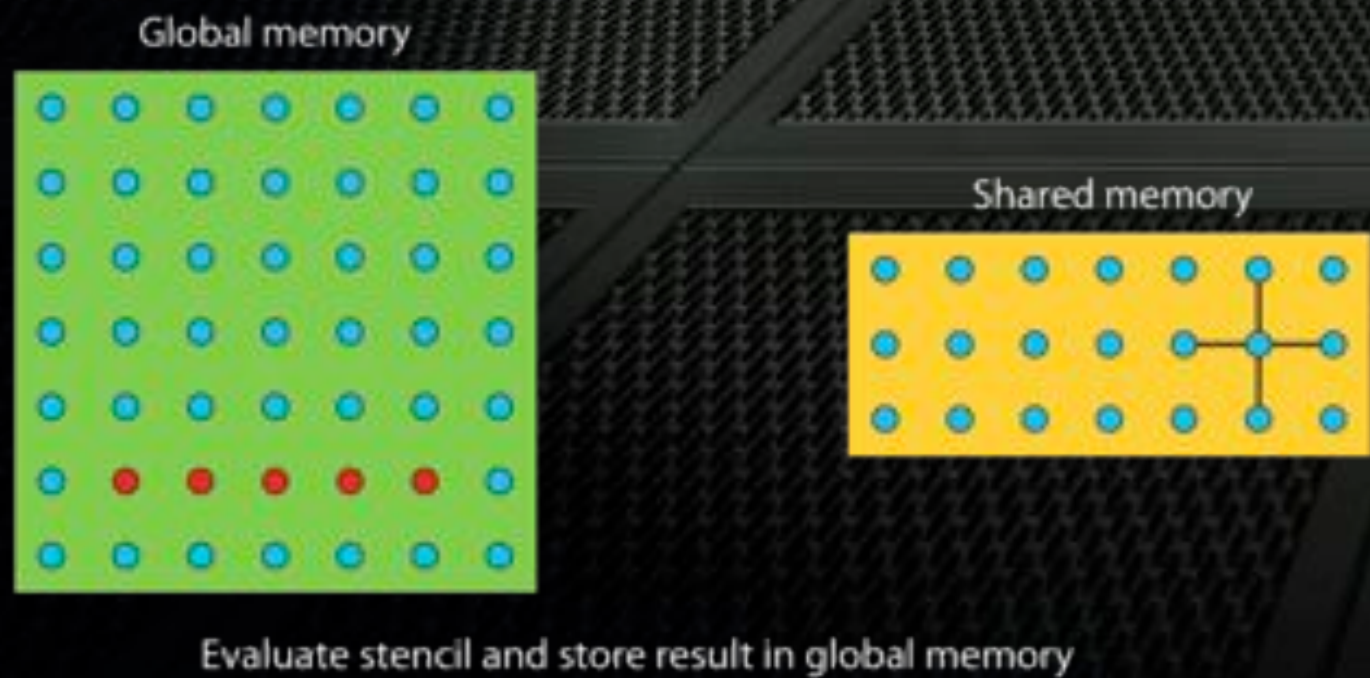
CUDA strategy



CUDA strategy



CUDA strategy



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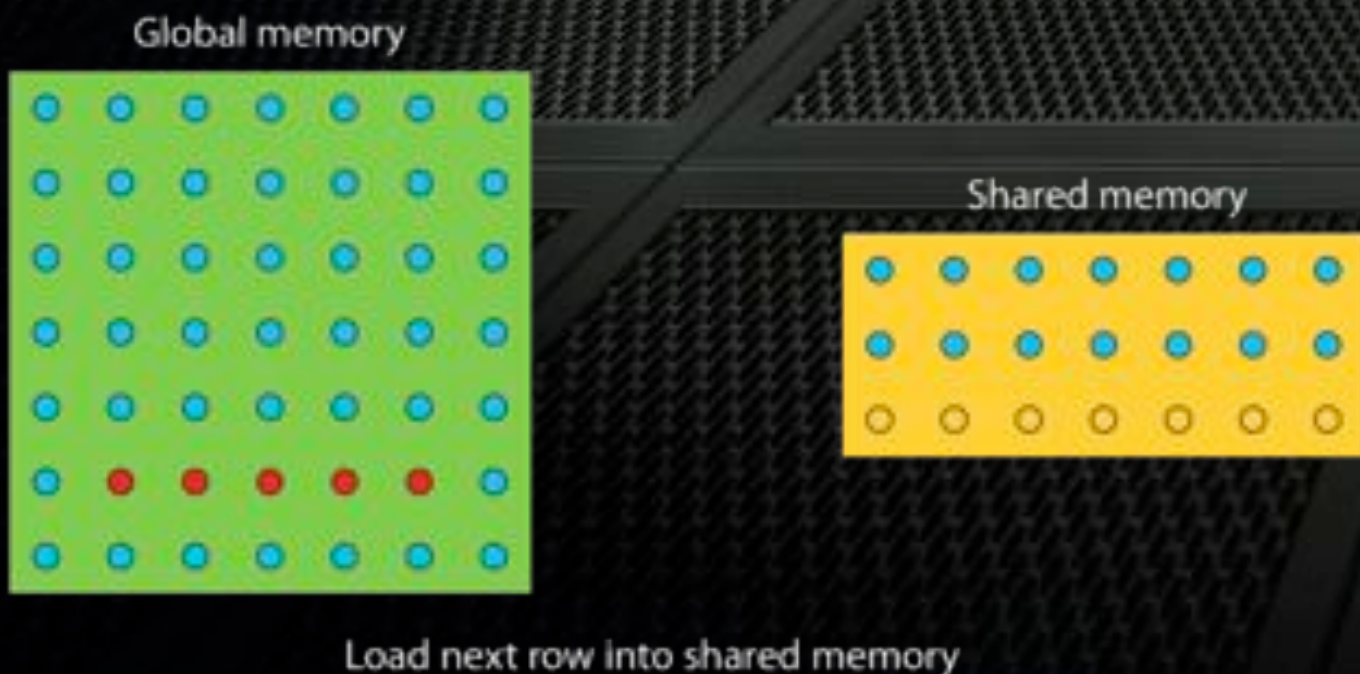

