

Introduction to GPU Computing and Programming

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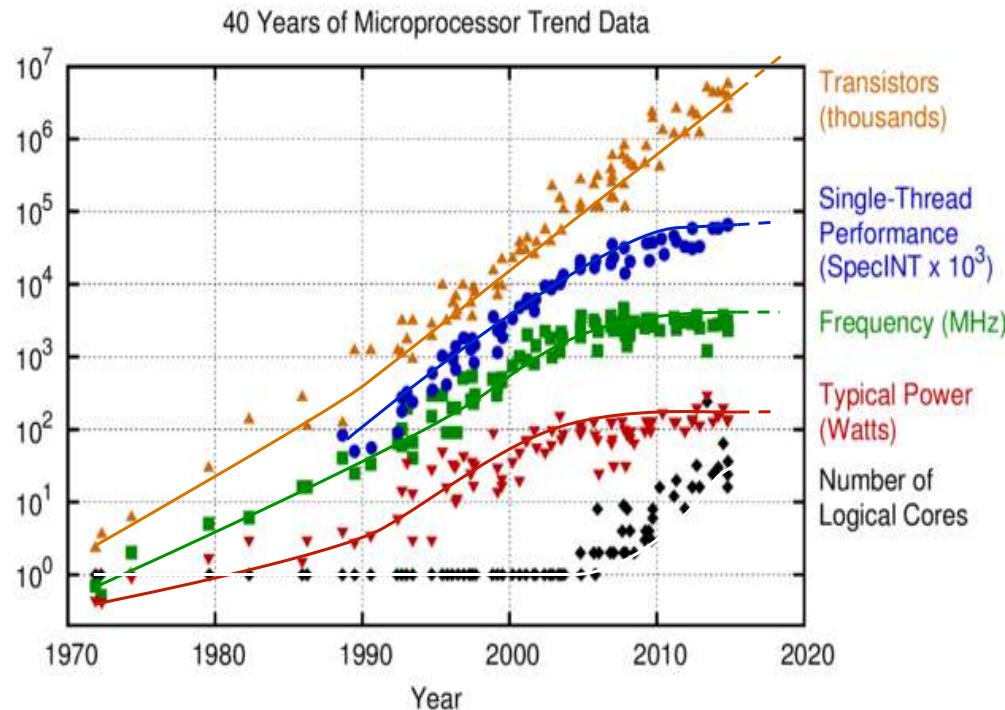
Course Overview

- GPU history / hardware overview
- GPU accelerated software examples
- CUDA C programming basics
- GPU enabled libraries
- OpenAcc introduction
- Exercises on SDSC Comet

What is a GPU?

CPU design trends

- Cannot increase single processor performance by increasing number of transistors
 - Cannot further increase clock speed
 - Replicate compute cores instead



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2015 by K. Rupp

What is a GPU?

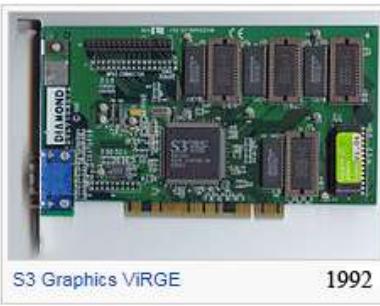
- **Graphics Processing Unit**

- ‘Specialist’ processor for accelerating the rendering of computer graphics.
- Initially designed for 2D Acceleration (Windows)
- 3D Acceleration invented by 3DFX (Later bought by NVIDIA) in 1997.
- Originally fixed function pipelines
 - Invention of OpenGL added programmability.
 - Pixels can be programmed with specific textures.
 - Onboard memory for storing textures.
- Development driven by \$150 billion gaming industry.



Tseng Labs ET4000/W32p

1991



S3 Graphics ViRGE

1992



Voodoo3 2000 AGP card

1999



GeForce 6600 GT Personal Cinema

2004



NVIDIA GeForce GTX 280

2008

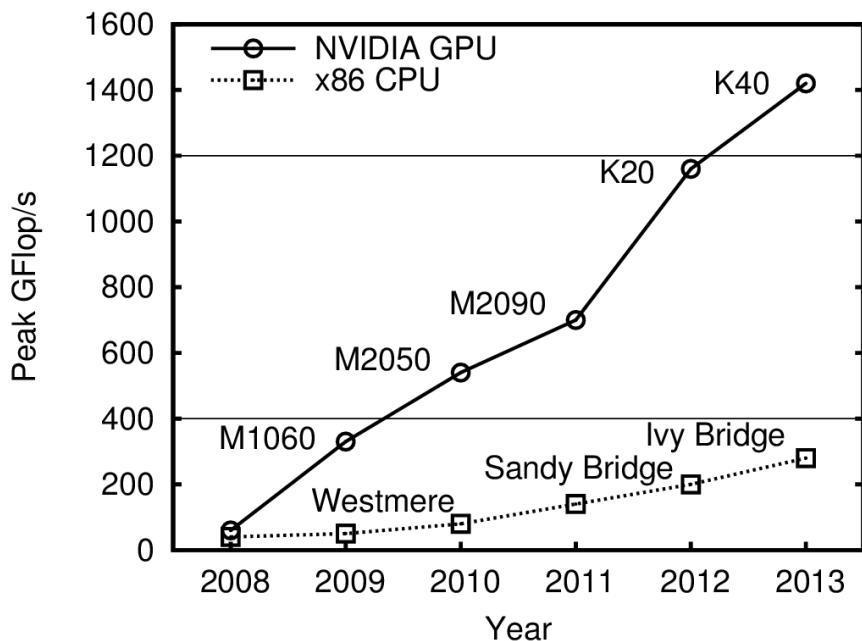
What is a GPU?

- **Modern GPUs are programmable for general purpose computations**
- **GPUs have specialized processing cores**
 - Simplified design compared to CPU cores
 - Larger number on a chip
 - Reduced power consumption
- **Simplified core design**
 - Limited architectural features, e.g. branch caches
 - Partially exposed memory hierarchy

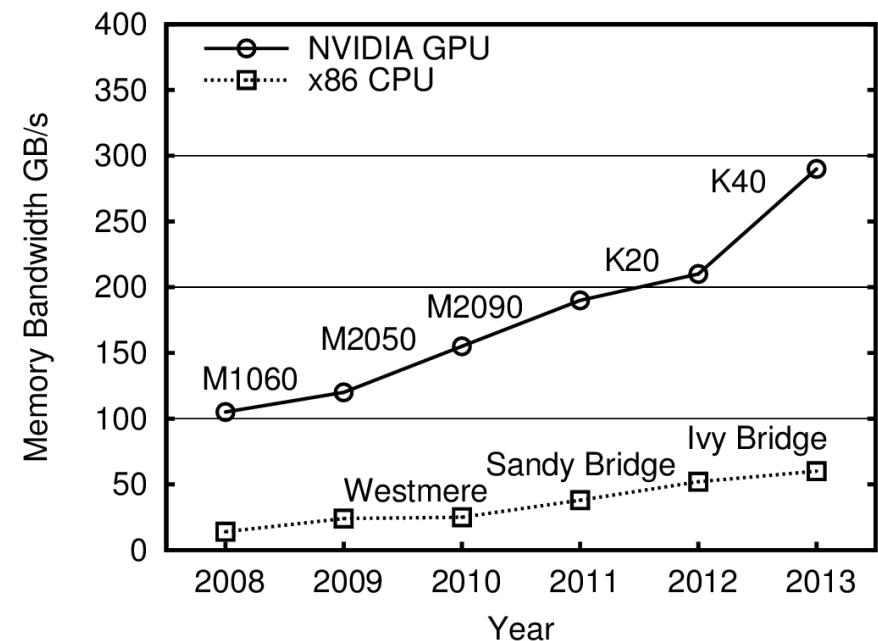
Why Interest in GPUs?

Performance comparison CPU vs GPU

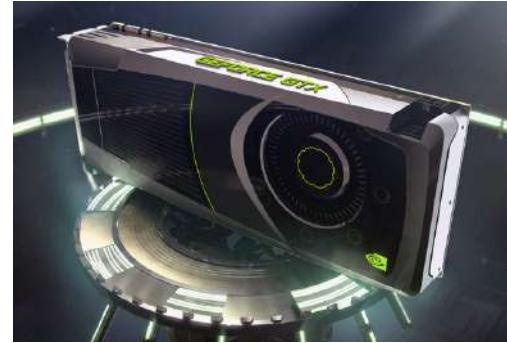
Double precision Flop/s



Memory Bandwidth



Why Interest in GPUs?



Dual Socket Intel Haswell E5-2680v3 2.5GHz

- 12 core
- \$1,900 – each

(approx prices, May 2015)

NVIDIA GTX980

- GM204 GPU
- 4 GB RAM
- \$590 – each

NVIDIA Tesla K80

- 2x GK210 GPU
- 2x 12 GB RAM
- \$4,000 – each

Why Interest in GPUs?



ASCI White (LLNL)

- 12.3 Tflop/s, #1 Top 500, Nov 2001.
- Cost - \$110 million (*in 2001!*)

SDSC Comet

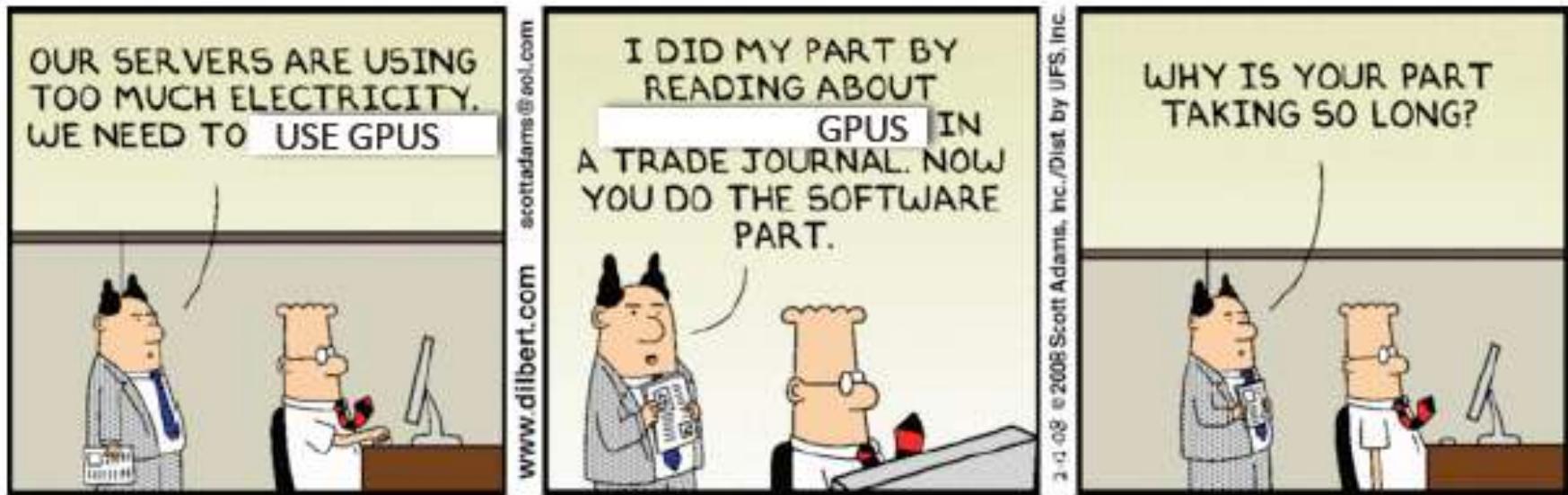
- ~2.0 Pflop/s aggregate
- 1 GPU node (total 36 GPU nodes)
5.8 Tflop/s DP, 35.0 Tflop/s SP
- Cost - \$12 million



DIY 4x GTX980 box

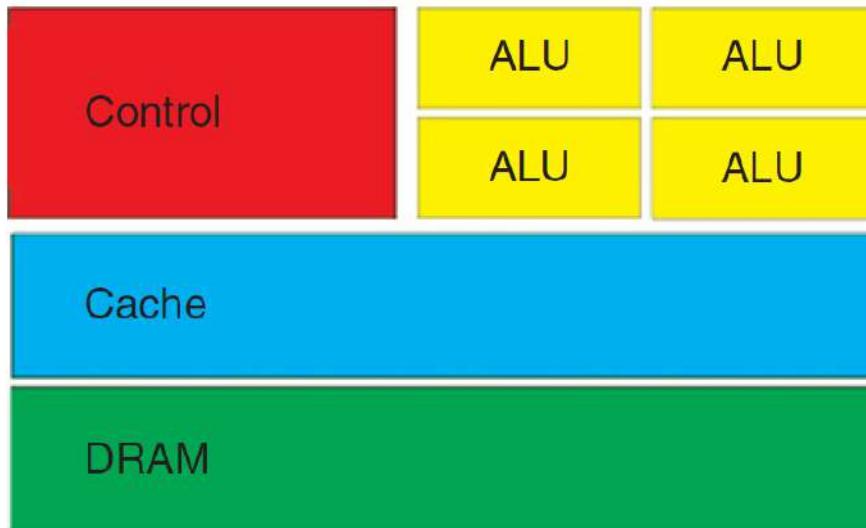
- 0.6 Tflop/s DP, 18.4 Tflop/s SP
- Cost - < \$5 thousand

What's the Catch?

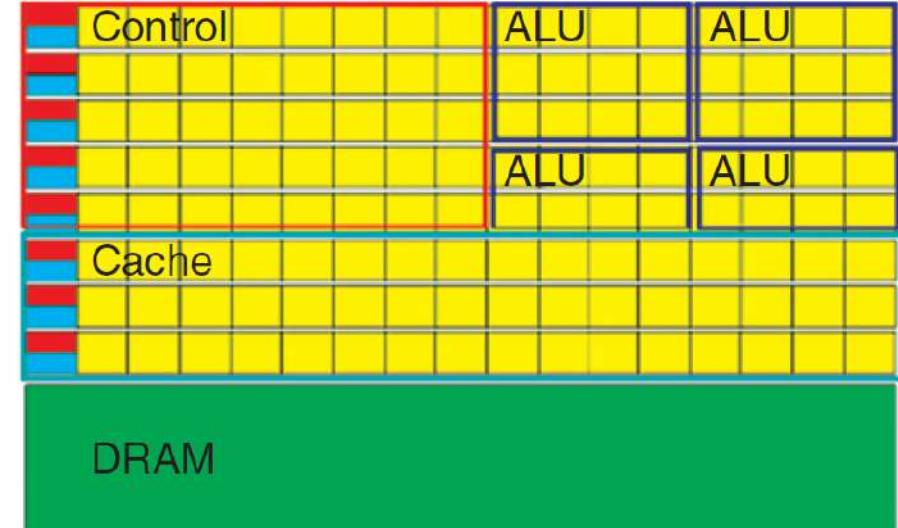


GPUs Require Rewriting Code

(a) CPU



(b) GPU



- Few processing cores with sophisticated hardware
- Multi-level caching
- Prefetching
- Branch prediction
- Thousands of simplistic compute cores
- Operate in lock-step
- Vectorized loads/stores to memory

History of GPU Computing

- **2003 - First attempts to use GPUs for general computing.**
 - Programmed as graphics primitives (heroic)
 - Problems had to be expressed in terms of vertex coordinates, textures and shader programs.
 - Hardware lacking certain ‘features’ – No random reads or writes etc.
- **2004 – ‘Brook’ programming language for GPUs.**
- **2007 – NVIDIA announce CUDA at SC07**
 - Release GPUs with specific ‘computational’ features.
- **2008 – OpenCL language ratified.**
 - Mainly aimed at embedded devices but has features for GPU computation.
- **2010 – CUDA Fortran language defined.**
- **2011 – OpenACC compiler directive language ratified.**
 - Provides OpenMP like directives for use with GPUs.

