Introduction to CUDA® Programming

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Fall 2017 HPRC Short Course

09/28/2017

Relevant Short Courses and Workshops

Intermediate CUDA Programming

https://hprc.tamu.edu/training/intermediate_cuda.html

Bring-Your-Own-Code Workshop

https://coehpc.engr.tamu.edu/byoc/

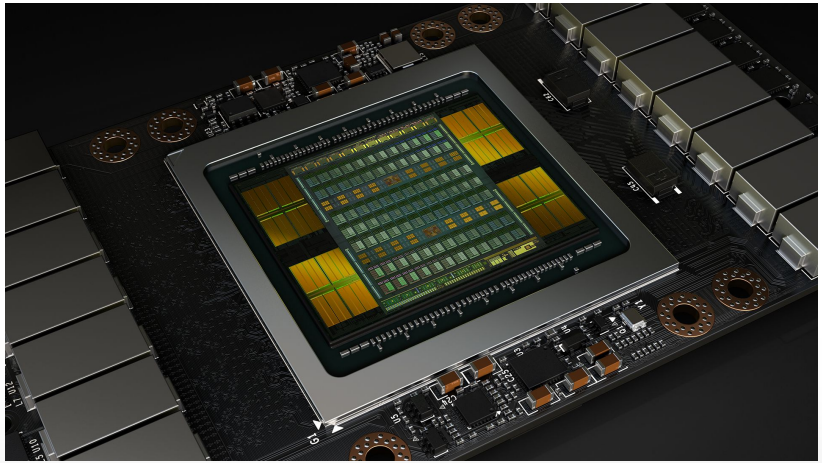
Offered regularly

GPU as an Accelerator

CPU

GPU Accelerator

NVIDIA Tesla V100 with 21.1 Billion Transistors

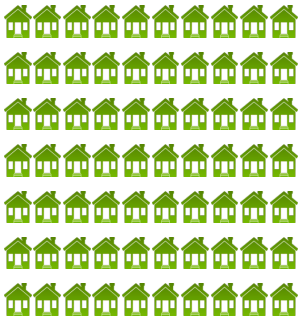


Why Computing Perf/Watt Matters?

2.3 PFlops

7.0 Megawatts

7000 homes

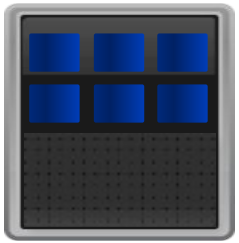


7.0 Megawatts

Traditional CPUs are not economically feasible

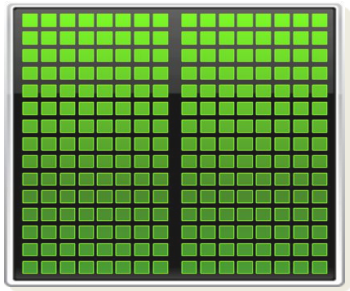
CPU

Optimized for Serial Tasks



GPU Accelerator

Optimized for Many Parallel Tasks



GPU-accelerated computing started a new era

GPU Computing Applications

GPU Computing Applications

Libraries and Middleware

cuDNN TensorRT	cuFFT cuBLAS cuRAND cuSPARSE	CULA MAGMA	Thrust NPP	VSIPL SVM OpenCurrent	PhysX OptiX iRay	MATLAB Mathematica

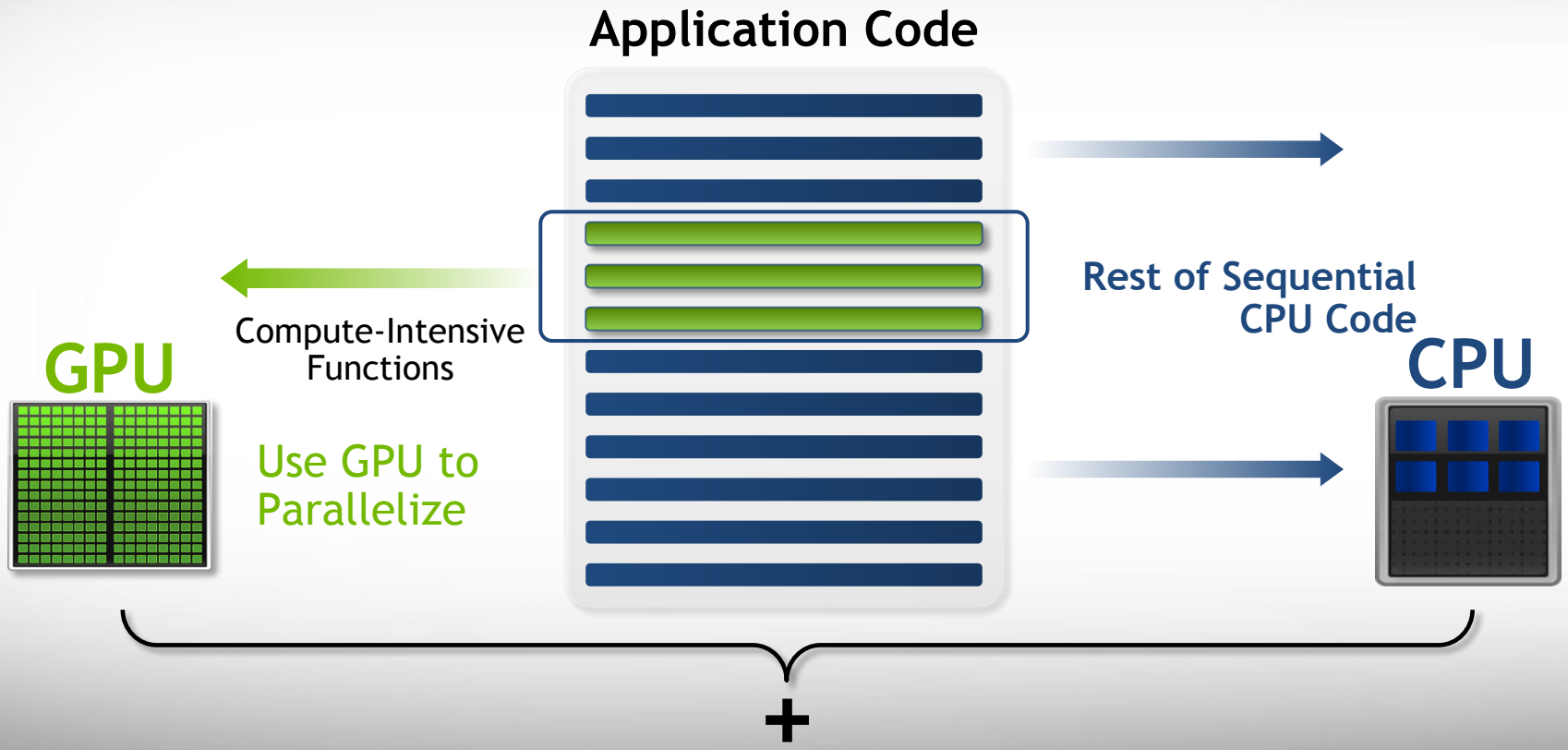
Programming Languages

C	C++	Fortran	Java Python Wrappers	DirectCompute	Directives (e.g. OpenACC)