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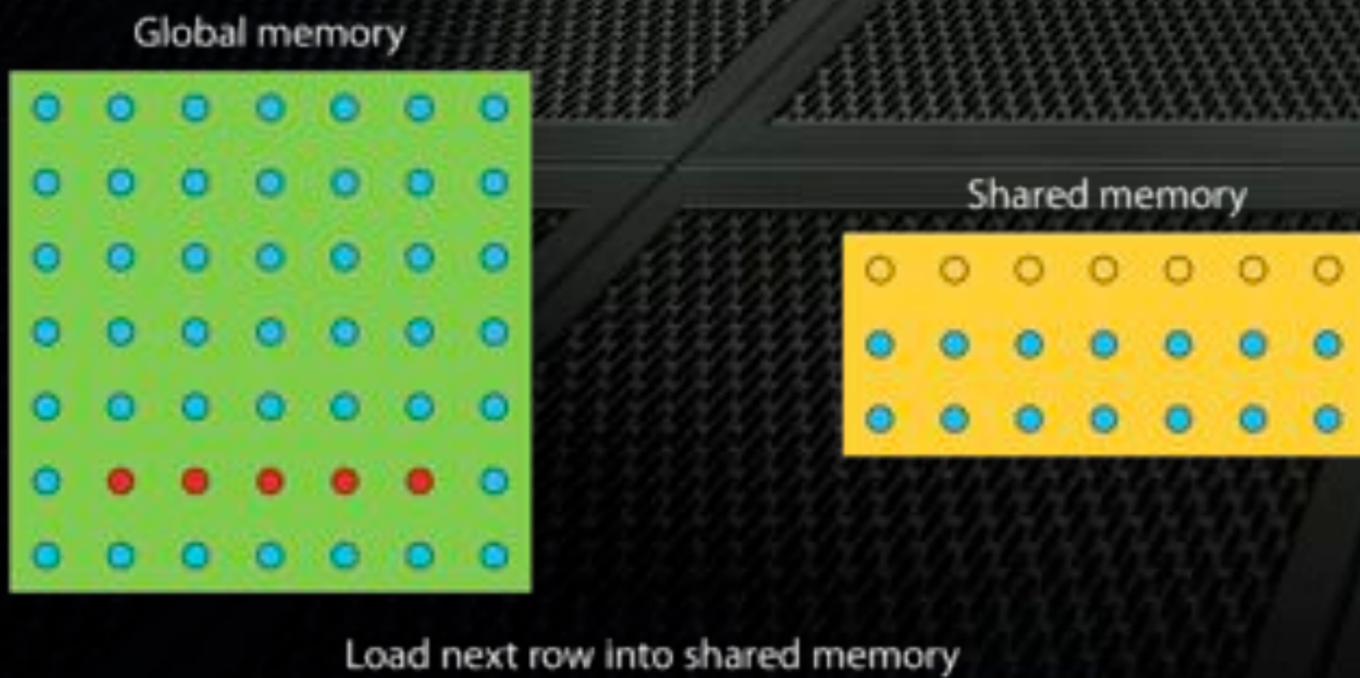

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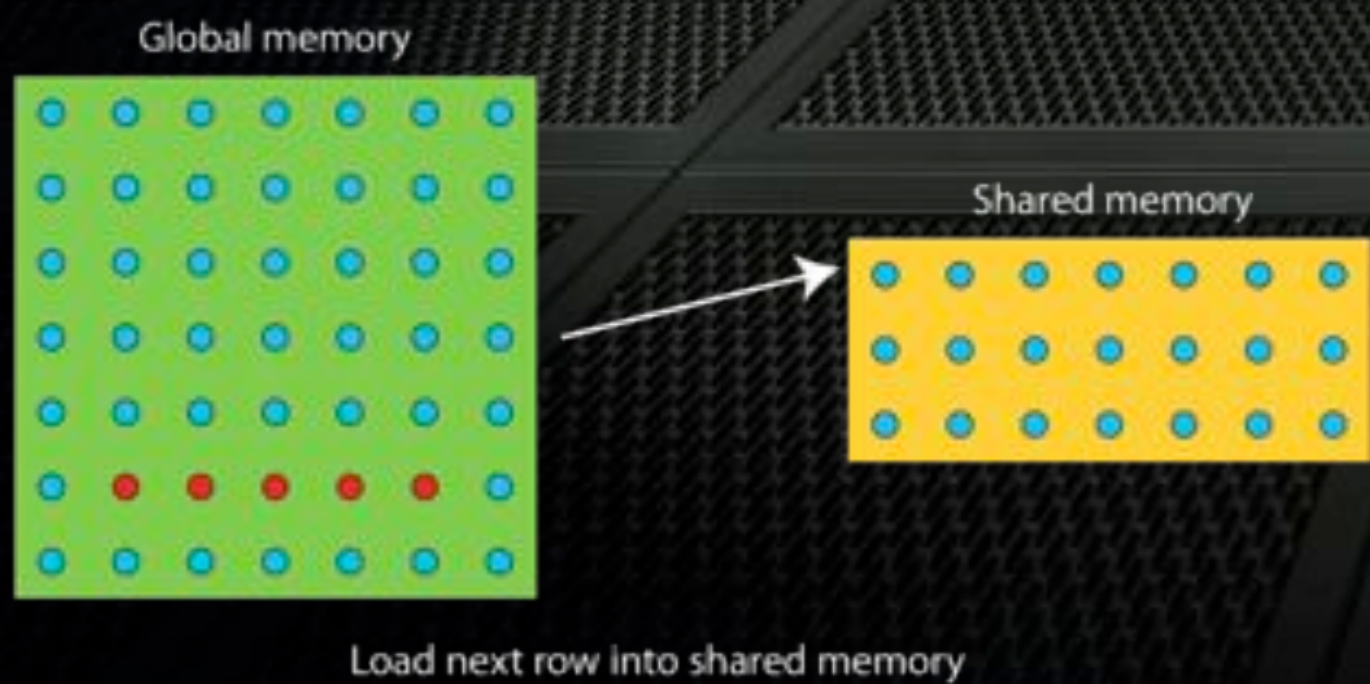

