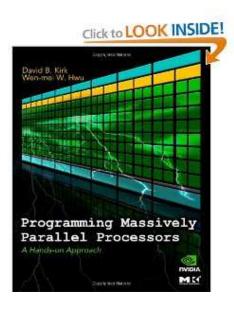
# Introduction to GPU programming

#### **Overview**

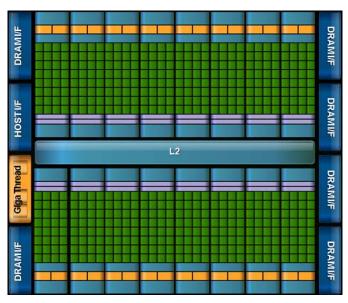
- GPUs & computing
- Principles of CUDA programming
- One good reference: David B. Kirk and Wen-mei W. Hwu, Programming Massively Parallel Processors, Morgan Kaufmann Publishers, 2010.



# **New trends of microprocessors**

- Since 2003, there has been two main trajectories for microprocessor design
- Multicore a relatively small number of cores per chip, each core is a full-flesh processor in the "traditional sense"
- Many-core a large number of much smaller and simpler cores
  - NVIDIA Tesla K40 GPU has 2880 "cores" (streaming processors), each is heavily multi-threaded, in-order, single-instruction issue processor.
  - Peak performance of many-core GPUs can be 10 fold the peak performance of multicore CPUs
  - GPUs have larger memory bandwidth (simpler memory models and fewer legacy requirements)
- Since 2013, Intel's many-integrated-core (MIC) technology has arrived

#### **NVIDIA's Fermi architecture**



- Designed for GPU computing
- 16 streaming multiprocessors (SMs)
- 32 CUDA cores (streaming processors) in each SM (512 cores in total)
- Each streaming processor is massively threaded
- 6 DRAM 64-bit memory interfaces
- Peak double-precision floating-point rate: 768 GFLOPs

### **NVIDIA's Kepler architecture**



- Each streaming multiprocessor is more powerful than Fermi
- Dynamic parallelism (nested kernels)
- Hyper-Q allows multiple CPU threads/processes to use a single GPU
- Peak double-precision floating-point rate of K40: 1430 GFLOPs

### Massive (but simple) parallelism

- One streaming processor is the most fundamental execution resource
- Simpler than a CPU core
- But capable of executing a large number of threads simultaneously, where the threads carry out same instruction to different data elements —- single-instruction-multiple-data (SIMD)
- A number of streaming processors constitute one streaming multiprocessor (SM) simultaneously

#### **CUDA**

- CUDA Compute Unified Device Architecture
- C-based programming model for GPUs
- Introduced together with GeForce 8800
- Joint CPU/GPU execution (host/device)
- A CUDA program consists of one of more phases that are executed on either host or device
- User needs to manage data transfer between CPU and GPU
- A CUDA program is a unified source code encompassing both host and device code

#### **More about CUDA**

- To a CUDA programmer, the computing system consists of a host (CPU) and one or more devices (GPUs)
- Data must be explicitly copied from host to device (and back)
- On device, there is so-called global memory
- Device global memory tends to have long access latencies and finite bandwidth
- On-chip memories: registers and shared memory (per SM block) have limited capacity, but are much faster
- Registers are private for individual threads
- All threads with a thread block can access variables in the shared memory
- Shared memory is an efficient means for threads to cooperate, by sharing input data and intermediate results

# **Programming GPUs for computing (1)**

- Kernel functions the computational tasks on GPU
  - An application or library function may consist of one or more kernels
  - Kernels can be written in C, extended with additional keywords to express parallelism
- Once compiled, each kernel makes use of many threads that execute the same program in parallel
- Multiple threads are grouped into thread blocks
  - All threads in a thread block run on a single SM
  - Within a thread block, threads cooperate and share memory
  - A thread block is divided into warps of 32 threads
    - Warp is the fundamental unit of dispatch within an SM
  - Threads blocks may execute in any order

# **Programming GPUs for computing (2)**

- When a kernel is invoked on host, a grid of parallel threads are generated on device
- Threads in a grid are organized in a two-level hierarchy
  - each grid consists of one or more thread blocks
  - all blocks in a grid have the same number of threads
  - each block has a unique 3D coordinate blockIdx.x, blockIdx.y and blockIdx.z
  - each thread block is organized as a 3D array of threads threadIdx.x, threadIdx.y, threadIdx.z
- The grid and thread block dimensions are set when a kernel is invoked
- A centralized scheduler

# **Programming GPUs for computing (3)**

Syntax for invoking a kernel

```
dim3 dimGrid(64,32,1)
dim3 dimBlock(4,2,2);
KernelFunction<<<dimGrid, dimBlock>>>(...);
```

- gridDim and blockDim contain the dimension info
- All threads in a block share the same blockIdx
- Each thread has its unique threadIdx within a block
- Values of blockIdx and threadIdx can be used to determine which data element(s) that a thread is to work on
- Often, one thread is used to compute one data element (fine-grain parallelism)