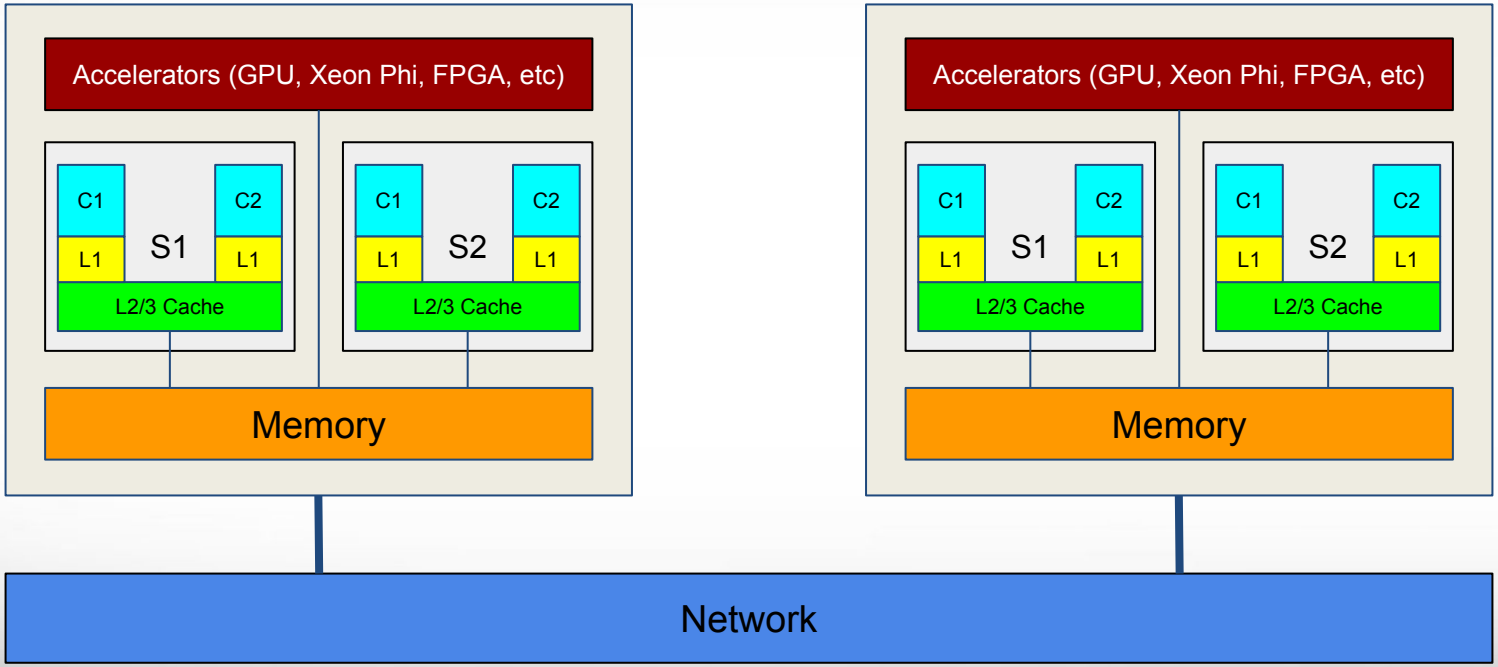
CUDA-Enabled NVIDIA GPUs

Volta Architecture (compute capabilities 7.x)				Tesla V Series
Pascal Architecture (compute capabilities 6.x)		GeForce 1000 Series	Quadro P Series	Tesla P Series
Maxwell Architecture (compute capabilities 5.x)	Tegra X1	GeForce 900 Series	Quadro M Series	Tesla M Series
Kepler Architecture (compute capabilities 3.x)	Tegra K1	GeForce 700 Series GeForce 600 Series	Quadro K Series	Tesla K Series
				

Add GPUs: Accelerate Science Applications



HPC - Distributed Heterogeneous System



Programming Models: MPI + (CUDA, OpenCL, OpenMP, OpenACC, etc.)

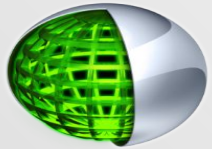
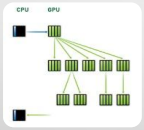
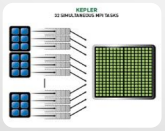
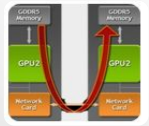
Amdahl's Law

$$S_{\text{latency}}(s) = \frac{1}{(1-p) + \frac{p}{s}}$$

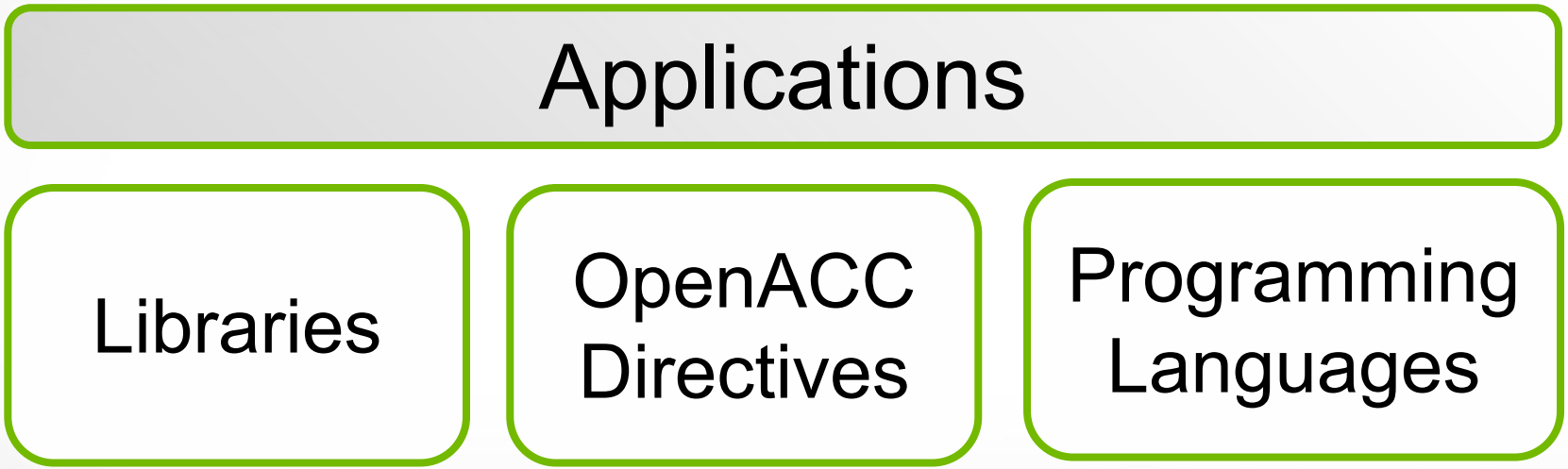
S is the theoretical speedup of the execution of the whole task; ***s*** is the speedup of the part of the task that benefits from improved system resources; ***p*** is the proportion of execution time that the part benefiting from improved resources originally occupied.