GPU Programming ‘Languages’

- **Brook**
 - First widely adopted programming model for general purpose GPU (GPGPU) programming
 - Extends C with data-parallel constructs
 - Concepts such as streams, kernels, reduction operators
- **CUDA – based on ideas of Brook**
 - Solution to run C seamlessly on GPUs (NVIDIA only)
 - CUDA Toolkit contains compiler, math libraries, debugging and profiling tools
 - Lots of code samples, programming guides and other documentation available

GPU Programming 'Languages'

- **CUDA Fortran**
 - Supports CUDA like extensions for Fortran
 - Supported by Portland Group Compilers
- **OpenACC**
 - OpenMP like compiler directives language for C and Fortran
 - Designed to make porting to GPUs easy and quick
 - Full support by Portland Group Compilers
 - Partial support by GNU compilers
(experimental since version 5.1)

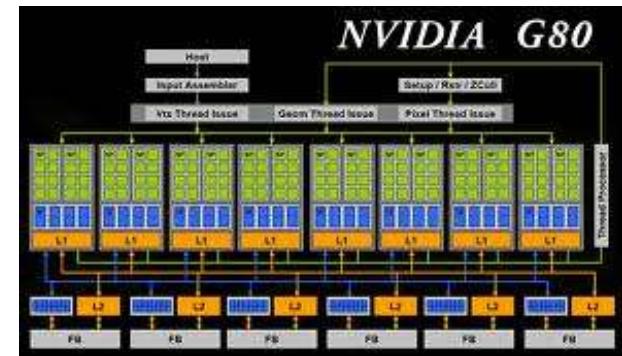
Hardware Complexities

- **Hardware characteristics change across GPU models and generations**
 - Single Precision / Double Precision floating point performance
 - Number of compute cores and multiprocessors
 - Number of threads that the hardware can execute
 - Number of Registers
 - Available GPU Memory, Device / Shared
- **Memory hierarchy needs to be explicitly managed**
 - CPU / GPU global, shared, texture, constant
- **Different vendors work in different ways**
 - NVIDIA vs AMD

Hardware Complexities

C870 – Nov 2006

- First ‘programmable’ Card
- Single Precision Only
- 1.5GB RAM



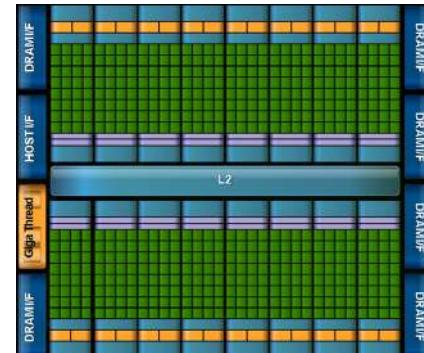
C1060 – Jun 2008

- DP / SP = 1 / 8
- 4GB RAM



C2050 – Nov 2010

- DP / SP = 1 / 2
- 3GB RAM



Hardware Complexities

K10 – Jun 2012

- DP / SP = 1 / 24
- 2 GPUs on 1 board
- 4GB RAM per GPU



K20 – Nov 2012

- DP / SP = 1 / 3
- 5GB RAM



K80 – Nov 2014

- DP / SP = 1 / 3
- 2 GPUs per board
- 2 x 12GB RAM

K40 – Nov 2013

- DP / SP = 1 / 3
- 12GB RAM

Hardware Complexities

M40 – Q4 2015

- DP / SP = 1 / 3
- 12 or 24GB RAM



P100 – Q4 2016

- DP / SP = 1 / 2
- 16GB RAM

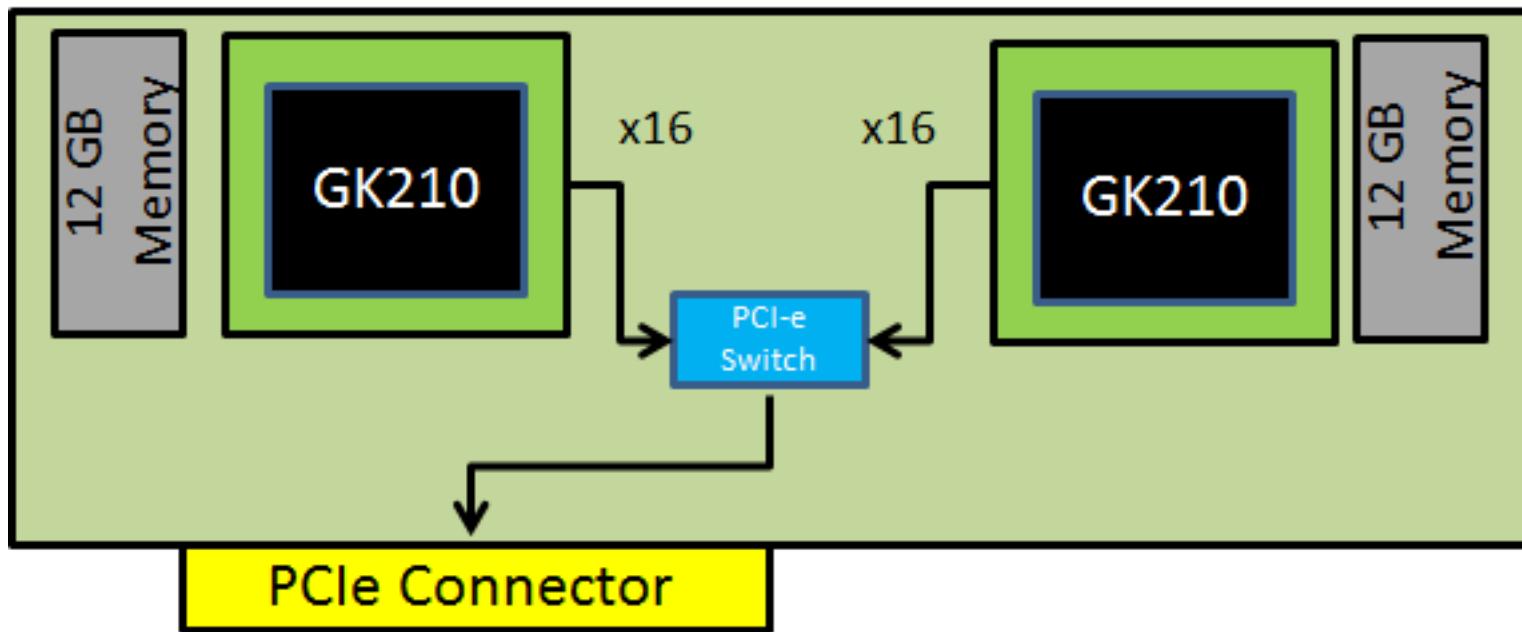


	C2050	K10	K20	K40	K80	M40	P100
#Multi Proc	14	8 (x2)	13	15	13 (x2)	24	56
SP Cores per MP	32	192	192	192	192	128	64
#Cores	448	1,536 (x2)	2,496	2,880	2,496 (x2)	3,072	3,584
Warp Size	32	32	32	32	32	32	32
DP Gflop/s	515	95 (x2)	1,170	1,680	1,455 (x2)	213	5,304

Hardware Complexities

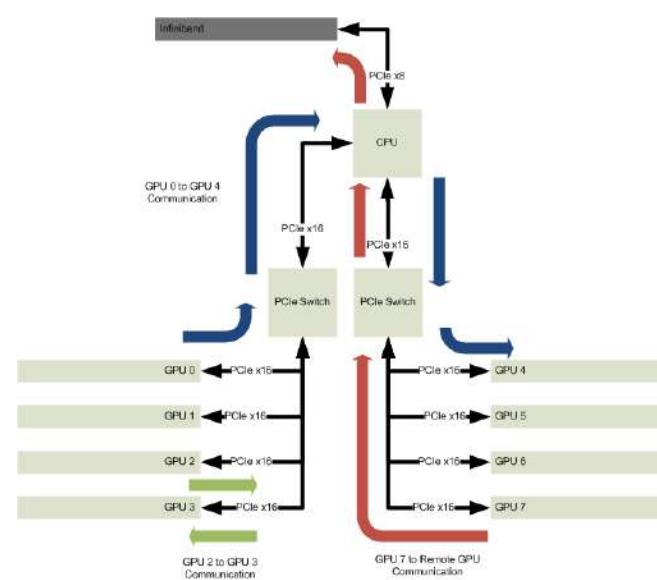
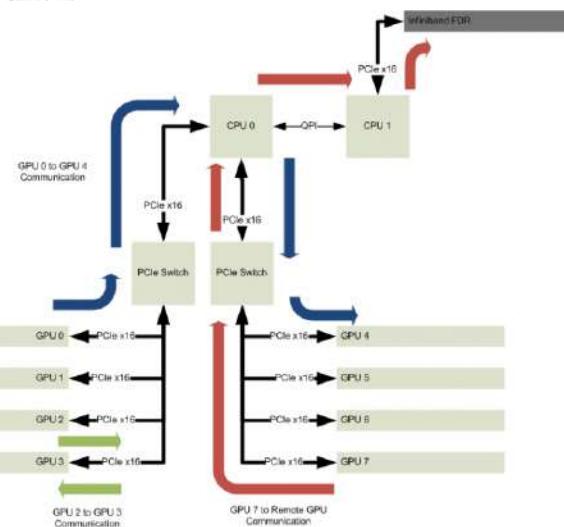
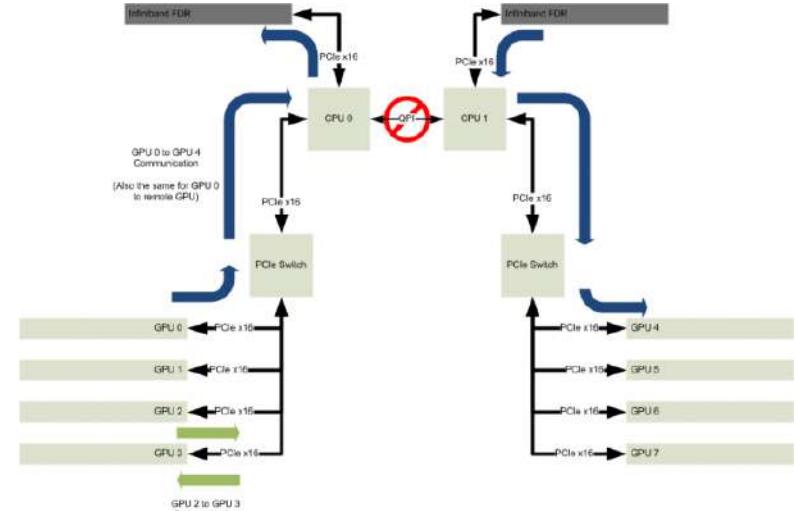
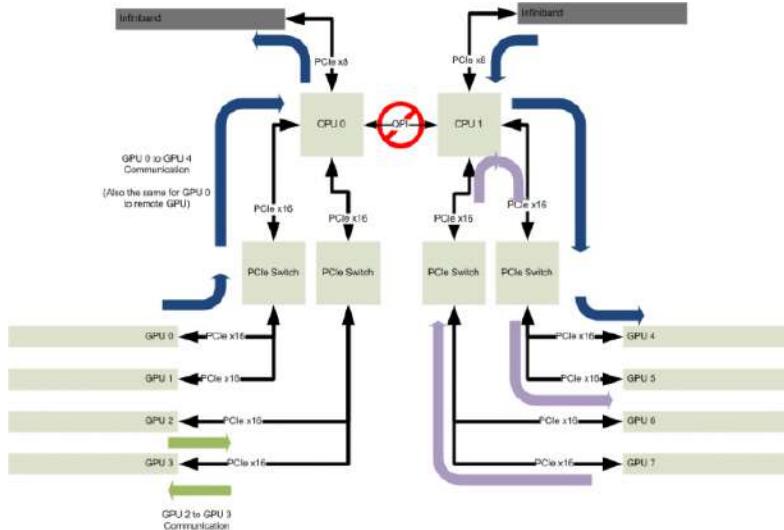
- K80 – 2 GPUs per card

Tesla K80 Block Diagram



Hardware Complexities

PCI-E Hierarchies



Compute Capability

Compute capability (version)	GPUs	Cards
1.0	G80, G92, G92b, G94, G94b	GeForce 8800GTX/Ultra, 9400GT, 9600GT, 9800GT, Tesla C/D/S870, FX4/5600, 360M, GT 420
1.1	G86, G84, G98, G96, G96b, G94, G94b, G92, G92b	GeForce 8400GS/GT, 8600GT/GTS, 8800GT/GTS, 9600 GSO, 9800GTX/GX2, GTS 250, GT 120/30/40, FX 4/570, 3/580, 17/18/3700, 4700x2, 1xxM, 32/370M, 3/5/770M, 16/17/27/28/36/37/3800M, NVS420/50
1.2	GT218, GT216, GT215	GeForce 210, GT 220/40, FX380 LP, 1800M, 370/380M, NVS 2/3100M
1.3	GT200, GT200b	GeForce GTX 260, GTX 275, GTX 280, GTX 285, GTX 295, Tesla C/M1060, S1070, Quadro CX, FX 3/4/5800
2.0	GF100, GF110	GeForce (GF100) GTX 465, GTX 470, GTX 480, Tesla C2050, C2070, S/M2050/70, Quadro Plex 7000, Quadro 4000, 5000, 6000, GeForce (GF110) GTX 560 Ti 448, GTX570, GTX580, GTX590
2.1	GF104, GF114, GF116, GF108, GF106	GeForce 610M, GT 430, GT 440, GTS 450, GTX 460, GT 545, GTX 550 Ti, GTX 560, GTX 560 Ti, 500M, Quadro 600, 2000
3.0	GK104, GK106, GK107	GeForce GTX 690, GTX 680, GTX 670, GTX 660 Ti, GTX 660, GTX 650 Ti BOOST, GTX 650 Ti, GTX 650, GT 640, GeForce GTX 680MX, GeForce GTX 680M, GeForce GTX 675MX, GeForce GTX 675M, GeForce GTX 670MX, GTX 660M, GeForce GT 650M, GeForce GT 645M, GeForce GT 640M, Quadro K600, Quadro K2000, Quadro K4000, Quadro K5000
3.5	GK110	Tesla K20X, K20, GeForce GTX TITAN

- Double Precision Support Begins at V1.3
- Latest compute capability is V6.1
(for Pascal architecture, May 2016)

See: <http://en.wikipedia.org/wiki/CUDA>

Feature support (unlisted features are supported for all compute capabilities)	Compute capability (version)										
	1.0	1.1	1.2	1.3	2.x	3.0	3.5	3.7	5.0	5.2	
Integer atomic functions operating on 32-bit words in global memory	No	Yes									
atomicExch() operating on 32-bit floating point values in global memory	No	Yes									
Integer atomic functions operating on 32-bit words in shared memory	No	Yes									
atomicExch() operating on 32-bit floating point values in shared memory	No	Yes									
Integer atomic functions operating on 64-bit words in global memory	No	Yes									
Warp vote functions	No	Yes									
Double-precision floating-point operations	No	Yes									
Atomic functions operating on 64-bit integer values in shared memory	No	Yes									
Floating-point atomic addition operating on 32-bit words in global and shared memory	No	Yes									
_ballot()	No	Yes									
_threadfence_system()	No	Yes									
_syncthreads_count(), _syncthreads_and(), _syncthreads_or()	No	Yes									
Surface functions	No	Yes									
3D grid of thread block	No	Yes									
Warp shuffle functions	No	Yes									
Funnel shift	No	Yes									
Dynamic parallelism	No	Yes									
Feature support (unlisted features are supported for all compute capabilities)	1.0	1.1	1.2	1.3	2.x	3.0	3.5	3.7	5.0	5.2	
Compute capability (version)											

Technical specifications	Compute capability (version)						
	1.0	1.1	1.2	1.3	2.x	3.0	3.5
Maximum dimensionality of grid of thread blocks	2						3
Maximum x-, y-, or z-dimension of a grid of thread blocks	65535						$2^{31}-1$
Maximum dimensionality of thread block	3						
Maximum x- or y-dimension of a block	512						1024
Maximum z-dimension of a block	64						
Maximum number of threads per block	512						1024
Warp size	32						
Maximum number of resident blocks per multiprocessor	8						16
Maximum number of resident warps per multiprocessor	24	32	48	64			
Maximum number of resident threads per multiprocessor	768	1024	1536	2048			
Number of 32-bit registers per multiprocessor	8 K	16 K	32 K	64 K			
Maximum number of 32-bit registers per thread	128						63
Maximum amount of shared memory per multiprocessor	16 KB						48 KB
Number of shared memory banks	16						32
Amount of local memory per thread	16 KB						512 KB
Constant memory size	64 KB						
Cache working set per multiprocessor for constant memory	8 KB						
Cache working set per multiprocessor for texture memory	Device dependent, between 6 KB and 8 KB						
Maximum width for 1D texture reference bound to a CUDA array	8192						65536
Maximum width for 1D texture reference bound to linear memory	2^{27}						
Maximum width and number of layers for a 1D layered texture reference	8192 x 512						16384 x 2048
Maximum width and height for 2D texture reference bound to a CUDA array	65536 x 32768						65536 x 65535
Maximum width and height for 2D texture reference bound to a linear memory	65000 x 65000						65000 x 65000
Maximum width and height for 2D texture reference bound to a CUDA array supporting texture gather	N/A						16384 x 16384
Maximum width, height, and number of layers for a 2D layered texture reference	8192 x 8192 x 512						16384 x 16384 x 2048
Maximum width, height and depth for a 3D texture reference bound to linear memory or a CUDA array	2048 x 2048 x 2048						4096 x 4096 x 4096