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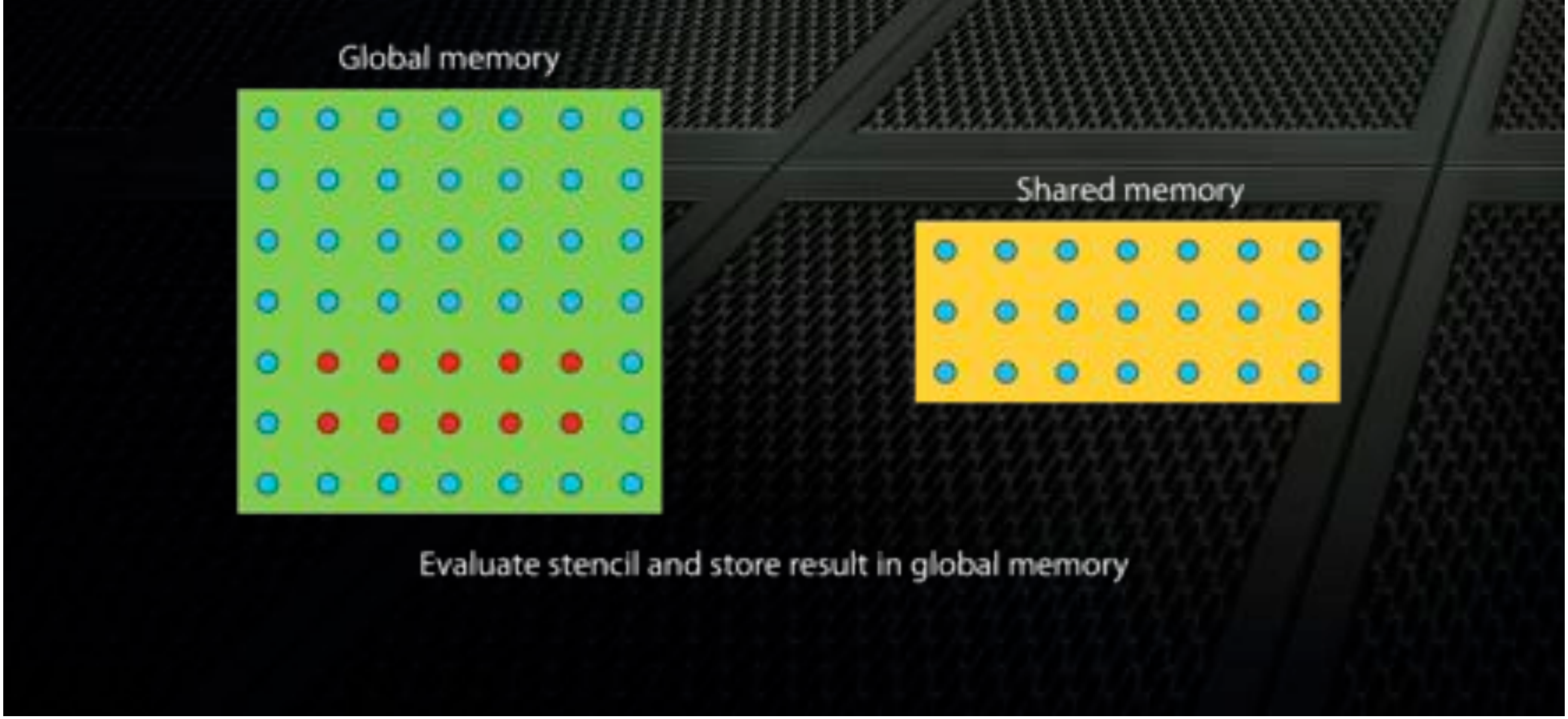