CUDA Parallel Computing Platform

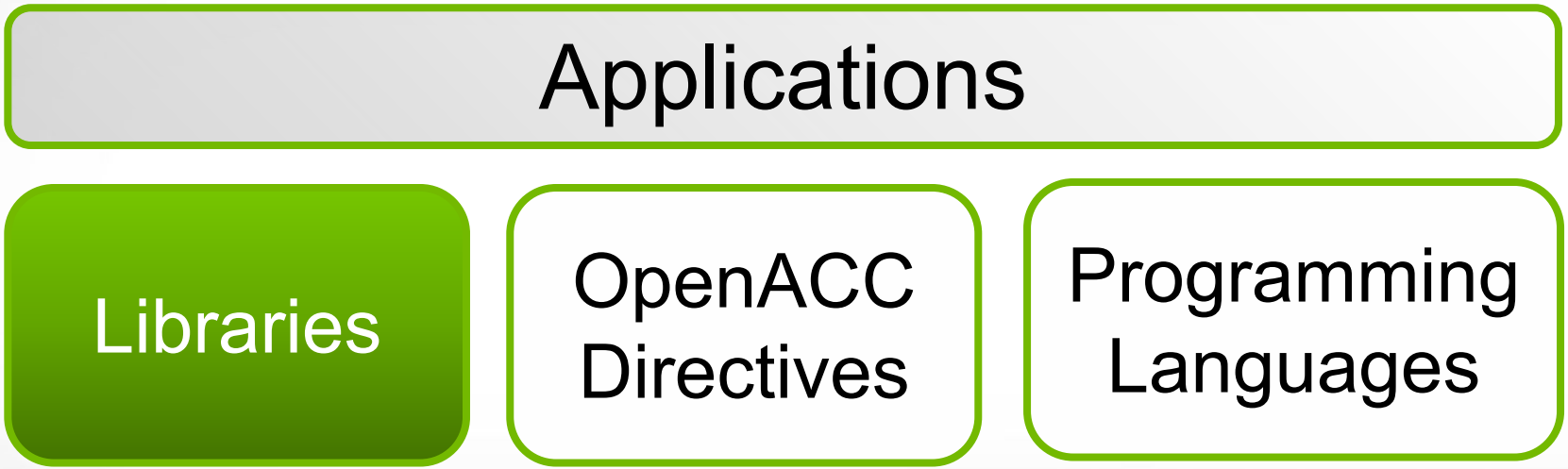
https://developer.nvidia.com/cuda-toolkit

Programming Approaches	Libraries "Drop-in" Acceleration	OpenACC Directives Easily Accelerate Apps	Programming Languages Maximum Flexibility
Development Environment		Nsight IDE Linux, Mac and Windows GPU Debugging and Profiling	CUDA-GDB debugger NVIDIA Visual Profiler
Open Compiler Tool Chain		Enables compiling new languages to CUDA platform, and CUDA languages to other architectures	
Hardware Capabilities	SMX 	Dynamic Parallelism 	HyperQ 	GPUDirect 

3 Ways to Accelerate Applications



3 Ways to Accelerate Applications



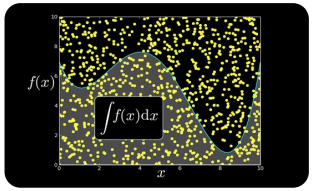
Libraries: Easy, High-Quality Acceleration

- **Ease of use:** Using libraries enables GPU acceleration without in-depth knowledge of GPU programming
- **"Drop-in":** Many GPU-accelerated libraries follow standard APIs, thus enabling acceleration with minimal code changes
- **Quality:** Libraries offer high-quality implementations of functions encountered in a broad range of applications
- **Performance:** NVIDIA libraries are tuned by experts

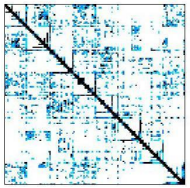
Some GPU-accelerated Libraries

https://developer.nvidia.com/gpu-accelerated-libraries

NVIDIA cuBLAS



NVIDIA cuRAND



NVIDIA cuSPARSE

NVIDIA NPP

GPU VSIPL

Vector Signal Image Processing

CULA tools

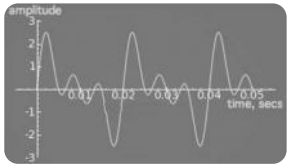
GPU Accelerated Linear Algebra

MAGMA

ICL UT

Matrix Algebra on GPU and Multicore

open source initiative



NVIDIA cuFFT

ROGUE WAVE SOFTWARE

IMSL Library

ArrayFire Matrix Computations

CUSP

Sparse Linear Algebra

open source initiative

Thrust

C++ STL Features for CUDA

open source initiative

CUDA-accelerated Application with Libraries

- **Step 1:** Substitute library calls with equivalent CUDA library calls

  `saxpy ( … )` ► `cublasSaxpy ( … )`

- **Step 2:** Manage data locality

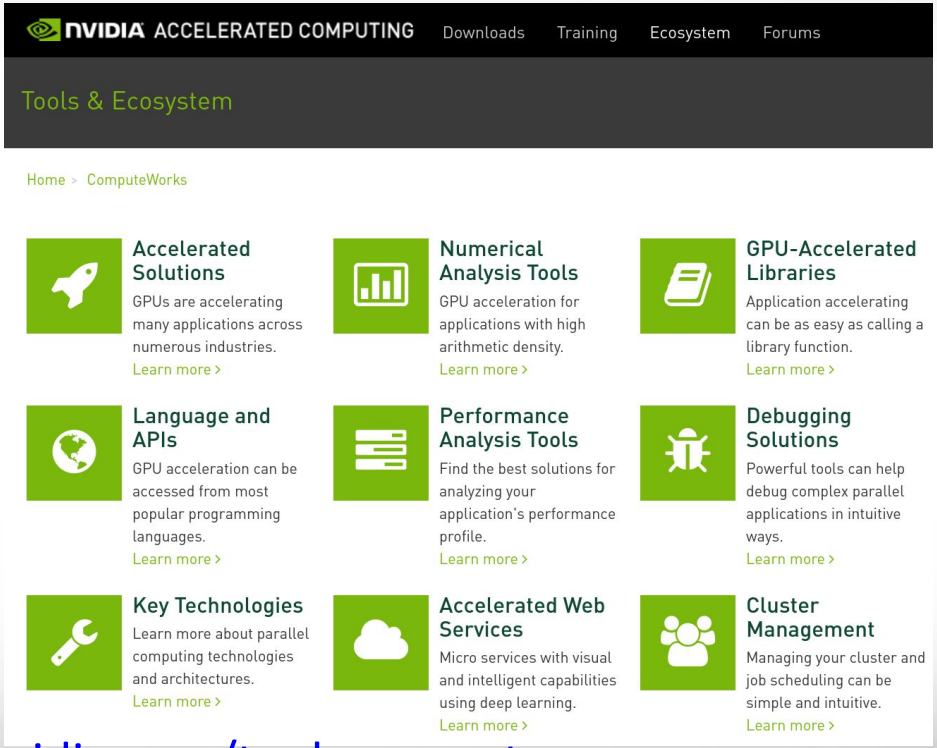
  - with CUDA: `cudaMalloc()`, `cudaMemcpy()`, etc.
  - with CUBLAS: `cublasAlloc()`, `cublasSetVector()`, etc.

