

A large, semi-transparent NVIDIA logo watermark is positioned in the center of the slide. It features the iconic green stylized 'G' shape composed of three overlapping curved surfaces, set against a dark, textured background.

# Hands-on with CUDA: C/C++ and Fortran

ISC13 Tutorial



# Goals

- Learn how to start programming with CUDA
- Understand how to use NVIDIA tools to identify performance issues and learn how to fix them
- Learn how CUDA can be combined with CUDA enabled libraries

# Schedule

0900      Introduction to GPU computing and CUDA  
Basic Programming with CUDA



1100      Break

1130      Optimize a CUDA application with NVIDIA tools



1300      Close

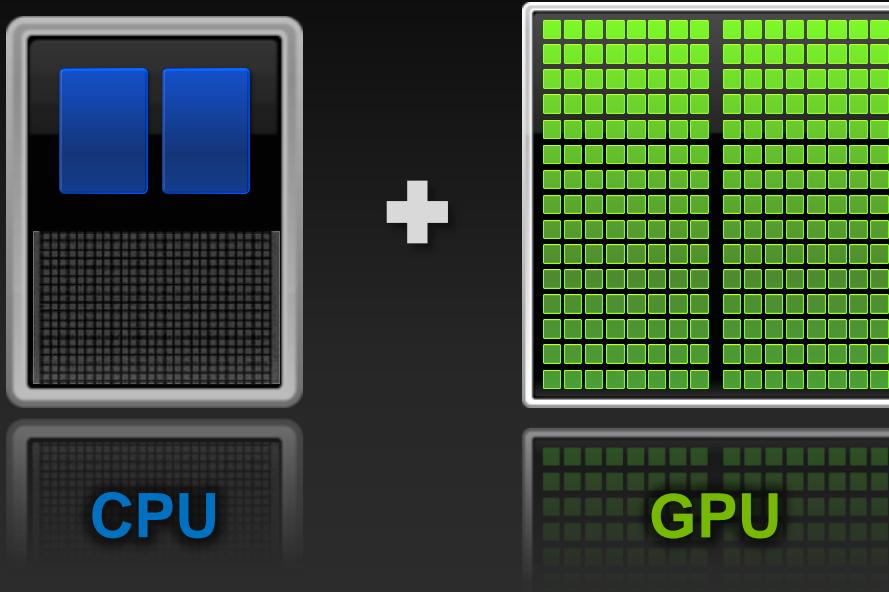


# Introduction to GPU Programming

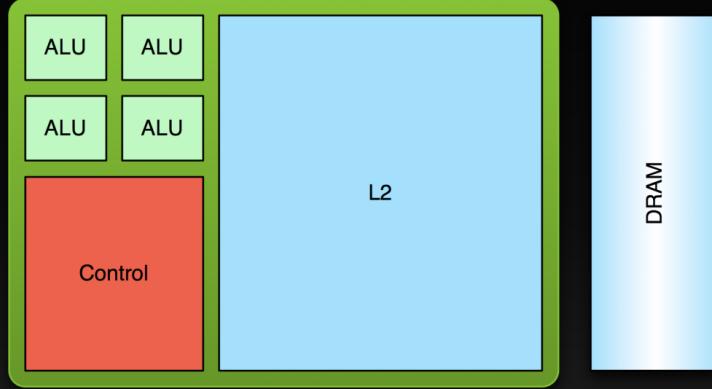
Jiri Kraus, NVIDIA

# GPGPU Revolutionizes Computing

*Latency Processor + Throughput processor*

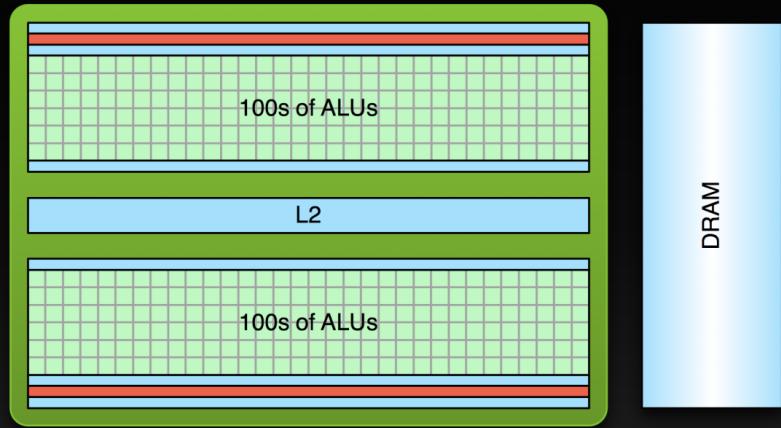


# Low Latency or High Throughput?



## CPU

- Optimized for low-latency access to cached data sets
- Control logic for out-of-order and speculative execution

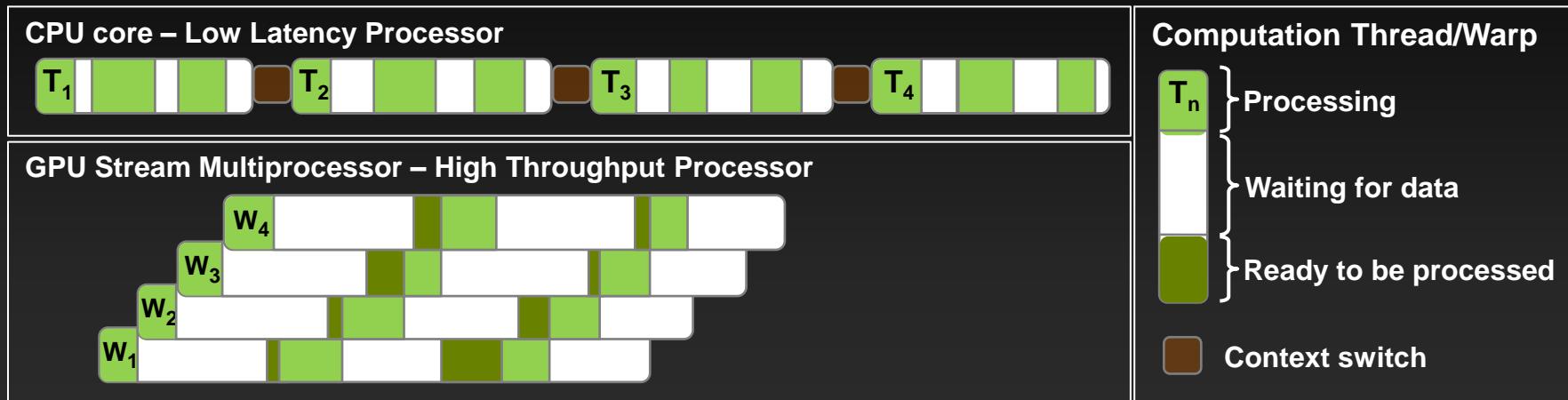


## GPU

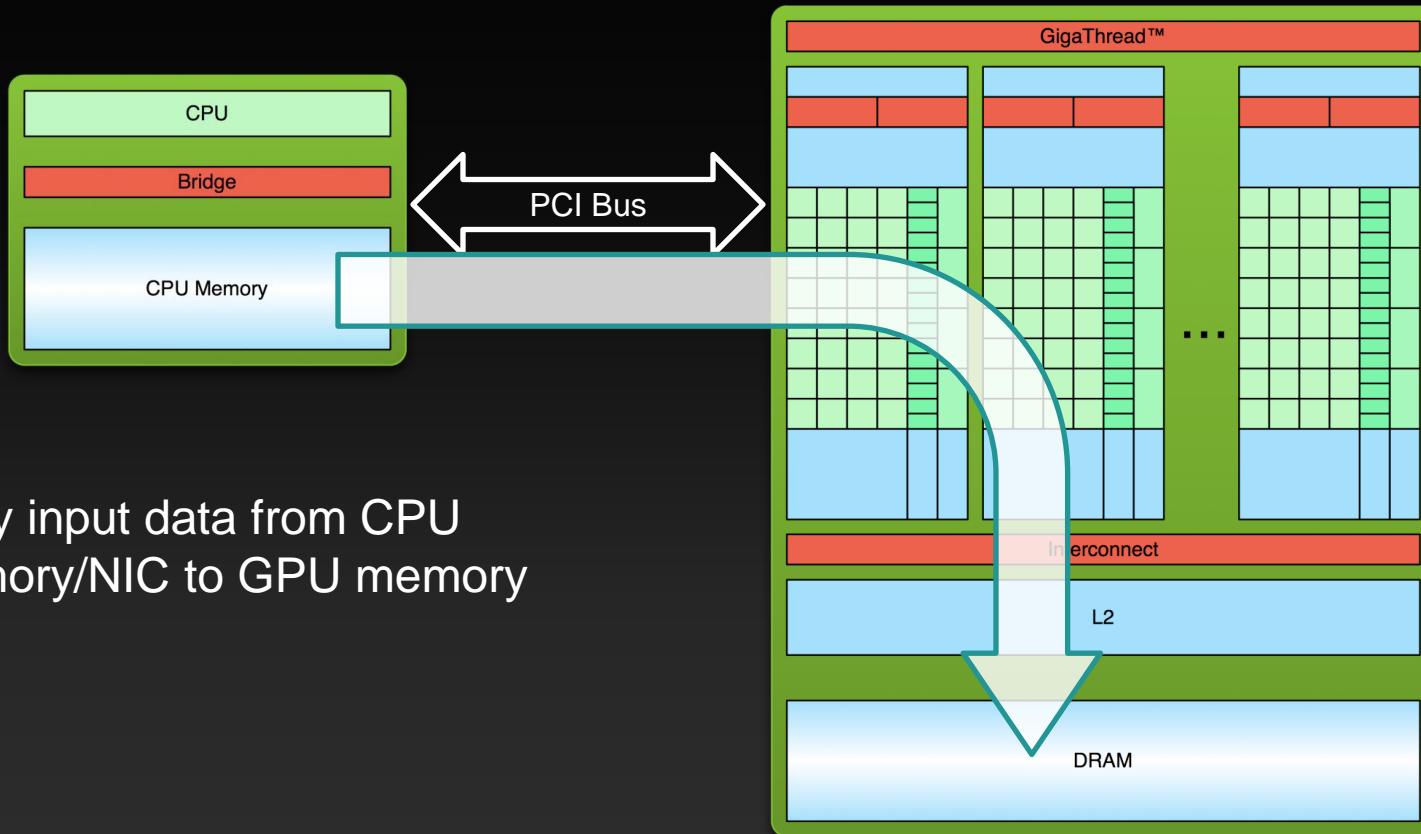
- Optimized for data-parallel, throughput computation
- Architecture tolerant of memory latency
- More transistors dedicated to computation

# Low Latency or High Throughput?

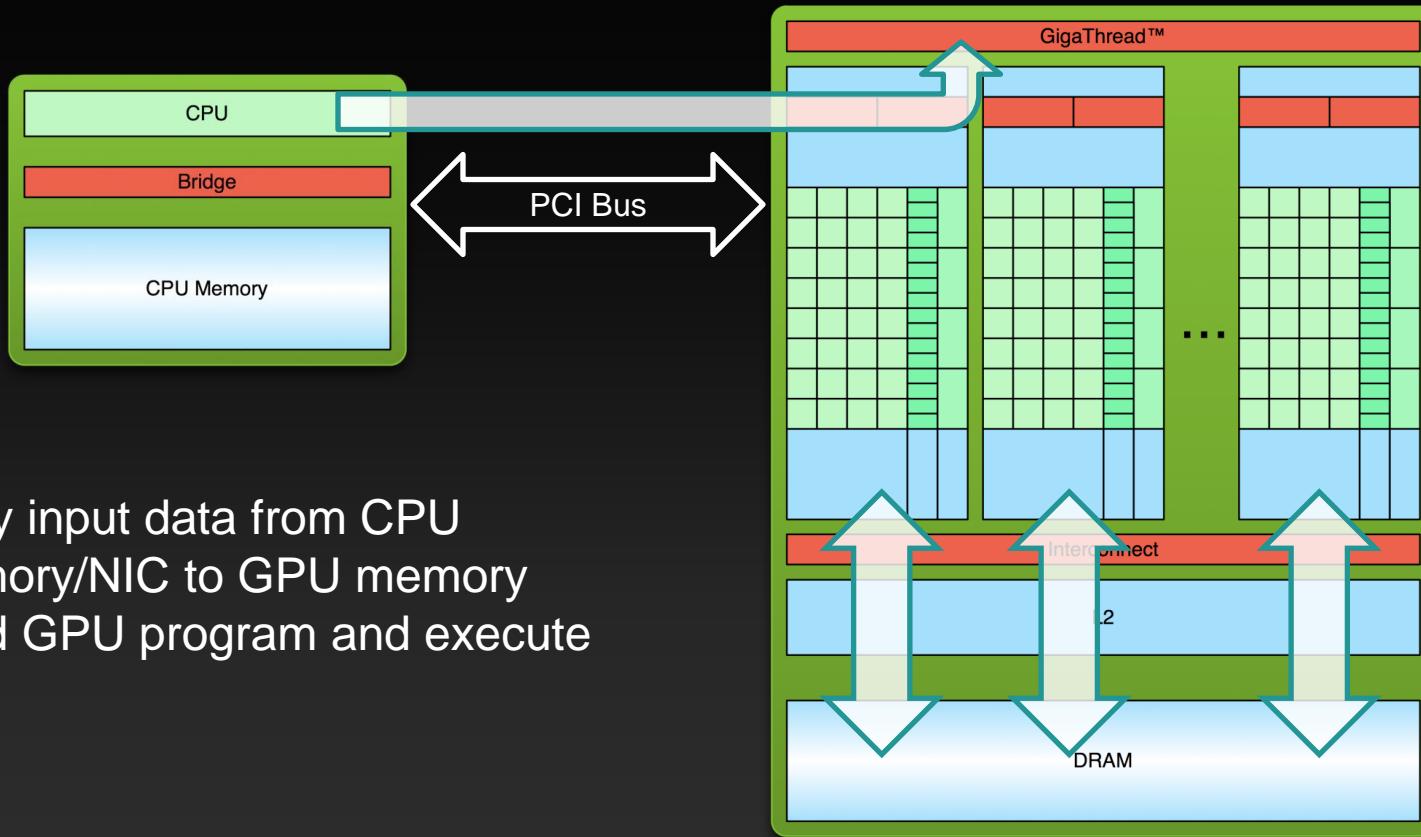
- CPU architecture must minimize latency within each thread
- GPU architecture hides latency with computation from other thread warps