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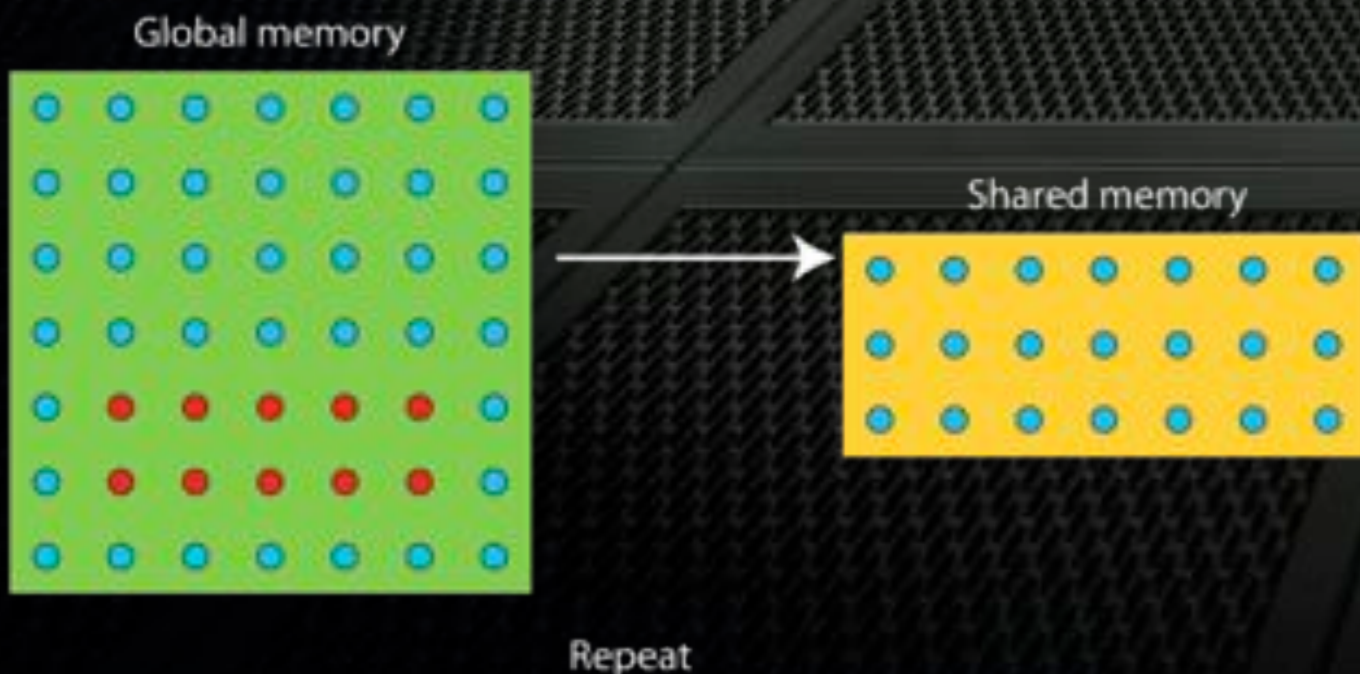

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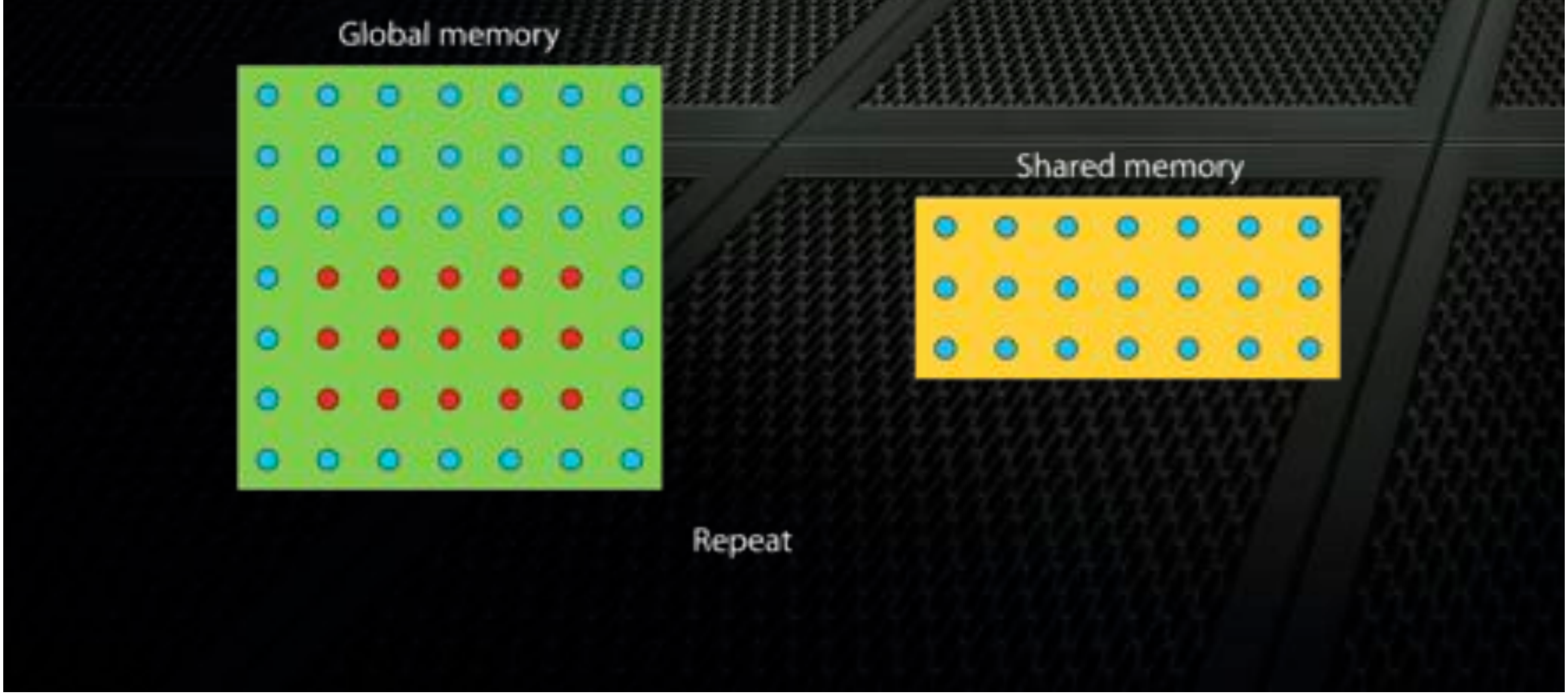

