GPU Acceleration

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Outline

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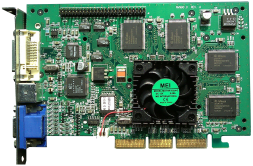
GPUs

- Originally: accelerate graphics (for games)



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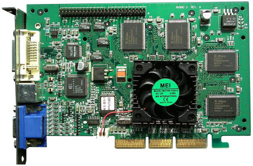

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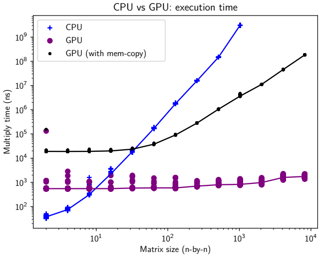
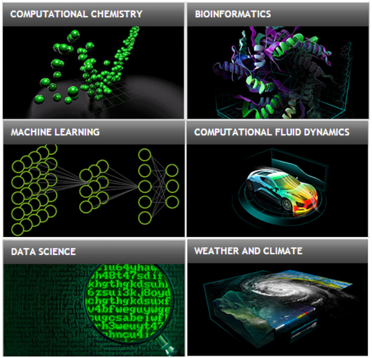
- Much more performant than CPUs

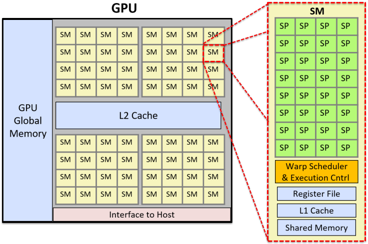


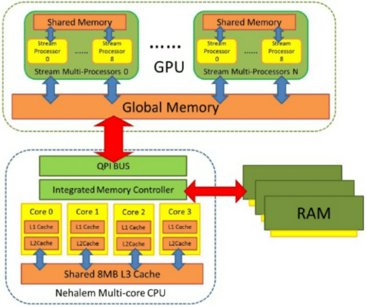
GPUs

- Originally: accelerate graphics (for games)
- Programmable shaders: flexibility
- Much more performant than CPUs
- General purpose (CUDA, 2007)



GPUs


GPU
GPU Global Memory
SM
L2 Cache
Interface to Host
SP
Warp Scheduler & Execution Cntrl
Register File
L1 Cache
Shared Memory


Shared Memory
Stream Processor 0
Stream Processor 8
Stream Multi-Processors 0
GPU
Stream Multi-Processors N
Global Memory
QPI BUS
Integrated Memory Controller
RAM
Core 0
Core 1
Core 2
Core 3
L1 Cache
L2Cache
Shared 8MB L3 Cache
Nehalem Multi-core CPU

Outline

CUDA Workflow

- Identify parallel parts of workload

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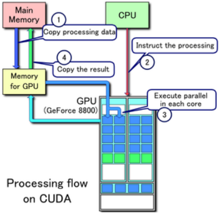

CUDA Workflow

- Identify parallel parts of workload
- Allocate input/output buffers on GPU
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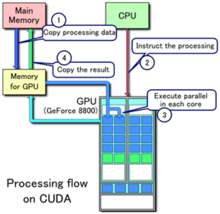

CUDA Workflow

- Identify parallel parts of workload
- Allocate input/output buffers on GPU
- Copy input from CPU to GPU
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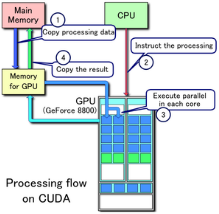
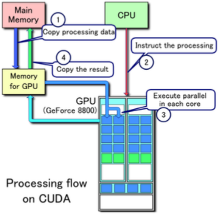


CUDA Workflow

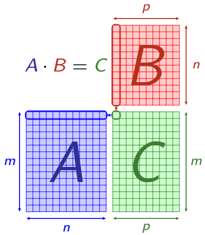
- Identify parallel parts of workload
- Allocate input/output buffers on GPU
- Copy input from CPU to GPU
- Start GPU computation
- Copy output from GPU to CPU



Outline

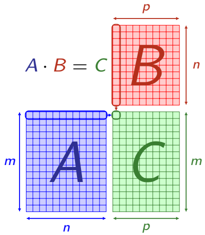
Example

- Naive matrix multiply



Example

- Naive matrix multiply
- Each element in C is independently computed



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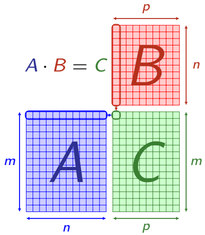