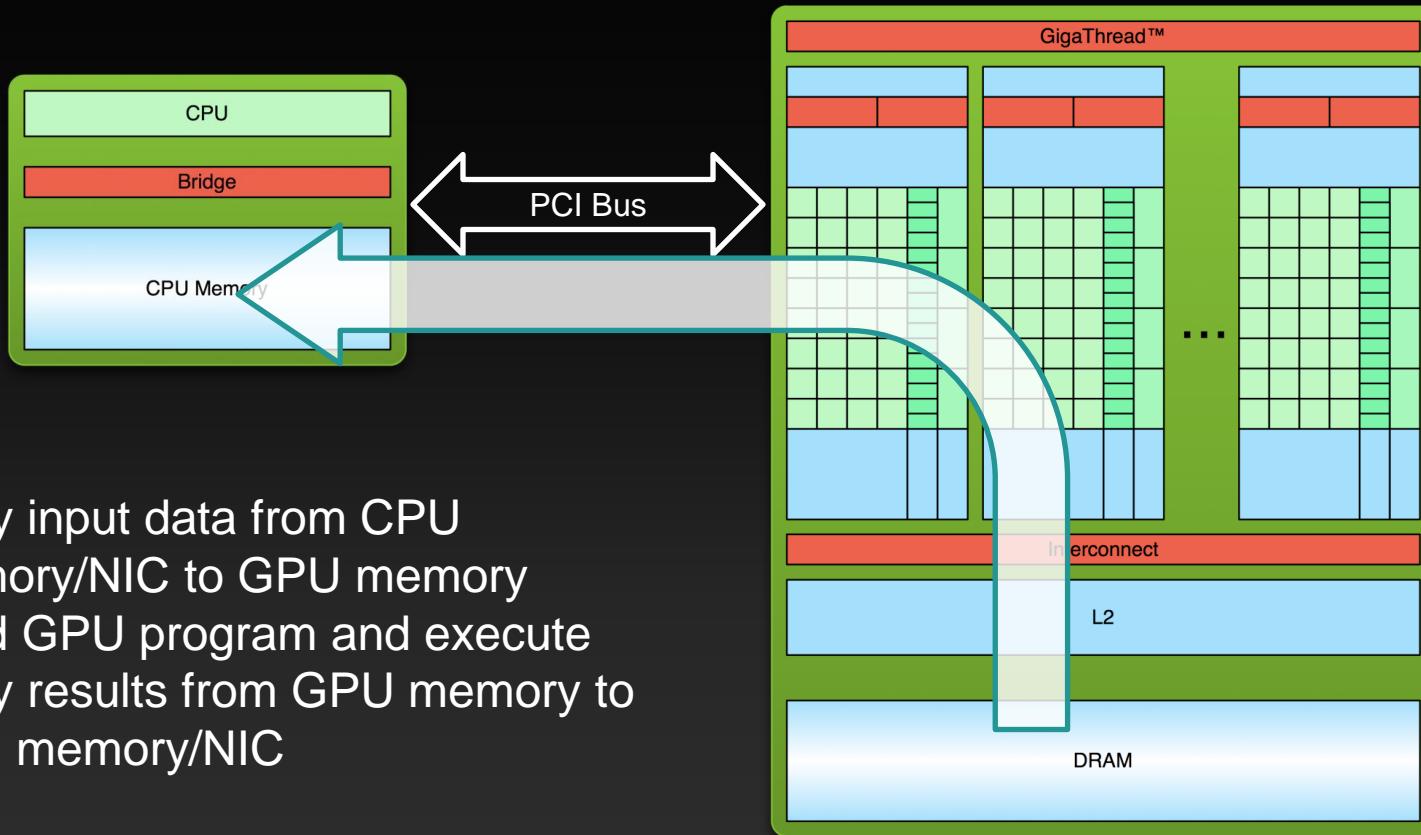
# Simple Processing Flow



# Simple Processing Flow



# Simple Processing Flow



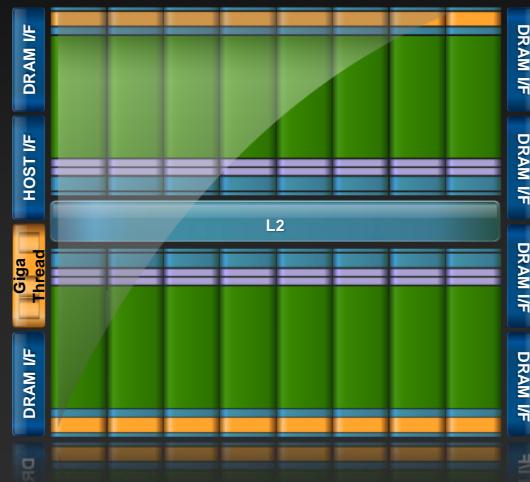
# GPU Architecture: Two Main Components

## ▪ Global memory

- Analogous to RAM in a CPU server
- Accessible by both GPU and CPU
- Currently up to **6 GB** per GPU
- Bandwidth currently up to ~**250 GB/s** (Tesla products)
- **ECC on/off** (Quadro and Tesla products)

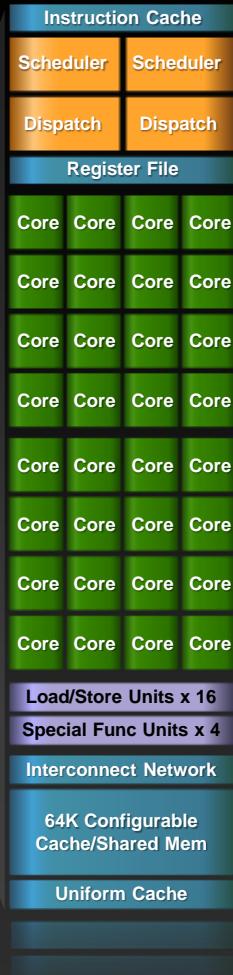
## ▪ Streaming Multiprocessors (SMs)

- Perform the actual computations
- Each SM has its own:
  - Control units, registers, execution pipelines, caches



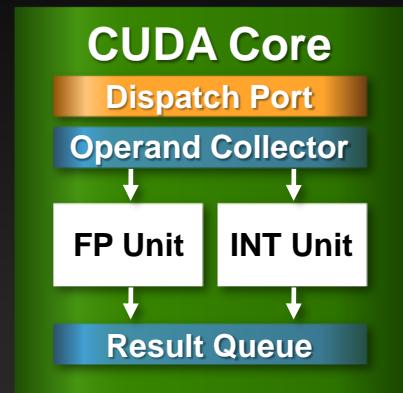
# GPU Architecture – Fermi: Streaming Multiprocessor (SM)

- 32 CUDA Cores per SM
  - 32 fp32 ops/clock
  - 16 fp64 ops/clock
  - 32 int32 ops/clock
- 2 warp schedulers
  - Up to 1536 threads concurrently
- 4 special-function units
- 64KB shared mem + L1 cache
- 32K 32-bit registers



# GPU Architecture – Fermi: CUDA Core

- Floating point & Integer unit
  - IEEE 754-2008 floating-point standard
  - Fused multiply-add (FMA) instruction for both single and double precision
- Logic unit
- Move, compare unit
- Branch unit

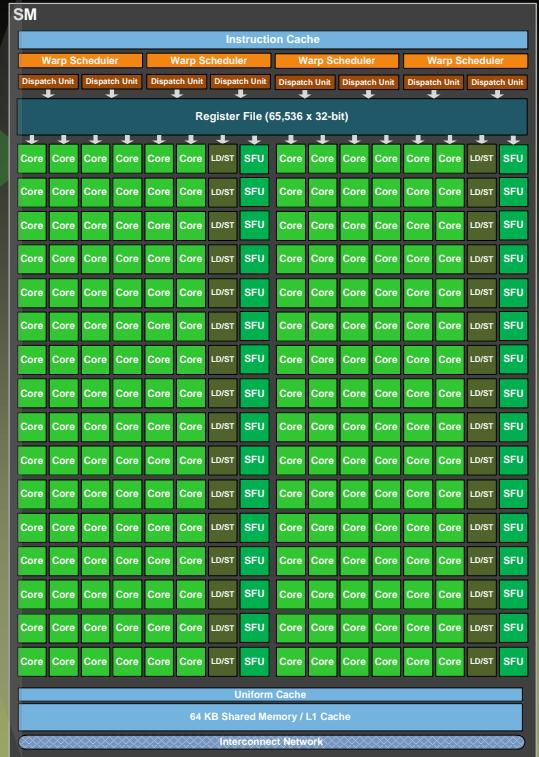
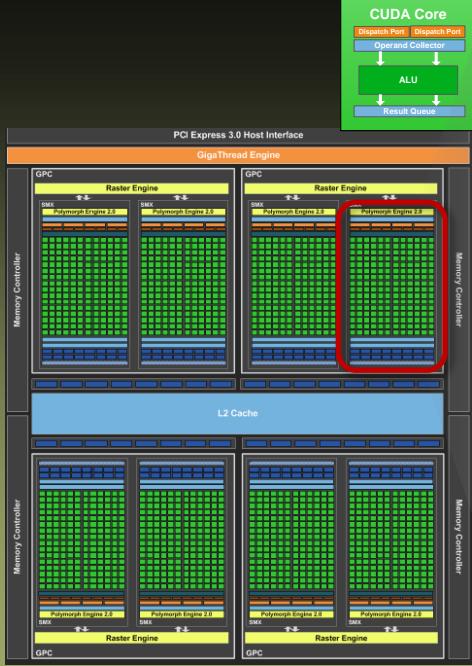


# Kepler

## Fermi



## Kepler



CUDA Review

# PROGRAMMING MODEL

# Anatomy of a CUDA Application

```
#include <iostream>
#include <cmath>
using namespace std;

#define N 1024
#define RADIUS 3
#define BLOCK_SIZE 16

__global__ void stencil_1d(in<int>*in, int*out) {
    __shared__ int temp[BLOCK_SIZE + 2 * RADIUS];
    int index = threadIdx.x * blockDim.x * blockDim.x * RADIUS;
    int index += blockIdx.x * blockDim.x * RADIUS;

    // Read the elements into shared memory
    temp[threadIdx.x - RADIUS] = in[index - RADIUS];
    if (threadIdx.x < RADIUS) {
        temp[threadIdx.x + RADIUS] = in[index + RADIUS];
        temp[threadIdx.x] = in[index];
        temp[threadIdx.x + 1] = in[index + 1];
    }

    // Synchronize (ensure all the data is available)
    __syncthreads();

    // Apply the stencil
    int result = 0;
    for (int offset = -RADIUS; offset <= RADIUS; offset++) {
        result += temp[index + offset];
    }

    // Store the result
    out[index] = result;
}

void fill_ints(int*& in, int n) {
    fill(in, in + n, 1);
}

int main() {
    int *h_in, *h_out; // host copies of a, b, c
    int *d_in, *d_out; // device copies of a, b, c
    int size = (N + 2 * RADIUS) * sizeof(int);

    // Alloc space for host copies and setup values
    in = (int *)malloc(size); fill_ints(in, N + 2 * RADIUS);
    out = (int *)malloc(size); fill_ints(out, N + 2 * RADIUS);

    // Alloc space for device copies
    cudaMalloc(void **&d_in, size);
    cudaMalloc(void **&d_out, size);

    // Copy to device
    cudaMemcpy(d_in, in, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_out, out, size, cudaMemcpyHostToDevice);

    // Launch stencil_1d() kernel on GPU
    stencil_1d<N,BLOCK_SIZE,BLOCK_SIZE>>(d_in + RADIUS, d_out + RADIUS);

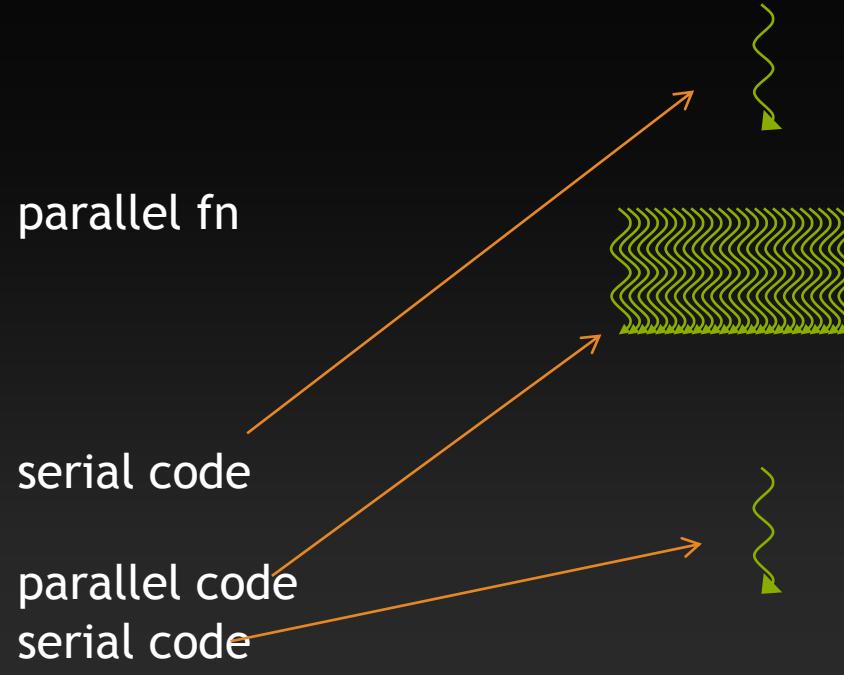
    // Copy result back to host
    cudaMemcpy(d_out, out, size, cudaMemcpyDeviceToHost);

    // Clean up
    free(in); free(out);
    cudaFree(d_in); cudaFree(d_out);
    return 0;
}
```

parallel fn

serial code

parallel code  
serial code



# CUDA Kernels

- Parallel portion of application: execute as a **kernel**
  - Entire GPU executes kernel, many threads
- CUDA threads:
  - Lightweight
  - Fast switching
  - 1000s execute simultaneously

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CPU	Host	Executes functions
GPU	Device	Executes kernels

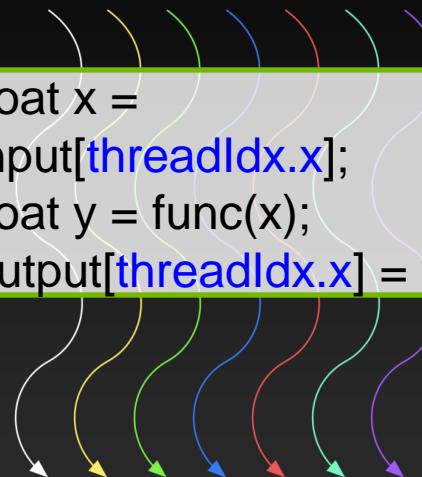
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# CUDA Kernels: Parallel Threads

- A **kernel** is a function executed on the GPU as an array of threads in parallel
- All threads execute the same code, can take different paths
- Each thread has an ID
  - Select input/output data
  - Control decisions



```
float x =  
    input[threadIdx.x];  
float y = func(x);  
output[threadIdx.x] = y;
```