NVIDIA GPU Model Summary

Hardware Version 3.0 / 3.5 (Kepler I / Kepler II)

- Tesla *K20 / K20X / K40 / K80*
- Tesla *K10 / K8*
- GTX-Titan / *GTX-Titan-Black / GTX-Titan-Z*
- *GTX770 / 780* (780Ti only Exxact/RCW custom)
- *GTX670 / 680 / 690*
- Quadro cards supporting SM3.0 or 3.5

Hardware Version 2.0 (Fermi)

- Tesla M2090
- Tesla C2050/C2070/C2075 (and M variants)
- *GTX560 / 570 / 580 / 590*
- *GTX465 / 470 / 480*
- Quadro cards supporting SM2.0

Hardware Version 6.1 (Pascal GP102/104)

- Titan-XP [aka Pascal Titan-X]
- *GTX-1080TI / 1080 / 1070 / 1060*
- Quadro P6000 / P5000
- P4 / P40

Hardware Version 6.0 (Pascal P100/DGX-1)

- Quadro GP100 (with optional NVLink)
- P100 12GB / P100 16GB / DGX-1

Hardware Version 5.0 / 5.5 (Maxwell)

- M4, M40, M60
- *GTX-Titan-X*
- *GTX970 / 980 / 980Ti*
- Quadro cards supporting SM5.0 or 5.5

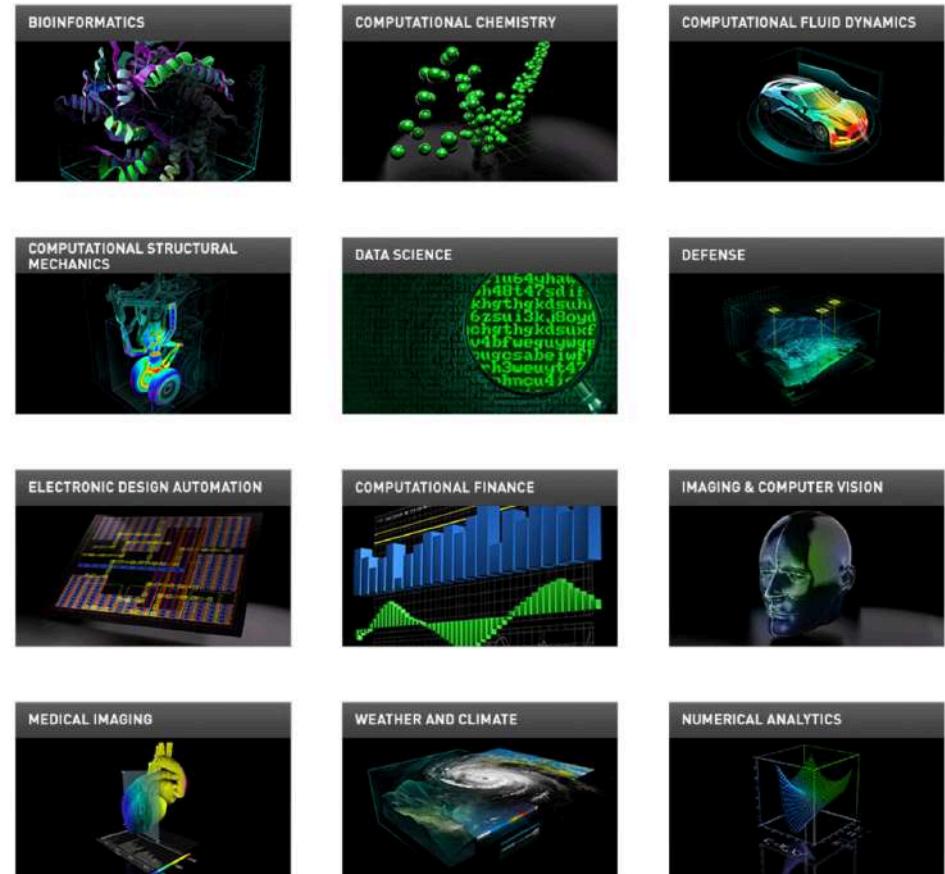
What this all means

- **Never write your code with any assumption for how many threads it will use.**
- **Use CUDA calls to determine the specs of the GPU you are running on.**
- **Avoid using double precision where not specifically needed.**

GPU Accelerated Software Examples

What GPU Codes Exist?

- **Exhaustive list on:**
<http://www.nvidia.com/object/gpu-applications.html>
- **Examples available from almost all fields**
 - Chemistry
 - Life Sciences
 - Astrophysics
 - Finance
 - Medical Imaging
 - Natural Language Processing
 - Social Sciences
 - etc



GPU Computing Applications

Libraries and Middleware						
cuFFT cuBLAS curAND cuSPARSE	CULA MAGMA	Thrust NPP	VSIPL SVM OpenCurrent	PhysX OptiX iRay	cuDNN TensorRT	MATLAB Mathematica
Programming Languages						
C	C++	Fortran	Java Python Wrappers	DirectCompute	Directives (e.g. OpenACC)	
CUDA-enabled NVIDIA GPUs						
Pascal Architecture (compute capabilities 6.x)	GeForce 1000 Series		Quadro P Series		Tesla P Series	
Maxwell Architecture (compute capabilities 5.x)	GeForce 900 Series		Quadro M Series		Tesla M Series	
Kepler Architecture (compute capabilities 3.x)	GeForce 700 Series GeForce 600 Series		Quadro K Series		Tesla K Series	
Fermi Architecture (compute capabilities 2.x)	GeForce 500 Series GeForce 400 Series		Quadro Fermi Series		Tesla 20 Series	
	Entertainment	Professional Graphics	High Performance Computing			

Source: CUDA C Programming Guide

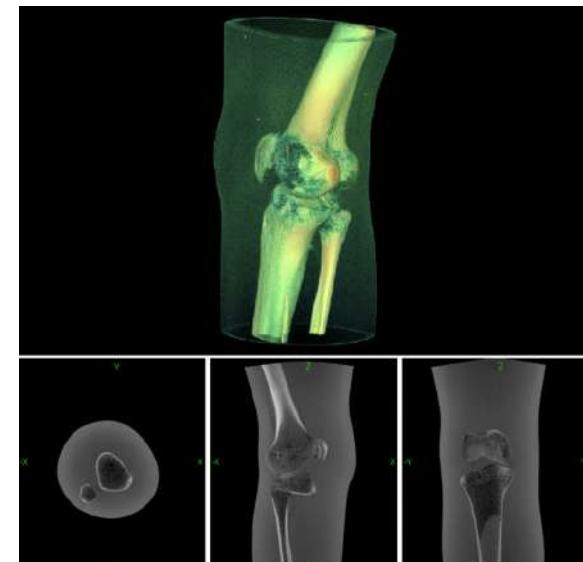
Medical Imaging

- One of the earliest applications to take advantage of GPU acceleration
- E.g. real-time solutions for time-critical imaging



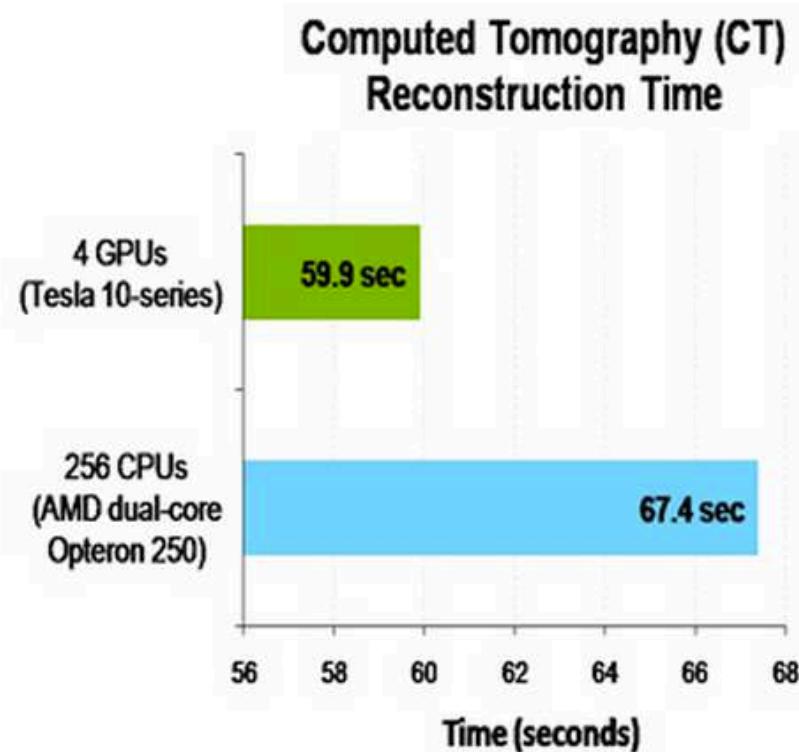
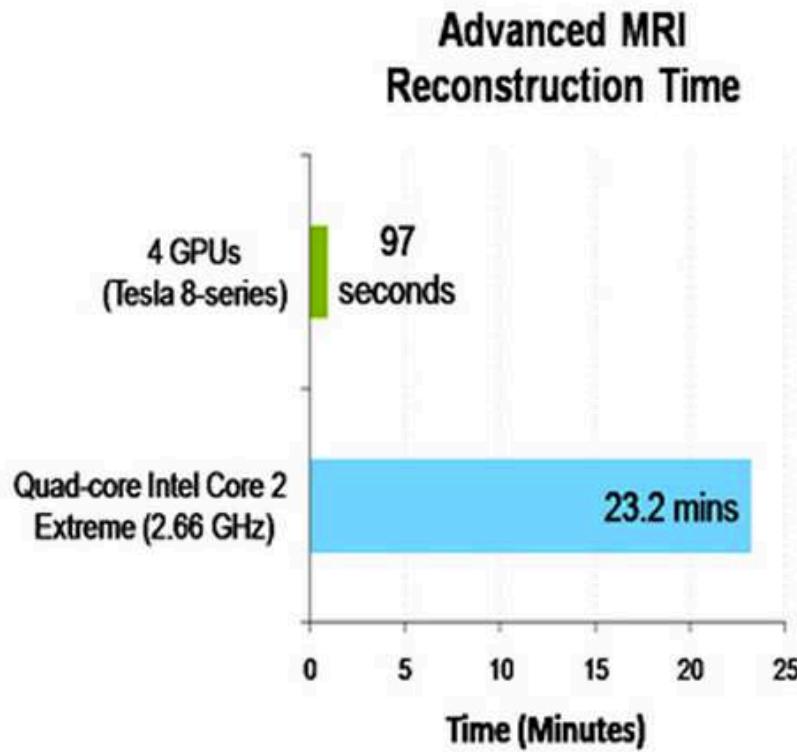
$$p(\mathbf{r}) = \int_{\Lambda} d\lambda \omega^2(\lambda, \mathbf{r}) g_F(u(\lambda, \mathbf{r}), v(\lambda, \mathbf{r})), \quad \mathbf{r}(x, y, z) \in R^3,$$

$$\omega[u, \quad v, \quad 1]^T = \quad \mathbf{M}(\lambda) \cdot [x, \quad y, \quad z, \quad 1]^T.$$

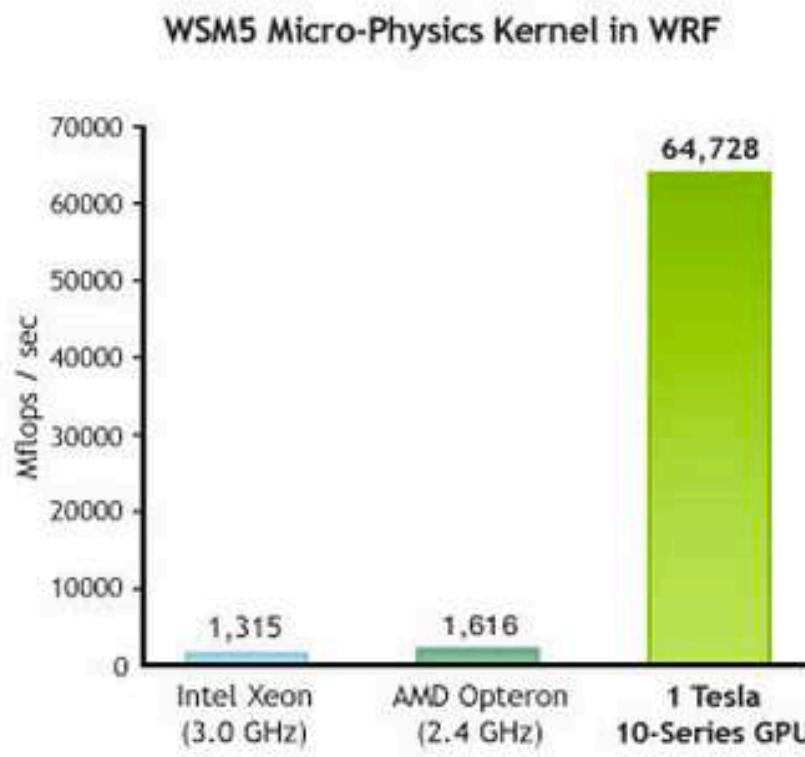


Medical Imaging

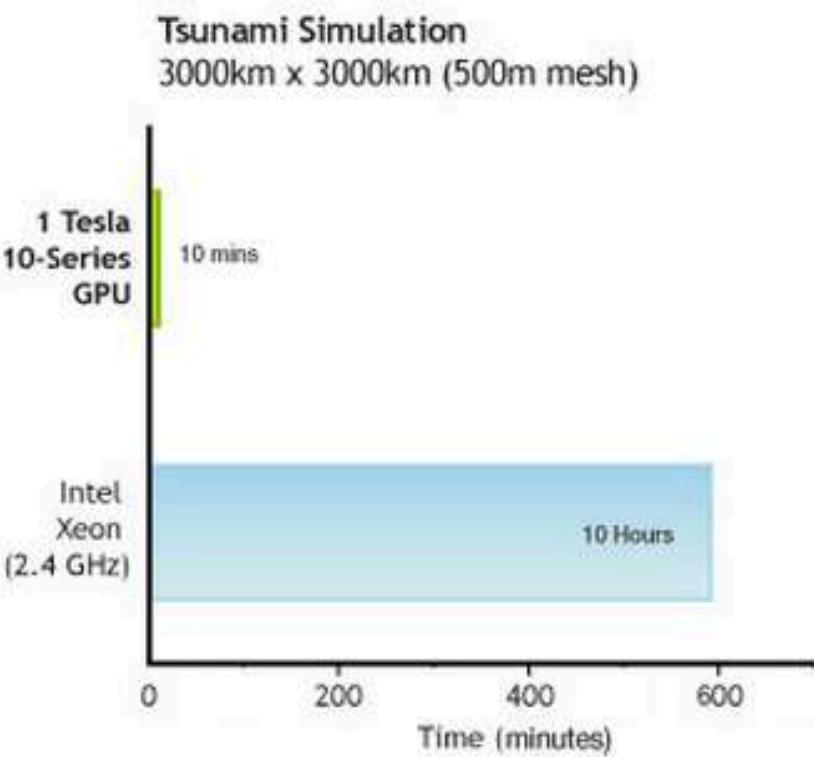
- Advanced MRI, Computed Tomography (CT) etc
- Time to solution CPU vs GPU implementations