- **Step 3:** Rebuild and link the CUDA-accelerated library

```
$nvcc myobj.o –l cublas
```

Explore the CUDA (Libraries) Ecosystem

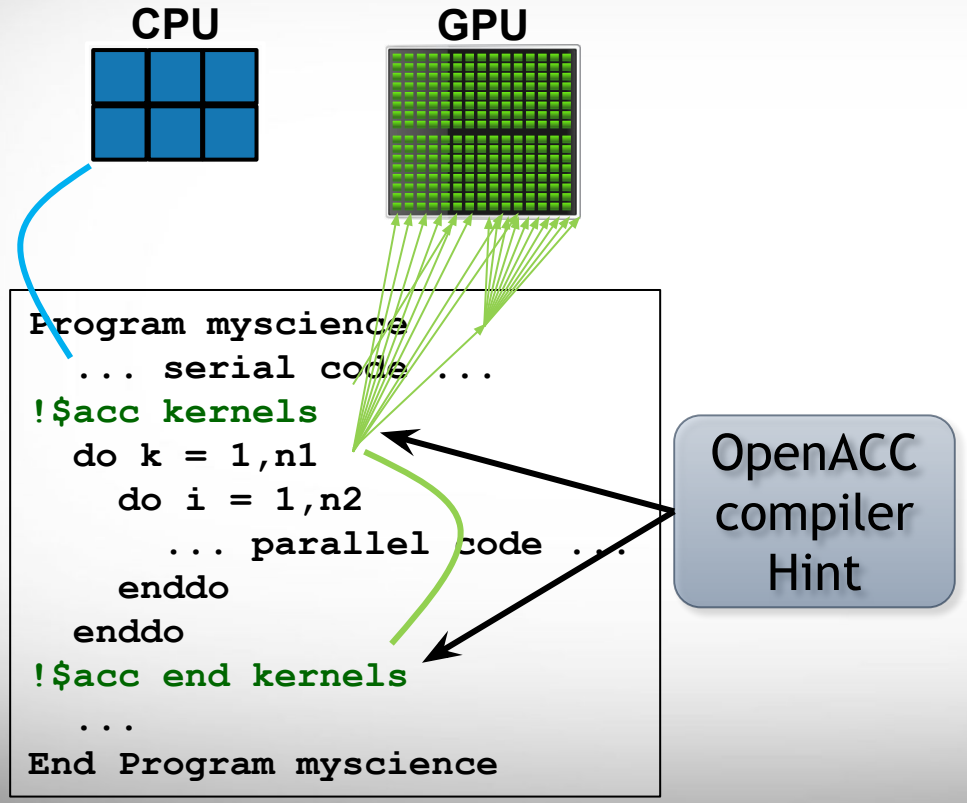
- CUDA Tools and Ecosystem described in detail on NVIDIA Developer Zone.



https://developer.nvidia.com/tools-ecosystem

3 Ways to Accelerate Applications

OpenACC Directives



Simple Compiler hints

Compiler Parallelizes code

Works on many-core GPUs & multicore CPUs

OpenACC

The Standard for GPU Directives

- **Easy:** Directives are the easy path to accelerate compute intensive applications
- **Open:** OpenACC is an open GPU directives standard, making GPU programming straightforward and portable across parallel and multi-core processors
- **Powerful:** GPU Directives allow complete access to the massive parallel power of a GPU

Directives: Easy & Powerful

Real-Time Object Detection

Global Manufacturer of Navigation Systems

5x in 40 Hours

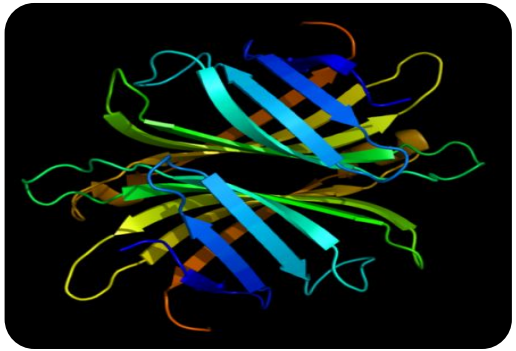
Valuation of Stock Portfolios using Monte Carlo

Global Technology Consulting Company

2x in 4 Hours

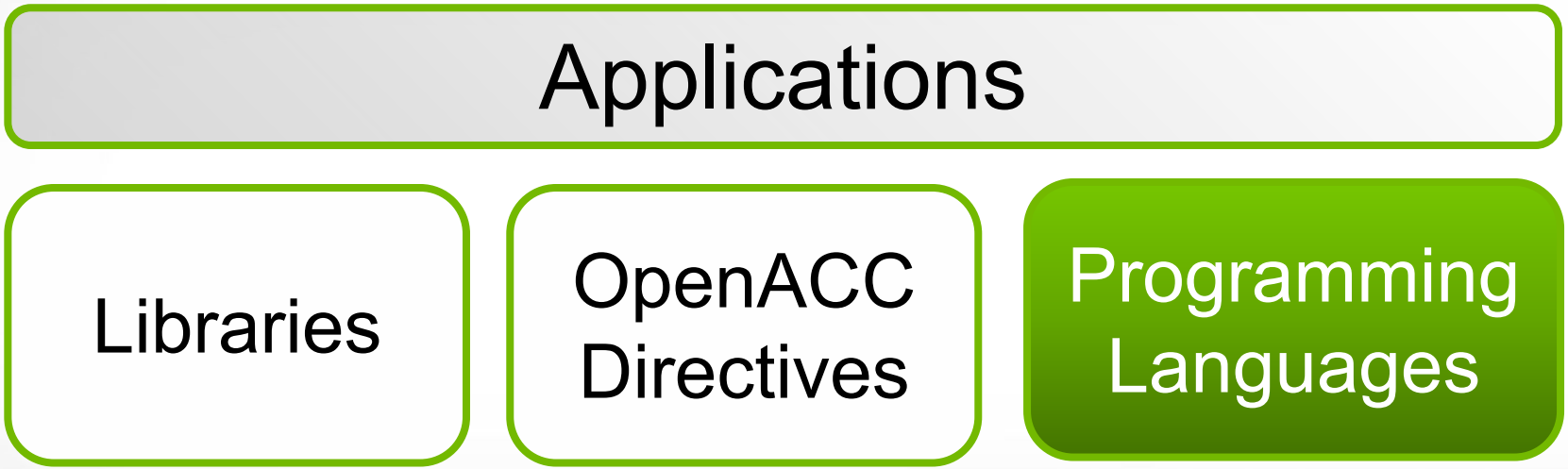
Interaction of Solvents and Biomolecules

University of Texas at San Antonio



5x in 8 Hours

3 Ways to Accelerate Applications



GPU Programming Languages

Numerical analytics	MATLAB, Mathematica, LabVIEW
Fortran	OpenACC, CUDA Fortran
C	OpenACC, CUDA C, OpenCL
C++	Thrust, CUDA C++, OpenCL
Python	PyCUDA, PyOpenCL, Copperhead
Java / F#	JCuda / Alea GPU

Rapid Parallel C++ Development

- Resembles C++ STL
- High-level interface
  - Enhances developer productivity
  - Enables performance portability between GPUs and multicore CPUs
- Flexible
  - CUDA, OpenMP, and TBB backends
  - Extensible and customizable
  - Integrates with existing software
- Open source


```
// generate 32M random numbers on host
thrust::host_vector<int> h_vec(32 << 20);
thrust::generate(h_vec.begin(),
                 h_vec.end(),
                 rand);

// transfer data to device (GPU)
thrust::device_vector<int> d_vec = h_vec;

// sort data on device
thrust::sort(d_vec.begin(), d_vec.end());

// transfer data back to host
thrust::copy(d_vec.begin(),
             d_vec.end(),
             h_vec.begin());
```

https://thrust.github.io/

Learn More

These languages are supported on all CUDA-capable GPUs.

You might already have a CUDA-capable GPU in your laptop or desktop PC!