# CUDA Kernels: Subdivide into Blocks

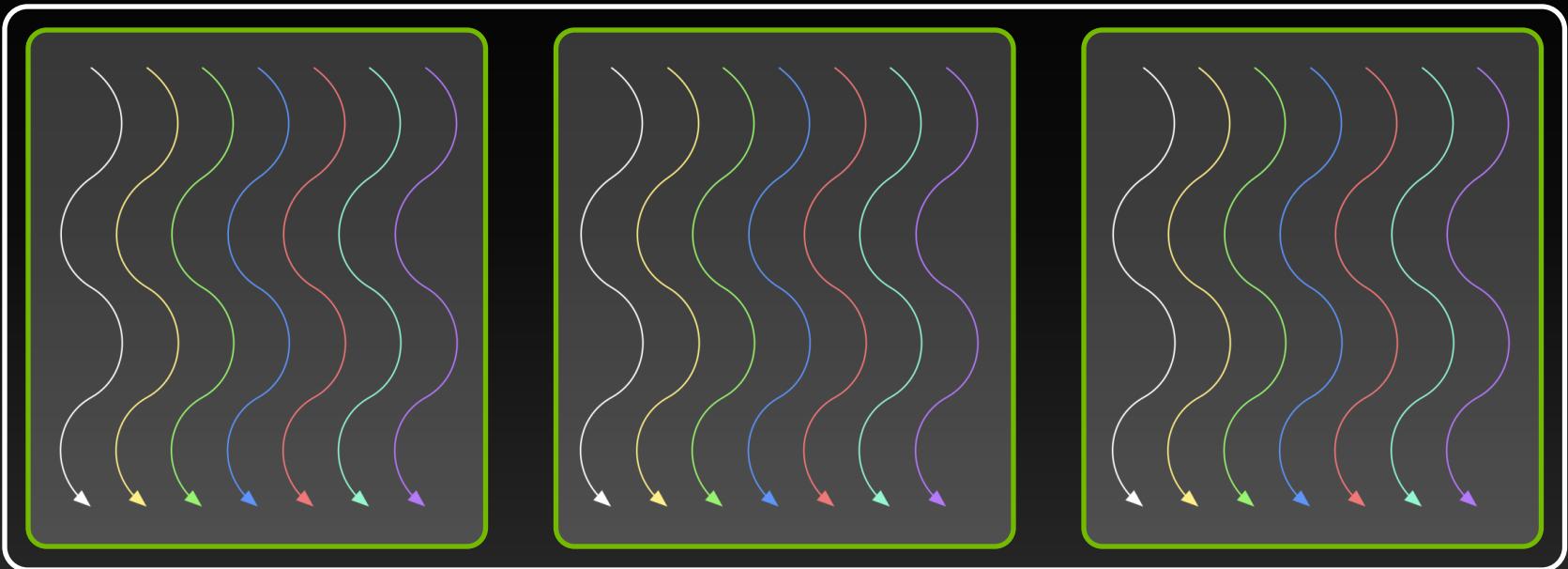


# CUDA Kernels: Subdivide into Blocks



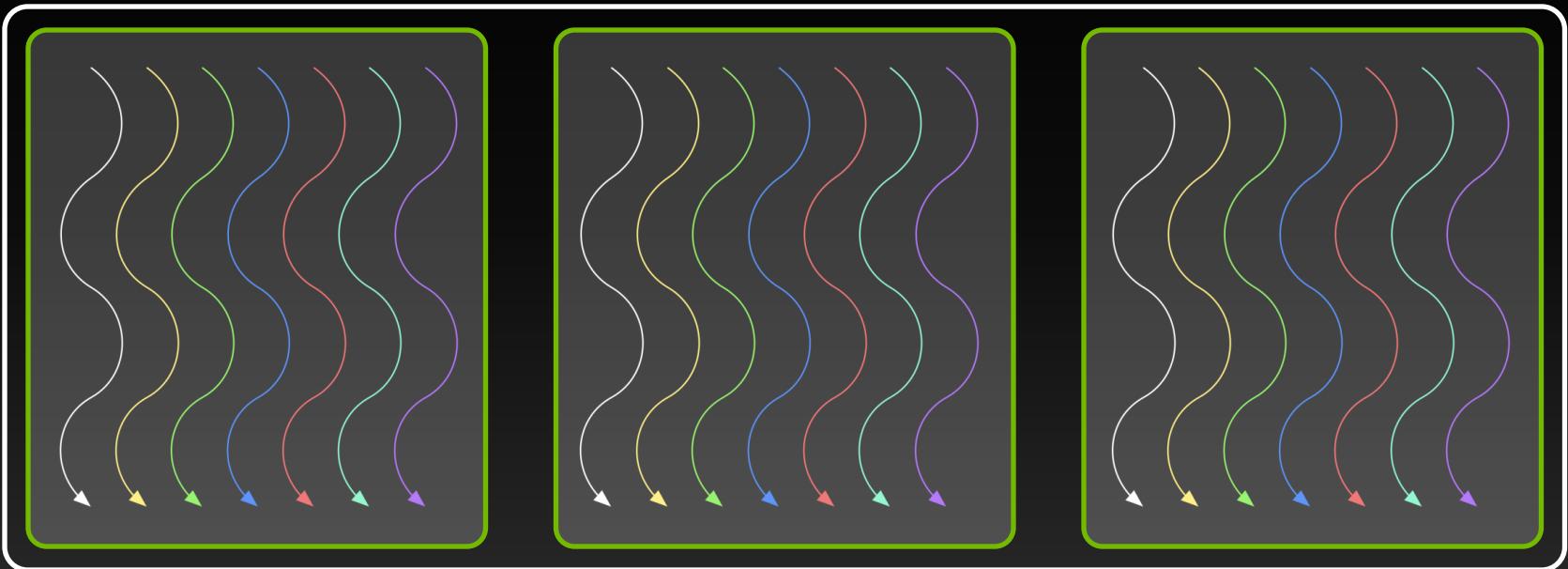
- Threads are grouped into **blocks**

# CUDA Kernels: Subdivide into Blocks



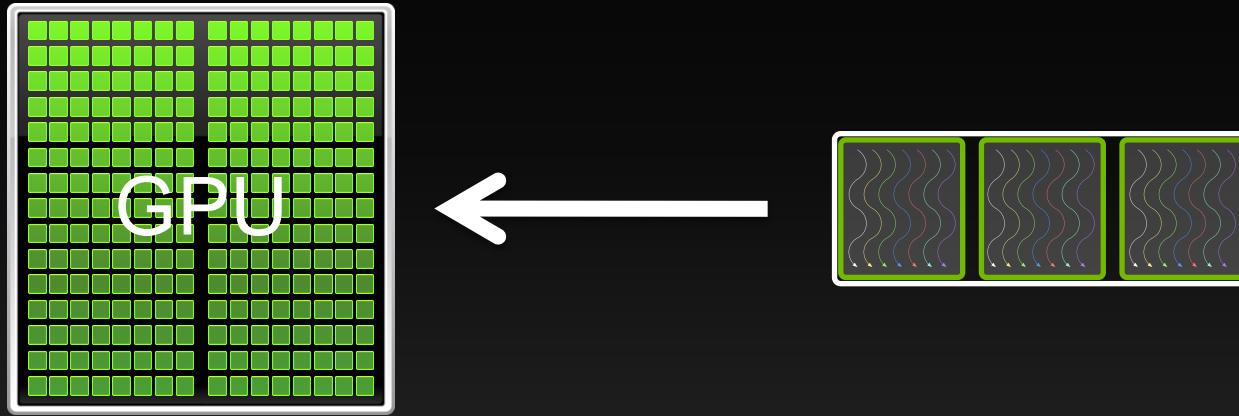
- Threads are grouped into **blocks**
- **Blocks** are grouped into a grid

# CUDA Kernels: Subdivide into Blocks



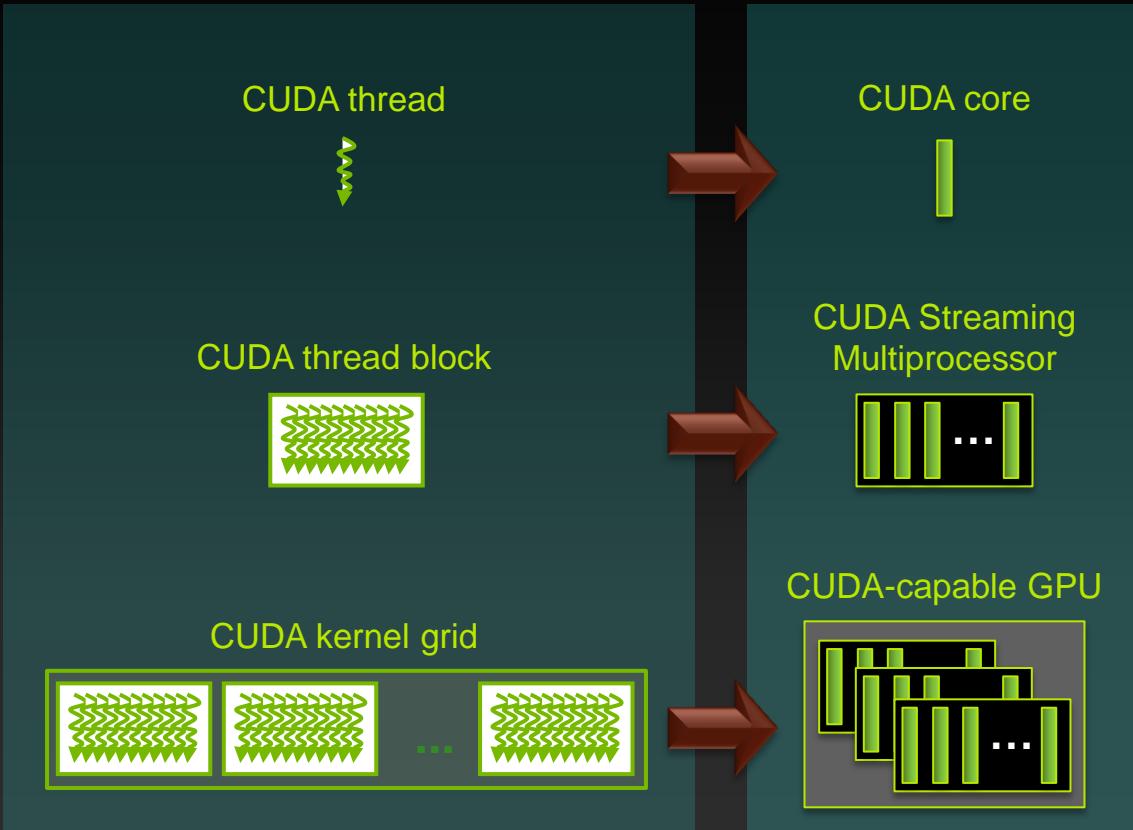
- Threads are grouped into **blocks**
- **Blocks** are grouped into a **grid**
- A **kernel** is executed as a **grid of blocks of threads**

# CUDA Kernels: Subdivide into Blocks



- Threads are grouped into **blocks**
- **Blocks** are grouped into a **grid**
- A **kernel** is executed as a **grid of blocks of threads**

# Kernel Execution



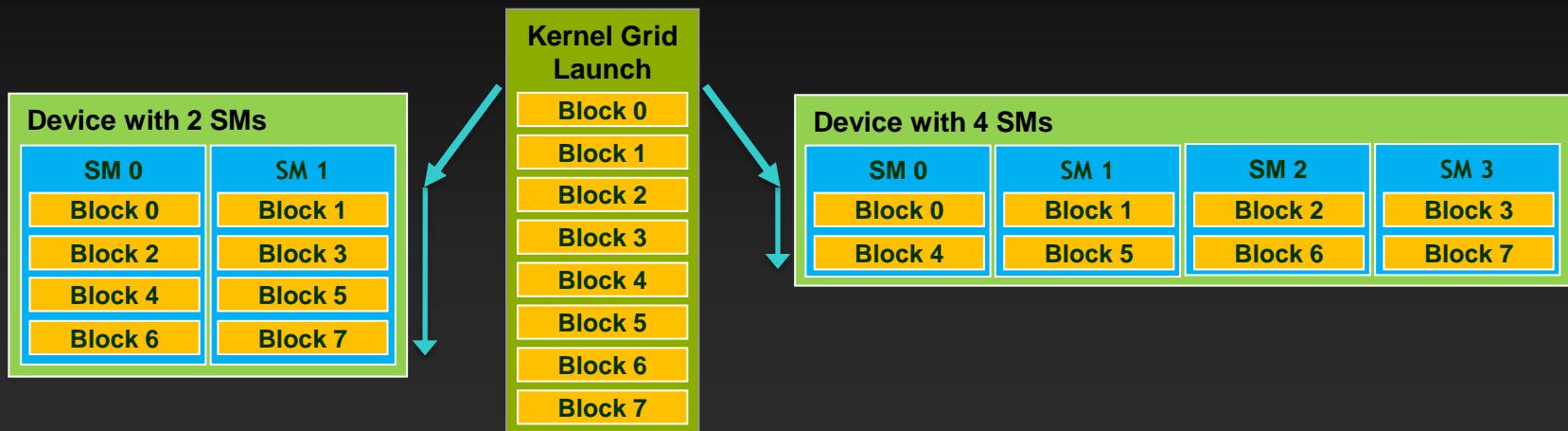
- Each thread is executed by a core
- Each block is executed by one SM and does not migrate
- Several concurrent blocks can reside on one SM depending on the blocks' memory requirements and the SM's memory resources
- Each kernel is executed on one device
- Multiple kernels can execute on a device at one time

# Communication Within a Block

- Threads may need to cooperate
  - Memory accesses
  - Share results
- Cooperate using shared memory
  - Accessible by all threads within a block
- Restriction to “within a block” permits scalability
  - Fast communication between N threads is not feasible when N large

# Thread blocks allow scalability

- Blocks can execute in any order, concurrently or sequentially
- This independence between blocks gives scalability:
  - A kernel scales across any number of SMs



# CUDA C

## *Standard C Code*

```
void saxpy(int n, float a,
           float *x, float *y)
{
    for (int i = 0; i < n; ++i)
        y[i] = a*x[i] + y[i];
}

int N = 1<<20;

// Perform SAXPY on 1M elements
saxpy(N, 2.0, x, y);
```

## *Parallel C Code*

```
__global__
void saxpy(int n, float a,
           float *x, float *y)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;
    if (i < n) y[i] = a*x[i] + y[i];
}

int N = 1<<20;
cudaMemcpy(x, h_x, N, cudaMemcpyHostToDevice);
cudaMemcpy(y, h_y, N, cudaMemcpyHostToDevice);

// Perform SAXPY on 1M elements
saxpy<<<4096,256>>>(N, 2.0, x, y);

cudaMemcpy(h_y, y, N, cudaMemcpyDeviceToHost);
```

# What's Next?

- Start learning CUDA
- See how to use NVIDIA tools to identify performance issues and learn how to fix them.



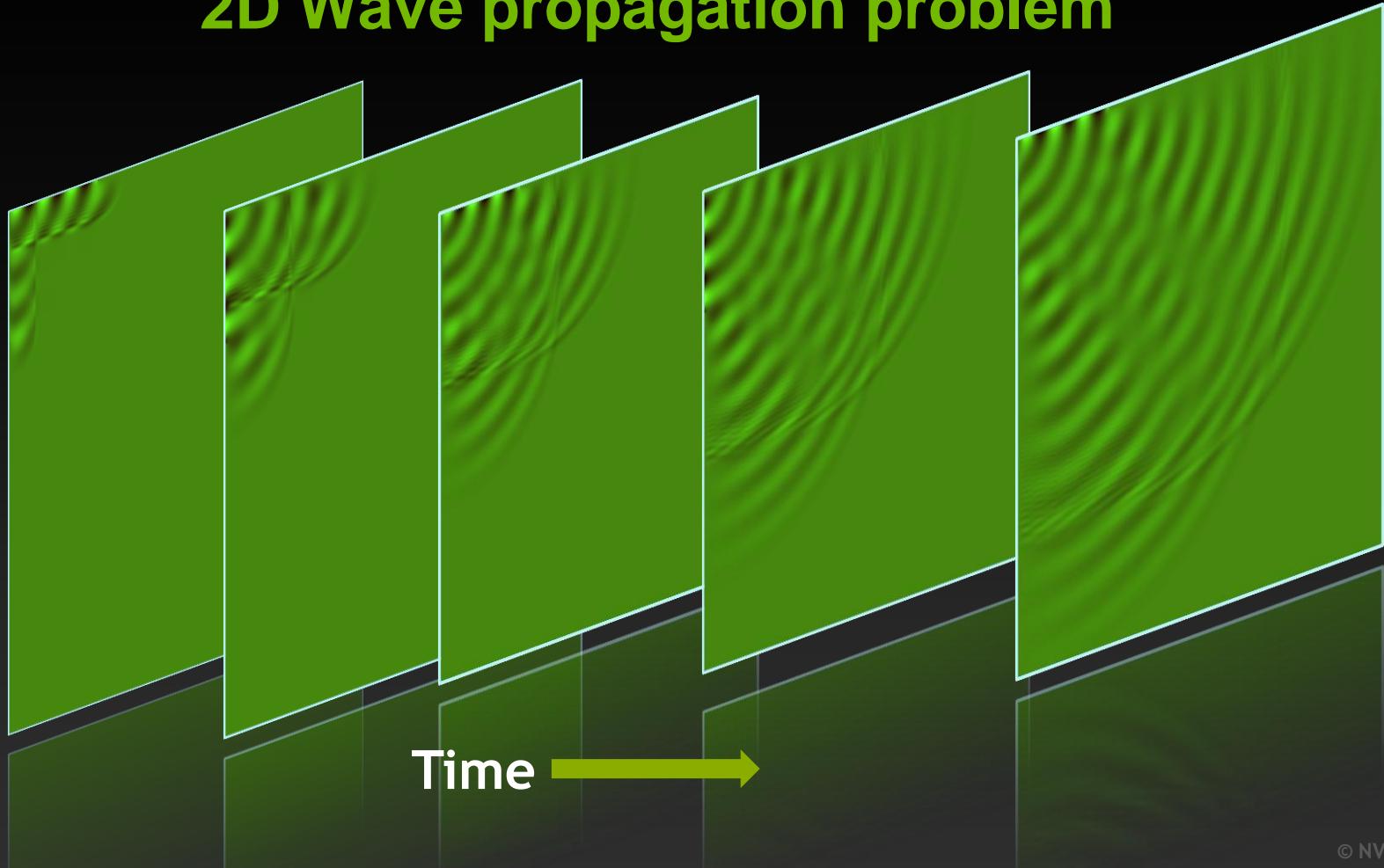
# Hands-On Overview

Jiri Kraus, NVIDIA

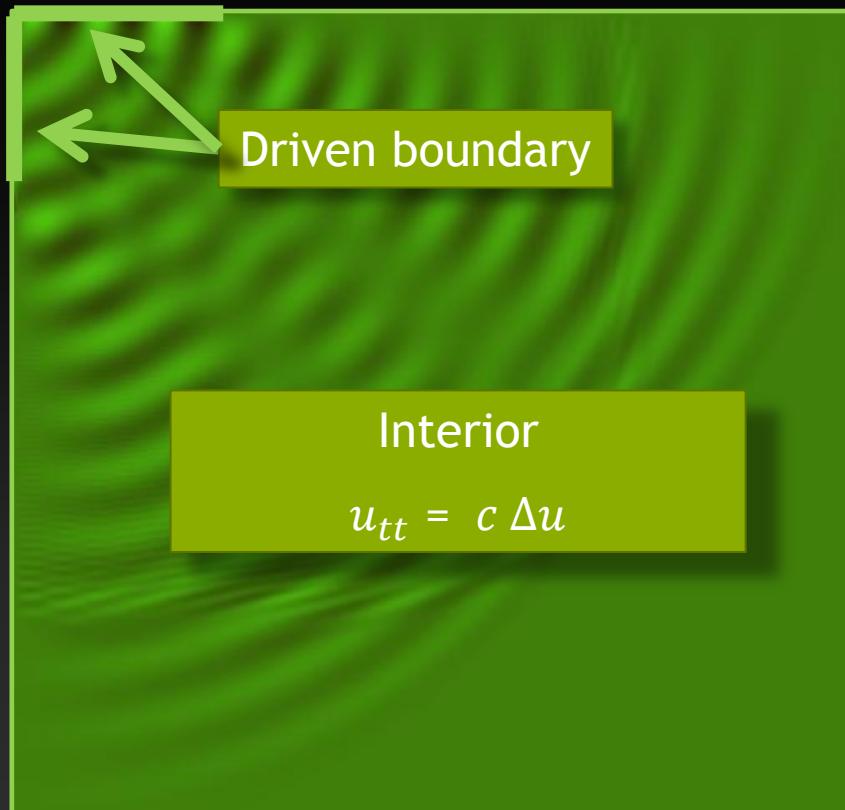
# Hands-On

- We will use a basic 2D scalar wave solver as an example
  - Introduced next
- The tutorial examples are provided for
  - CUDA-Fortran in `~/euler/CUDA-Fortran`
  - CUDA C in `~/euler/CUDA-C`
- You can use
  - CUDA C or CUDA-Fortran
  - make + the editor of your choice and NVIDIA Visual Profiler
  - Nsight eclipse edition