Weather, atmospheric, ocean modeling



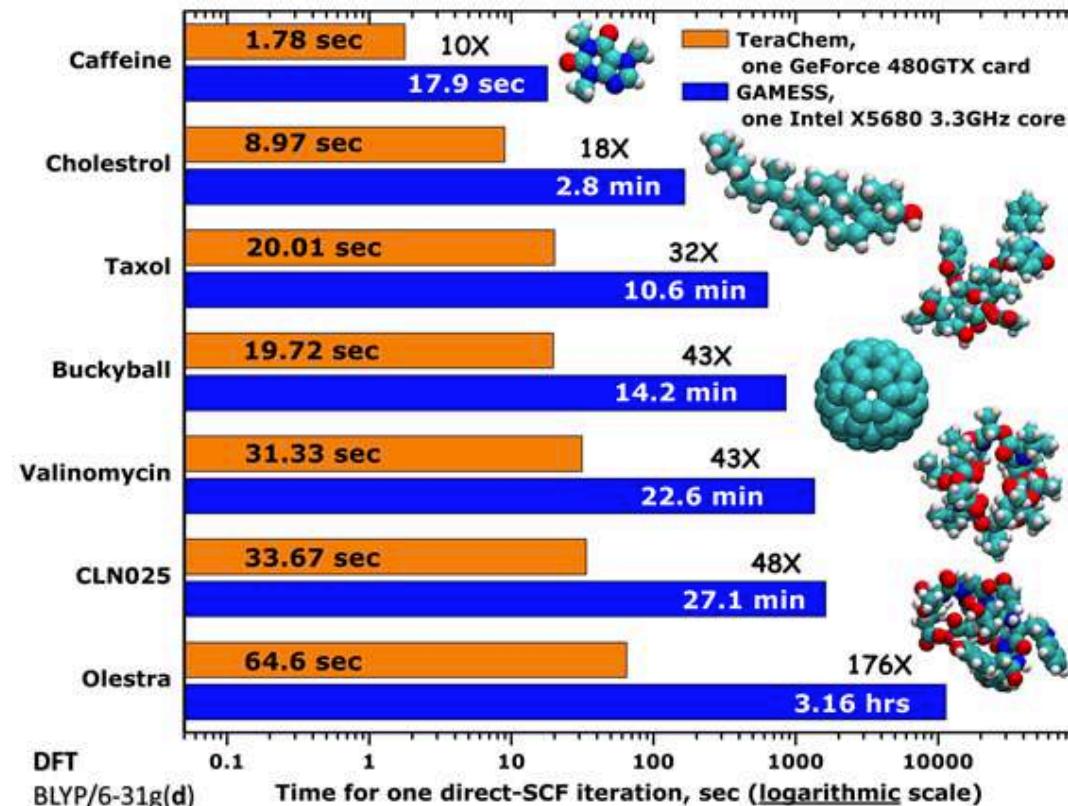
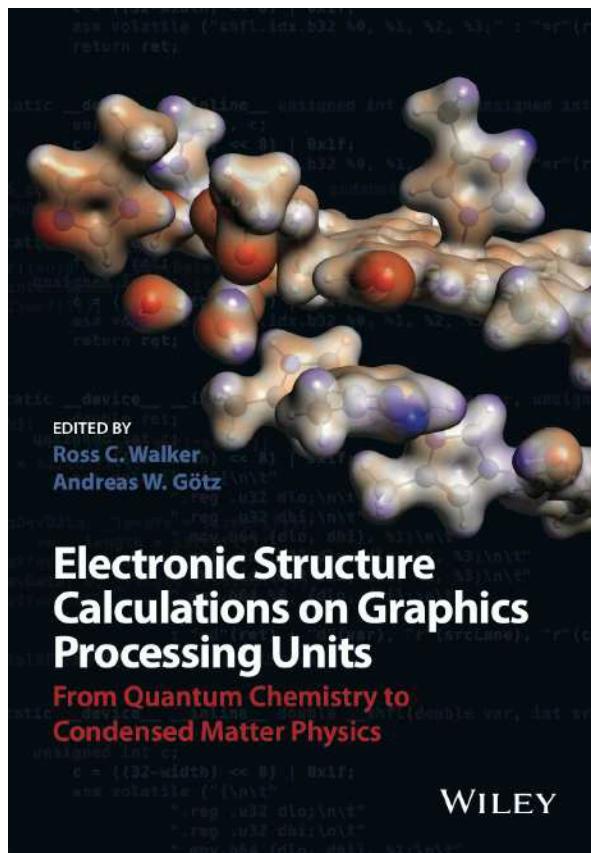
Weather forecasting



Tsunami modeling

Quantum Chemistry

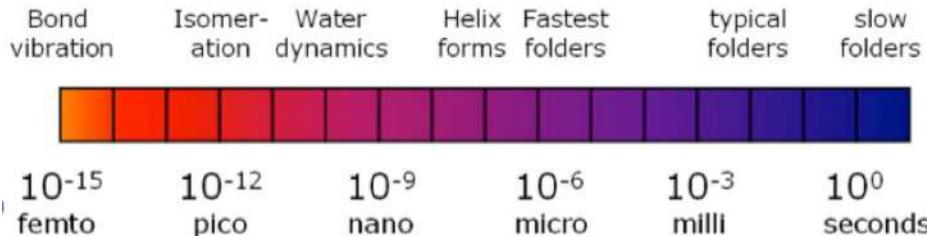
- Prediction of molecular properties from Quantum Mechanics



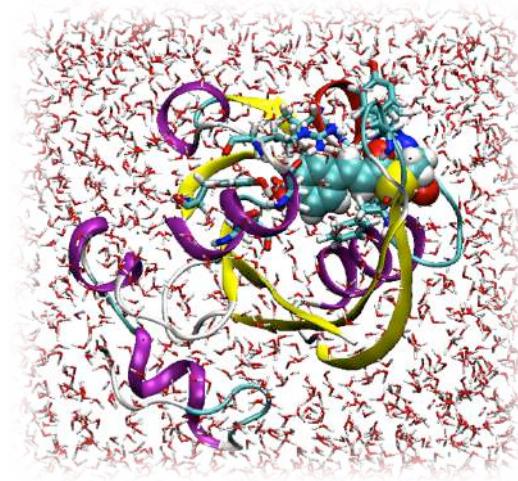
Molecular Dynamics

- Drug design, biocatalysis
- Atomistic simulation of condensed phase systems
- Classical pairwise potentials
- Time evolution
- Simulation time step 2 fs

Relevant timescales



$$V_{\text{AMBER}} = \sum_i^{n_{\text{bonds}}} b_i(r_i - r_{i,\text{eq}})^2 + \sum_i^{n_{\text{angles}}} a_i(\theta_i - \theta_{i,\text{eq}})^2 \\ + \sum_i^{n_{\text{dihedrals}}} \sum_n^{n_{i,\text{max}}} (V_{i,n}/2)[1 + \cos(n\phi_i - \gamma_{i,n})] \\ + \sum_{i < j}^{n_{\text{atoms}}} \left(\frac{A_{ij}}{r_{ij}^{12}} - \frac{B_{ij}}{r_{ij}^6} \right) + \sum_{i < j}^{n_{\text{atoms}}} \frac{q_i q_j}{4\pi \epsilon_0 r_{ij}}$$



- 500 million steps to reach 1 μ s
=> MD step must take < 5 ms to simulate 1 μ s in 1 week

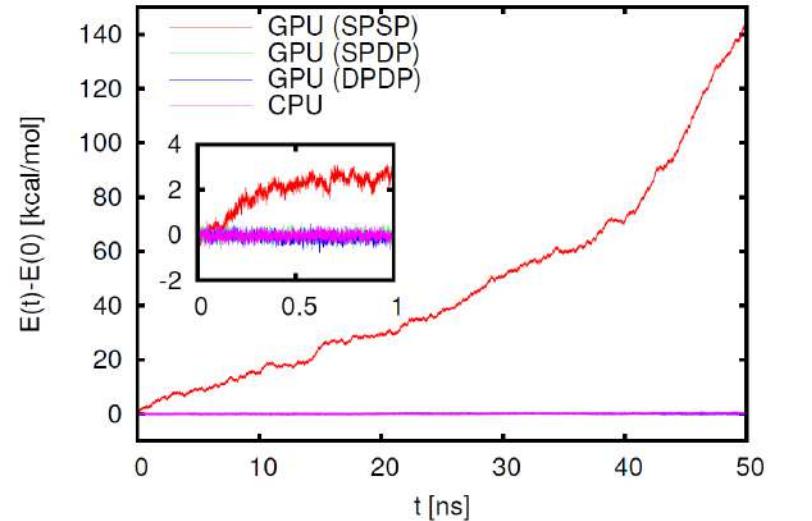
Molecular Dynamics

Precision matters

- **SPSP**
Only single precision
- **SPDP**
Single precision for calculation
Double precision for accumulation
- **DPDP**
Full double precision
- **SPFP**

Single / Double / Fixed precision hybrid.

Uses atomic ops for FP accumulation. Fully deterministic, faster and more precise than SPDP, minimal memory overhead



Q24.40 for Forces, Q34.30 for Energies / Virials

AMBER MD package

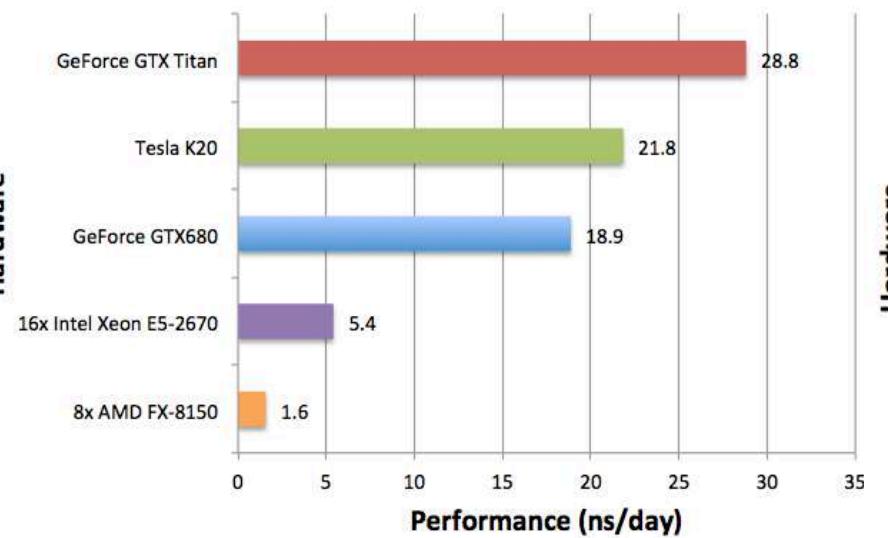
Götz, Williamson, Xu, Poole, Le Grand, Walker, *JCTC* **8** (2012) 1542.

Le Grand, Götz, Walker, *Comp. Phys. Comm.* **184** (2013) 374.

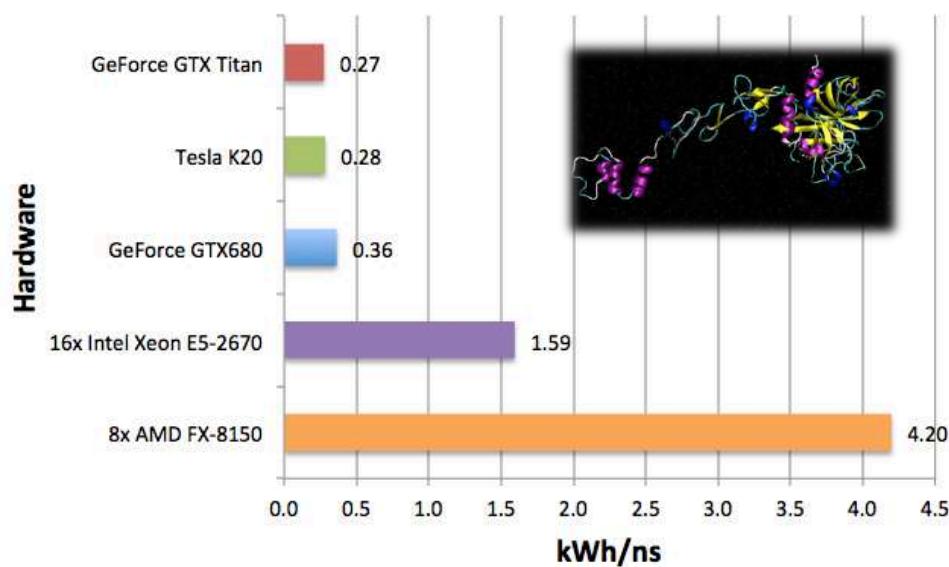
Salomon-Ferrer, Götz, Poole, Le Grand, Walker, *JCTC* **9** (2013) 3878.

Amber Molecular Dynamics

Factor IX (90k atoms, NVE, 2 fs time step)



Factor IX (90k atoms, NVE, 2 fs time step)



- 5x speedup
- 5x power savings

vs single, state-of-the-art CPU node

CUDA Parallel Computing Platform

partly based on material by
Will Ramey - NVIDIA corporation

CUDA Toolkit

- <http://nvidia.com/getcuda>
- **Compiler (nvcc)**
- **Development tools**
 - Debuggers (CUDA-gdb, CUDA-memcheck)
 - Profilers (nvprof, nvvp)
 - Nsight IDE for Eclipse and Visual Studio
- **Libraries**
 - cuBLAS, cuFFT, cuRAND, cuSPARSE, cuSolver, NPP, cuDNN, Thrust, CUDA Math Library,
- **CUDA code samples**

3 Ways to Use GPUs

Applications

Libraries

“Drop-in”
Acceleration

OpenACC
Directives

Easily Accelerate
Applications

Programming
Languages

Maximum
Flexibility

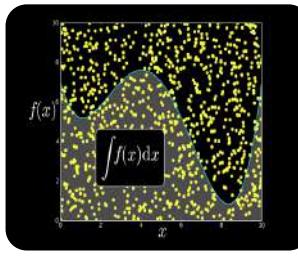
Libraries

- **Ease of use**
 - GPU acceleration without in-depth knowledge of GPU programming
- **“Drop-in”**
 - Many GPU accelerated libraries follow standard APIs
 - Minimal code changes required
- **Quality**
 - High-quality implementations of functions encountered in a broad range of applications
- **Performance**
 - Libraries are tuned by experts
- **Use if you can – (do not write your own matmul)**

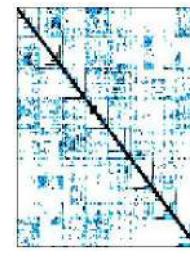
Some GPU accelerated libraries



NVIDIA cuBLAS



NVIDIA cuRAND



NVIDIA cuSPARSE



NVIDIA NPP



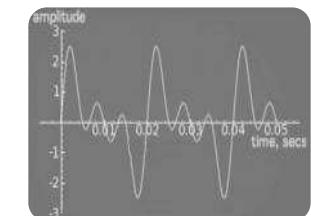
Vector Signal
Image Processing



GPU Accelerated
Linear Algebra



Matrix Algebra
on GPU and
Multicore



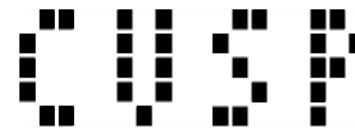
NVIDIA cuFFT



IMSL Library



ArrayFire Matrix
Computations



Sparse Linear
Algebra



C++ STL
Features for
CUDA



3 Steps to Using Libraries

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

saxpy (...) $\xrightarrow{\hspace{1cm}}$ cublasSaxpy (...)