CUDA C/C++
http://developer.nvidia.com/cuda-toolkit

Thrust C++ Template Library
http://developer.nvidia.com/thrust

CUDA Fortran
https://developer.nvidia.com/cuda-fortran

PyCUDA (Python)
https://developer.nvidia.com/pycuda

Alea GPU
http://www.aleagpu.com

MATLAB
http://www.mathworks.com/discovery/matlab-gpu.html

Mathematica
http://www.wolfram.com/mathematica/new-in-8/cuda-and-opencl-support/

CUDA C/C++ BASICS

What is CUDA?

- CUDA Architecture
  - Used to mean “Compute Unified Device Architecture”
  - Expose GPU parallelism for general-purpose computing
  - Retain performance
- CUDA C/C++
  - Based on industry-standard C/C++
  - Small set of extensions to enable heterogeneous programming
  - Straightforward APIs to manage devices, memory etc.

A Brief History of CUDA

- Researchers used OpenGL APIs for general purpose computing on GPUs before CUDA.
- In 2007, NVIDIA released first generation of Tesla GPU for general computing together their proprietary CUDA development framework.
- Current stable version of CUDA is 8.0 (as of Sept. 2017).
- CUDA 9 Release Candidate is available.

Heterogeneous Computing

- Terminology:
  - *Host* The CPU and its memory (host memory)
  - *Device* The GPU and its memory (device memory)