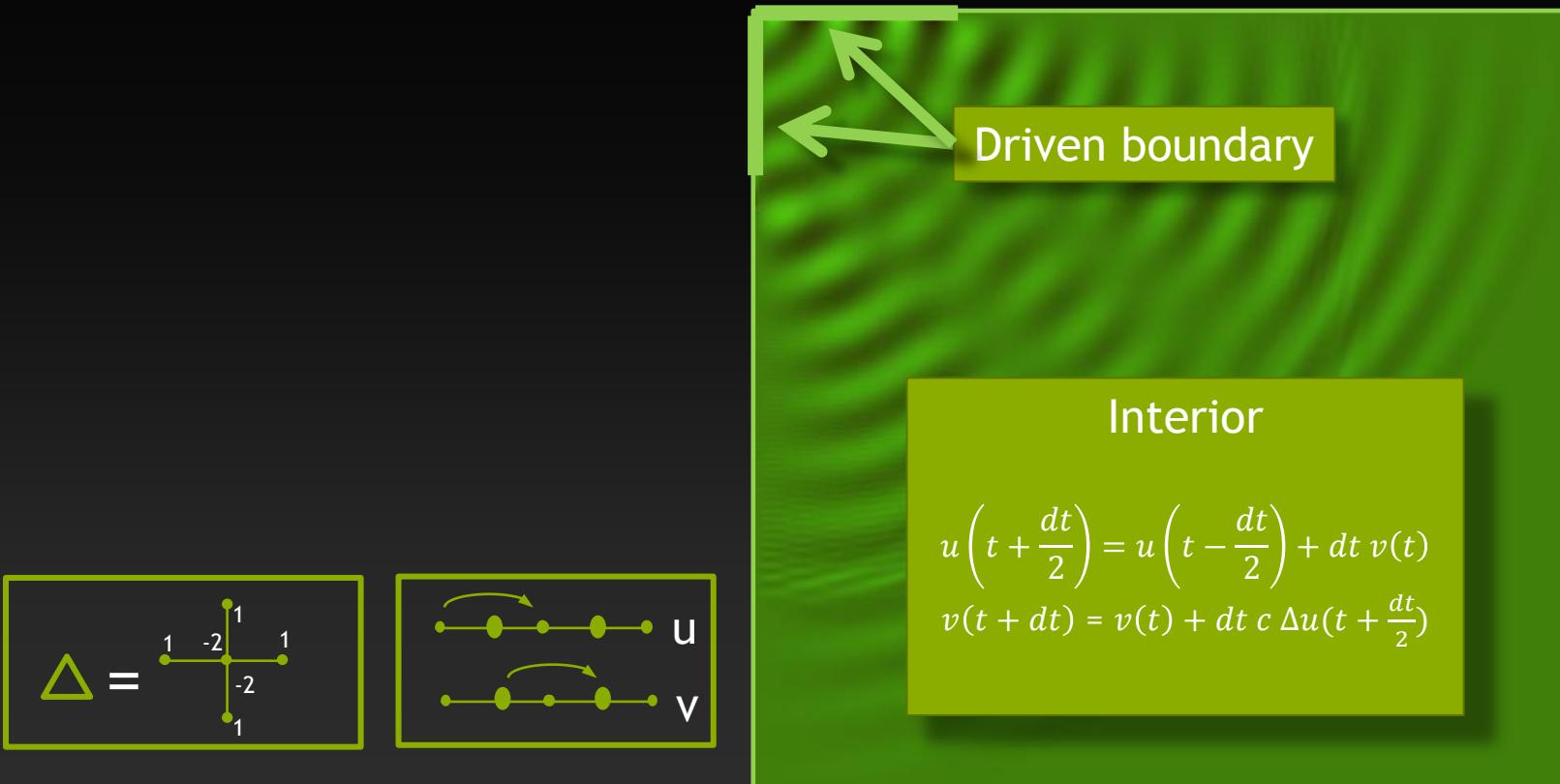
# 2D Wave propagation problem



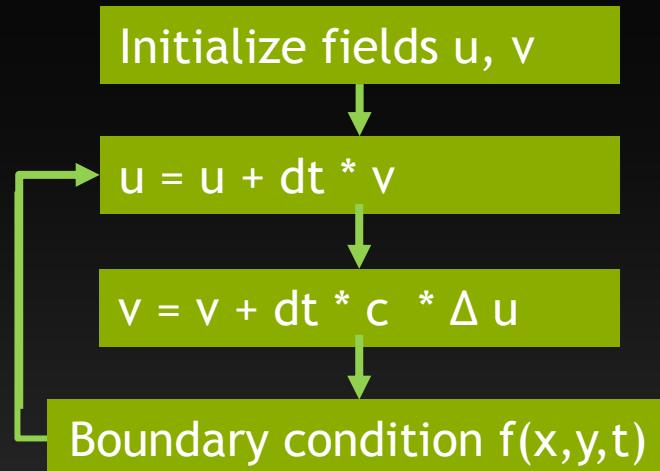
# A basic 2D scalar wave solver: $u_{tt} = c \Delta u$



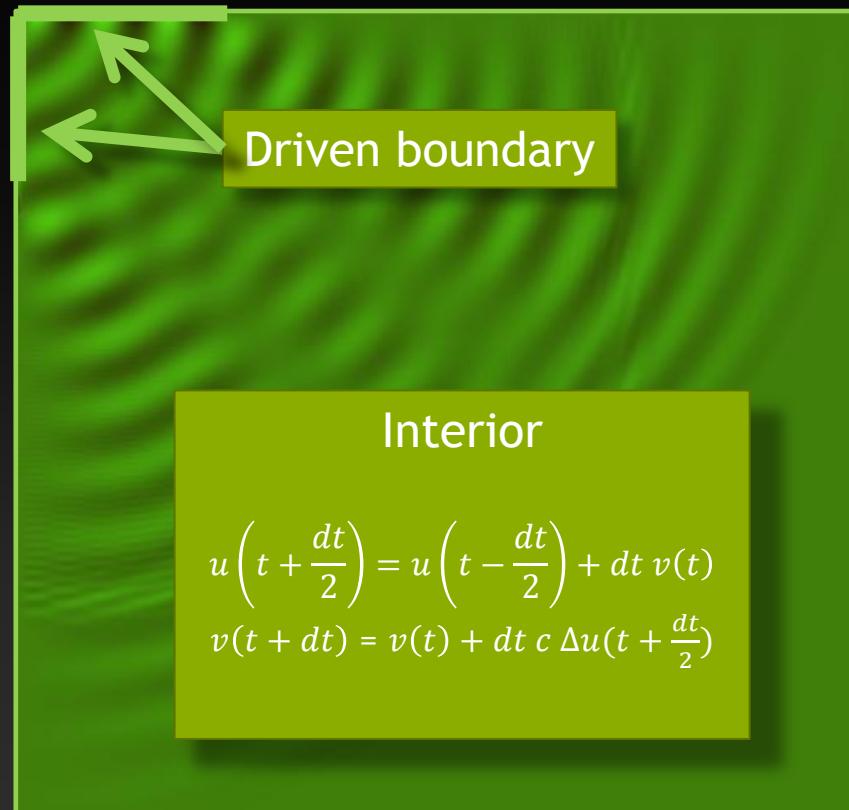
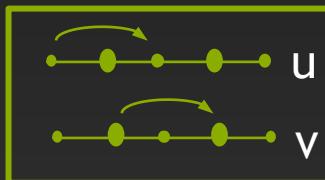
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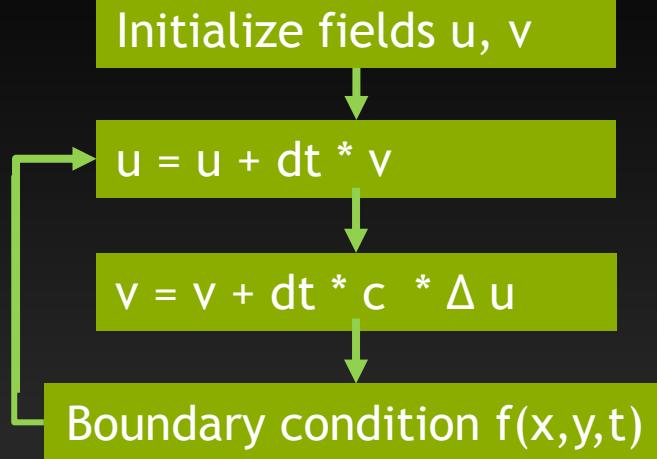
# A basic 2D scalar wave solver: $u_{tt} = c\Delta u$



$$\Delta = \begin{array}{c} & 1 \\ & -2 \\ \begin{matrix} 1 \\ -2 \\ 1 \end{matrix} & \\ & -2 \\ & 1 \end{array}$$



# Sample: Basic Euler Solver



```
do t = 1, 1000
    u(:, :) = u(:, :) + dt * v(:, :)
    do y=2, ny-1
        do x=2,nx-1
            v(x,y) = v(x,y) + dt * c * ( &
                (u(x,y+1) - 2*u(x,y) + u(x,y-1)) / dy2 + &
                (u(x+1,y) - 2*u(x,y) + u(x-1,y)) / dx2 )
        end do
    end do
    call BoundaryCondition(u)
end do
```

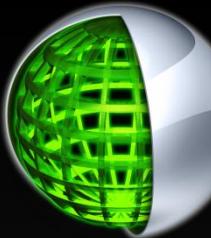
# NVIDIA CUDA C Compiler NVCC

- **Use NVIDIA's CUDA C Compiler to compile CUDA C programs**
  - Replace compiler and linker with nvcc (e.g. nvcc instead of gcc)
  - rename files to \*.cu
  - Add –arch flag matching the architecture of your GPU
    - We are using Fermi: -arch=sm\_20
- **nvcc splits source file in host part and device part**
  - Host part is passed through to host compiler (e.g. gcc)
    - Use –Xcompiler to pass command line options to host compiler

# **PGI CUDA Fortran Compiler pgf90**

- **PGIs Fortran Compiler comes with CUDA Fortran**
  - add **-Mcuda=cc20** to your command line
  - add **-Mcuda** to your linker line
  - Rename files to **\*\*.CUF**

# NVIDIA® Nsight™ Eclipse Edition



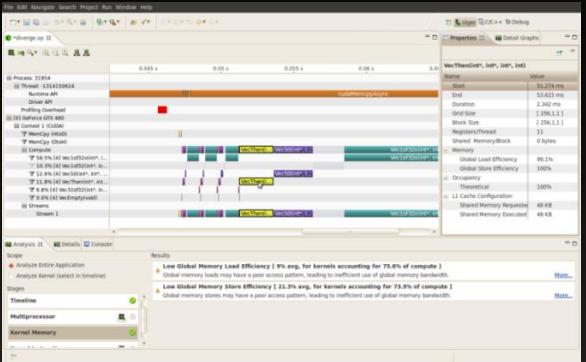
CUDA-Aware Editor

```
uint32_t deviceFindMax(const uint32_t array[], uint32_t *index, const uint32_t arrayLength) {
    uint32_t max = array[0];
    uint32_t maxIndex = 0;
    for (int i = 1; i < arrayLength; i++) {
        if (array[i] > max) {
            max = array[i];
            maxIndex = i;
        }
    }
    return max;
}
```

```
Max number is 8000000 with index 2737998
Running multi-threaded device code
```

Nsight Debugger

```
for (i = 1; i < ARRAY_SIZE; i += threadsCount) {
    nextElementIndex = firstElementIndex + threadsCount;
    if (nextElementIndex > max) {
        max = nextElementIndex;
        maxIndex = i;
    }
}
threadIndex[threadIndex] = max;
threadIndex[threadIndex] = maxIndex;
```



Available for Linux and Mac OS

- Automated CPU to GPU code refactoring
- Semantic highlighting of CUDA code
- Integrated code samples & docs

## Nsight Debugger

- Simultaneously debug of CPU and GPU
- Inspect variables across CUDA threads
- Use breakpoints & single-step debugging

## Nsight Profiler

- Quickly identifies performance issues
- Integrated expert system
- Automated analysis
- Source line correlation

# Task 1: Setup Compilation tool chain

- Update Makefile and rename files
  - CUDA C:
    - use nvcc instead of gcc
    - add –arch=sm\_20
    - rename \*.c -> \*.cu
  - CUDA Fortran:
    - add –Mcuda=cc20 flag
    - rename \*.F90 -> \*.CUF
  - Follow TODOs in Makefile
- Compile and run
- Optional: Use Nsight Eclipse Edition (explained next)

# How to connect to Amazon EC2?

- 1. If you have not done already:**
  - Download and install OpenNX
  - Instructions: <https://developer.nvidia.com/cuda-cloud>
- 2. Surf to <https://nvidia.qwiklab.com/>**
  1. Sign in and select appropriate class
  2. Find the correct lab's listing, and once enabled press Start Lab
  3. Enter the Token number provided when prompted
- 3. Setting up OpenNX Client Connection**

# Setting up OpenNX Client Connection I (demo)

The image shows a split-screen setup for connecting to a lab session.

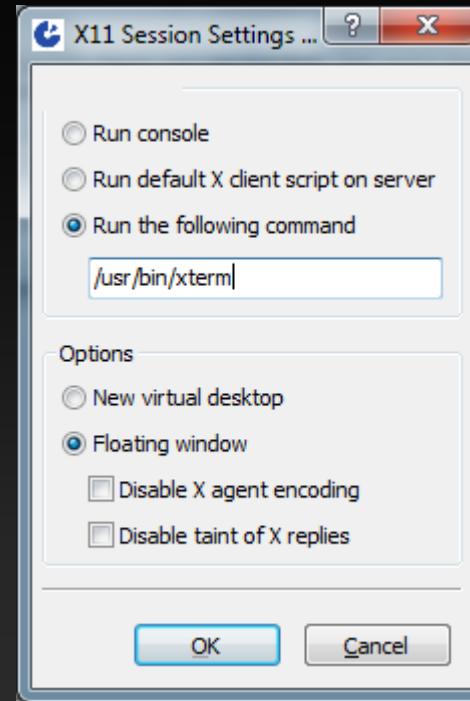
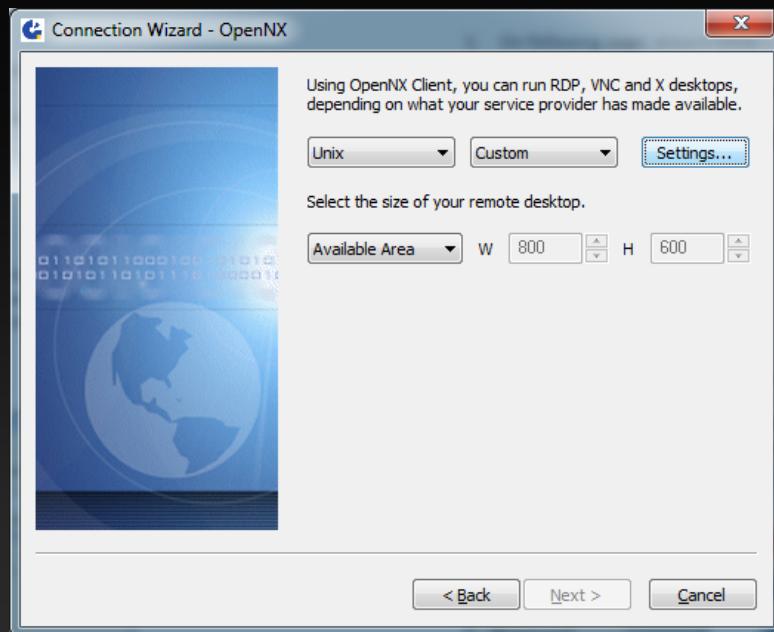
**Left Side (QwikLab):**

- URL: <https://nvidia.qwiklab.com/focuses/219>
- NVIDIA logo at the top.
- TIME ELAPSED: 12 days, 20:18m
- Session details:
  - Duration (minutes): 30
  - Setup time (minutes): 10
  - AWS Region: [us-east-1] US East (N. Virginia)
  - Creator: Enis Konuk
  - Date Created: Friday, May 3, 2013
  - Lab Type: student
  - Platform: Ubuntu
- Lab Connection: Please follow the lab instructions
- Custom settings:
  - User Name: gpudev1
  - Password: Bd9R5B5CFCZ
  - Endpoint: **ec2-54-242-245-173.compute-1.amazonaws.com** (highlighted with a red oval)

**Right Side (OpenNX Connection Wizard):**

- Session Name: Any Session Name
- Host: 245-173.compute-1.amazonaws.com Port: 22
- Select the type of your internet connection:
  - MODEM
  - ISDN
  - ADSL
  - WAN
  - LAN
- Buttons: < Back, Next >, Cancel, End Lab (highlighted with a red arrow pointing from the QwikLab Endpoint field).