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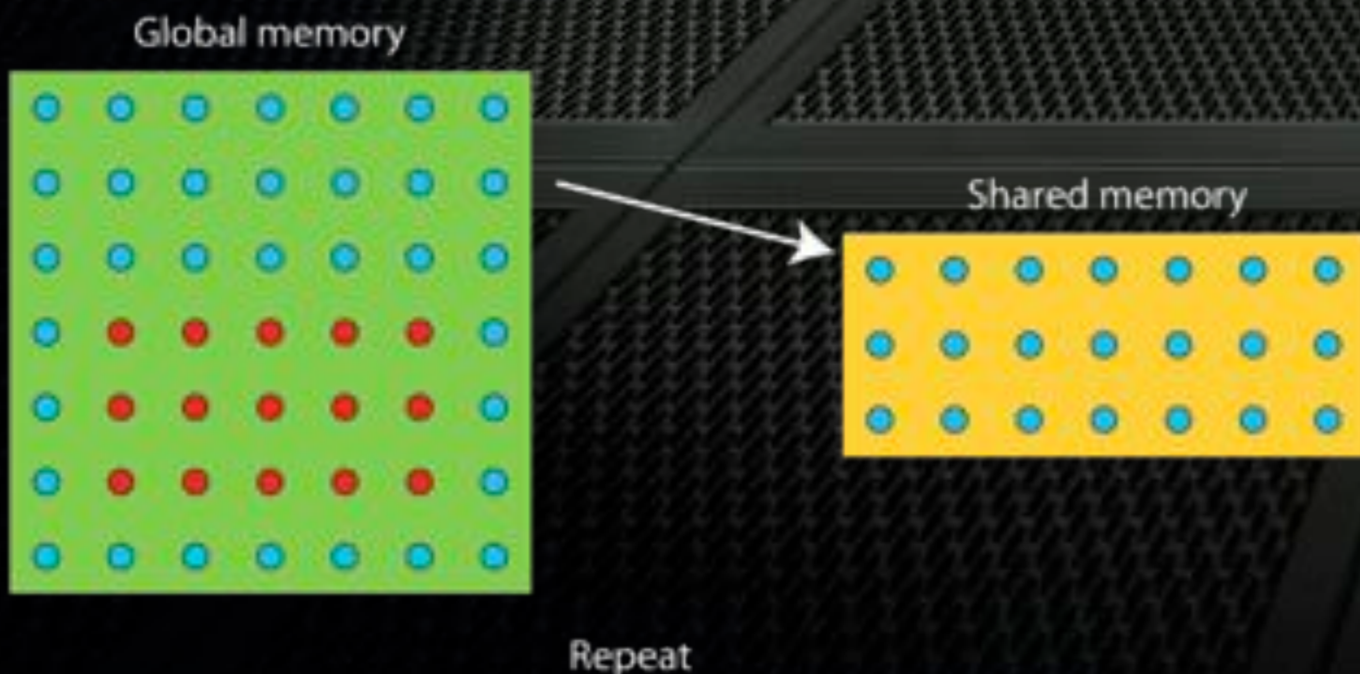

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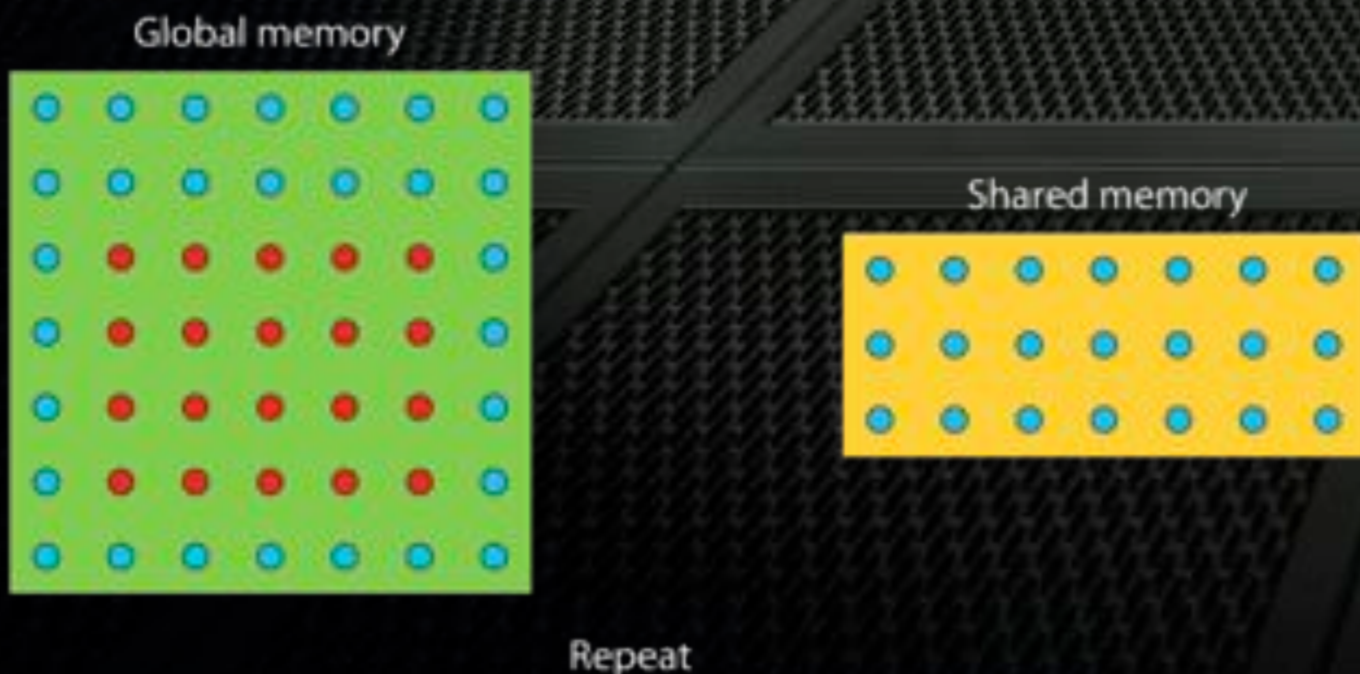