- **Step 2:** Manage data locality

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

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

nvcc myobj.o -l cublas

CUBLAS Library example

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

CUBLAS Library Example

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

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

Add “cublas” prefix
and use device
variables

CUBLAS Library Example

```
int N = 1 << 20;  
cublasCreate(&handle);
```



Initialize CUBLAS

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

```
cublasDestroy(handle);
```



Shut down CUBLAS

CUBLAS Library Example

```
int N = 1 << 20;  
cublasCreate(&handle);  
cudaMalloc((void**)&d_x, N*sizeof(float));  
cudaMalloc((void**)&d_y, N*sizeof(float));
```

Allocate device
vectors

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

```
cudaFree(d_x);  
cudaFree(d_y);  
cublasDestroy(handle);
```

Deallocate device
vectors

CUBLAS Library Example

```
int N = 1 << 20;  
cublasCreate(&handle);  
cudaMalloc((void**)&d_x, N*sizeof(float));  
cudaMalloc((void**)&d_y, N*sizeof(float));  
  
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);  
cublasDestroy(handle);
```

Exercises on SDSC Comet

Hands-on exercises

- CUDA source code examples are available in the SI2017 github repository

`https://github.com/sdsc/sdsc-summer-institute-2017`
directory: `hpc0_gpu`

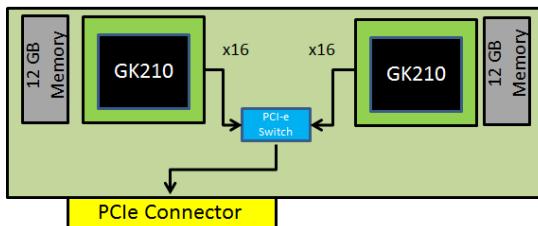
- You are encouraged to compile/execute/modify/play with these examples
- We will use GPU nodes on SDSC Comet

SDSC Comet Supercomputer

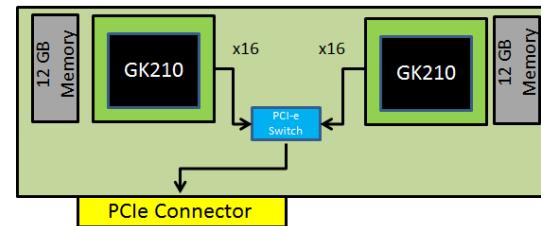
- Contains a GPU Partition
 - 36 GPU nodes
 - 2 x K80 GPUs per node
 - Each K80 = 2 GPUs
 - 4 'physical' GPUs per node
 - You can request 1 GPU on shared GPU nodes



Tesla K80 Block Diagram



Tesla K80 Block Diagram



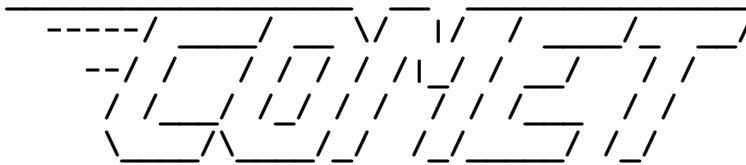
Comet GPU nodes

- **Login to Comet**

```
$> ssh agoetz@comet.sdsc.edu
Last login: Tue Aug  2 15:45:49 2016 from 137.110.219.183
Rocks 6.2 (SideWinder)
Profile built 16:44 08-Feb-2016

Kickstarted 17:18 08-Feb-2016
```

WELCOME TO



- **Check available queues**

```
agoetz@comet-ln2:~> qstat -q
Queue          Memory  CPU Time   Walltime Node  Run Que Lm State
-----        -----
compute        --      -- 48:00:00    72  387  404  --  E R
debug          --      -- 00:30:00     4    0    0  --  E R
shared          --      -- 48:00:00     1  381   65  --  E R
gpu            --      -- 48:00:00     4    18   239  --  E R
gpu-shared      --      -- 48:00:00     1   28   13  --  E R
large-shared    --      -- 48:00:00     1    8    4  --  E R
monitor         --      --      --      --    0    0  --  E R
maint           --      --      --      --    0    0  --  E R
-----
```

We will use
the queue
gpu-shared

Comet GPU nodes

- **Get 2h interactive access to GPU node**

```
agoetz@comet-ln2:~> srun --partition=gpu-shared --nodes=1 --ntasks-per-node=6 \
                     --gres=gpu:1 --reservation=SI2017DAY3 -t 02:00:00 \
                     --pty --wait=0 --export=ALL /bin/bash
srun: job 3650128 queued and waiting for resources
srun: job 3650128 has been allocated resources
```

- **Load CUDA module and check Nvidia CUDA C compiler**

```
[agoetz@comet-30-03 ~]$ module load cuda
[agoetz@comet-30-03 ~]$ nvcc --version
nvcc: NVIDIA (R) Cuda compiler driver
Copyright (c) 2005-2015 NVIDIA Corporation
Built on Mon_Feb_16_22:59:02_CST_2015
Cuda compilation tools, release 7.0, v7.0.27
```

- **Load PGI module and check PGI C compiler**

```
[agoetz@comet-30-03 ~]$ module load pgi
[agoetz@comet-30-03 ~]$ pgcc --version

pgcc 16.10-0 64-bit target on x86-64 Linux -tp haswell
The Portland Group - PGI Compilers and Tools
Copyright (c) 2016, NVIDIA CORPORATION. All rights reserved.
```

Comet GPU nodes

- Use Nvidia system management interface to check available GPUs

```
agoetz@comet-31-13:~/nvidia-smi
```

```
Wed May 6 20:45:15 2015
```

NVIDIA-SMI 346.46 Driver Version: 346.46						
GPU	Name	Persistence-M	Bus-Id	Disp.A	Volatile	Uncorr. ECC
Fan	Temp	Perf	Pwr:Usage/Cap	Memory-Usage	GPU-Util	Compute M.
0	Tesla K80	Off	0000:05:00.0	Off	0%	Default
N/A	41C	P0	56W / 149W	55MiB / 11519MiB	0%	Default
1	Tesla K80	Off	0000:06:00.0	Off	0%	Default
N/A	34C	P0	71W / 149W	55MiB / 11519MiB	0%	Default
2	Tesla K80	Off	0000:84:00.0	Off	0%	Default
N/A	44C	P0	55W / 149W	55MiB / 11519MiB	0%	Default
3	Tesla K80	Off	0000:85:00.0	Off	98%	Default
N/A	36C	P0	74W / 149W	55MiB / 11519MiB		
Processes:						
GPU	PID	Type	Process name	GPU Memory Usage		
No running processes found						

Comet GPU nodes

- Other jobs may already be running on the nodes
(we are using shared nodes)

Processes:				GPU Memory Usage
GPU	PID	Type	Process name	
0	79513	C	pmemd.cuda	68MiB

- The nodes of the shared GPU queue are configured for the CUDA runtime to use only one of the GPUs
- Check environment variable **CUDA_VISIBLE_DEVICES** for the GPU that has been assigned to you

CUDA Toolkit code samples

```
[agoetz@comet-31-16 ~]$ cuda-install-samples-7.0.sh ./
Copying samples to ./NVIDIA_CUDA-7.0_Samples now...
Finished copying samples.
[agoetz@comet-31-16 ~]$ cd NVIDIA_CUDA-7.0_Samples/
[agoetz@comet-31-16 NVIDIA_CUDA-7.0_Samples]$ ls
0_Simple      2_Graphics   4_Finance    6_Advanced    common      Makefile
1_Utils       3_Imaging     5_Simulations 7_CUDALibraries EULA.txt
[agoetz@comet-31-16 NVIDIA_CUDA-7.0_Samples]$ make -j 6
make[1]: Entering directory `/home/agoetz/NVIDIA_CUDA-7.0_Samples/0_Simple/
simpleMultiCopy'
/usr/local/cuda-7.0/bin/nvcc -ccbin g++ -I../../common/inc -m64 -gencode
arch=compute_20,code=sm_20 -gencode arch=compute_30,code=sm_30 -gencode
arch=compute_35,code=sm_35 -gencode arch=compute_37,code=sm_37 -gencode
arch=compute_50,code=sm_50 -gencode arch=compute_52,code=sm_52 -gencode
arch=compute_52,code=compute_52 -o simpleMultiCopy.o -c simpleMultiCopy.cu
```

Copy and compile CUDA code samples

- **Compilation takes a while**
(executables will be in sub dir `bin/x86_64/linux/release/`)
- **Compile individual examples, e.g.**
`1_Utils/deviceQuery`
- **Have a look at some of the code samples**

CUDA Toolkit code samples

```
[agoetz@comet-31-16 NVIDIA_CUDA-7.0_Samples]$ cd 1_Utils/deviceQuery  
[agoetz@comet-31-16 deviceQuery]$ make  
/usr/local/cuda-7.0/bin/nvcc -ccbin g++ -I../../common/inc -m64 -gencode  
arch=compute_30  
...  
[agoetz@comet-31-16 deviceQuery]$ ./deviceQuery ← Run CUDA  
./deviceQuery Starting... code samples
```

CUDA Device Query (Runtime API) version (CUDART static linking)

Detected 1 CUDA Capable device(s)

Device 0: "Tesla K80"

CUDA Driver Version / Runtime Version	8.0 / 7.0
CUDA Capability Major/Minor version number:	3.7
Total amount of global memory: bytes)	11440 MBytes (11995578368
(13) Multiprocessors, (192) CUDA Cores/MP:	2496 CUDA Cores
GPU Max Clock rate:	824 MHz (0.82 GHz)
Memory Clock rate:	2505 Mhz

- **deviceQuery gives information on available GPUs**

CUDA Toolkit code samples

- **Matrix multiplication example**

```
agoetz@comet-30-11:~/cd NVIDIA_CUDA-7.0_Samples/0_Simple/  
agoetz@comet-30-11:~/NVIDIA_CUDA-7.0_Samples/0_Simple>./matrixMul/matrixMul  
[Matrix Multiply Using CUDA] - Starting...  
GPU Device 0: "Tesla K80" with compute capability 3.7  
  
MatrixA(320,320), MatrixB(640,320)  
Computing result using CUDA Kernel...  
done  
Performance= 231.28 GFlop/s, Time= 0.567 msec, Size= 131072000 Ops, WorkgroupSize= 1024 threads/block  
Checking computed result for correctness: Result = PASS
```

NOTE: The CUDA Samples are not meant for performance measurements. Results may vary when GPU Boost is enabled.

- **Matrix multiplication example with CUBLAS**

```
agoetz@comet-30-11:~/NVIDIA_CUDA-7.0_Samples/0_Simple>./matrixMulCUBLAS/matrixMulCUBLAS  
[Matrix Multiply CUBLAS] - Starting...  
GPU Device 0: "Tesla K80" with compute capability 3.7  
  
MatrixA(320,640), MatrixB(320,640), MatrixC(320,640)  
Computing result using CUBLAS...done.  
Performance= 952.24 GFlop/s, Time= 0.138 msec, Size= 131072000 Ops  
Computing result using host CPU...done.  
Comparing CUBLAS Matrix Multiply with CPU results: PASS
```

CUDA C Basics

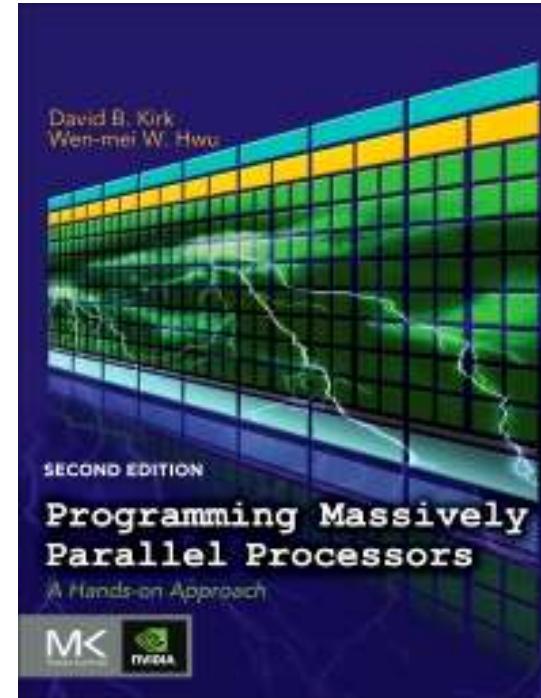
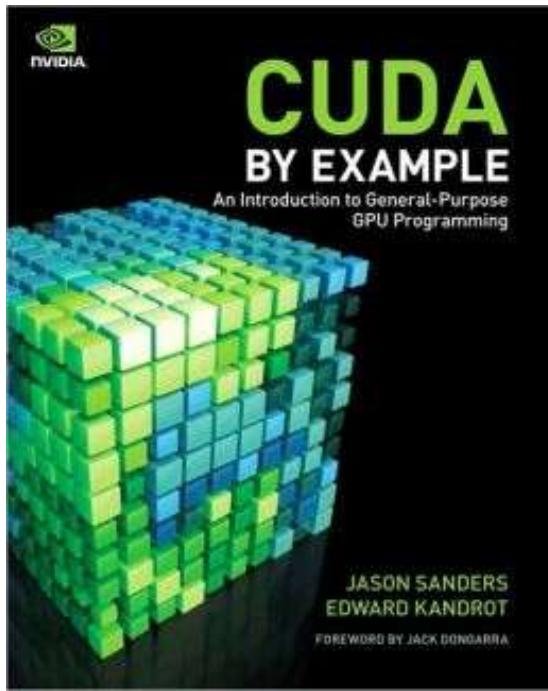
partly based on material by
Mark Harris - NVIDIA corporation

Content Overview

Learn how to write massively parallel programs for GPUs using CUDA:

- Start from “Hello World!” program
- Write and launch CUDA C kernels
- Manage GPU memory
- Manage communication and synchronization
- Query device properties
- Error handling
- Asynchronous operations, CUDA streams

Recommended Reading



- CUDA Programming Guide

<http://docs.nvidia.com/cuda/cuda-c-programming-guide/>

Code samples for this course

- In SI2017 github repository

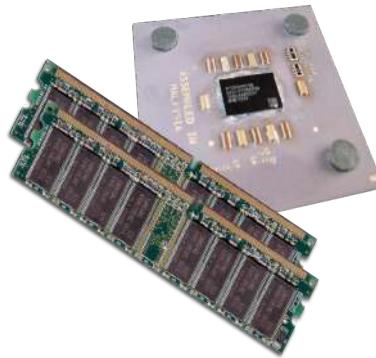
<https://github.com/sdsc/sdsc-summer-institute-2017>

directory: `hpc0_gpu/cuda-samples`

- “Hello world”
- Addition, vector addition
- Squaring matrix elements
- 1D stencil
- **We will discuss these simple code samples**

Heterogeneous Computing

- **Host** The CPU and its memory
- **Device** The GPU and its memory
- Device code is launched from Host code