# Setting up OpenNX Client Connection II (demo)

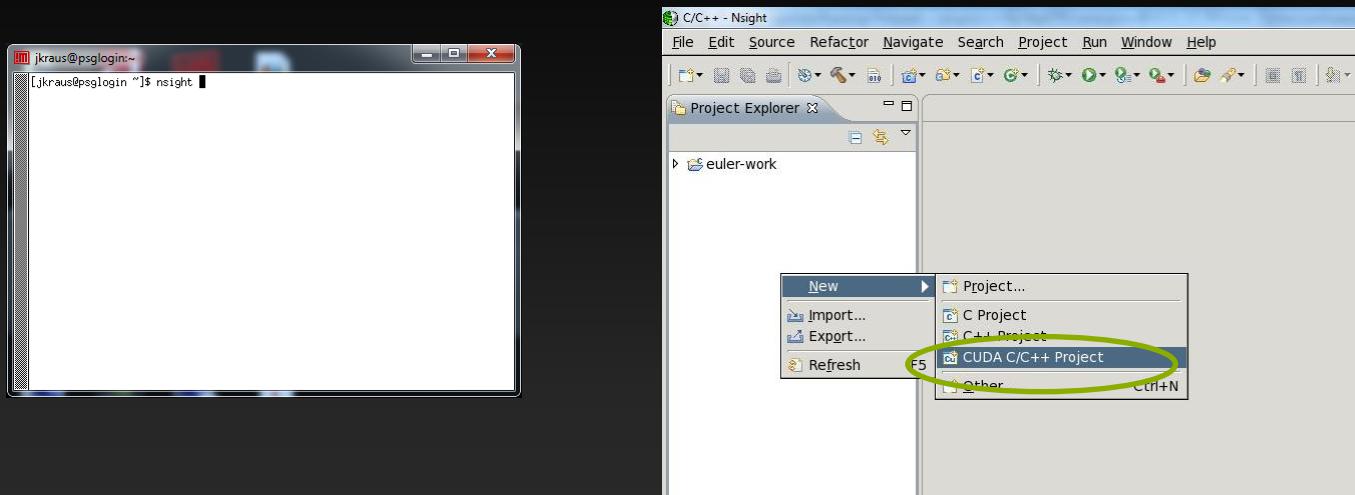


# Setting up OpenNX Client Connection III (demo)

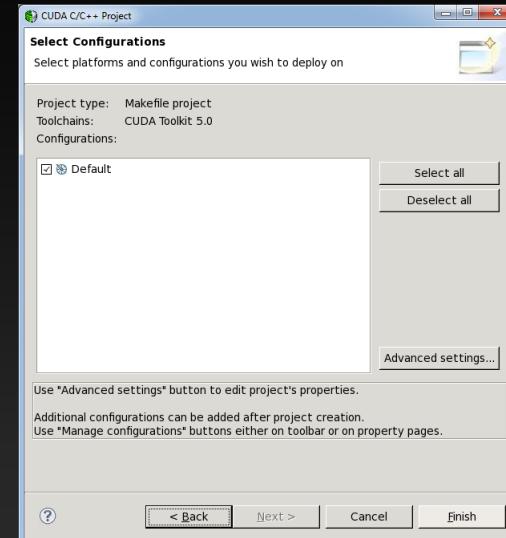
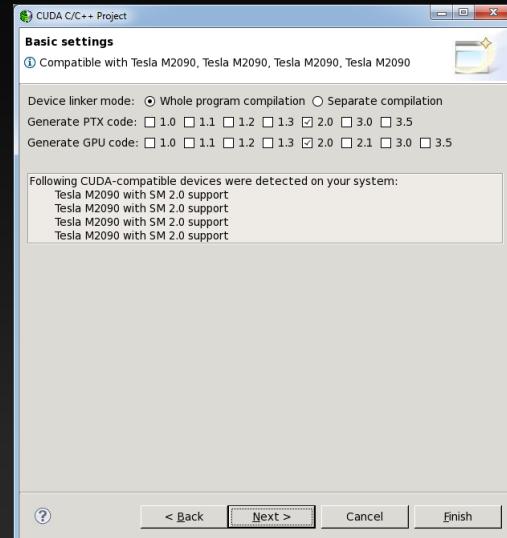
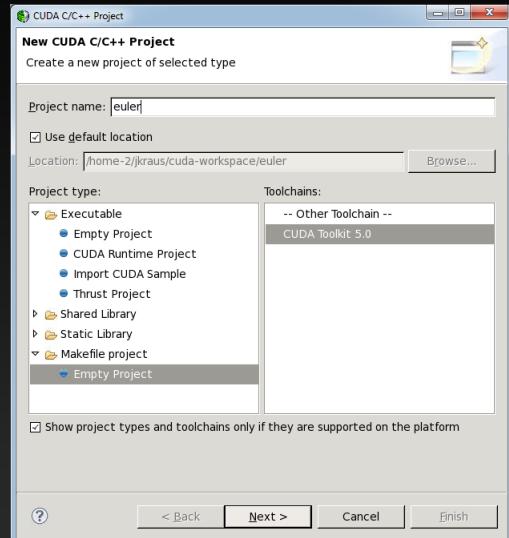


A terminal window titled "gpudev1@ip-10-16-7-41: ~" displays the command "gpudev1@ip-10-16-7-41:~\$". This indicates a successful connection to the specified host and session.

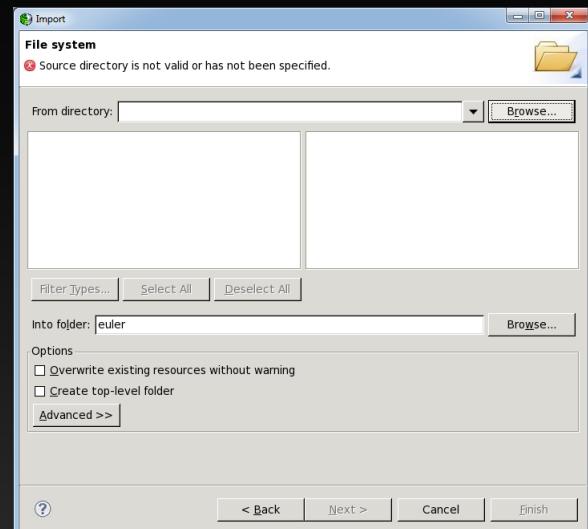
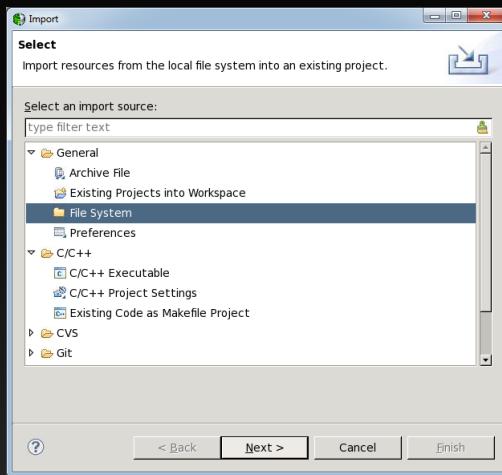
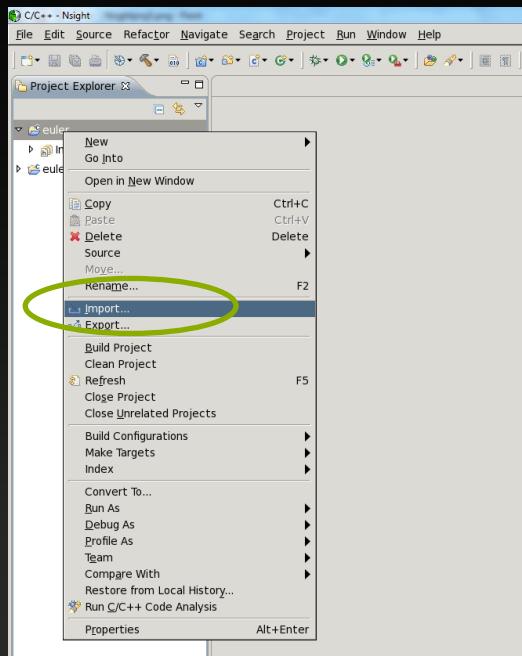
# Use Nsight Eclipse Edition – Import existing Makefile project (demo)



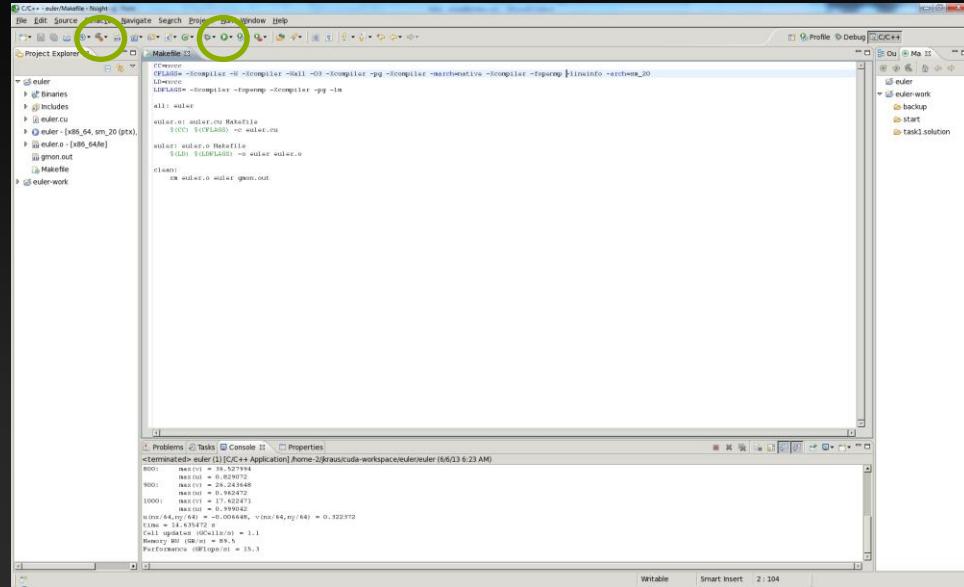
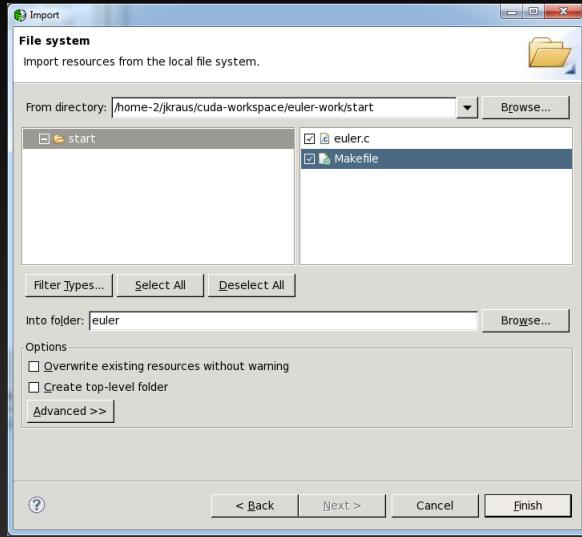
# Use Nsight Eclipse Edition – Import existing Makefile project (demo)



# Use Nsight Eclipse Edition – Import existing Makefile project (demo)



# Use Nsight Eclipse Edition – Import existing Makefile project (demo)



# Prepare Hand-On

- **OpenNX Instructions:**  
<https://developer.nvidia.com/cuda-cloud>
- **Examples are in:**  
~/euler/CUDA-C  
~/euler/CUDA-Fortran
- **Task 1:**
  - **Follow TODOs in**  
~/euler/CUDA-Fortran/task1/Makefile  
~/euler/CUDA-C/task1/Makefile

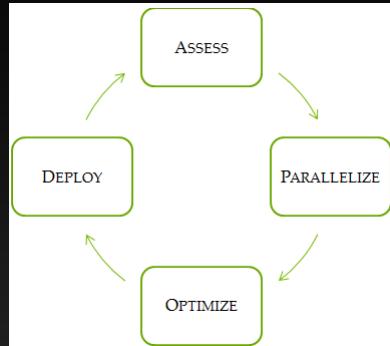


# First CUDA Kernel

Jiri Kraus, NVIDIA

# Assess, Parallelize, Optimize, Deploy

- This Tutorial follows the Access, Parallelize, Optimize, Deploy cycle



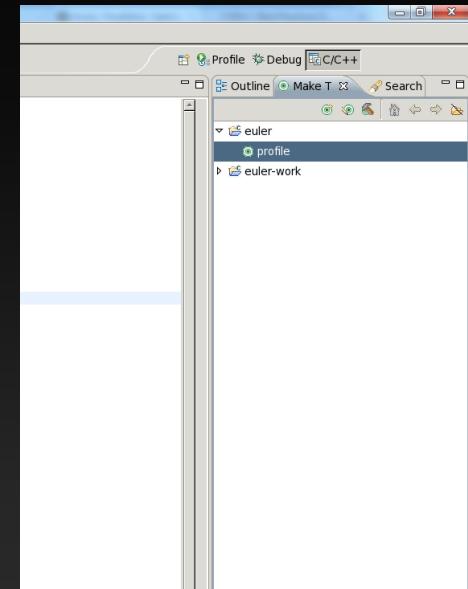
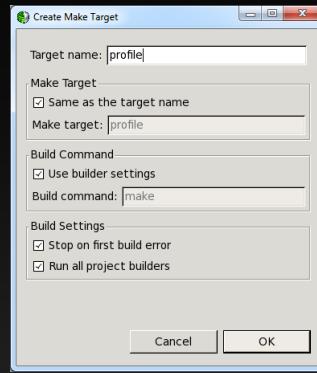
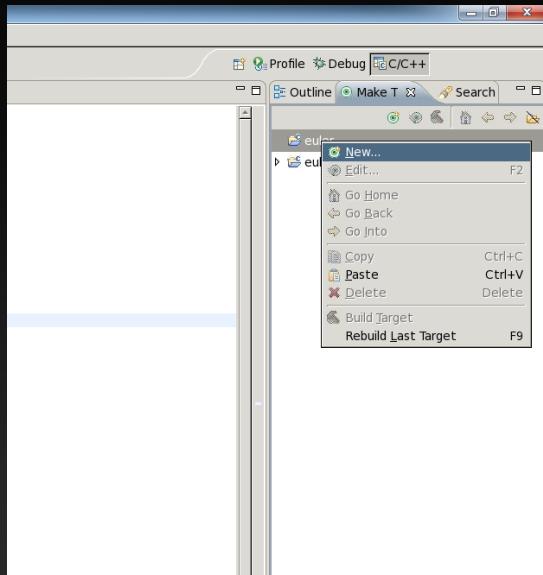
See also:

- CUDA C Best Practices Guide  
<http://docs.nvidia.com/cuda/cuda-c-best-practices-guide/>
- Parallel Forall: Assess, Parallelize, Optimize, Deploy  
<https://developer.nvidia.com/content/assess-parallelize-optimize-deploy>

# Asses CPU Version (demo)

- Use gprof to identify most time consuming CPU method

# Asses CPU Version (demo)



# Asses CPU Version (demo)

```
gprof ./euler
```

```
Flat profile:
```

```
Each sample counts as 0.01 seconds.
```

%	cumulative	self	calls	self	total	
time	seconds	seconds		ms/call	ms/call	name
73.93	45.02	45.02	1000	45.02	45.02	update_v
25.25	60.40	15.38	1000	15.38	15.38	update_u
0.40	60.64	0.24	20	12.03	12.03	max_value
0.05	60.67	0.03				main
0.02	60.68	0.01	1000	0.01	0.01	calc_bc

# CUDA Version of Euler

## Basic necessary steps (besides compiler and linker)

- Initialize CUDA:

CUDA-C: `cudaSetDevice( device-ordinal )`

CUDA-Fortran: `use cudafor`

- Shutdown CUDA:

CUDA-C: `cudaDeviceReset()`

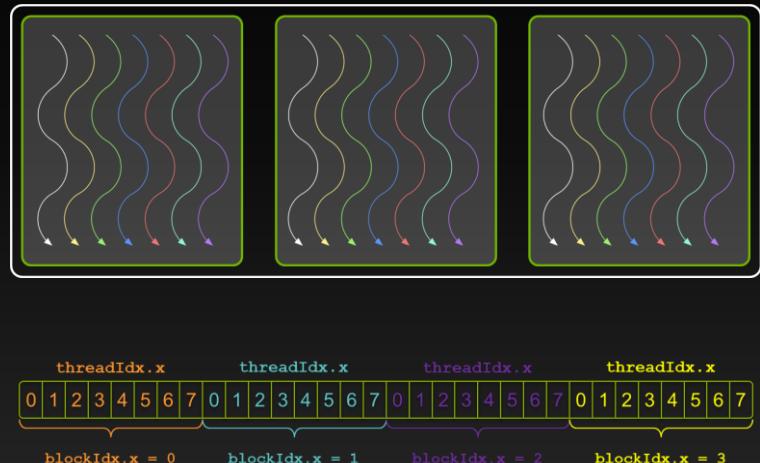
# update\_v

```
void update_v(double* v, double* u,
    int nx, int ny, double dt,
    double dx2, double dy2)
{
    for (int y=1; y<(ny-1); ++y) {
        for (int x=1; x<(nx-1); ++x) {
            v[y*nx+x] = v[y*nx+x] + dt * 100.0 * (
                (u[(y+1)*nx+x]) - 2.0*u[y*nx+x]
                + u[(y-1)*nx+x])/dy2 +
                (u[y*nx+(x+1)]) - 2.0*u[y*nx+x]
                + u[y*nx+(x-1)])/dx2 );
        }
    }
}
```