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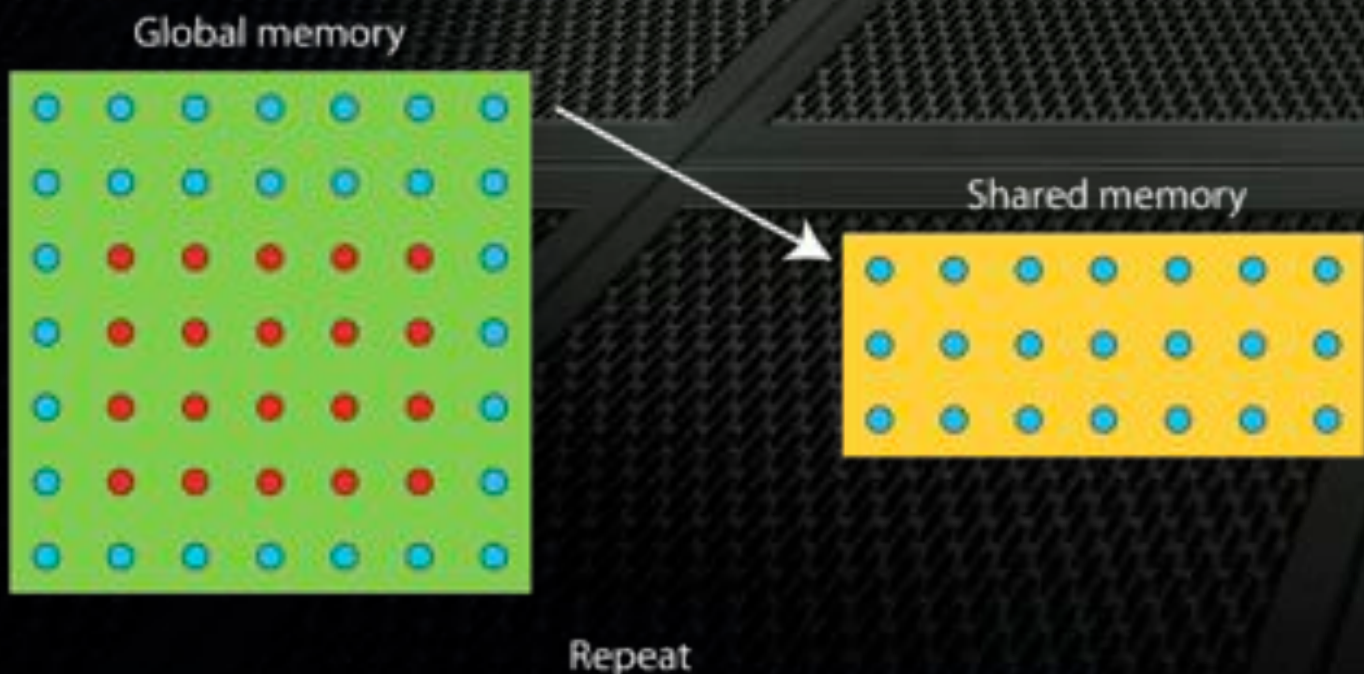

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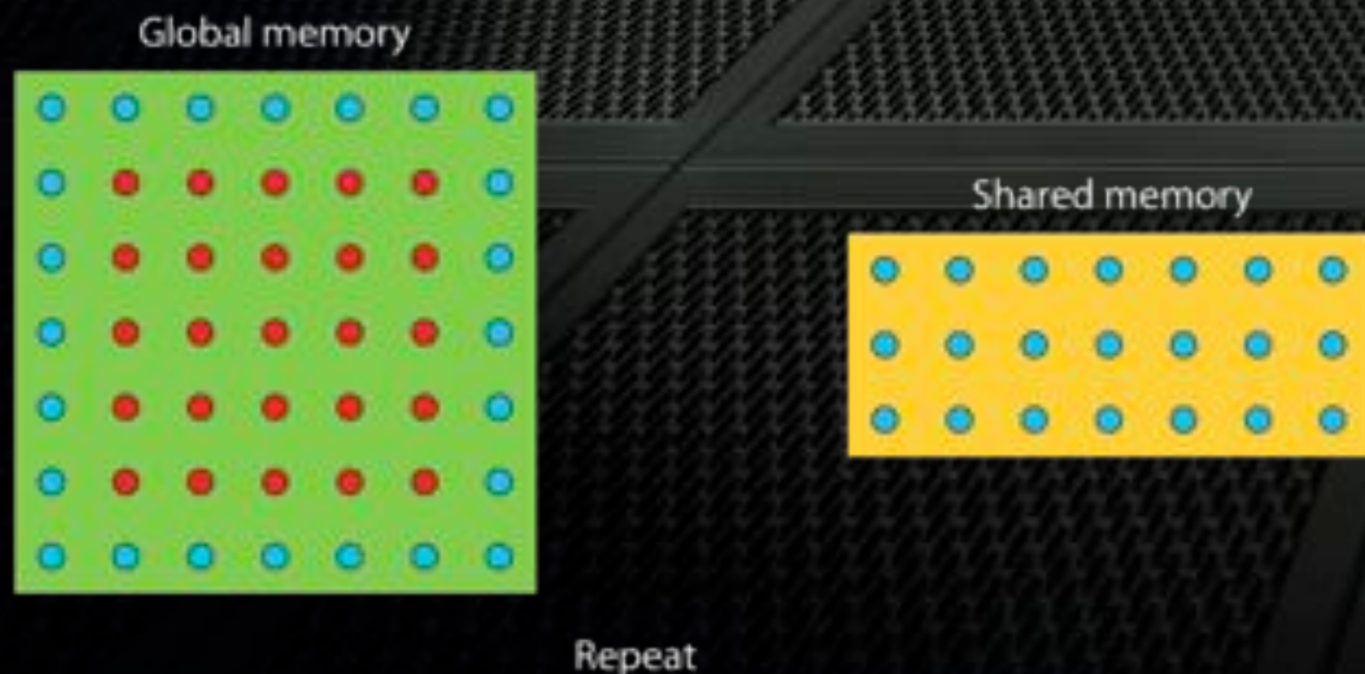