Host

Device

Heterogeneous Computing

```
#include <iostream>
#include <algorithm>

using namespace std;

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

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

        // Read input elements into shared memory
        temp[lindex] = in[gindex];
        if (threadIdx.x < RADIUS) {
                temp[lindex - RADIUS] = in[gindex - RADIUS];
                temp[lindex + BLOCK_SIZE] = in[gindex +
BLOCK_SIZE];
        }

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

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

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

void fill_ints(int *x, int n) {
        fill_n(x, n, 1);
}

int main(void) {
        int *in, *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(out, d_out, size, cudaMemcpyDeviceToHost);

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

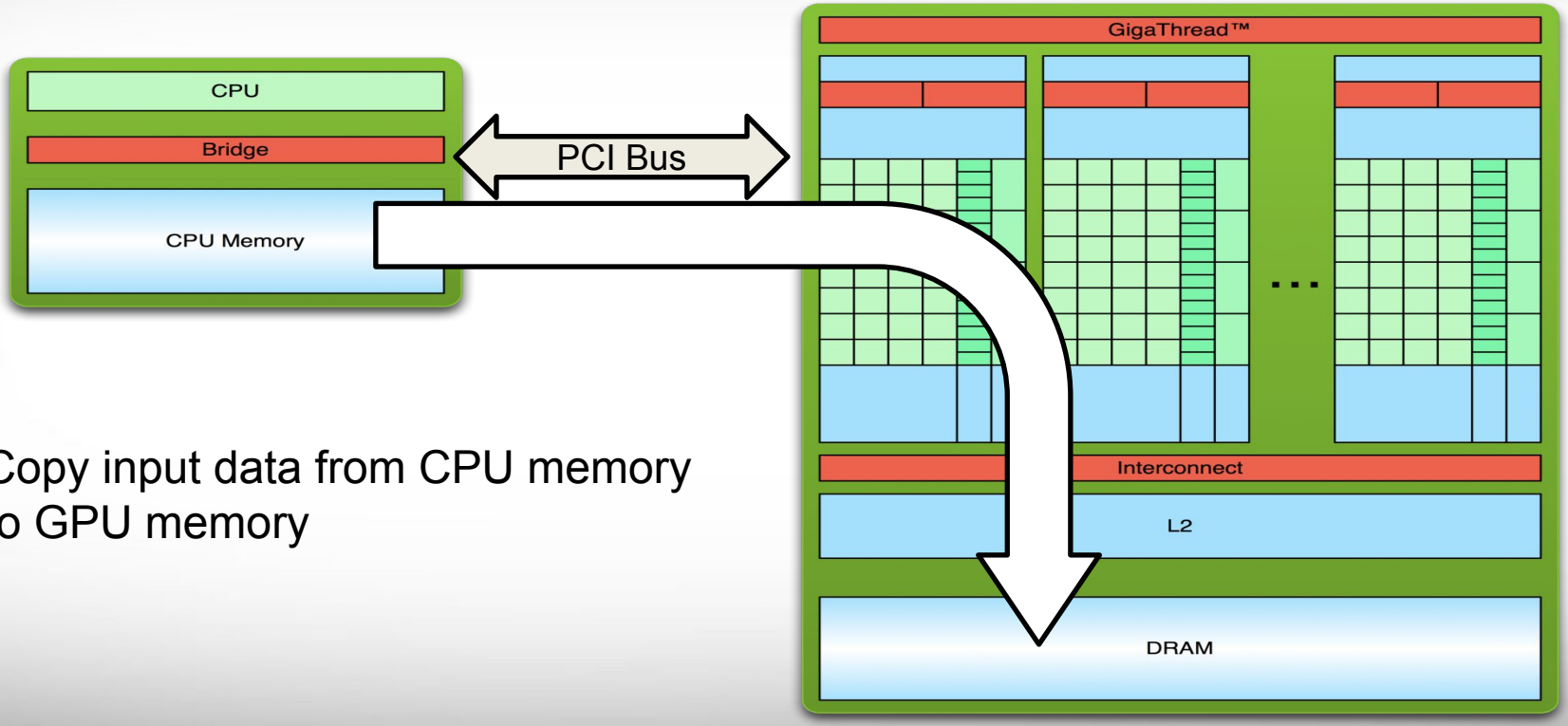
parallel function

serial code

parallel code

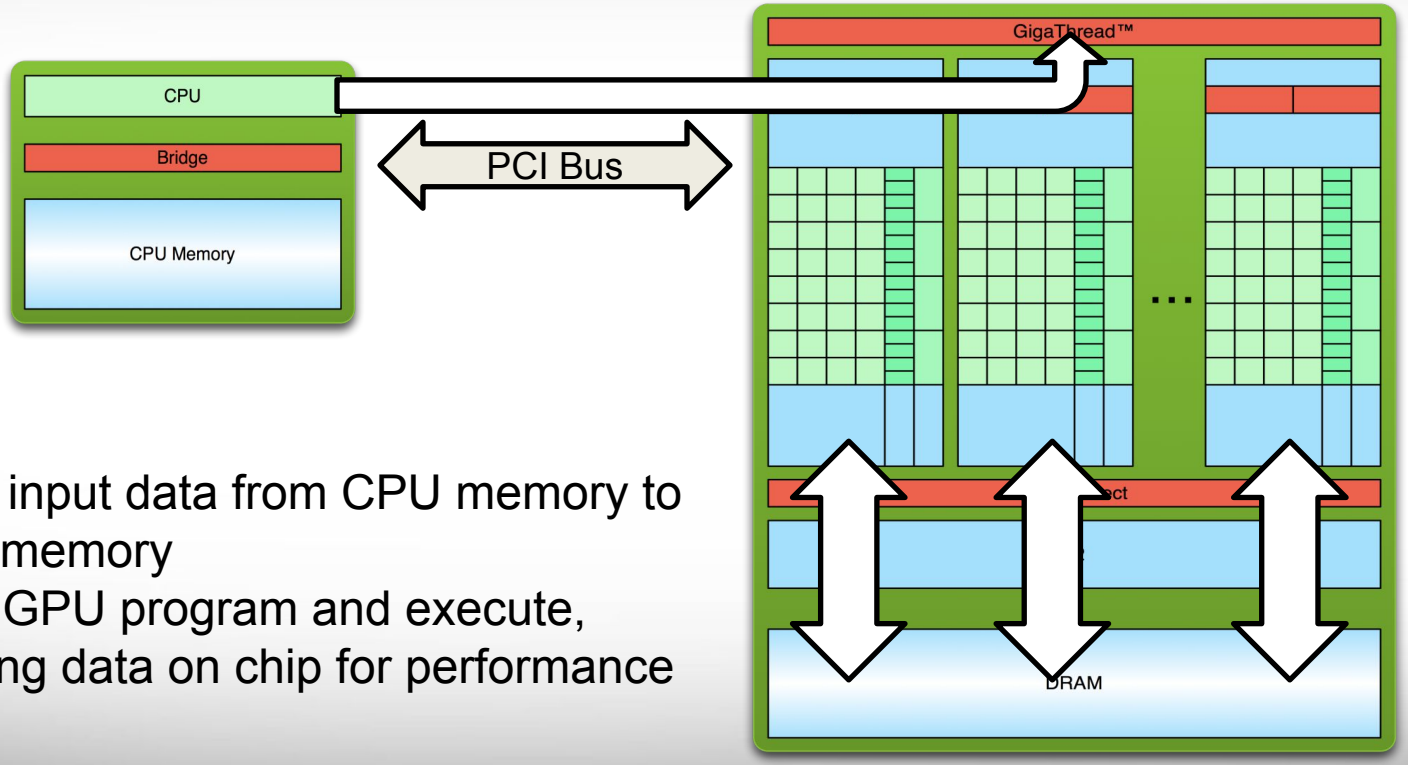
serial code

Simple Processing Flow



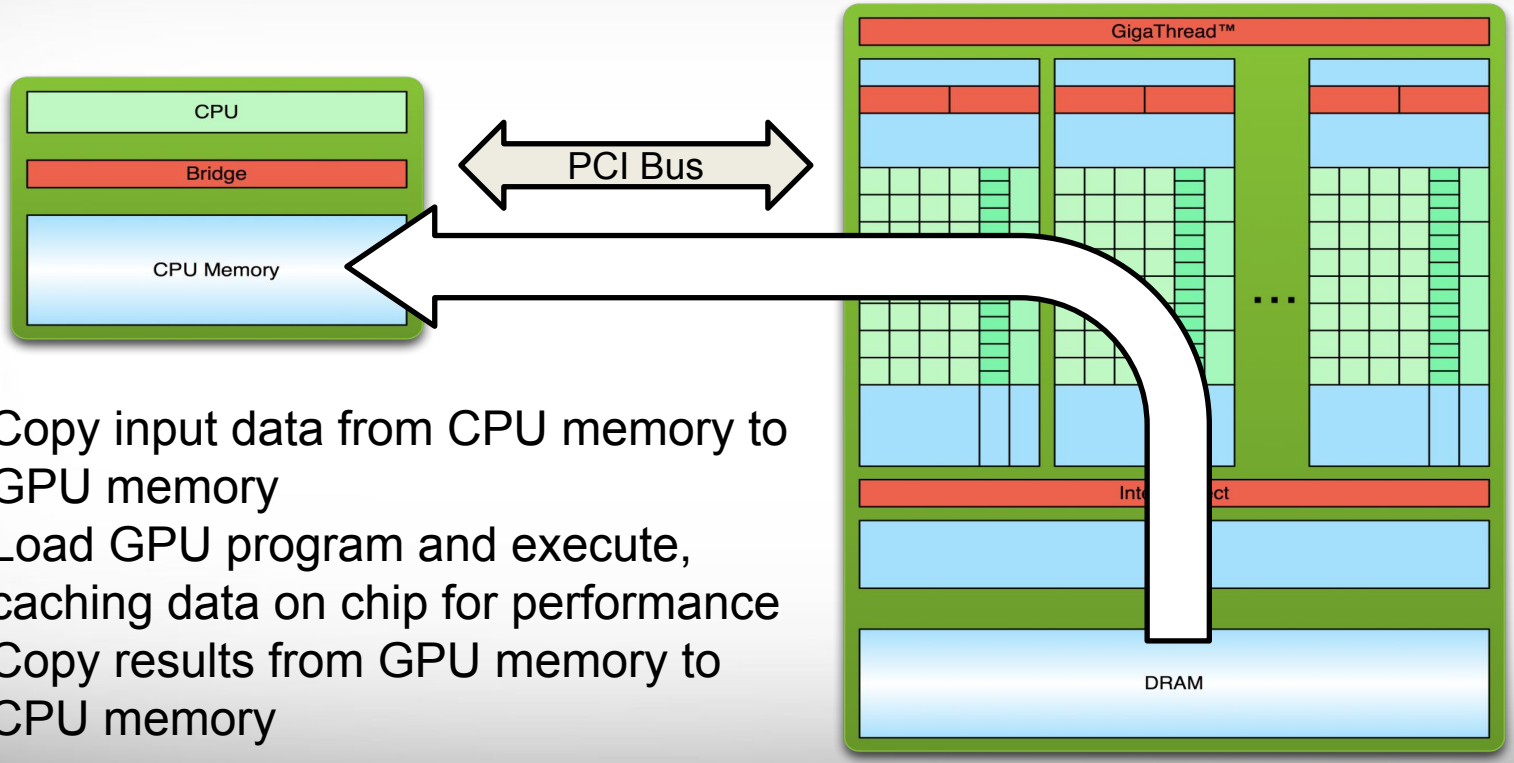
1. Copy input data from CPU memory to GPU memory

Simple Processing Flow



1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance

Simple Processing Flow

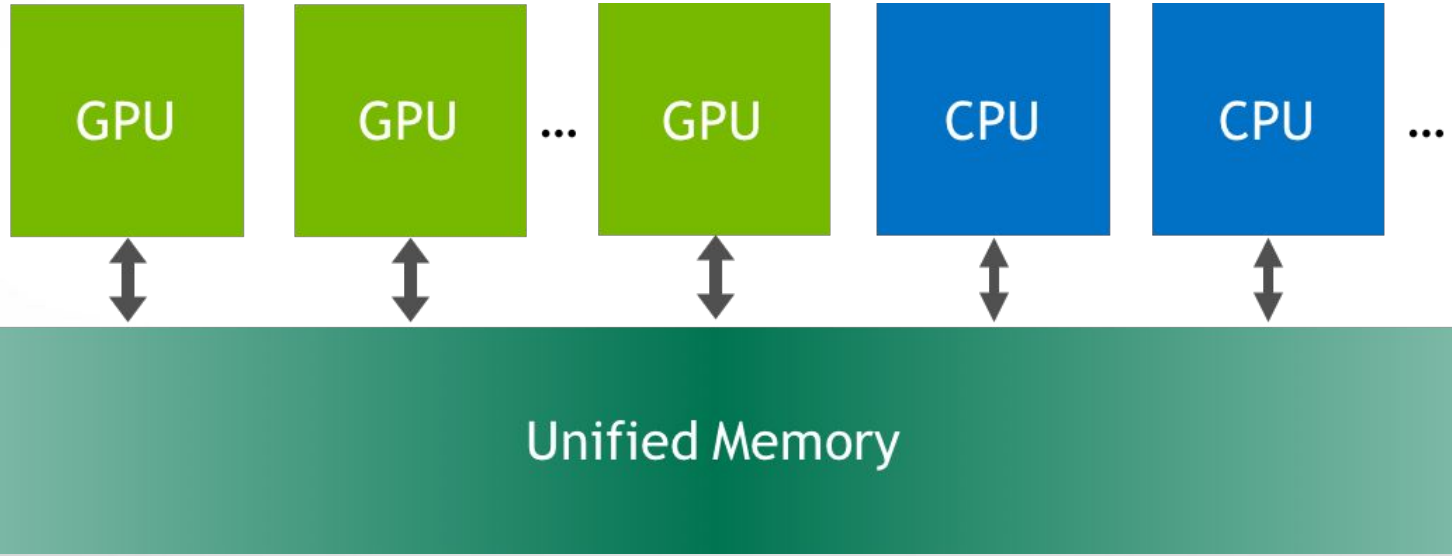


1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance
3. Copy results from GPU memory to CPU memory

Unified Memory

Software: CUDA 6.0 in 2014

Hardware: Pascal GPU in 2016



Unified Memory

- A managed memory space where all processors see a single coherent memory image with a common address space.
- Memory allocation with **`cudaMallocManaged()`**.
- Synchronization with **`cudaDeviceSynchronize()`**.
- Eliminates the need for **`cudaMemcpy()`**.
- Enables simpler code.
- Hardware support since Pascal GPU.

Hello World!