#### Thread execution

- Launching a CUDA kernel will generate a 1D or 2D or 3D array of thread blocks, each having a 1D or 2D or 3D array of threads
- The thread blocks can execute in any order relative to each other
- CUDA runtime system bundles several threads for simultaneous execution, by partitioning each thread block into warps (32 threads)
- Scheduling of warps is taken care by CUDA runtime system
- The hardware executes same instruction for all threads in the same warp
- If-tests can cause thread divergence, which will require multiple passes of divergent paths (involving all threads of a warp)

### Simple example of CUDA program

Use GPU to calculate the square each element of an array

```
// Kernel that executes on the CUDA device
__global__ void square_array(float *a, int N)
{
    // 1D thread blocks and 1D thread array inside each block
    // N is the length of the data array a, stored in device memory
    int idx = blockIdx.x * blockDim.x + threadIdx.x;
    if (idx<N) a[idx] = a[idx] * a[idx];
}</pre>
```

### Simple example of CUDA program (cont'd)

```
// main routine that executes on the CPU host
int main(void)
 float *a_h, *a_d; // Pointer to host & device arrays
 const int N = 10; // Number of elements in arrays
 size t size = N * sizeof(float);
 cudaMalloc((void **) &a_d, size); // Allocate array on device
 // Initialize host array and copy it to CUDA device
 for (int i=0; i<N; i++) a h[i] = (float)i;
 cudaMemcpy(a_d, a_h, size, cudaMemcpyHostToDevice);
 // Do calculation on device:
 int block size = 4;
 int n blocks = N/block size + (N%block size == 0 ? 0:1);
 square array <<< n blocks, block size >>> (a d, N);
 // Retrieve result from device and store it in host array
 cudaMemcpy(a h, a d, sizeof(float)*N, cudaMemcpyDeviceToHost);
 // Print results
 for (int i=0; i<N; i++) printf("%d %f\n", i, a h[i]);
 // Cleanup
 free(a h); cudaFree(a d);
```

# Matrix multiplication, example 1

- ▶ We want to compute  $Q = M \times N$ , assuming Q, M, N are all square matrices of same size Width×Width
- Each matrix has a 1D contiguous data storage
- Naive kernel implementation

# Matrix multiplication, example 2

- The previous implementation is not memory efficient
- Each thread reads 2×Width values from global memory
- A better approach is to let a patch of TILE\_WIDTH×TILE\_WIDTH threads share the 2×TILE\_WIDTH×Width data reads
- That is, each thread reads 2×Width/TILE\_WIDTH values from global memory
- Shared memory is important for performance!
- Also beware that size of shared memory is limited

### Matrix multiplication, example 2 (cont'd)

```
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Qd,
                                int Width)
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
 shared float Nds[TILE WIDTH][TILE WIDTH];
 int bx = blockIdx.x; int by = blockIdx.y;
 int tx = threadIdx.x; int ty = threadIdx.y;
 int Row = by \star TILE WIDTH + ty;
 int Col = bx * TILE WIDTH + tx;
 float Qvalue = 0;
 for (int m = 0; m<Width/TILE WIDTH; ++m) {
   Mds[ty][tx] = Md[Row*Width + (m*TILE WIDTH + tx)];
   Nds[ty][tx] = Nd[(m*TILE WIDTH + ty)*Width + Col];
   __syncthreads();
   for (int k=0; k<TILE WIDTH; ++k)
     Ovalue += Mds[ty][k] * Nds[k][tx];
    syncthreads();
 Od[Row*Width+Col] = Ovalue;
```

### 7-point stencil in CUDA

```
_global___ void stencil (double * device_u, double * device_u_new,
                       double alpha, double beta, int Nx, int Ny)
  int qid x = blockIdx.x*blockDim.x + threadIdx.x + 1;
  int gid_y = blockIdx.y*blockDim.y + threadIdx.y + 1;
  int gid_z = blockIdx.z*blockDim.z + threadIdx.z + 1;
  double (*in)[Ny][Nx];
  double (*out)[Ny][Nx];
  in = (double (*)[Ny][Nx])device_u;
  out = (double (*)[Ny][Nx])device_u_new;
  out[qid_z][qid_y][qid_x]=(alpha*in[qid_z][gid_y][gid_x])+
                           beta*(in[gid_z][gid_y][gid_x-1]
                                 +in[gid_z][gid_y][gid_x+1]
                                 +in[qid_z][qid_y-1][qid_x]
                                 +in[gid_z][gid_y+1][gid_x]
                                 +in[qid_z-1][qid_y][qid_x]
                                 +in[qid_z+1][qid_y][qid_x]);
```

One mesh point is computed by one lightweight thread

## **Mint:** automated C-to-CUDA code generator



- Domain-specific targeting stencil computations
- User only annotates a serial C code with Mint pragmas
- https://sites.google.com/site/mintmodel/
- Online demo: http://mint.simula.no/

```
pragma mint copy(U,toDevice,(n+2),(m+2),(k+2))
pragma mint copy(Unew,toDevice,(n+2),(m+2),(k+2))
pragma mint parallel default(shared) {
pragma mint for nest(all) tile(16,16,1)

for (int z=1; z<= k; z++)

for (int y=1; y<= m; y++)

for (int x=1; x<= n; x++)

Unew[z][y][x] = c0*U[z][y][x] +

c1*(U[z][y][x-1] + U[z][y][x+1] +

U[z][y-1][x] + U[z][y][x]);</pre>
```

oragma mint copy(Unew,toHost,(n+2),(m+2),(k+2))