CUDA example

```
__global__ void smooth_kernel(float sf, float *a_d, float *b_d)
{
__shared__ float a[16][5][3];  // shared memory array
```

CUDA example

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__global__ void smooth_kernel(float sf, float *a_d, float *b_d)
{
__shared__ float a[16][5][3];  // shared memory array
a[i][j][0] = a_d[i0m10];       // fetch first three planes
a[i][j][1] = a_d[i000];
a[i][j][2] = a_d[i0p10];
__syncthreads();               // make sure planes are loaded
```

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__global__ void smooth_kernel(float sf, float *a_d, float *b_d)
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a[i][j][0] = a_d[i0m10];       // fetch first three planes
a[i][j][1] = a_d[i000];
a[i][j][2] = a_d[i0p10];
__syncthreads();               // make sure planes are loaded
// compute the stencil: //
b_d[i000]  = sf1*a[i][j][1] +
           + sfd6*(a[i-1][j][1] + a[i+1][j][1]
                 + a[i][j][0]   + a[i][j][2]
                 + a[i][j-1][1] + a[i][j+1][1])
// load next "k" plane and repeat //
```
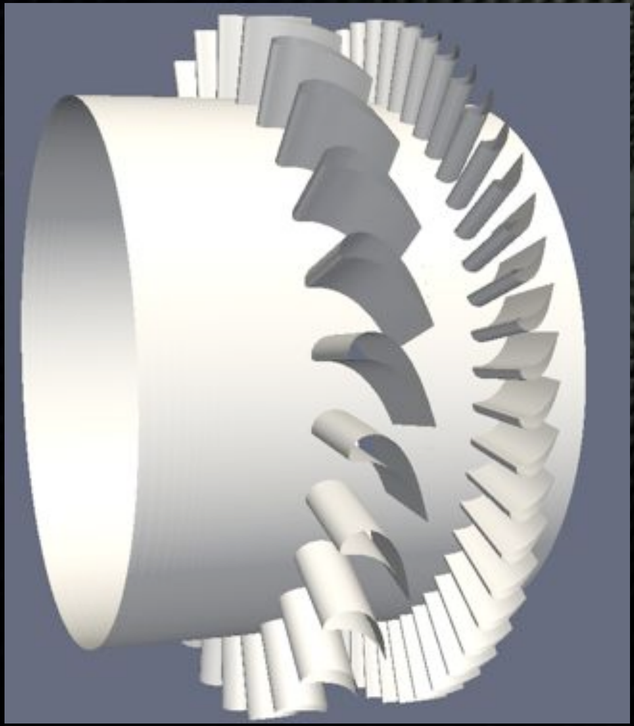
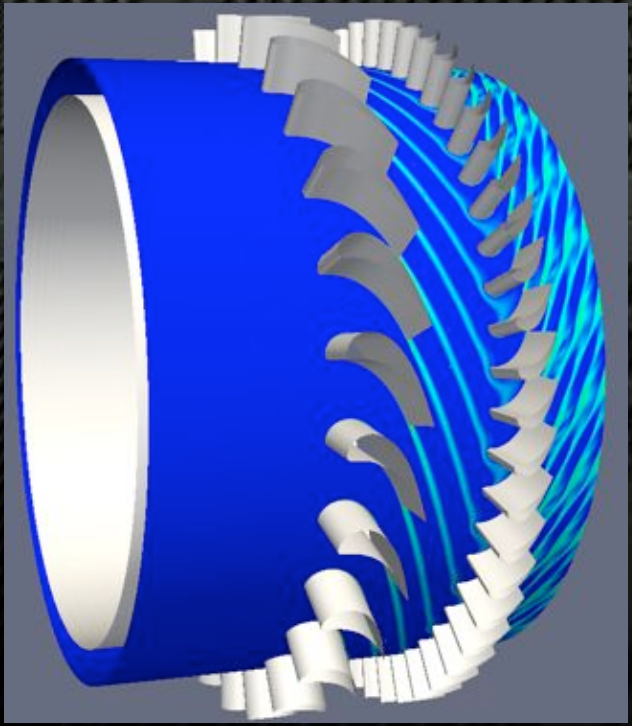

Turbostream

- CUDA port of existing FORTRAN code (TBLOCK)
- 15,000 lines FORTRAN
- 5,000 lines kernel definitions -> 30,000 lines of CUDA
- Runs on CPU or multiple GPUs
- 20x speedup on Tesla C1060 as compared to all cores of a modern Intel core2 quad.