- Write of  $v[y^*nx+x]$  depends on
  - Itself
  - elements of  $u$
- $u$  does not change in **update\_v (read only)**
- Conclusion: all updates of  $v$  are independent

# Threads/Blocks/Grids

- Threads are grouped into blocks
  - Up to 1536 per block for Fermi
  - Identified with `threadIdx.x`
- Blocks are grouped into a grid
  - Identified with `blockIdx.x`
  - Blocksize is given by `blockDim.x`

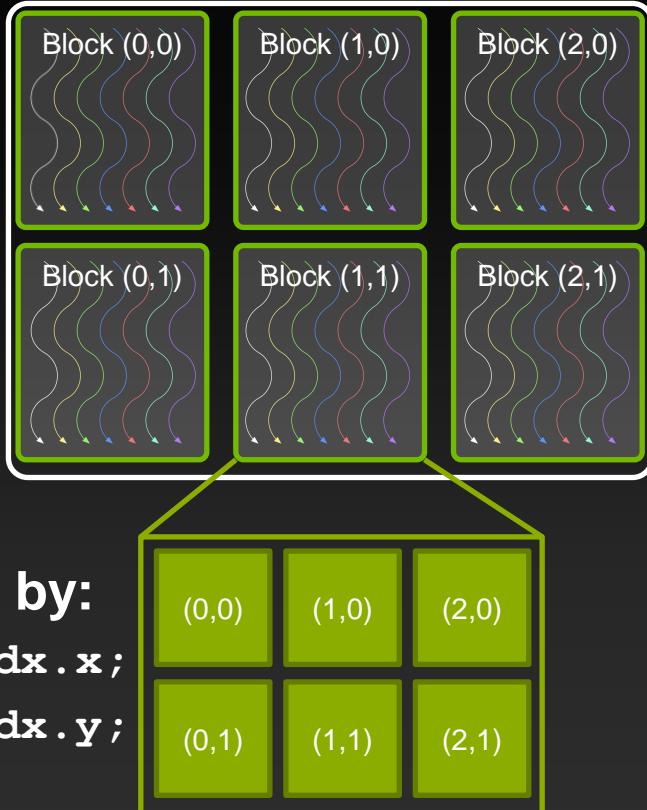


A unique index for each thread is given by:

```
int index = blockIdx.x * blockDim.x + threadIdx.x;
```

# Threads/Blocks/Grids

- Blocks/Grids can be 1D/2D/3D
- 2D blocks
  - `threadIdx.x`
  - `threadIdx.y`
- 2D grid
  - `blockIdx.x` and `blockDim.x`
  - `blockIdx.y` and `blockDim.y`



A unique coordinate for each thread is given by:

```
int x = blockIdx.x * blockDim.x + threadIdx.x;  
int y = blockIdx.y * blockDim.y + threadIdx.y;
```

# How to parallelize update\_v

- We need lots of parallelism to fill the GPU and hide latencies
- Start one thread per cell in the domain

# update\_v kernel – CUDA C

```
void update_v(double* v, double* u,
    int nx, int ny, double dt,
    double dx2, double dy2)
{
    for (int y=1; y<(ny-1); ++y) {
        for (int x=1; x<(nx-1); ++x) {
            v[y*nx+x] = v[y*nx+x] + dt * 100.0 * (
                (u[(y+1)*nx+x]) - 2.0*u[y*nx+x]
                + u[(y-1)*nx+x])/dy2 +
                (u[y*nx+(x+1)]) - 2.0*u[y*nx+x]
                + u[y*nx+(x-1)])/dx2 );
        }
    }
}
```

```
__global__ void update_v_kernel(
    double* v, double* u, int nx, int ny,
    double dt, double dx2, double dy2){
    int x = blockIdx.x * blockDim.x + threadIdx.x;
    int y = blockIdx.y * blockDim.y + threadIdx.y;
    if( x > 0 && x<(nx-1) && y > 0 && y<(ny-1) ){
        v[y*nx+x] = v[y*nx+x] + dt * 100.0 * (
            (u[(y+1)*nx+x]) - 2.0*u[y*nx+x]
            + u[(y-1)*nx+x])/dy2 +
            (u[y*nx+(x+1)]) - 2.0*u[y*nx+x]
            + u[y*nx+(x-1)])/dx2 );
    }
}
```

# update\_v kernel – CUDA Fortran

```
subroutine update_v(v,u,nx,ny,dt,dx2,dy2)
implicit none
real*8, dimension(nx*ny) :: v
real*8, dimension(nx*ny) :: u
integer :: nx, ny, x, y
real*8 :: dt, dx2, dy2
do y=2, ny-1
    do x=2,nx-1
        v((y-1)*nx + x) = v((y-1)*nx + x)+&
            dt * 100.0 * (&
            (u((y+1-1)*nx+x)-2.0*u((y-1)*nx+x) &
            +u((y-1-1)*nx+x))/dy2 + &
            (u((y-1)*nx+(x+1))-2.0*u((y-1)*nx+x) &
            + u((y-1)*nx+(x-1)))/dx2 )
    end do
end do
end subroutine update_v
```

```
attributes(global) &
subroutine update_v(u,v,nx,ny,dt,dx2,dy2)
implicit none
real*8, dimension(nx*ny) :: v
real*8, dimension(nx*ny) :: u
integer :: nx, ny, x, y
real*8 :: dt, dx2, dy2
x = (blockIdx%x-1)*blockDim%x + threadIdx%x
y = (blockIdx%y-1)*blockDim%y + threadIdx%y
if( (x .ge. 2) .and. (x .le. nx-1) .and. &
    (y .ge. 2) .and. (y .le. ny-1)) then
    v((y-1)*nx + x) = v((y-1)*nx + x)+&
        dt * 100.0 * (&
        (u((y+1-1)*nx+x)-2.0*u((y-1)*nx+x) &
        +u((y-1-1)*nx+x))/dy2 + &
        (u((y-1)*nx+(x+1))-2.0*u((y-1)*nx+x) &
        + u((y-1)*nx+(x-1)))/dx2 )
endif
end subroutine update_v
```

# update\_v kernel – How to launch?

- Kernels are launched with

```
<<<, >>>
```

- Launch configuration is passed with

```
<<<dimGrid, dimBlock>>>
```

- Use

```
struct dim3 {  
    unsigned int x, y, z;  
}
```

to define launch configuration.

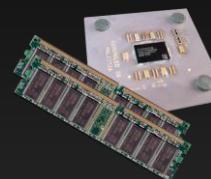
```
void update_v(double* v, double* u,  
             int nx, int ny, double dt,  
             double dx2, double dy2) {  
    double* ud, vd;  
    dim3 dimBlock(16,16);  
    dim3 dimGrid((nx/dimBlock.x)+1,  
                  (ny/dimBlock.y)+1);  
    update_v_kernel<<<dimGrid, dimBlock>>>  
        (v, u, nx, ny, dt, dx2, dy2);  
}
```

# CUDA Fortran syntax

```
subroutine update_v(u, v, nx, ny, dt, dx2, dy2)
implicit none
real*8, dimension(nx*ny), device :: v
real*8, dimension(nx*ny), device :: u
integer :: nx, ny, x, y, istat
real*8 :: dt, dx2, dy2
type(dim3) :: dimGrid, dimBlock
dimBlock = dim3(16, 16, 1)
dimGrid = dim3((nx/dimBlock%x)+1, (ny/dimBlock%y)+1, 1)
call update_v_kernel<<<dimGrid, dimBlock>>>(u,v,nx,ny,dt,dx2,dy2)
end subroutine update_v
```

# Memory Management

- Host and device memory are separate entities
  - **Device** pointers point to GPU memory
    - May be passed to/from host code
    - May *not* be dereferenced in host code
  - **Host** pointers point to CPU memory
    - May be passed to/from device code
    - May *not* be dereferenced in device code
- Simple CUDA API for handling device memory
  - `cudaMalloc()`, `cudaFree()`, `cudaMemcpy()`
  - Similar to the C equivalents `malloc()`, `free()`, `memcpy()`



# update\_v kernel – Memory Management

```
void update_v(double* v, double* u,
    int nx, int ny, double dt,
    double dx2, double dy2) {
    double* ud, vd;
    cudaMalloc((void**)&ud, nx*ny*sizeof(double));
    cudaMalloc((void**)&vd, nx*ny*sizeof(double));
    cudaMemcpy(ud, u, nx*ny*sizeof(double),
        cudaMemcpyHostToDevice);
    cudaMemcpy(vd, v, nx*ny*sizeof(double),
        cudaMemcpyHostToDevice);
    dim3 dimBlock(16,16);
    dim3 dimGrid((nx/dimBlock.x)+1,
        (ny/dimBlock.y)+1);
    update_v_kernel<<<dimGrid, dimBlock>>>
        (vd, ud, nx, ny, dt, dx2, dy2);
    cudaMemcpy(v, vd, nx*ny*sizeof(double),
        cudaMemcpyDeviceToHost);
    cudaFree( ud );
    cudaFree( vd );
}
```

```
subroutine update_v( v, u, nx, ny, dt, dx2, dy2)
use cudafor
implicit none
real*8, dimension(nx*ny) :: v
real*8, dimension(nx*ny) :: u
integer :: nx, ny, x, y, istat
real*8 :: dt, dx2, dy2
real*8, dimension(nx*ny), device :: d_u
real*8, dimension(nx*ny), device :: d_v
type(dim3) :: dimGrid, dimBlock
d_u = u
d_v = v
dimBlock = dim3(16, 16, 1);
dimGrid = dim3((nx/16)+1, (ny/16)+1, 1);
call update_v_kernel<<<dimGrid, dimBlock>>> &
    (d_u, d_v, nx, ny, dt, dx2, dy2)
u = d_u
v = d_v
end subroutine update_v
```

# Parallelize -Task 2: update\_v

Follow TODOs in `task2/euler.cu` - `task2/euler.CUF`

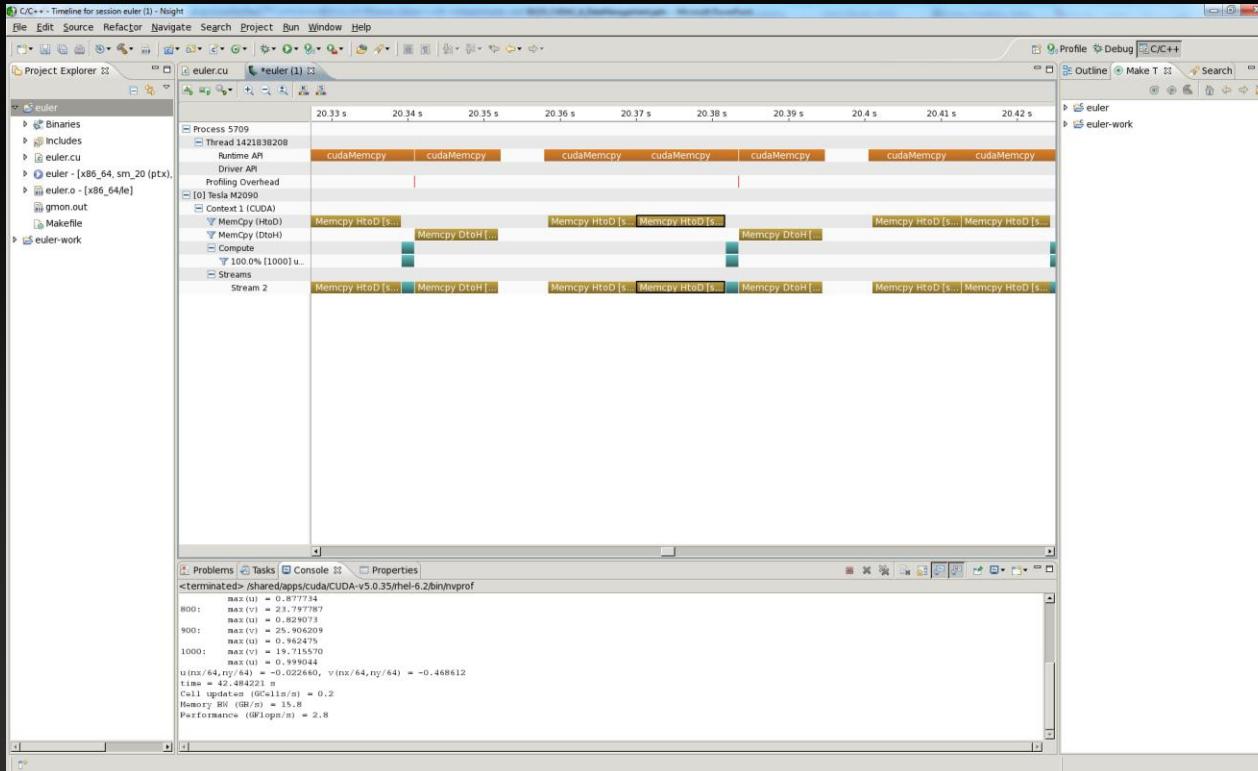
- Initialize/Shutdown CUDA:
  - `cudaSetDevice( device-ordinal )` / `use cudafor`
  - `cudaDeviceReset()`
- Memory management:
  - `cudaMalloc()` /, `device` , `cudaFree()`, `cudaMemcpy()` / =
- Kernel Launch
  - `__global__` / `attributes(global)`
  - `dim3 dimBlock, dimGrid;` / `type(dim3)`
  - `<<<dimGrid, dimBlock>>>`



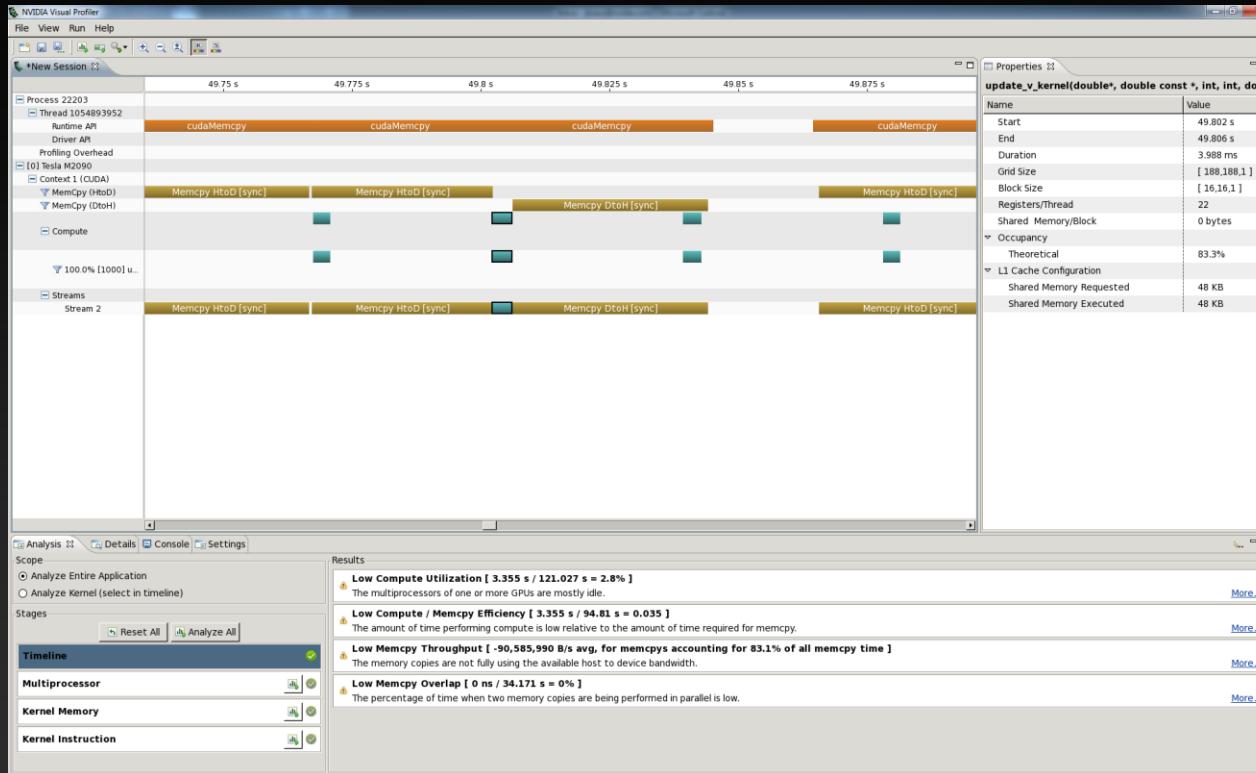
# Data Management

Jiri Kraus, NVIDIA

# Assess with Nsight Eclipse edition (demo)



# Assess with NVIDIA Visual Profiler (demo)



# Assess

- Why is CUDA version with explicit data management slower than expected?
  - Most of the time is spend in memory copies
- Remedy:
  - Copy `u` and `v` only once before and after the time loop
  - Need to also use CUDA for `update_u` and `calc_bc`
  - As an intermediate step leave `max_value` on the CPU and copy `u` and `v` every 100 iterations to the CPU.