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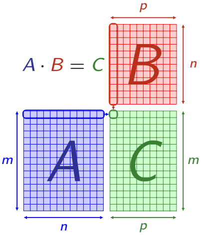

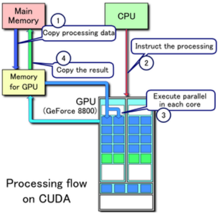

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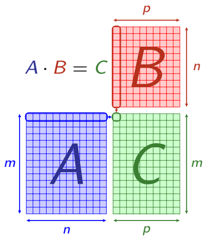

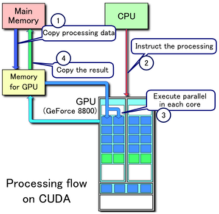

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  1. Starting C++ code
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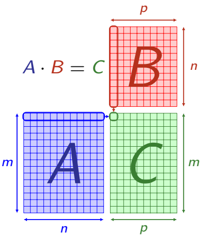
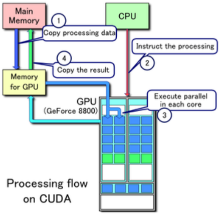
  3. Copy A, B to GPU
  4. Start kernel (using $m \cdot p$ GPU threads)





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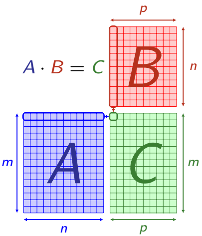

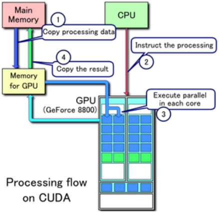

Kernel

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Global	Special case: entry point from CPU to GPU

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- Host and device can be combined (same code runs on CPU and GPU)

Kernel

- Call from CPU to GPU using global function

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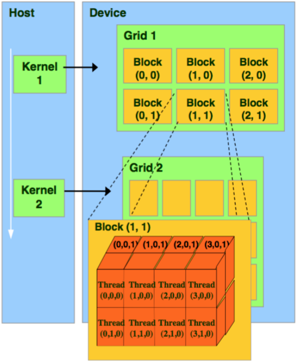
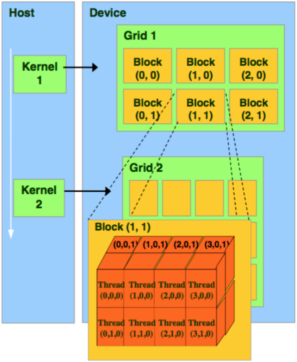
- Call from CPU to GPU using global function
- When calling, specify number of threads



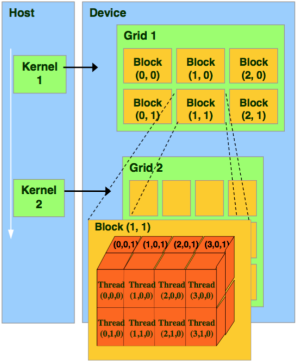
Kernel

- Call from CPU to GPU using global function
- When calling, specify number of threads
  - Threads are grouped in blocks



Kernel

- Call from CPU to GPU using global function
- When calling, specify number of threads
  - Threads are grouped in blocks
  - All blocks form one grid



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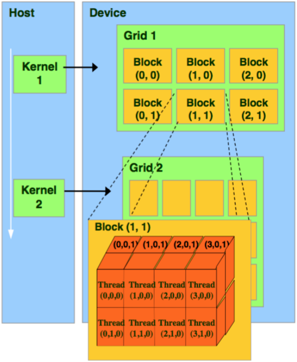
  - Sizes can be specified in 1D, 2D, or 3D



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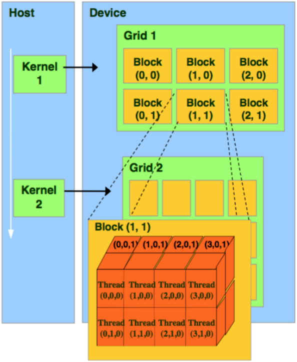
  - At runtime: 32 threads form a warp



Kernel

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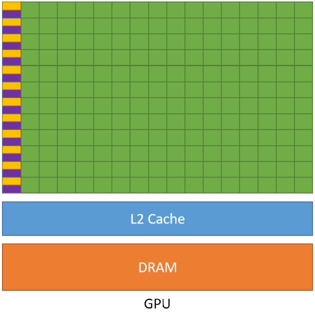

Kernel

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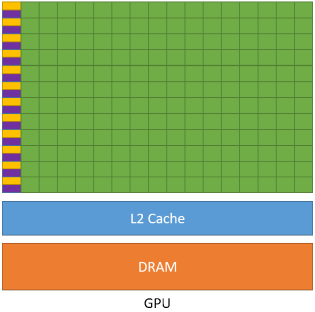
Branches

For performance: make sure all warps are full, i.e. threads are taking the same branch in groups of 32. This can be across warps, since they will be re-grouped if need be.