Turbostream

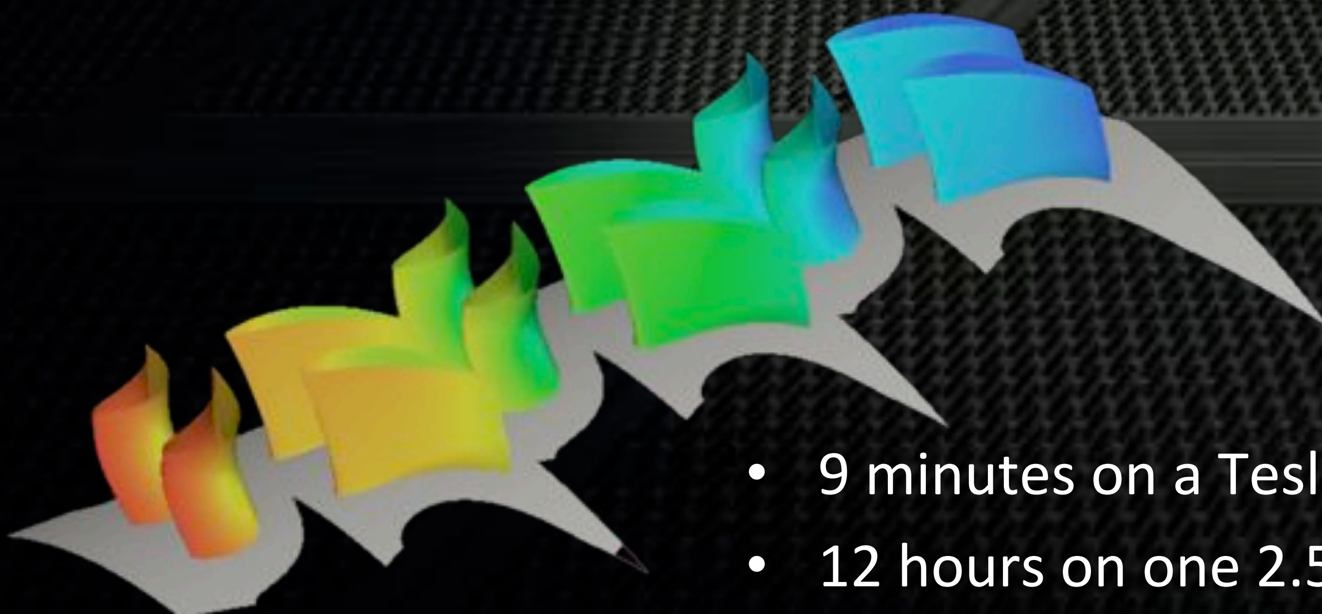


Turbine geometry



Flow solution

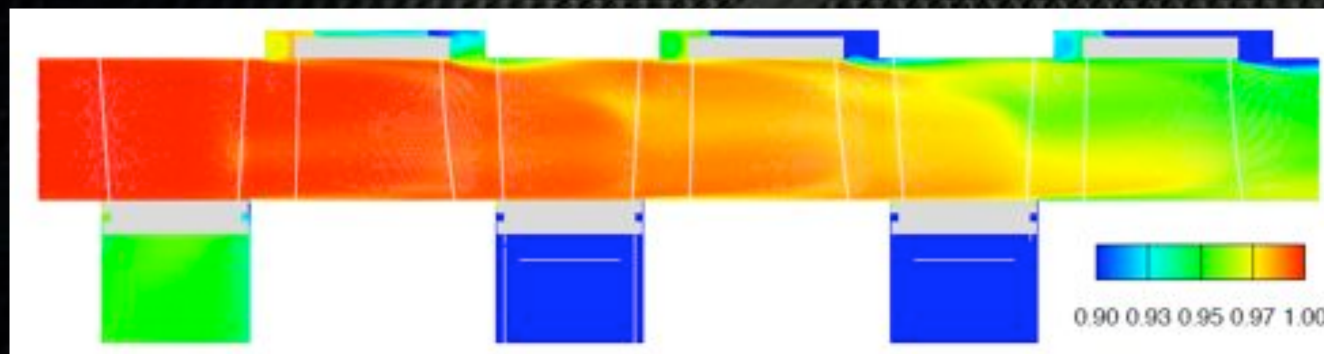
Turbostream



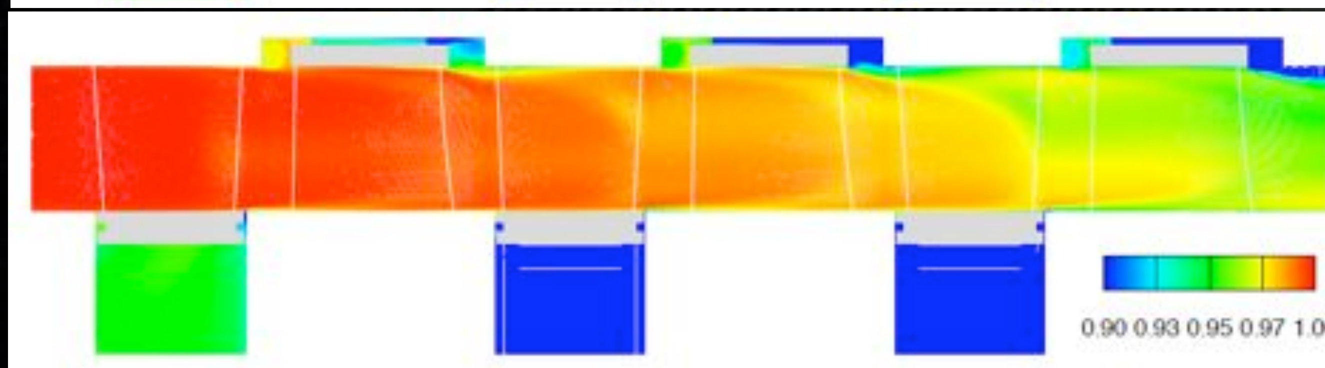
- 9 minutes on a Tesla S870 (4 GPUs)
- 12 hours on one 2.5GHz CPU core

FORTRAN & CUDA comparison

Fortran



CUDA



Impact of GPU accelerated CFD

- Tesla Personal Supercomputer enables
  - Full turbine in 10 minutes (not 12 hours)
  - One blade (for design) in 2 minutes
- Tesla cluster enables
  - Interactive design of blades for first time
  - Use of higher accuracy methods at early stage in design process

Summary

- Many science applications fit the SIMD model used in GPUs
- CUDA enables science developers to access to NVIDIA GPUs without cumbersome graphics APIs
- Existing codes have to be analysed and re-coded to best fit the many-core architecture
- The speedups are such that this can be worth doing
- For our application, the step-change in capability is revolutionary

More information

www.many-core.group.cam.ac.uk