```
int main(void) {
    printf("Hello World!\n");
    return 0;
}
```

- Standard C that runs on the host
- NVIDIA compiler (nvcc) can be used to compile programs with no *device* code

Output:

```
$ nvcc hello_world.cu
$ ./a.out
$ Hello World!
```

Hello World! with Device Code

```
__global__ void mykernel(void) {
}

int main(void) {
    mykernel<<<1,1>>>();
    printf("Hello World!\n");
    return 0;
}
```

- Two new syntactic elements…

Hello World! with Device Code

```
__global__ void mykernel(void) {
}
```

- CUDA C/C++ keyword `__global__` indicates a function that:
  - Runs on the device
  - Is called from host code
- `nvcc` separates source code into host and device components
  - Device functions (e.g. **`mykernel()`**) processed by NVIDIA compiler
  - Host functions (e.g. **`main()`**) processed by standard host compiler
    - **gcc, icc, etc.**

Hello World! with Device Code

```
mykernel<<<1,1>>>();
```

- Triple angle brackets mark a call from *host* code to *device* code
  - Also called a “kernel launch”
  - We’ll return to the parameters (1,1) in a moment
- That’s all that is required to execute a function on the GPU!

Hello World! with Device Code

```
__global__ void mykernel(void){
}
int main(void) {
    mykernel<<<1,1>>>();
    printf("Hello World!\n");
    return 0;
}
```

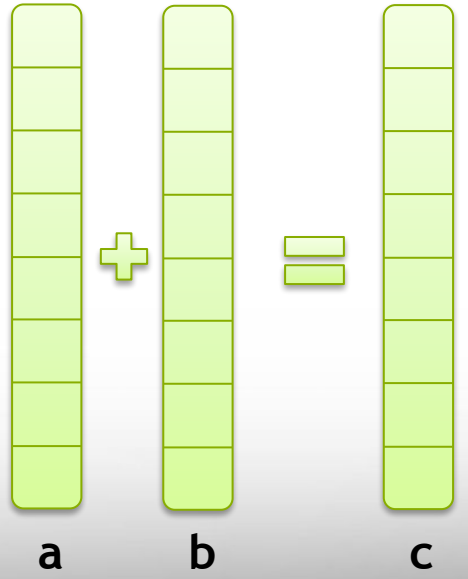
Output:

```
$nvcc hello.cu
$./a.out
Hello World!
```

- `mykernel()` does nothing!

Parallel Programming in CUDA C/C++

- But wait… GPU computing is about massive parallelism!
- We need a more interesting example…
- We'll start by adding two integers and build up to vector addition



Addition on the Device

- A simple kernel to add two integers

```
__global__ void add(int *a, int *b, int *c) {
    *c = *a + *b;
}
```

- As before `__global__` is a CUDA C/C++ keyword meaning
  - `add()` will execute on the device
  - `add()` will be called from the host

Addition on the Device

- Note that we use pointers for the variables

```
__global__ void add(int *a, int *b, int *c) {
    *c = *a + *b;
}
```

- `add()` runs on the device, so `a`, `b` and `c` must point to device memory
- We need to allocate memory on the GPU.

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()`**

Addition on the Device: `add()`

- Returning to our `add()` kernel

```
__global__ void add(int *a, int *b, int *c) {
    *c = *a + *b;
}
```

- Let's take a look at main()…

Addition on the Device: `main()`

```
int main(void) {
    int a, b, c;                // host copies of a, b, c
    int *d_a, *d_b, *d_c;       // device copies of a, b, c
    int size = sizeof(int);

    // Allocate space for device copies of a, b, c
    cudaMalloc((void **)&d_a, size);
    cudaMalloc((void **)&d_b, size);
    cudaMalloc((void **)&d_c, size);

    // Setup input values
    a = 2;
    b = 7;
```

Addition on the Device: `main()`

```
    // Copy inputs to device
    cudaMemcpy(d_a, &a, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, &b, size, cudaMemcpyHostToDevice);

    // Launch add() kernel on GPU
    add<<<1,1>>>(d_a, d_b, d_c);

    // Copy result back to host
    cudaMemcpy(&c, d_c, size, cudaMemcpyDeviceToHost);

    // Cleanup
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

Moving to Parallel

- GPU computing is about massive parallelism
  - So how do we run code in parallel on the device?

```
add<<< 1, 1 >>>();
```

```
add<<< N, 1 >>>();
```

- Instead of executing `add()` once, execute N times in parallel

Vector Addition on the Device

- With **`add()`** running in parallel we can do vector addition
- Terminology: each parallel invocation of **`add()`** is referred to as a **block**
  - The set of blocks is referred to as a **grid**
  - Each invocation can refer to its block index using `blockIdx.x`

```
__global__ void add(int *a, int *b, int *c) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- By using `blockIdx.x` to index into the array, each block handles a different index

Vector Addition on the Device

```
__global__ void add(int *a, int *b, int *c) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- On the device, each block can execute in parallel:

Block 0

```
c[0]  = a[0] + b[0];
```

Block 1

```
c[1]  = a[1] + b[1];
```

Block 2

```
c[2]  = a[2] + b[2];
```

Block 3

```
c[3]  = a[3] + b[3];
```

Vector Addition on the Device: `add()`

- Returning to our parallelized `add()` kernel

```
__global__ void add(int *a, int *b, int *c) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- Let's take a look at main()…

Vector Addition on the Device: `main()`

```
#define N 512
int main(void) {
 int *a  *b  *c            // host copies of a, b, c
 int *d_a, *d_b, *d_c;     // device copies of a, b, c
 int size = N * sizeof(int);

 // Alloc space for device copies of a, b, c
 cudaMalloc((void **)&d_a, size);
 cudaMalloc((void **)&d_b, size);
 cudaMalloc((void **)&d_c, size);

 // Alloc space for host copies of a, b, c and set up input values
 a = (int *)malloc(size); random_ints(a, N);
 b = (int *)malloc(size); random_ints(b, N);
 c = (int *)malloc(size);
```

Vector Addition on the Device: `main()`