Starting Code

```
struct matrix {
    float &at(int row, int col) {
        return data[row * cols + col];
    }
    float *data; int rows; int cols;
};
void dot(matrix a, matrix b, matrix c, int row, int col) {
    c.at(row, col) = 0;
    for(int k = 0; k < a.cols; k++)
        c.at(row, col) += a.at(row, k) * b.at(k, col);
}
void matmul_cpu(matrix a, matrix b, matrix c) {
    for(int row = 0; row < c.rows; row++) {
        for(int col = 0; col < c.cols; col++)
            dot(a, b, c, row, col);
    }
}
// ...
matrix a, b, c;
// Initialize a, b here
// ...
matmul_cpu(a, b, c);
```

Steps

Recall steps from before:

1. Starting C++ code

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Steps

Recall steps from before:

1. Starting C++ code
2. Allocate GPU memory
3. Copy A, B to GPU
4. Start kernel (using $m \cdot p$ GPU threads)
5. Copy C to CPU

Allocate GPU memory

```
matrix a, b, c;
// Assume a, b, c are initialized
matrix a_gpu, b_gpu, c_gpu;
a_gpu.rows = a.rows; a_gpu.cols = a.cols;
cudaMalloc(&a_gpu.data, a.rows * a.cols * sizeof(float));
b_gpu.rows = b.rows; b_gpu.cols = b.cols;
cudaMalloc(&b_gpu.data, b.rows * b.cols * sizeof(float));
c_gpu.rows = c.rows; c_gpu.cols = c.cols;
cudaMalloc(&c_gpu.data, c.rows * c.cols * sizeof(float));
```

`cudaMalloc(void **devPtr, size_t bytes)` allocates `bytes` bytes of GPU memory, storing the pointer in `devPtr`.

Copy A, B to GPU

```
cudaMemcpy(a_gpu.data, a.data, a.rows * a.cols * sizeof(float), cudaMemcpyDefault);
cudaMemcpy(b_gpu.data, b.data, b.rows * b.cols * sizeof(float), cudaMemcpyDefault);
```

`cudaMemcpy(void *dst, const void *src, size_t bytes, cudaMemcpyKind kind)` copies `bytes` bytes from `src` to `dst`. The final argument, `kind`, specifies the direction.
On recent CUDA versions (CUDA 4+), this can be inferred using `cudaMemcpyDefault`.

Copy A, B to GPU

```
cudaMemcpy(a_gpu.data, a.data, a.rows * a.cols * sizeof(float), cudaMemcpyDefault);
cudaMemcpy(b_gpu.data, b.data, b.rows * b.cols * sizeof(float), cudaMemcpyDefault);
```

`cudaMemcpy(void *dst, const void *src, size_t bytes, cudaMemcpyKind kind)` copies `bytes` bytes from `src` to `dst`. The final argument, `kind`, specifies the direction.

On older CUDA versions, this should be one of

- `cudaMemcpyHostToDevice`: CPU to GPU
- `cudaMemcpyDeviceToHost`: GPU to CPU
- `cudaMemcpyDeviceToDevice`: GPU to GPU

Start kernel

```
// TODO: we will implement this later
__global__ void matmul_gpu(matrix a, matrix b, matrix c);

...

// specify grid (thread and block sizes)
dim3 threads = dim3(1024, 1024); // CUDA prefers powers of two
dim3 blocks = dim3(c.rows / 1024 + 1, c.cols / 1024 + 1);
// launch kernel
matmul_gpu<<<blocks, threads>>>(a_gpu, b_gpu, c_gpu);
cudaDeviceSynchronize();
```

The `__global__` attribute specifies `matmul_gpu` as a global (CPU to GPU) function.