# Parallelize - Task 3: update\_u, calc\_bc

Follow TODOs in `task3/euler.cu` `task3/euler.CUF`:

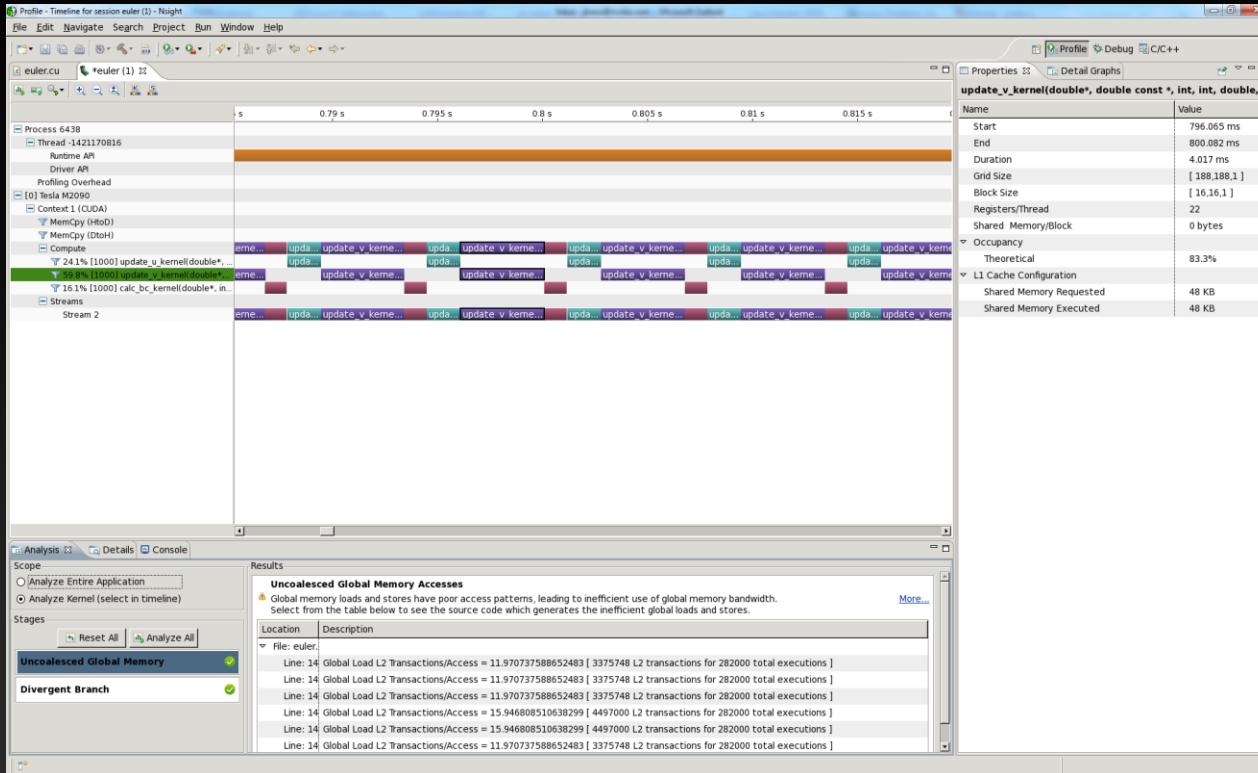
- Copy `u` and `v` to GPU before loop over time steps
- Copy `u` and `v` to host every 100 iterations for max calculation
- Copy `u` and `v` to host after loop over time steps
- Parallelize `update_u` with CUDA (`calc_bc` is already done in `task3/euler.cu` `task3/euler.CUF`)
- **Memory management:**
  - `cudaMalloc()` / `device`, `allocatable`, `cudaFree()`, `cudaMemcpy()`
- **Kernel Launch**
  - `dim3 dimBlock, dimGrid; / type(dim3)`
  - `<<<dimGrid, dimBlock>>>`



# Kernel Optimization

Jiri Kraus, NVIDIA

# Assess (demo)



# Assess

- Analyze longest running Kernel (`update_v`)
- Why does `update_v` has so many uncoalesced memory accesses?
  1. Access to left ( $x-1$ ) and right ( $x+1$ ) neighbors does not always align with cache line boundaries.
    - Not much we can do about this in this tutorial
  2. The accesses to the elements of all rows except the first row are not aligned to cache line boundaries.
- Remedy: Pad rows to align all rows of the domain to fix 2

# Memory coalescing

- **Scenario:**
  - Warp requests 32 aligned, consecutive 4-byte words
- **Addresses fall within 1 cache-line**
  - Warp needs 128 bytes
  - 128 bytes move across the bus
  - Bus utilization: 100%



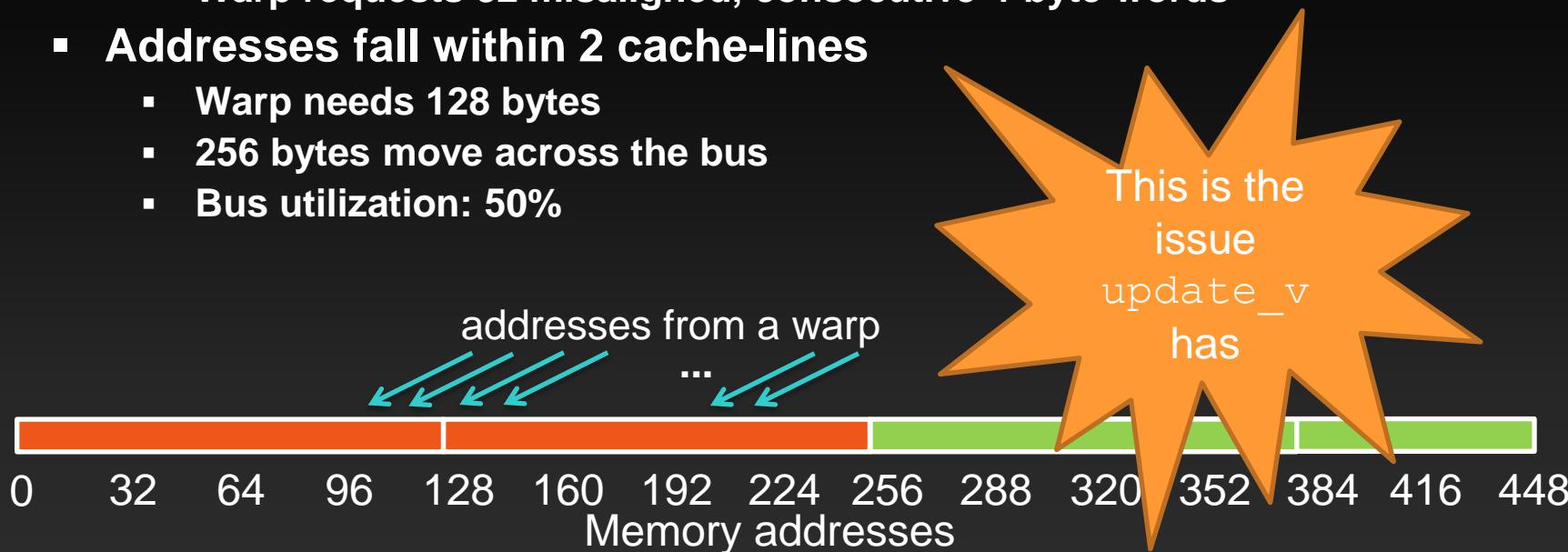
# Memory coalescing

- Scenario:
  - Warp requests 32 aligned, permuted 4-byte words
- Addresses fall within 1 cache-line
  - Warp needs 128 bytes
  - 128 bytes move across the bus
  - Bus utilization: 100%



# Memory coalescing

- Scenario:
  - Warp requests 32 misaligned, consecutive 4-byte words
- Addresses fall within 2 cache-lines
  - Warp needs 128 bytes
  - 256 bytes move across the bus
  - Bus utilization: 50%



# Memory coalescing

- **Scenario:**
  - Warp requests 32 scattered 4-byte words
- **Addresses fall within  $N$  cache-lines**
  - Warp needs 128 bytes
  - $N \times 128$  bytes move across the bus on a miss
  - Bus utilization:  $128 / (N \times 128)$

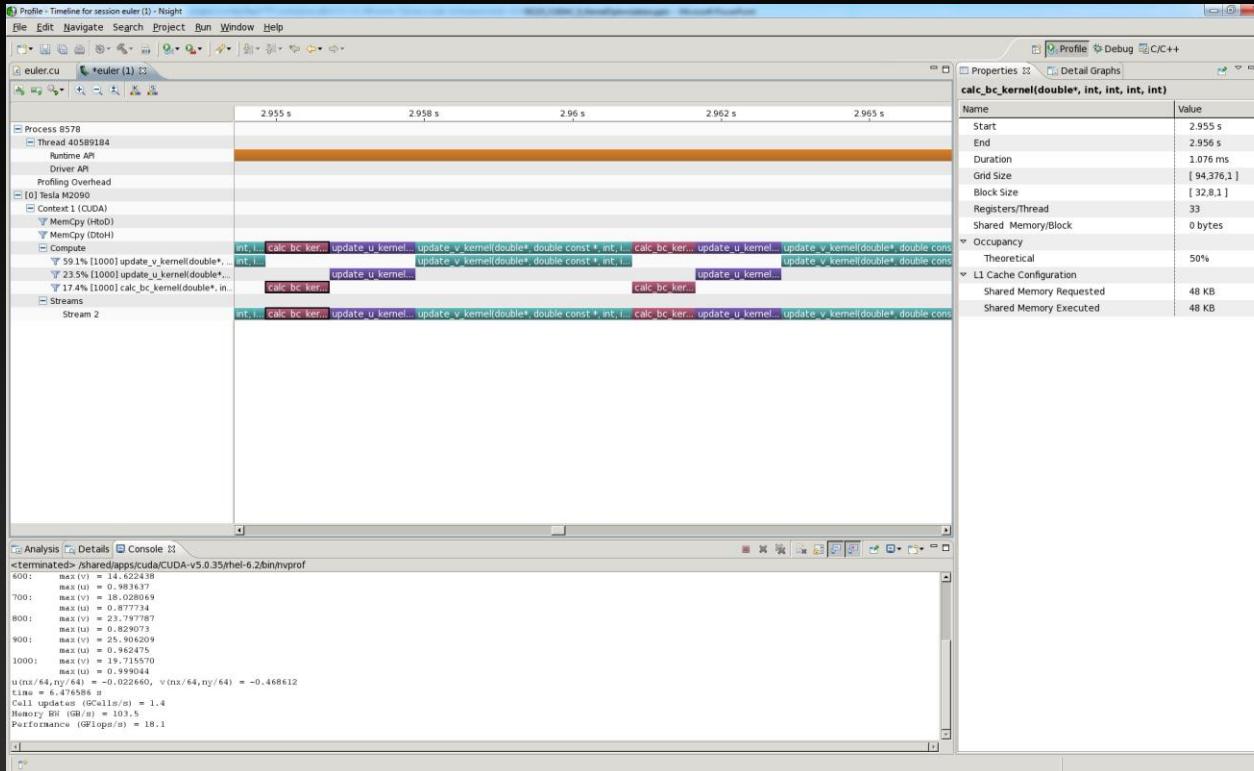


# Optimize - Task 4: memory coalescing

Follow TODOs in `task4/euler.cu` `task4/euler.CUF`:

- Pad rows of `u` and `v` to align all rows of the domain to 128 byte
  - for simplicity just change `nx` to an appropriate value

# Assess (demo)

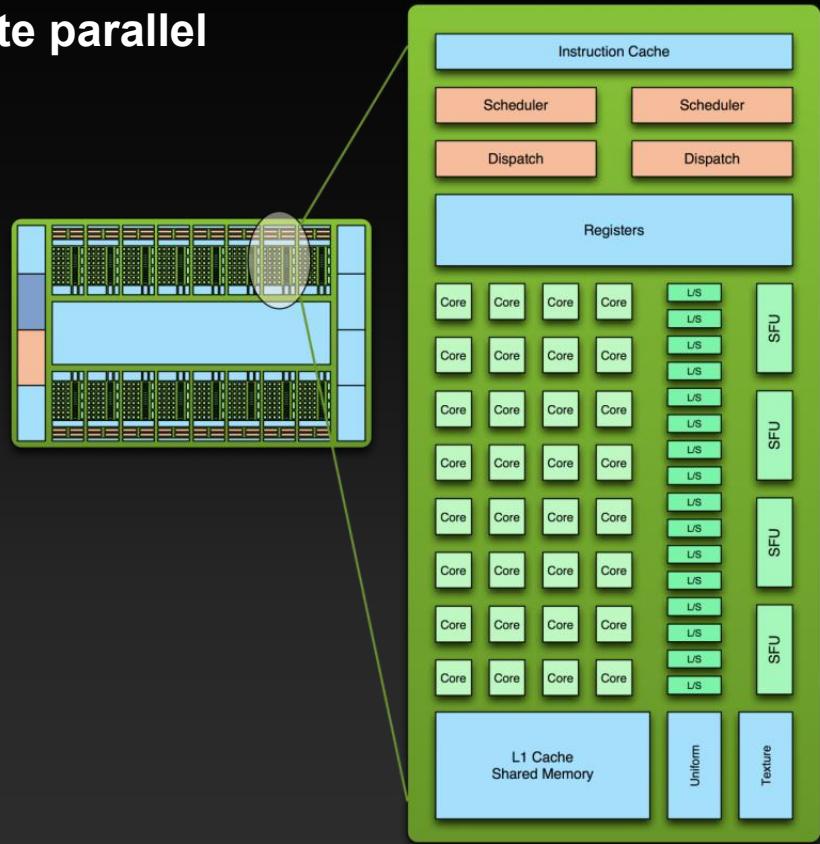


# Assess

- Why is the occupancy of `update_v` and `calc_bc` not 100%?
  - Suboptimal launch configuration
- Remedy:
  - Use CUDA Occupancy calculator to derive optimal launch configuration for all 3 Kernels

# 20-Series Architecture

- 512 **Scalar Processor (SP) cores** execute parallel thread instructions
- 16 **Streaming Multiprocessors (SMs)** each contains
  - 32 scalar processors
    - 32 fp32 / int32 ops / clock,
    - 16 fp64 ops / clock
  - 4 Special Function Units (SFUs)
  - Shared register file (128KB)
  - **48 KB / 16 KB Shared memory**
  - 16KB / 48 KB L1 data cache



# Occupancy

- We need as much threads a possible on deck to hide latencies
- SM resources limit the maximum number of threads on deck:
  - Maximum number of threads: 1536
    - If we hit this limit we have an optimum of 100% theoretical occupancy
  - Maximum number of thread blocks: 8
    - Thread blocks that are smaller than  $1536/8 = 192$  can hit this limit
  - Register file size: 32768 32bit registers
    - This is often limiting the occupancy
  - Shared memory: 48kb
    - We do not use shared memory so this limit does not apply for us
- Use CUDA Occupancy calculator to maximize occupancy

# CUDA Occupancy calculator (demo)

CUDA GPU Occupancy Calculator

Just follow steps 1, 2, and 3 below! (or click here for help)

1.) Select Compute Capability (click): 2.0 (Help)

1.b) Select Shared Memory Size Config (bytes): 49152

2.) Enter your resource usage:

Threads Per Block	256
Registers Per Thread	33
Shared Memory Per Block (bytes)	0

(Don't edit anything below this line)

3.) GPU Occupancy Data is displayed here and in the graphs:

Active Threads per Multiprocessor	768
Active Warps per Multiprocessor	24
Active Thread Blocks per Multiprocessor	3
Occupancy of each Multiprocessor	50%

Physical Limits for GPU Compute Capability: 2.0

Threads per Warp	32
Warpes per Multiprocessor	48
Threads per Multiprocessor	1536
Thread Blocks per Multiprocessor	8
Total # of 32-bit registers per Multiprocessor	32768
Register allocation unit size	64
Register allocation granularity	warp
Registers per Thread	63
Shared Memory per Multiprocessor (bytes)	49152
Shared Memory Allocation unit size	128
Warp allocation granularity	2
Maximum Thread Block Size	1024

Allocated Resources Per Block Limit Per SM Blocks Per SM = Allocatable

Warpes (Threads Per Block / Threads Per Warp)	8	48	6
Registers (Warp limit per SM due to per-warp reg count)	8	30	3
Shared Memory (Bytes)	0	49152	8

Note: SM is an abbreviation for (Streaming)Multiprocessor

Click Here for detailed instructions on how to use this occupancy calculator.  
For more information on NVIDIA CUDA, visit <http://developer.nvidia.com/cuda>

Your chosen resource usage is indicated by the red triangle on the graphs. The other data points represent the range of possible block sizes, register counts, and shared memory allocation.