```
    // Copy inputs to device
    cudaMemcpy(d_a, a, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, b, size, cudaMemcpyHostToDevice);

    // Launch add() kernel on GPU with N blocks
    add<<<N,1>>>(d_a, d_b, d_c);

    // Copy result back to host
    cudaMemcpy(c, d_c, size, cudaMemcpyDeviceToHost);

    // Cleanup
    free(a); free(b); free(c);
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
    return 0;
}
```

Vector Addition with Unified Memory

```
__global__ void VecAdd(int *ret, int a, int b) {
    ret[threadIdx.x] = a + b + threadIdx.x;
}
int main() {
    int *ret;
    cudaMallocManaged(&ret, 1000 * sizeof(int));
    VecAdd<<< 1, 1000 >>>(ret, 10, 100);
    cudaDeviceSynchronize();
    for(int i=0; i<1000; i++)
        printf("%d: A+B = %d\n", i, ret[i]);
    cudaFree(ret);
    return  0;
}
```

Vector Addition with Managed Global Memory

```
__device__ __managed__  int  ret[1000];

__global__ void VecAdd(int *ret, int a, int b) {
    ret[threadIdx.x] = a + b + threadIdx.x;
}
int main() {
    VecAdd<<< 1, 1000 >>>(ret, 10, 100);
    cudaDeviceSynchronize();
    for(int i=0; i<1000; i++)
        printf("%d: A+B = %d\n", i, ret[i]);
    return  0;
}
```

Profiling with nvprof

```
$nvprof add_parallel
```

```
==28491== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
 43.45%  4.3520us         1  4.3520us  4.3520us  4.3520us  add(int*, int*, int*)
 30.35%  3.0400us         2  1.5200us  1.3120us  1.7280us  [CUDA memcpy HtoD]
 26.20%  2.6240us         1  2.6240us  2.6240us  2.6240us  [CUDA memcpy DtoH]

==28491== API calls:
Time(%)      Time     Calls       Avg       Min       Max  Name
 99.34%  231.73ms         3  77.242ms  6.1990us  231.71ms  cudaMalloc
  0.33%  766.63us       182  4.2120us     171ns  143.74us  cuDeviceGetAttribute
  0.15%  357.72us         2  178.86us  173.06us  184.67us  cuDeviceTotalMem
  0.08%  175.05us         3  58.351us  6.6470us  147.94us  cudaFree
  0.03%  75.722us         1  75.722us  75.722us  75.722us  cudaLaunch
  0.03%  74.091us         3  24.697us  10.865us  35.014us  cudaMemcpy
  0.03%  65.073us         2  32.536us  30.391us  34.682us  cuDeviceGetName
  0.00%  4.6390us         3  1.5460us     221ns  3.9590us  cudaSetupArgument
  0.00%  4.4490us         3  1.4830us     434ns  3.3590us  cuDeviceGetCount
  0.00%  2.7070us         6     451ns     196ns     777ns  cuDeviceGet
  0.00%  1.9940us         1  1.9940us  1.9940us  1.9940us  cudaConfigureCall
```

Review (1 of 2)

- Difference between *host* and *device*
  - *Host* CPU
  - *Device* GPU
- Using `__global__` to declare a function as device code
  - Executes on the device
  - Called from the host
- Passing parameters from host code to a device function

Review (2 of 2)

- Basic device memory management
  - **cudaMalloc()**
  - **cudaMemcpy()**
  - **cudaFree()**
- Launching parallel kernels
  - Launch **N** copies of **add()** with **add<<<N,1>>>(…)**.
  - Use **blockIdx.x** to access block index.
  - Use **nvprof** for collecting & viewing profiling data.

More Resources

You can learn more about the details at

- CUDA Programming Guide (docs.nvidia.com/cuda)
- CUDA Zone – tools, training, etc. (developer.nvidia.com/cuda-zone)
- Download CUDA Toolkit & SDK (www.nvidia.com/getcuda)
- Nsight IDE (Eclipse or Visual Studio) (www.nvidia.com/nsight)

Intermediate CUDA Programming Short Course

- GPU memory management and unified memory
- Parallel kernels in CUDA C
- Parallel communication and synchronization
- Running a CUDA code on Ada
- Profiling and performance evaluation

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Appendix

Running CUDA Code on Ada

https://github.com/jtao/coehpc

```
# load CUDA module
$ml CUDA/8.0.44-GCC-5.4.0-2.26

# copy sample code to your scratch space
$cd $SCRATCH
$cp -r /scratch/training/CUDA .

# compile CUDA code
$cd CUDA
$nvcc hello_world_host.cu -o hello_world

# edit job script & submit your first GPU job
$bsub < cuda_run.sh
```

1D Grid of Blocks in 1D, 2D, and 3D

```
__device__ int getGlobalIdx_1D_1D ()
{
  return blockIdx.x * blockDim.x + threadIdx.x;
}

__device__ int getGlobalIdx_1D_2D ()
{
  return blockIdx.x * blockDim.x * blockDim.y + threadIdx.y * blockDim.x +
    threadIdx.x;
}

__device__ int getGlobalIdx_1D_3D ()
{
  return blockIdx.x * blockDim.x * blockDim.y * blockDim.z
    + threadIdx.z * blockDim.y * blockDim.x + threadIdx.y * blockDim.x +
    threadIdx.x;
}
```

2D Grid of Blocks in 1D, 2D, and 3D

```
__device__ int getGlobalIdx_2D_1D ()
{
  int blockId = blockIdx.y * gridDim.x + blockIdx.x;
  int threadId = blockId * blockDim.x + threadIdx.x;
  return threadId;
}

__device__ int getGlobalIdx_2D_2D ()
{
  int blockId = blockIdx.x + blockIdx.y * gridDim.x;
  int threadId =
    blockId * (blockDim.x * blockDim.y) + (threadIdx.y * blockDim.x) + threadIdx.x;
  return threadId;
}

__device__ int getGlobalIdx_2D_3D ()
{
  int blockId = blockIdx.x + blockIdx.y * gridDim.x;
  int threadId = blockId * (blockDim.x * blockDim.y * blockDim.z)
    + (threadIdx.z * (blockDim.x * blockDim.y))
    + (threadIdx.y * blockDim.x) + threadIdx.x;
  return threadId;
}
```

3D Grid of Blocks in 1D, 2D, and 3D

```
__device__ int getGlobalIdx_3D_1D ()
{
  int blockId = blockIdx.x
    + blockIdx.y * gridDim.x + gridDim.x * gridDim.y * blockIdx.z;
  int threadId = blockId * blockDim.x + threadIdx.x;
  return threadId;
}

__device__ int getGlobalIdx_3D_2D ()
{
  int blockId = blockIdx.x
    + blockIdx.y * gridDim.x + gridDim.x * gridDim.y * blockIdx.z;
  int threadId = blockId * (blockDim.x * blockDim.y)
    + (threadIdx.y * blockDim.x) + threadIdx.x;
  return threadId;
}

__device__ int getGlobalIdx_3D_3D ()
{
  int blockId = blockIdx.x
    + blockIdx.y * gridDim.x + gridDim.x * gridDim.y * blockIdx.z;
  int threadId = blockId * (blockDim.x * blockDim.y * blockDim.z)
    + (threadIdx.z * (blockDim.x * blockDim.y))
    + (threadIdx.y * blockDim.x) + threadIdx.x;
  return threadId;
}
```