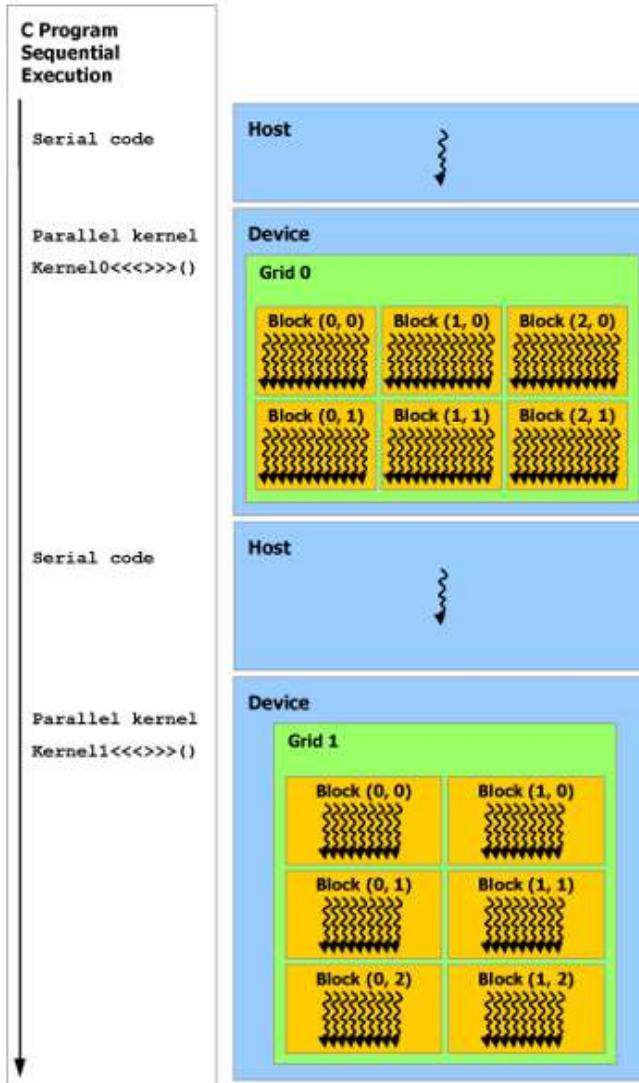


Host

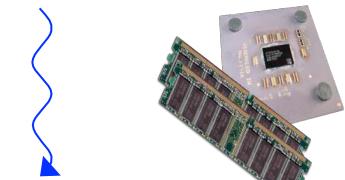


Device

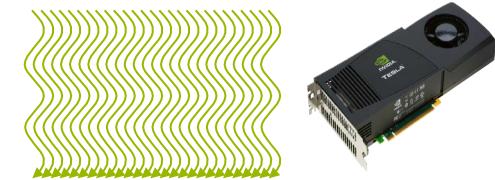
Heterogeneous Computing



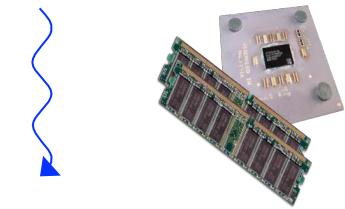
serial code



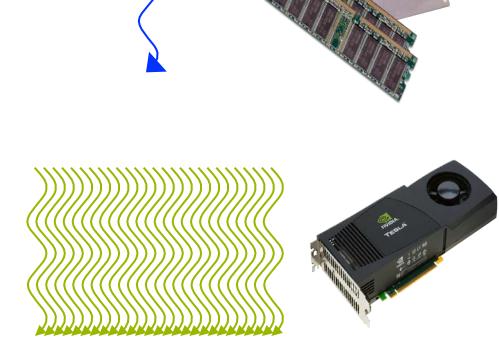
parallel code



serial code



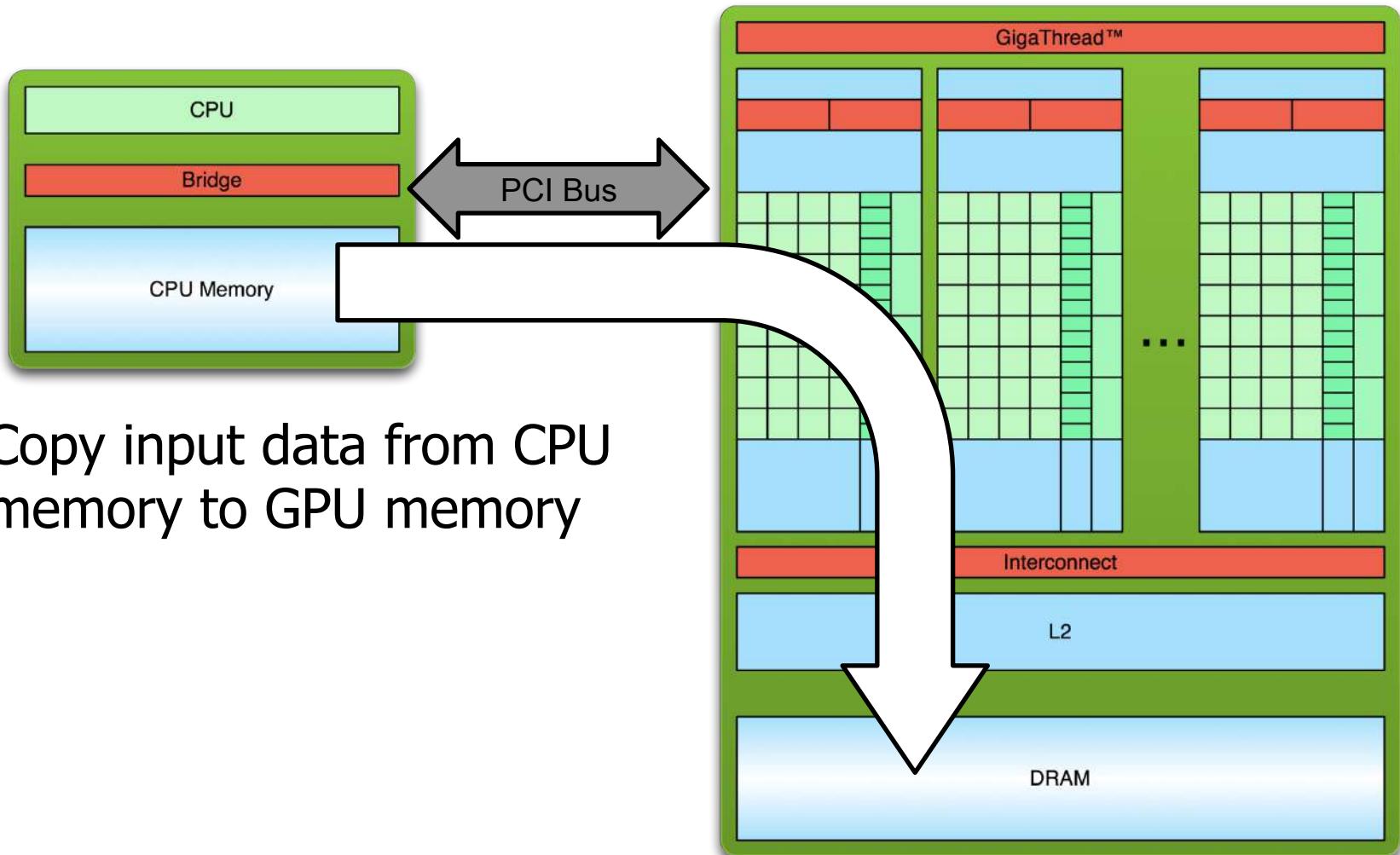
parallel code



Processing Flow

Host

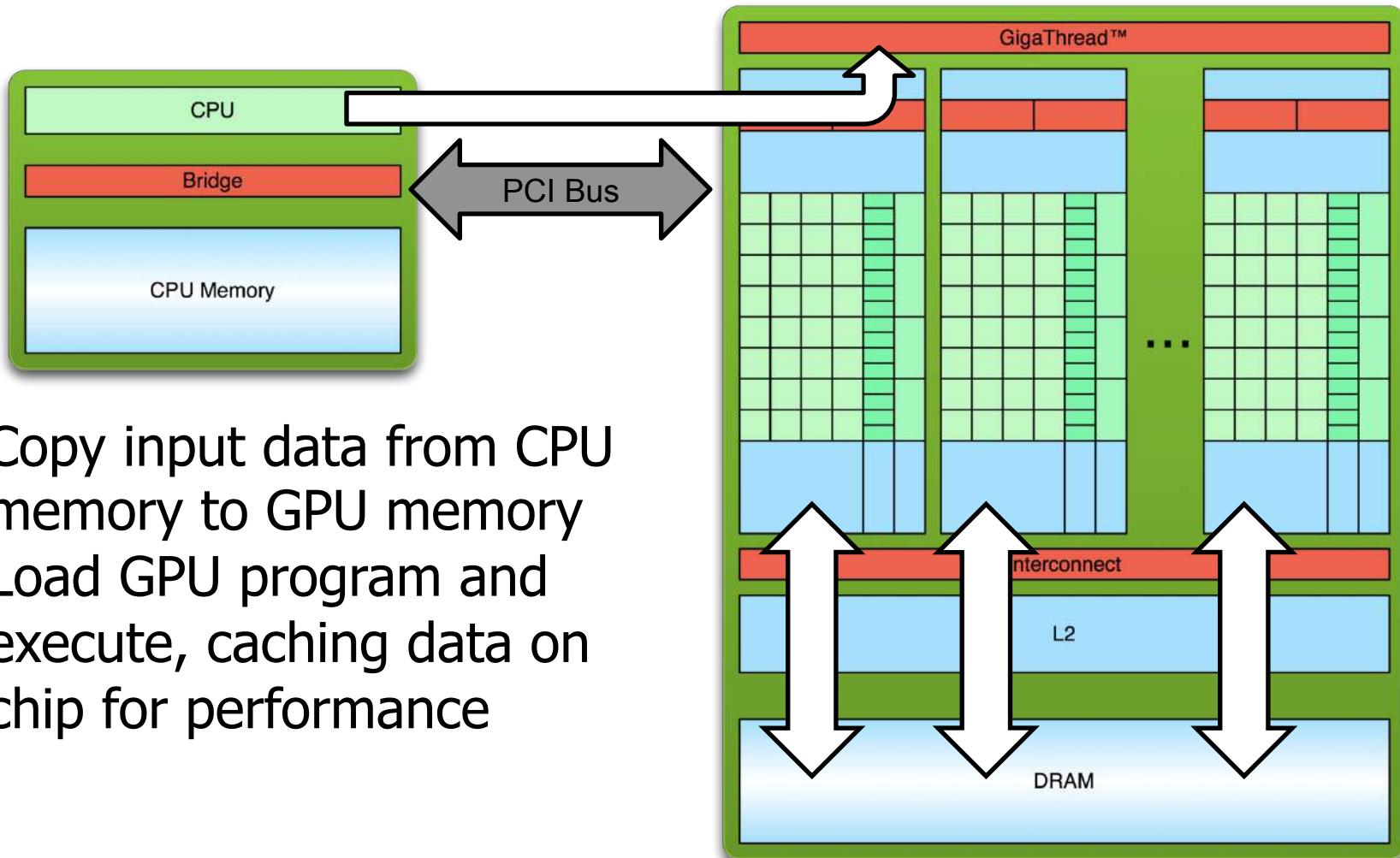
Device



Processing Flow

Host

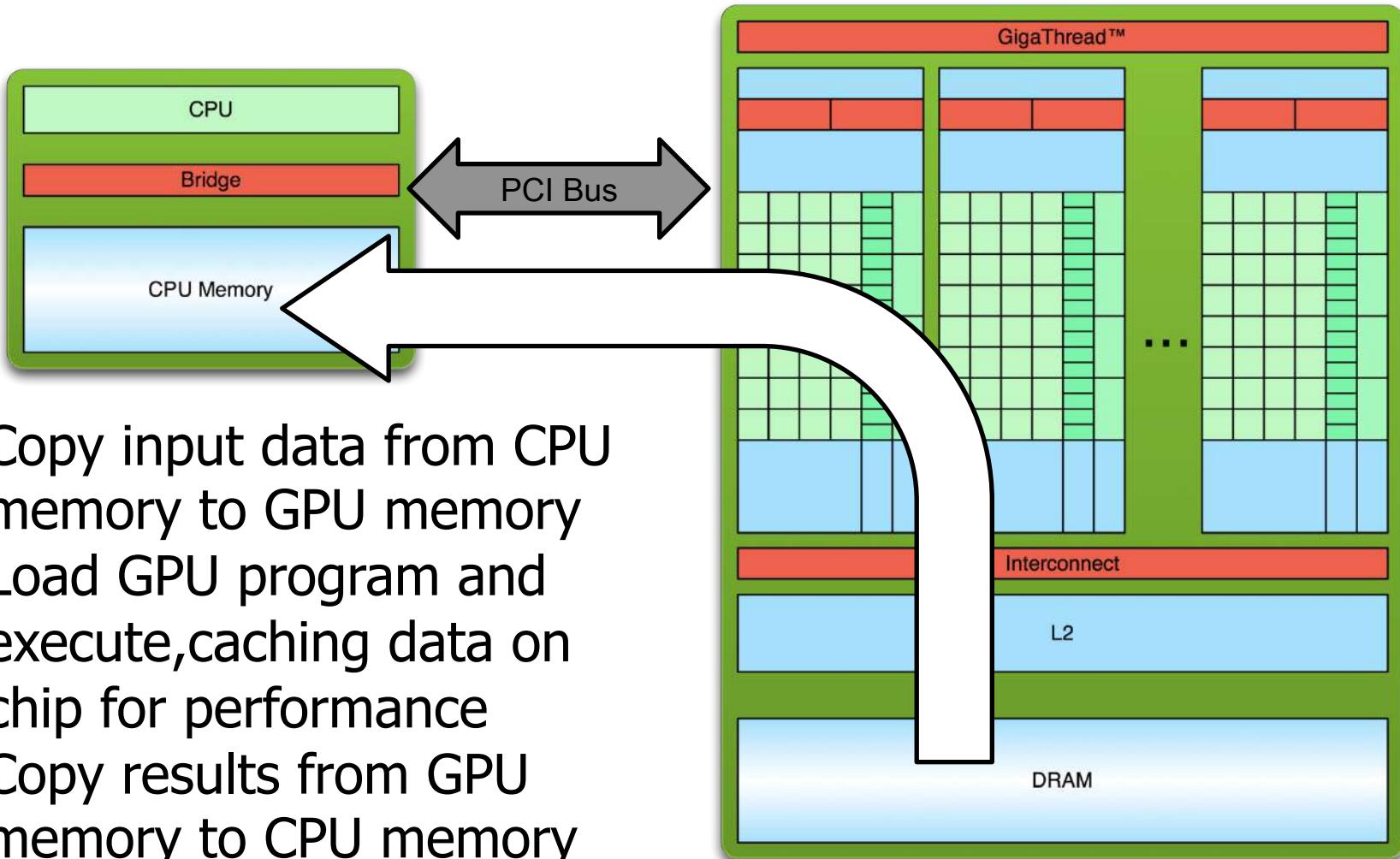
Device



Processing Flow

Host

Device



Hello World! CPU C code

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

- Standard C code that runs on the host
- NVIDIA compiler (nvcc) can be used to compile

```
$> nvcc hello_world_cpu.cu  
$> ./a.out  
Hello World!
```

Hello World! with Device Code

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

- Contains code that is executed on the device (though doing nothing)
- Two new syntactic elements...

Hello World! with Device Code

- CUDA C keyword `__global__` indicates a function that
 - runs on the device (and must return `void`)
 - is called from the host code

```
__global__ void my_kernel(void) {  
}
```

- `nvcc` separates source code into host and device components
 - device functions processed by `nvcc`
 - host functions processed by standard C compiler

Hello World! with Device Code

- Triple angle brackets mark a call from host code to device code
 - called kernel launch
 - Parameters in brackets explained later

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

- It's that simple to execute a function on the GPU

Hello World! with Device Code

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

- **my_kernel** does nothing...
- So let's make the GPU do some work...

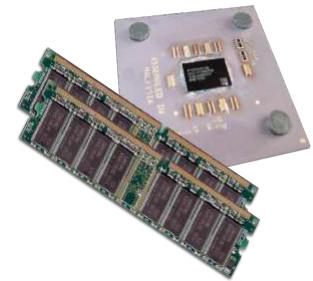
Addition on the device

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

- Remember: `__global__` is a CUDA C keyword, thus
 - `add()` will execute on the device
 - `add()` will be called from the host
- Thus `a`, `b` and `c` must point to device memory

Memory management

- Host and device memory are separate
 - Host pointers point to CPU memory
 - Can be passed to/from device code
 - Cannot be dereferenced in device code!
 - Device pointers point to GPU memory
 - Can be passed to/from host code
 - Cannot be dereferenced in host code!
- CUDA API handles device memory
 - `cudaMalloc()`, `cudaFree()`, `cudaMemcpy()`
 - equivalent to C `malloc()`, `free()`, `memcpy()`



Addition on the device

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

- How do we reserve memory on the device?
- How do we transfer data from the host to the device?
- This happens in the host C code that launches the kernel. Let's see how this works...