Recall that we had

- CPU-only (host) functions (using `__host__`)
- GPU-only (device) functions (using `__device__`)
- GPU to GPU entry point functions (using `__global__`)

Start kernel

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// TODO: we will implement this later
__global__ void matmul_gpu(matrix a, matrix b, matrix c);

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dim3 threads = dim3(1024, 1024); // CUDA prefers powers of two
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// launch kernel
matmul_gpu<<<blocks, threads>>>(a_gpu, b_gpu, c_gpu);
cudaDeviceSynchronize();
```

- Invoking global functions is always done by the `<<<blocks, threads>>>` syntax.
- Make sure none of the arguments have pointers to CPU memory!
- Kernel launches are asynchronous, we use `cudaDeviceSynchronize()` to have the CPU wait until the GPU is finished.

Copy C to CPU

```
cudaMemcpy(c.data, c_gpu.data, c.rows * c.cols * sizeof(float),
↪  cudaMemcpyDefault);
```

Same as before, `cudaMemcpy(void *dst, const void *src, size_t size, cudaMemcpyKind kind)` copies data.

Again, `cudaMemcpyDefault` is used to infer direction (older systems should use `cudaMemcpyDeviceToHost`).

Implement kernel

```
struct matrix {
    __host__ __device__ float &at(int row, int col) {
        return data[row * cols + col];
    }
    float *data; int rows; int cols;
};
__host__ __device__ void dot(matrix a, matrix b, matrix c, int row, int
↪  col) {
    c.at(row, col) = 0;
    for(int k = 0; k < a.cols; k++)
        c.at(row, col) += a.at(row, k) * b.at(k, col);
}
```

- We will use `matrix::at` and `dot` on both CPU and GPU
- To avoid code duplication, we make the compiler generate both from one definition
    - If we use `__host__`, we only get CPU
    - If we use `__device__`, we only get GPU
    - If we combine `__host__ __device__`, we get both

Implement kernel

```
__global__ void matmul_gpu(matrix a, matrix b, matrix c) {
    int row = blockIdx.x * blockDim.x + threadIdx.x;
    int col = blockIdx.y * blockDim.y + threadIdx.y;
    if(row >= c.rows || col >= c.cols) // out-of-bounds
        return;

    dot(a, b, c, row, col);
}
```

- `matmul_gpu` has to be called from the CPU, but run on the GPU, so it should be `__global__`

Implement kernel

```
__global__ void matmul_gpu(matrix a, matrix b, matrix c) {
    int row = blockIdx.x * blockDim.x + threadIdx.x;
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    if(row >= c.rows || col >= c.cols) // out-of-bounds
        return;

    dot(a, b, c, row, col);
}
```

- We launched $(\frac{\texttt{c.rows}}{1024} + 1, \frac{\texttt{c.cols}}{1024} + 1)$ blocks of $(1024, 1024)$ threads each
- We can get indices using builtin variables:
  - `threadIdx` holds the 3D thread index within a block
  - `blockIdx` holds the 3D block index within the grid
  - `blockDim` holds the 3D size of the block
- These indices can be out of bounds, so we need to check!

Implement kernel

```
__global__ void matmul_gpu(matrix a, matrix b, matrix c) {
    int row = blockIdx.x * blockDim.x + threadIdx.x;
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        return;

    dot(a, b, c, row, col);
}
```

- By making `dot` (and `matrix::at`) available on the GPU (using `__device__`), we can simply re-use the code.

Final code

```
struct matrix {
    __host__ __device__ float &at(int row, int col) {
        return data[row * cols + col];
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};
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↪ col) {
    c.at(row, col) = 0;
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__global__ void matmul_gpu(matrix a, matrix b, matrix c) {
    int row = blockIdx.x * blockDim.x + threadIdx.x;
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    if(row >= c.rows || col >= c.cols) // out-of-bounds
        return;