Impact of Varying Block Size

Multiprocessor Warp Occupancy (# warps)

Threads Per Block

Impact of Varying Register Count Per Thread

Multiprocessor Warp Occupancy (# warps)

Register Count Per Thread

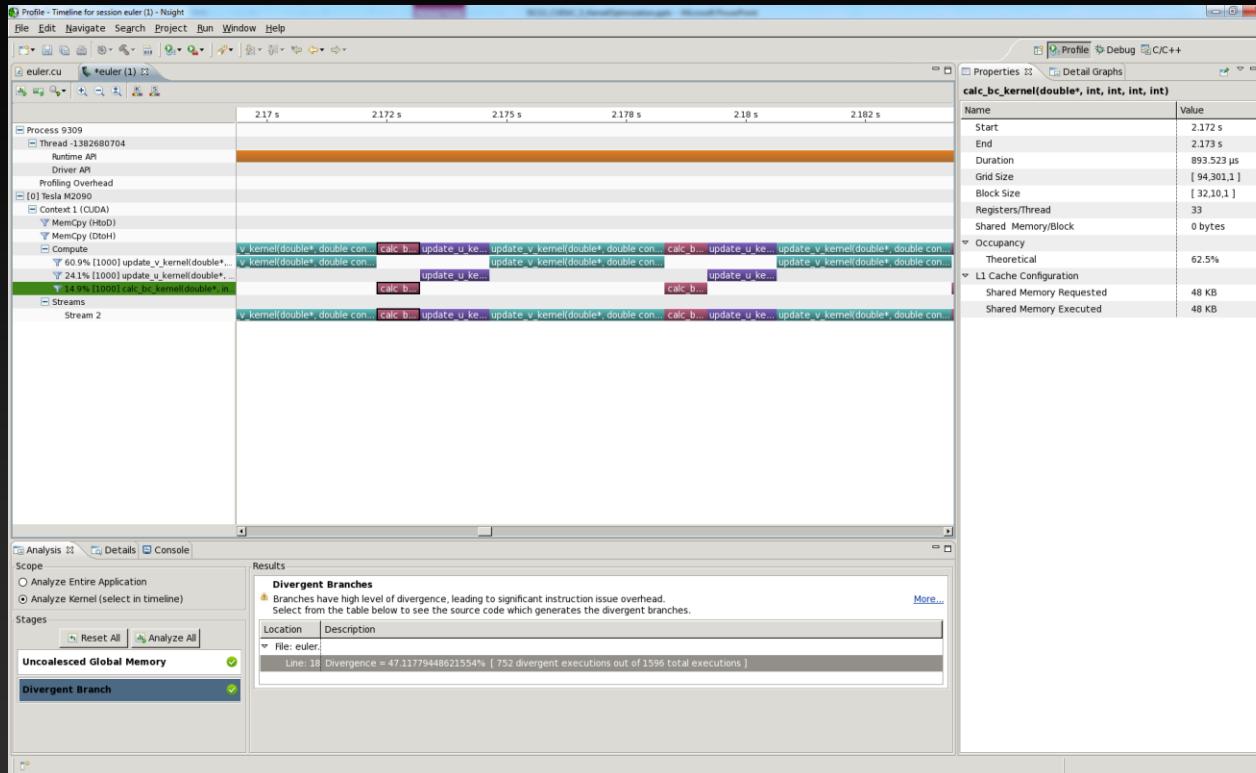
# Optimize - Task 5: launch configuration

Follow TODOs in `task5/euler.cu` `task5/euler.CUF`:

- Optimize thread block sizing of
  - `update_v_kernel`
  - `calc_bc`
- Use NVIDIA Visual Profiler or Nsight Eclipse edition profiler to determine current theoretical occupancy, block size and used 32bit registers
- Use the CUDA Occupancy calculator to calculate the optimal thread block sizing for all kernels

`/usr/local/cuda/tools/CUDA_Occupancy_Calculator.xls`

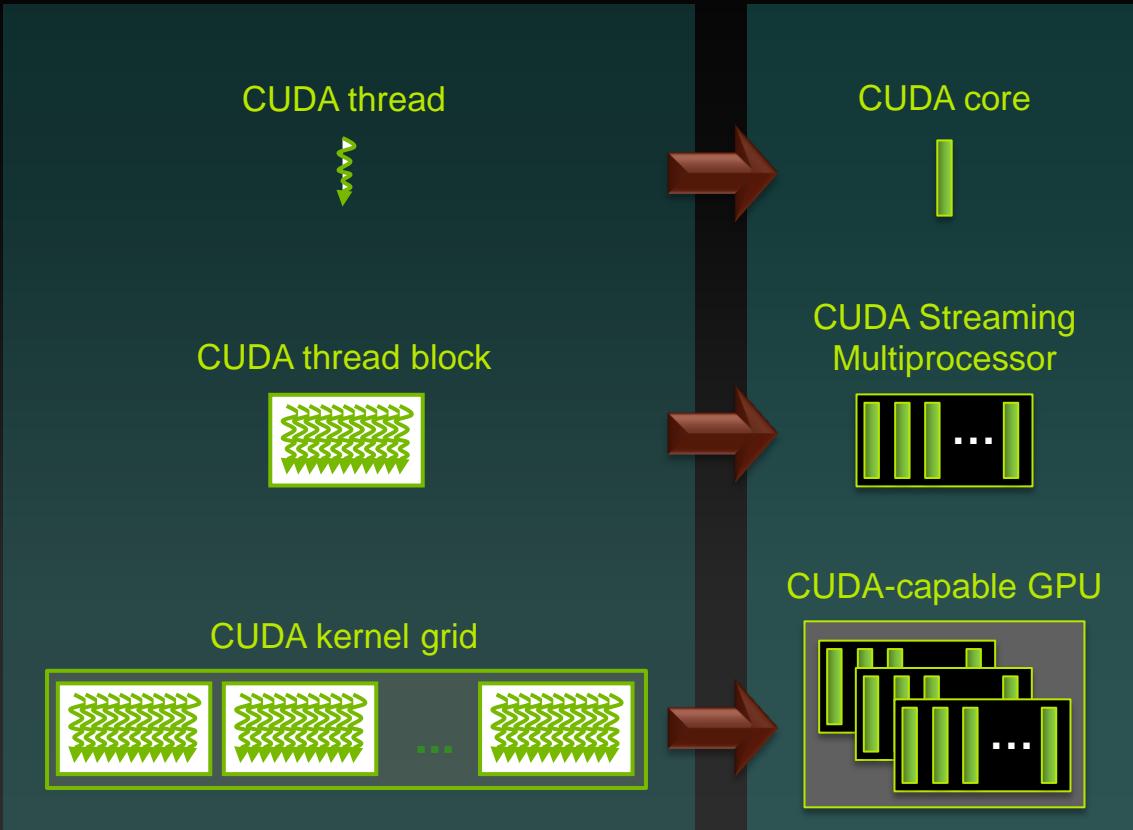
# Assess (demo)



# Assess

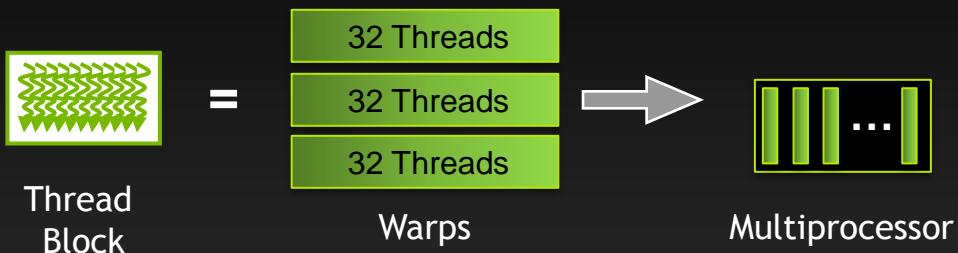
- **update\_v does not have memory or coalescing issue that we can address in this tutorial**
- **update\_u does not have memory or coalescing issue**
- **Why does calc\_c have so many divergent branches?**
  - Suboptimal organization of if clauses
  - Many threads are started that have nothing to
- **Remedy:**
  - Process boundary with a 1D thread layout and let each thread handle 4 elements.

# Kernel Execution



- Each thread is executed by a core
- Each block is executed by one SM and does not migrate
- Several concurrent blocks can reside on one SM depending on the blocks' memory requirements and the SM's memory resources
- Each kernel is executed on one device
- Multiple kernels can execute on a device at one time

# Warps



A thread block consists of 32-thread warps

A warp is executed physically in parallel (SIMD) on a multiprocessor

# Control Flow

- Instructions are issued per 32 threads (warp)
- Divergent branches:
  - Threads within a single warp take different paths
    - if-else, ...
  - Different execution paths within a warp are serialized
- Different warps can execute different code with no impact on performance
- Avoid diverging within a warp
  - Example with divergence:
    - `if (threadIdx.x > 2) {...} else {...}`
    - Branch granularity < warp size
  - Example without divergence:
    - `if (threadIdx.x / WARP_SIZE > 2) {...} else {...}`
    - Branch granularity is a whole multiple of warp size

# Optimize - Task 6: `clac_bc`

Follow TODOs in `task5/euler.cu`:

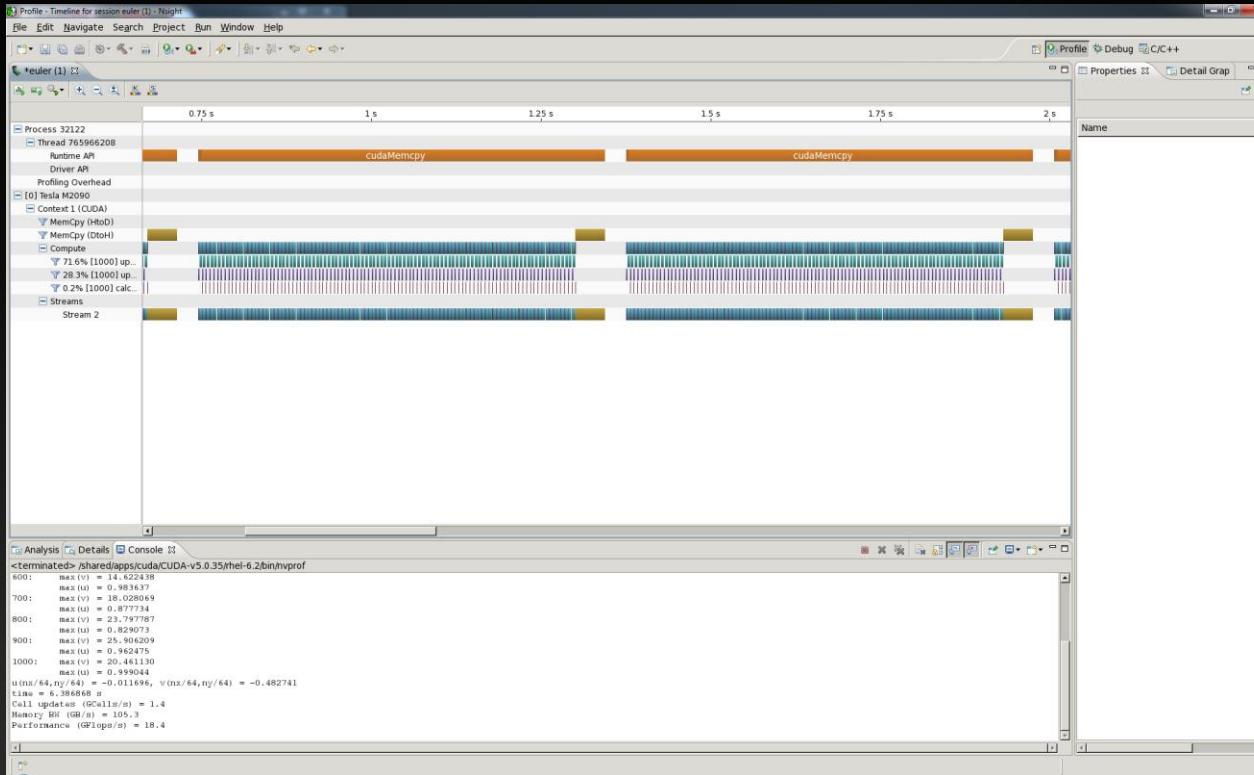
- Use a 1D block and grid instead of the 2D block and grid
- Start only  $\max( (nx/4) , (ny/4) )$  threads in total
  - Process 4 elements per thread



# Using CUDA Libraries

Jiri Kraus, NVIDIA

# Assess (demo)



# Assess

- Analyze timeline
- GPU is not utilize all of the time
  - Idle while CPU calculates `max_value`
  - Idle while `u` and `v` are copied to host
- Remedy: Calculate `max_value` on the GPU with CUBLAS NVIDIA's Basic Linear Algebra Subprogramms (BLAS) implementation.

# Using CUDA Libraries

- CUDA Libraries can be used like CPU libraries
  - Depending on library design host or device pointers need to be passed to libraries functions.
- Using CUBLAS as an example
  - Use IDAMAX to calculate max\_value on the GPU for  $u$  and  $v$

# How to use CUBLAS?

```
int N = 1 << 20;  
  
// Perform SAXPY on 1M elements: y[] = a*x[] + y[]  
saxpy(N, 2.0, d_x, 1, d_y, 1);
```

# How to use CUBLAS?

```
int N = 1 << 20;
```

```
// Perform SAXPY on 1M elements: d_y[] = a*d_x[] + d_y[]
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);
```



Add “cublas” prefix and use  
device variables

# How to use CUBLAS?

```
int N = 1 << 20;  
cublasInit();
```



Initialize CUBLAS

```
// Perform SAXPY on 1M elements: d_y[] = a * d_x[] + d_y[]  
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);
```

```
cublasShutdown();
```



Shut down CUBLAS

# How to use CUBLAS?

```
int N = 1 << 20;  
cublasInit();  
cublasAlloc(N, sizeof(float), (void**)&d_x);  
cublasAlloc(N, sizeof(float), (void*)&d_y);
```



Allocate device vectors

```
// Perform SAXPY on 1M elements: d_y[] = a * d_x[] + d_y[]  
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);
```

```
cublasFree(d_x);  
cublasFree(d_y);  
cublasShutdown();
```



Deallocate device vectors

# How to use CUBLAS?

```
int N = 1 << 20;
cublasInit();
cublasAlloc(N, sizeof(float), (void**)&d_x);
cublasAlloc(N, sizeof(float), (void*)&d_y);

cublasSetVector(N, sizeof(x[0]), x, 1, d_x, 1);
cublasSetVector(N, sizeof(y[0]), y, 1, d_y, 1);           ◀ Transfer data to GPU

// Perform SAXPY on 1M elements: d_y[] = a * d_x[] + d_y[]
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);

cublasGetVector(N, sizeof(y[0]), d_y, 1, y, 1);           ◀ Read data back GPU

cublasFree(d_x);
cublasFree(d_y);
cublasShutdown();
```

# Calling cuBLAS from CUDA Fortran

```
program cublasTest
use cublas
implicit none

real, allocatable :: a(:,:),b(:,:),c(:,:)
real, device, allocatable :: a_d(:,:),b_d(:,:),c_d(:,:)
integer :: k=4, m=4, n=4
real :: alpha=1.0, beta=2.0

allocate(a(m,k), b(k,n), c(m,n), a_d(m,k), b_d(k,n), c_d(m,n))

a = 1; a_d = a
b = 2; b_d = b
c = 3; c_d = c

call cublasSgemm('N', 'N', m, n, k, alpha, a_d, m, b_d, k, beta, c_d, m)

c=c_d

deallocate(a, b, c, a_d, b_d, c_d)

end program cublasTest
```

# Parallelize - Task 7: max\_value

Follow TODOs in `task7/euler.cu/CUF task7/Makefile`:

- Use CUBLAS IDAMAX instead of `max_value` to calculate the maximum absolute value of `u` and `v` and only download these values
  - Link CUBLAS `-lcublas`
  - Initialize CUBLAS
    - Include CUBLAS header `cublas_v2.h` (CUDA C)
    - Call `cublasCreate` (CUDA C)
    - use `cublas` (CUDA Fortran)
  - Call IDAMAX: `cudasIdamax`
  - Download elements of `u` and `v` with maximum value
  - Finalize CUBLAS `cublasDestroy` (CUDA C)

# Conclusion

- Know how to write a CUDA Kernel
- Know how to manage device memory and host to device memory transfers
- Know how to use NVIDIA Tools to identify performance limiters and how to fix them

Thank You!