    dot(a, b, c, row, col);
}
```

Final code

```
matrix a, b, c;
// Assume a, b, c are initialized
matrix a_gpu, b_gpu, c_gpu;
a_gpu.rows = a.rows; a_gpu.cols = a.cols;
cudaMalloc(&a_gpu.data, a.rows * a.cols * sizeof(float));
b_gpu.rows = b.rows; b_gpu.cols = b.cols;
cudaMalloc(&b_gpu.data, b.rows * b.cols * sizeof(float));
c_gpu.rows = c.rows; c_gpu.cols = c.cols;
cudaMalloc(&c_gpu.data, c.rows * c.cols * sizeof(float));
cudaMemcpy(a_gpu.data, a.data, a.rows * a.cols * sizeof(float),
↪  cudaMemcpyDefault);
cudaMemcpy(b_gpu.data, b.data, b.rows * b.cols * sizeof(float),
↪  cudaMemcpyDefault);
// specify grid (thread and block sizes)
dim3 threads = dim3(1024, 1024); // CUDA prefers powers of two
dim3 blocks = dim3(c.rows / 1024 + 1, c.cols / 1024 + 1);
// launch kernel
matmul_gpu<<<blocks, threads>>>(a_gpu, b_gpu, c_gpu);
cudaDeviceSynchronize();
cudaMemcpy(c.data, c_gpu.data, c.rows * c.cols * sizeof(float),
↪  cudaMemcpyDefault);
```

Outline

Errors

- CUDA functions return `cudaError_t`, useful with `cudaGetErrorString()`

```
#define CHECK(x) do { \
    const auto _ = (x); \
    if(_ != cudaSuccess) { \
        /* ... handle error using cudaGetErrorString(_) */\
    } \
} while(false)
```

Memory

- Manage GPU memory
- Allocate with `cudaMalloc(void **dev, size_t bytes)`
- Read/Write CPU-side with `cudaMemcpy(void *dst, const void *src, size_t bytes, cudaMemcpyKind kind)`
  - `cudaMemcpyDefault`: Inferred based on pointers (CUDA 4+)
  - `cudaMemcpyHostToDevice`: CPU →GPU
  - `cudaMemcpyDeviceToHost`: GPU →CPU
  - `cudaMemcpyDeviceToDevice`: GPU →GPU
  - `cudaMemcpyHostToHost`: CPU →CPU
- Unified Memory: `cudaMallocManaged(void **dev, size_t bytes)` (accessible on CPU & GPU)
- Free/Clean up with `cudaFree(void *dev)`

Synchronization

- Atomic functions like `atomicAdd`
- Across threads/warps in block: `__syncthreads()`
- Make CPU wait for GPU: `cudaDeviceSynchronize()`
- More advanced:
  - Selected threads using `cuda::barrier`
  - All threads across blocks: `this_grid().sync()` (requires Cooperative Groups and launch using `cudaLaunchCooperativeKernel`)

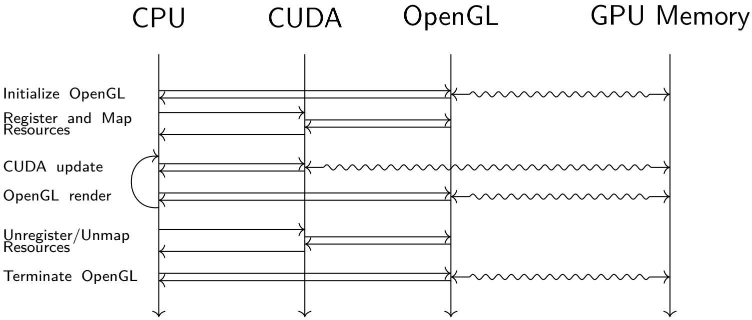
CUDA ↔ OpenGL

- High-performance GPU compute
- Real-time 3D graphics

If both are on the same GPU, they can communicate!

- CUDA can read from/write to OpenGL buffers
- OpenGL will use the updated data to render
- That all without using the CPU or any extensive memory copying
- (It's how I made the intro)

CUDA ↔ OpenGL


CPU
CUDA
OpenGL
GPU Memory
Initialize OpenGL
Register and Map Resources
CUDA update
OpenGL render
Unregister/Unmap Resources
Terminate OpenGL

CUDA ↔ OpenGL

- `__device__` functions can access OpenGL data

```
#include <cuda_gl_interop.h>
// set up on CPU
cudaGraphicsResource *resource; T *dev_ptr; size_t size;
cudaGraphicsGLRegisterBuffer(&resource, handle,
↪  cudaGraphicsRegisterFlagsNone);
cudaGraphicsMapResources(1, &resource);
cudaGraphicsResourceGetMappedPointer(
    reinterpret_cast<void **>(&dev_ptr), &size, resource
);
// ... do stuff with dev_ptr on GPU
// clean up on CPU
cudaGraphicsUnmapResources(1, &resource);
cudaGraphicsUnregisterResource(resource);
```