Addition on the device

```
int main(void) {
    int h_a, h_b, h_c;      // host copies
    int *d_a, *d_b, *d_c; // device copies
    int size = sizeof(int);

    // Allocate memory on device
    cudaMalloc((void **) &d_a, size);
    cudaMalloc((void **) &d_b, size);
    cudaMalloc((void **) &d_c, size);

    // Setup input values
    h_a = 5;
    h_b = 7;
```

Addition on the device

```
// Copy input data to device
cudaMemcpy(d_a, &h_a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, &h_b, size, cudaMemcpyHostToDevice);

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

// Copy results back to host
cudaMemcpy(&h_c, d_c, size, cudaMemcpyDeviceToHost);

// Deallocate memory
cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);

printf("%d + %d = %d", h_a, h_b, h_c)
return 0;
}
```

Addition on the device

- OK, so we know the basic workflow:
 1. Allocate memory on the device
 2. Copy input data to the device
 3. Launch a kernel on the device
 4. Copy results back to the host
 5. Deallocate memory on the device
- Let's move on to parallel computing on the GPU using CUDA

Parallelization with CUDA using blocks

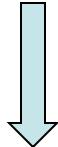
Parallelization with CUDA

- GPU computing is about massive parallelism
 - How do we run code in parallel using CUDA?
- Instead of executing the kernel `add()` once, we execute it N times in parallel
- The **central idea defining GPU computing:**
 - Kernels look like serial programs
 - Write programs as if they run on a single thread
 - The GPU will run that program on many threads

Parallelization with CUDA

- Executing `add()` N times

```
add<<<1,1>>>(); // launch 1 copy
```



```
add<<<N,1>>>(); // launch N copies
```

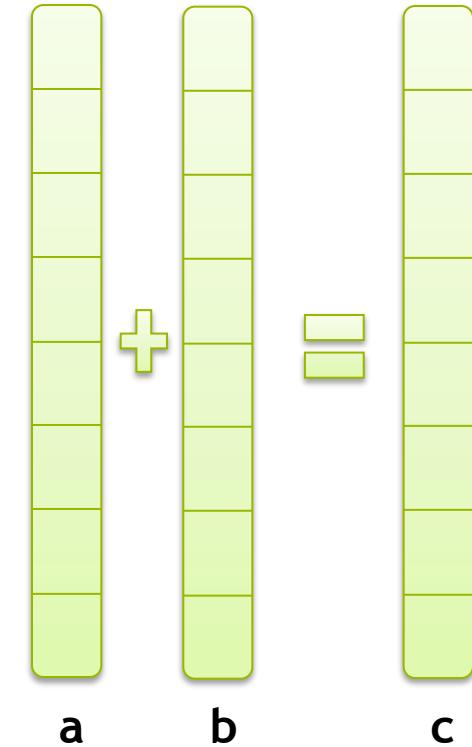
- The GPU is good at
 - efficiently launching lots of threads
 - running lots of threads in parallel
(many more than processors on the device)
- But why launch N identical copies?

Vector addition

- CPU code (serial) uses a loop

```
#define N 512
void vadd_cpu(int *a, int *b, int *c) {
    int i;
    for (i=0; i<N; i++) {
        c[i] = a[i] + b[i];
    }
}
```

- GPUs can do this in parallel by running N copies of the **add()** kernel, each copy working on a different vector element



Parallel vector addition (1)

- Parallelized `add()` kernel

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

- Each parallel invocation of `add()` is called a **block**. The set of blocks is called a **grid**
- Each kernel instance knows its block index
- By using its index, each block operates on different data

Parallel vector addition (1)

- We launch N blocks of the `add()` kernel

```
// launch N copies  
add<<<N,1>>>(d_a, d_b, d_c);
```

- Kernel call needs to be consistent with kernel implementation
- On the device, each block can execute in parallel, depending on the number of available compute cores

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];
```

Parallel vector addition (1)

```
// CUDA kernel for vector addition
__global__ void add(int *a, int *b, int *c) {
    int tid = blockIdx.x;
    c[tid] = a[tid] + b[tid];
}

#define N 512
int main(void) {
    int h_a[N], h_b[N], h_c[N]; // host copies
    int *d_a, *d_b, *d_c;       // device copies
    int size = N * sizeof(int);

    // Allocate memory on device
    cudaMalloc((void **) &d_a, size);
    cudaMalloc((void **) &d_b, size);
    cudaMalloc((void **) &d_c, size);
```

Parallel vector addition (1)

```
// Setup input values
get_input_vectors(h_a, h_b);

// Copy input data to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, h_b, size, cudaMemcpyHostToDevice);

// Launch N blocks of the add() kernel
add<<<N,1>>>(d_a, d_b, d_c);

// Copy results back to host
cudaMemcpy(h_c, d_c, size, cudaMemcpyDeviceToHost);

// Deallocate memory
cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);

return 0;
```

Review

- Distinguish host and device code
 - host = CPU
 - device = GPU
- CUDA keyword **__global__** declares functions as device code
 - execute on device
 - called from host
- Parameters can be passed from host code to device function

Review

- Basic device memory management
 - **cudaMalloc()**
 - **cudaMemcpy()**
 - **cudaFree()**
- Kernels are launched by CPU in parallel
 - Launch N blocks (copies) of `add()` with
add<<<N, 1>>>(...);
 - Use **blockIdx.x** to access block index

Parallelization with CUDA using blocks and threads

CUDA threads

- Blocks can be split into parallel **threads**
- Parallelized **add()** kernel **using threads**

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

- Each kernel instance knows its index
- Parallel kernel call needs to be consistent

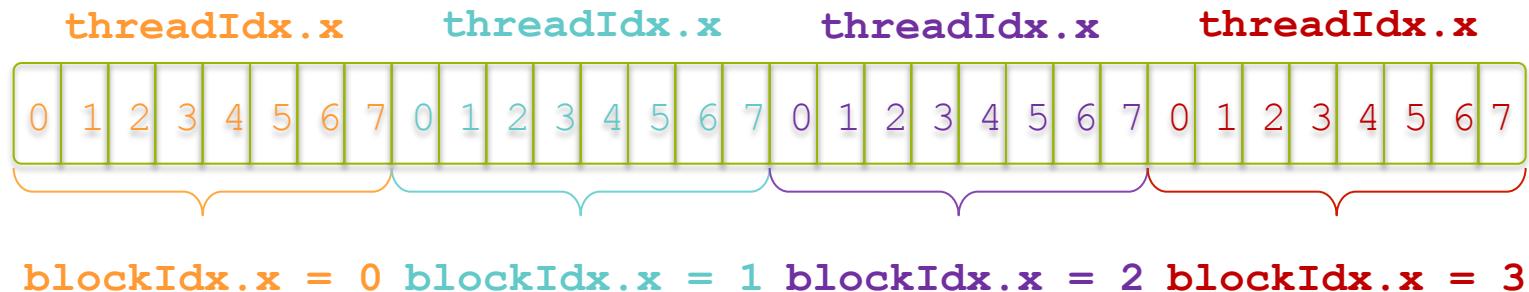
```
// launch N copies  
add<<<1,N>>>(d_a, d_b, d_c);
```

CUDA blocks and threads

- We can use blocks or threads
 - Many blocks with one thread
 - One block with many threads
- Number of allowed threads per block is limited by hardware (typically 1024)
- We can combine blocks and threads
 - need to take care with indexing
- CUDA supports 3D blocks and threads
(more later)

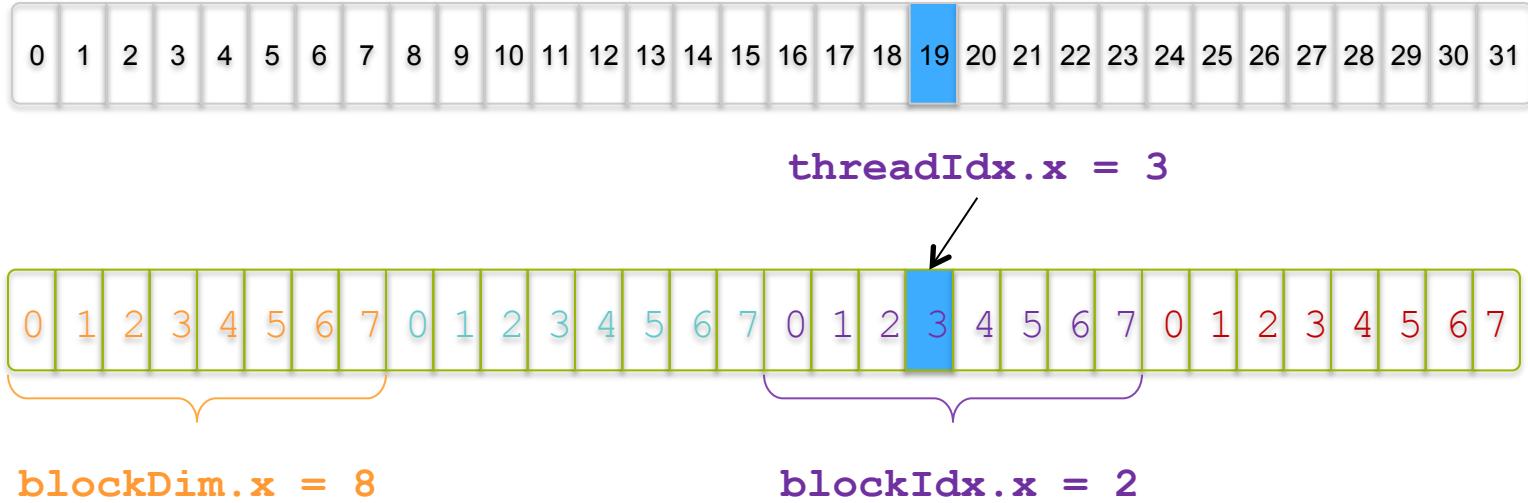
Indexing with blocks and threads

- Example to compute offset into an array
 - 1 element per thread
 - 8 threads per block



- Built-in variable **`blockDim.x`** knows number of threads per block (block dimension)
 - this makes it possible to calculate a unique index (e.g. offset into an array) for each kernel

Indexing with blocks and threads



- Calculate a unique index
(Example: blue field above has index 19)

```
int tid = threadIdx.x + blockIdx.x * blockDim.x
        = 3             + 2             * 8
        = 19
```

Parallel vector addition (2)

- Parallelized `add()` using blocks and threads

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

- Corresponding kernel call

```
// launch N/TPB copies with  
// TPB threads per block  
add<<<N/TPB,TPB>>>(d_a, d_b, d_c);
```

Handle arbitrary vector sizes (1)

- Problem size **N** is typically not a multiple of our chosen **blockDim.x**
- Launch a sufficient number of kernels

```
// launch at least N/TBP copies with
// TPB threads per block
add<<< (N+TBP-1)/TPB,TPB>>>(d_a, d_b, d_c, N);
```

- Ensure to stay within array boundaries

```
__global__ void add(int *a, int *b, int *c, int n){
    int tid = threadIdx.x + blockDim.x * blockIdx.x;
    if (tid < n)
        c[tid] = a[tid] + b[tid];
}
```

Why blocks and threads?

- Combination of threads and blocks seems to add complexity. Reason is mapping to hardware.
- Threads within a block can
 - communicate
 - synchronize
- The number of threads per block is limited by the hardware
- Note: Thread block size should be a multiple of 32 for performance reasons since kernels issue instructions in warps (32 threads)

Review

- We write a kernel that looks like it runs on one thread
- We can launch that kernel on any number of threads
 - Use `kernel<<<(N+TPB-1)/TPB, TPB>>>()`
- Each thread knows its index in the block and grid
 - use `blockIdx.x` to get the block index
 - use `blockDim.x` to get the block size
 - use `threadIdx.x` to get the thread index

```
tid = threadIdx.x + blockIdx.x * blockDim.x
```

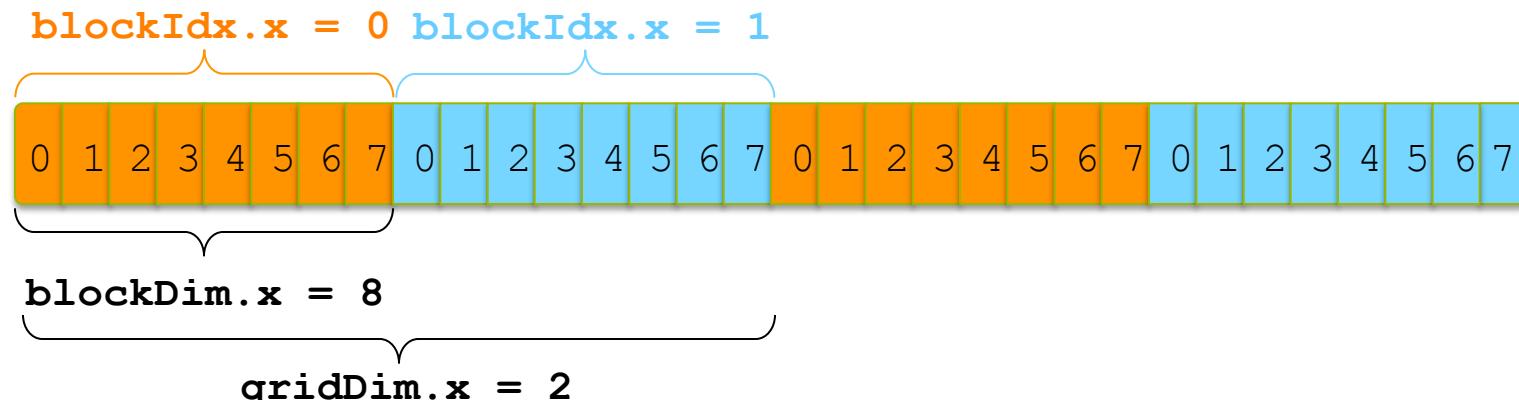
Handle arbitrary vector sizes (2)

- Maximum grid size is limited (usually 65,535)
- Maximum block size is limited (usually 1,024)
- We thus need to
 - launch a fixed number of blocks and threads
 - rewrite our kernel for fixed grid and block size
- Built-in variable `gridDim.x` knows number of blocks in grid
- For many kernels, performance will be optimal for a GPU-hardware dependent combination of grid / block size

Handle arbitrary vector sizes (2)

- Example: If we launch 2 blocks with 8 threads each, then kernels with

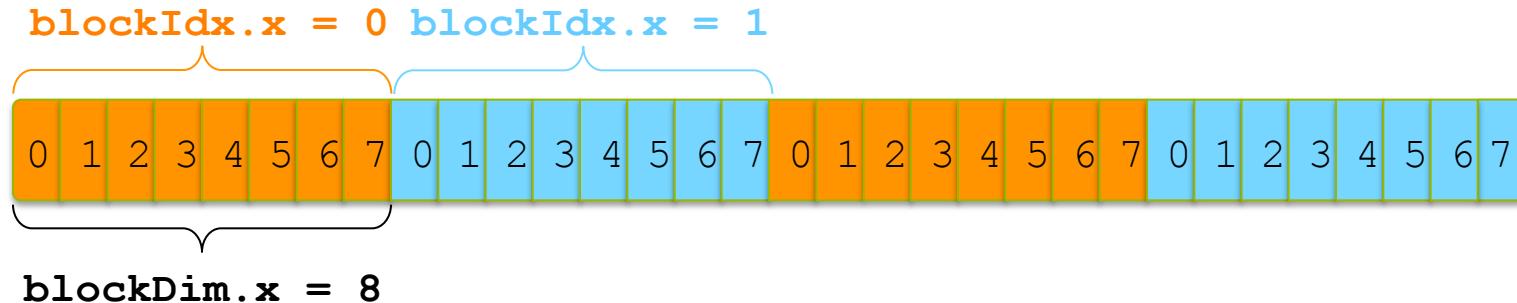
- `blockIdx.x=0` need to work on blocks 0 and 2
 - `blockIdx.x=1` need to work on blocks 1 and 3



- Each kernel needs to know the stride required for accessing its data elements

```
int stride = blockDim.x * gridDim.x
```

Handle arbitrary vector sizes (2)



```
__global__ void add(int *a, int *b, int *c, int n){  
    int tid = threadIdx.x + blockDim.x * blockIdx.x;  
    int stride = blockDim.x * gridDim.x;  
    while (tid < n) {  
        c[tid] = a[tid] + b[tid];  
        tid += stride  
    }  
}
```

- We can now launch a fixed number of kernels:

```
add<<<NBL,TPB>>>(d_a, d_b, d_c, N);
```

Vector Add Exercise

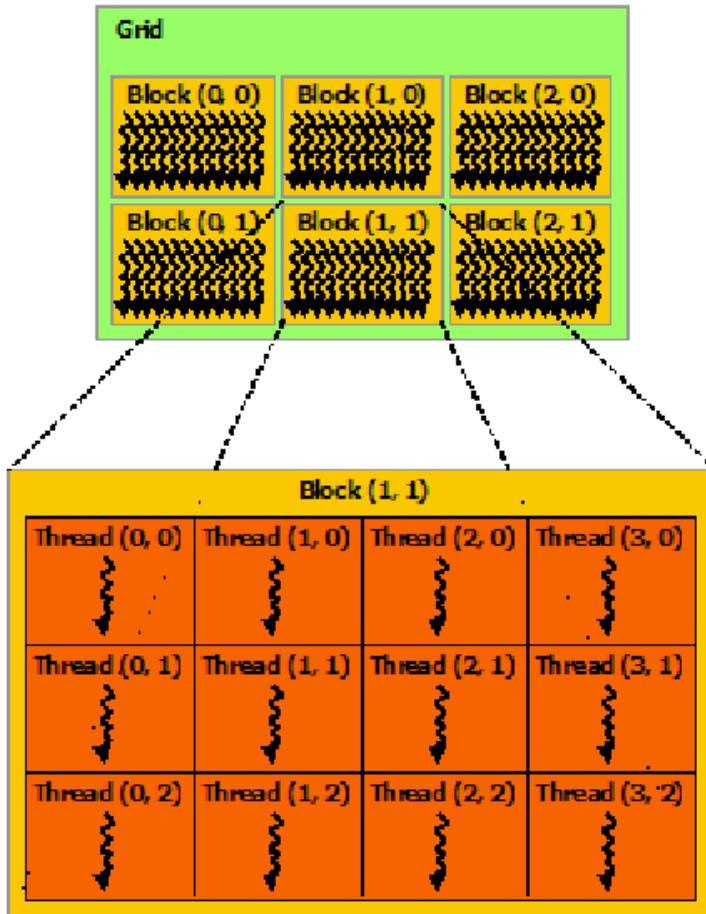
- Compile and run the code in `cuda-samples/addition`
- Go to subdirectory `exercise` and try to complete the code
- (look for `/* FIXME */` comments)

Multi-dimensional indexing

- CUDA supports
 - 3D grids of blocks and
 - 3D blocks of threads
- Convenient for mapping multi-dimensional problems (bitmaps, matrix operations etc)
- **grid3** data type, dimensions default to 1
- Launch grid of **(bx*by*bz)** blocks of **(tx*ty*tz)** threads with

```
kernel<<<dim3 (bx ,by ,bz) ,dim3 (tx ,ty ,tz)>>> () ;
```

Multi-dimensional indexing



- 2D grid with 2D blocks

```
kernel<<<dim3(2,3),  
        dim3(3,4)>>>();
```

- Launches many threads,
72 in this example

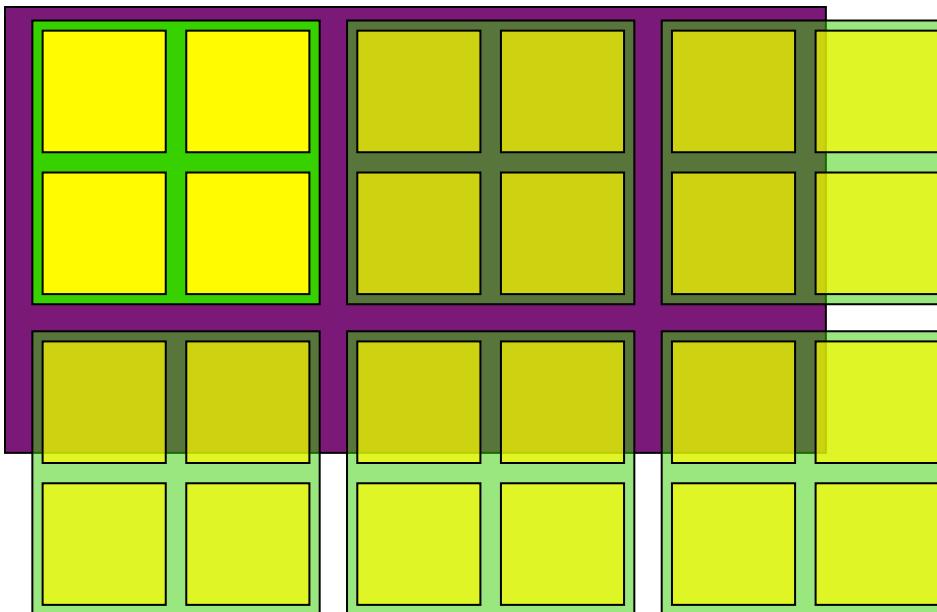
```
gridDim.x * gridDim.y  
* blockDim.x * blockDim.y
```

Multi-dimensional indexing

- Get grid dimension from
`gridDim.x`, `gridDim.y`, `gridDim.z`
- Get block index in grid from
`blockIdx.x`, `blockIdx.y`, `blockIdx.z`
- Get block dimension from
`blockDim.x`, `blockDim.y`, `blockDim.z`
- Get thread index in block from
`threadIdx.x`, `threadIdx.y`, `threadIdx.z`
- Use these to determine data access offsets and strides

Example: 2D array

- Example: Kernel that squares a 2D array using a 2D grid of 2D blocks:



- Matrix (purple)
- 2D grid (green, 2x2)
- 2D blocks (yellow)
- (threads not shown)

Example: 2D array

- Example: Kernel that squares a 2D array using a 2D grid of 2D blocks:

```
__global__ void square(int *arr, int maxrow, int maxcol) {
    // indices and strides
    int row = threadIdx.x + blockDim.x * blockIdx.x;
    int colinit = threadIdx.y + blockDim.y * blockIdx.y;
    int rowstride = gridDim.x * blockDim.x;
    int colstride = gridDim.y * blockDim.y;
    // operate on all 2D "submatrices"
    while (row < maxrow) {
        int col = colinit;
        while (col < maxcol) {
            pos = row * maxcol + col
            arr[pos] *= arr[pos]
            col += colstride
        }
        row += rowstride
    }
}
```

Example: 2D array

- We can launch the kernel for example with a grid of (16*16) blocks of (16*16) threads, i.e. a total of $256*256 = 65,536$ concurrent threads

```
#define NROW 2048
#define NCOL 512
int main(void){
    int h_a[NROW][NCOL];           // host copy
    int *d_a;                     // device copy
    int size = NROW * NCOL * sizeof(int);

    // Allocate memory on device
    cudaMalloc((void **) &d_a, size);

    // Setup input values
    get_input_array(h_a);
```

Example: 2D array

```
// Copy input data to device
cudaMemcpy(d_a, h_a, size, cudaMemcpyHostToDevice);

// Launch square() kernel
dim3 gridSize(16,16)
dim3 blockSize(16,16)
square<<<gridSize,blockSize>>>(d_a, NROW, NCOL);

// Copy results back to host
cudaMemcpy(h_a, d_a, size, cudaMemcpyDeviceToHost);

// Deallocate memory
cudaFree(d_a);

return 0;
}
```

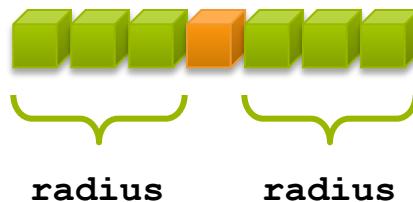
Square Array Exercise

- Compile and run the code in
`cuda-samples/square_array`
- Go to subdirectory exercise and try to complete the code
- (look for `/* FIXME */` comments)

Communication among threads – shared memory

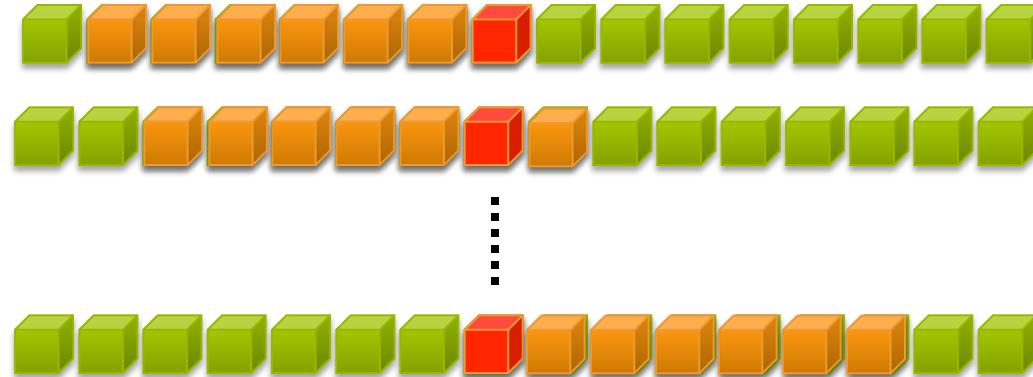
Example – 1D stencil

- 1D stencil for 1D array:
 - Each output elements is the sum of input elements within a given radius
- If the radius is 3, then each output element is the sum of 7 input elements:



1D stencil – using blocks

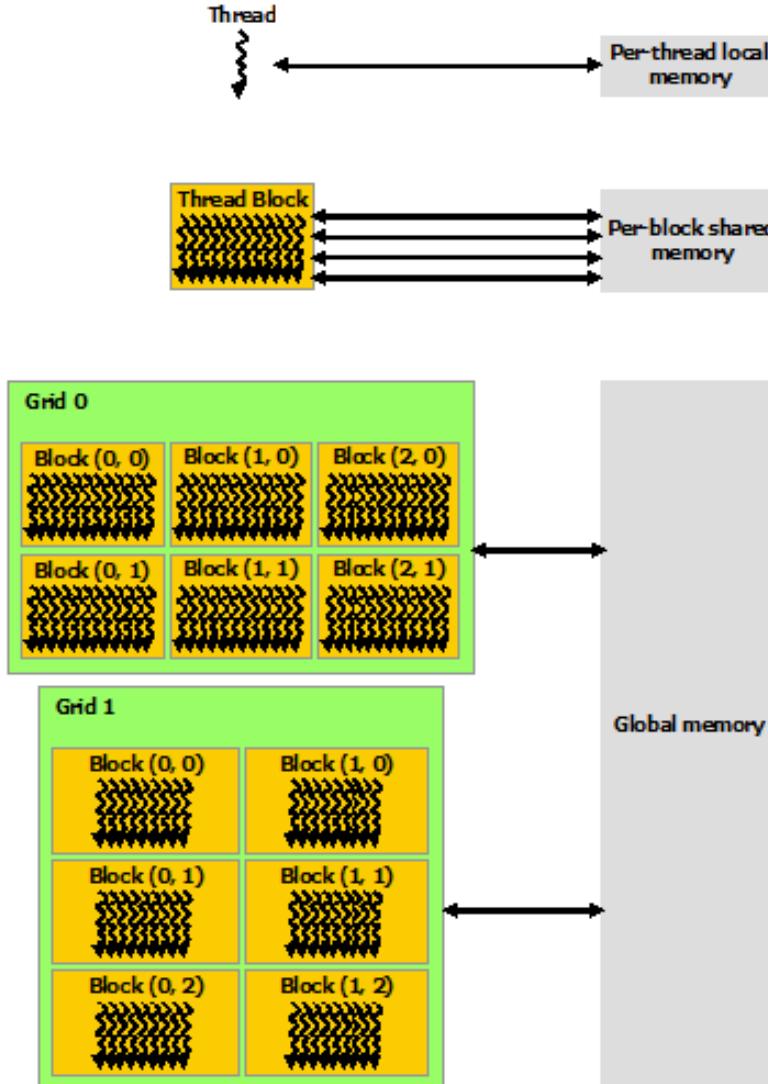
- Each thread processes one output element
 - `blockDim.x` elements are processed per block
- As a consequence, input elements have to be read several times from slow global memory
 - with radius 3, each input element is read 7 times!



Sharing data between threads

- Within a block, threads can share data via **shared memory**
- This is very fast on-chip memory
- Shared memory is user-managed
- Declare as **__shared__**, will be allocated per block
- Data in shared memory is not visible to other blocks

GPU memory hierarchy

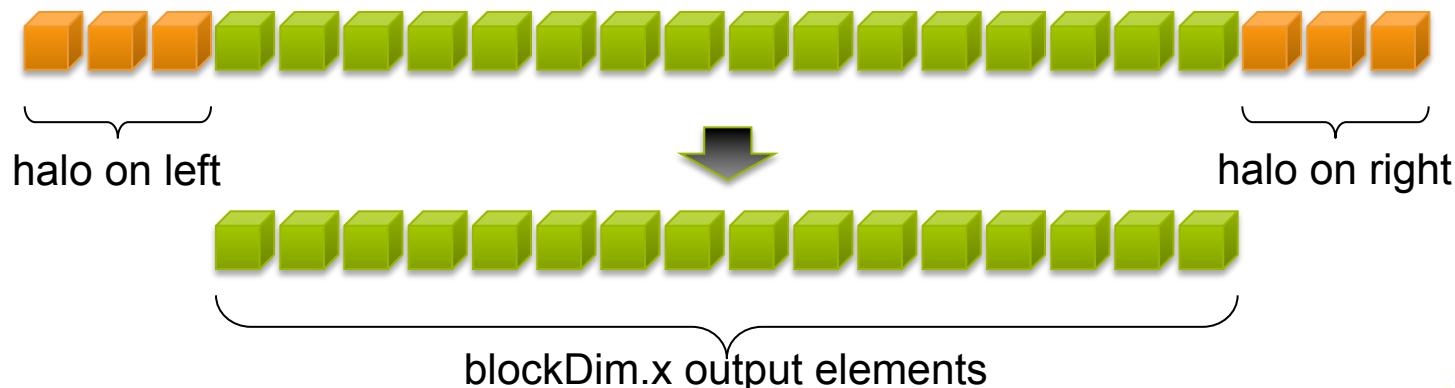


Memory	Latency (cycles)	Cached	Privacy
Global	100s	Yes	Application
Local	100s	Yes	Thread
Constant	1s-100s	Yes	Application
Texture	1s-100s	Yes	Application
Shared	1	–	Block
Register	1	–	Thread

- **On-chip**
 - Registers, shared mem
- **Off-chip**
 - Constant, texture cache (R/O)
 - Local, global memory

1D stencil using shared memory

- Cache data for use by different threads in shared memory
 - Read (`blockDim.x + 2 * radius`) input elements from global to shared memory
 - Compute `blockDim.x` output elements
 - Write `blockDim.x` output elements to global memory
 - Each block needs a “**halo**” of **radius** elements at each boundary



1D stencil kernel

```
__global__ void stencil_1D(int *in, int *out) {  
  
    __shared__ int temp[BLOCK_SIZE + 2*RADIUS];  
      
    int gindex = threadIdx.x + blockDim.x * blockIdx.x;  
    int lindex = threadIdx.x + RADIUS  
    int tid = threadIdx.x  
  
    // Read input elements into shared memory  
    temp[lindex] = in[gindex];  
      
    if (tid < RADIUS) {  
        temp[lindex - RADIUS] = in[gindex - RADIUS];  
          
        temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];  
          
    }  
}
```

1D stencil kernel

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

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

- Unfortunately the code as it is will not work
- What is the problem?

1D stencil kernel

- We have a data race!
- Suppose thread 15 reads the halo in position 19 before thread 0 has fetched it:

```
// Read input elements into shared memory
temp[lindex] = in[gindex]; // store at temp[18]
  
  
if (tid < RADIUS) { // skipped, tid > RADIUS
    temp[lindex - RADIUS] = in[gindex - RADIUS];
    temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];
}  
  
int result = 0;
result += temp[lindex+1]; // load from temp[19]

```

Synchronizing threads in a block

- To avoid race conditions we need to synchronize our threads in the block
 - used to prevent RAW / WAR / WAW hazards
- **void __syncthreads();**
- All threads in the block must reach the barrier
 - Similar to **MPI_Barrier()**
 - In conditional code, the condition must be uniform across the block to avoid deadlocks

1D stencil kernel

```
__global__ void stencil_1D(int *in, int *out) {  
  
    __shared__ int temp[BLOCK_SIZE + 2*RADIUS];  
  
    int gindex = threadIdx.x + blockDim.x * blockIdx.x;  
    int lindex = threadIdx.x + RADIUS  
    int tid = threadIdx.x  
  
    // Read input elements into shared memory  
    temp[lindex] = in[gindex];  
    if (tid < RADIUS) {  
        temp[lindex - RADIUS] = in[gindex - RADIUS];  
        temp[lindex + BLOCK_SIZE] = in[gindex + BLOCK_SIZE];  
    }  
  
    // Synchronize to ensure that all data is available  
    __syncthreads();
```

1D stencil kernel

```
// Now it is safe to apply the stencil
int result = 0;
for (int offset = -RADIUS; offset <= RADIUS; offset++) {
    result += temp[lindex + offset];
}

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

- This kernel improves performance by using shared memory and avoids race conditions by synchronizing the threads within a block

1D Stencil Exercise

- Compile and run the code in
`cuda-samples/1d_stencil`
- Go to subdirectory exercise and try to complete the code
- (look for `/* FIXME */` comments)

Review

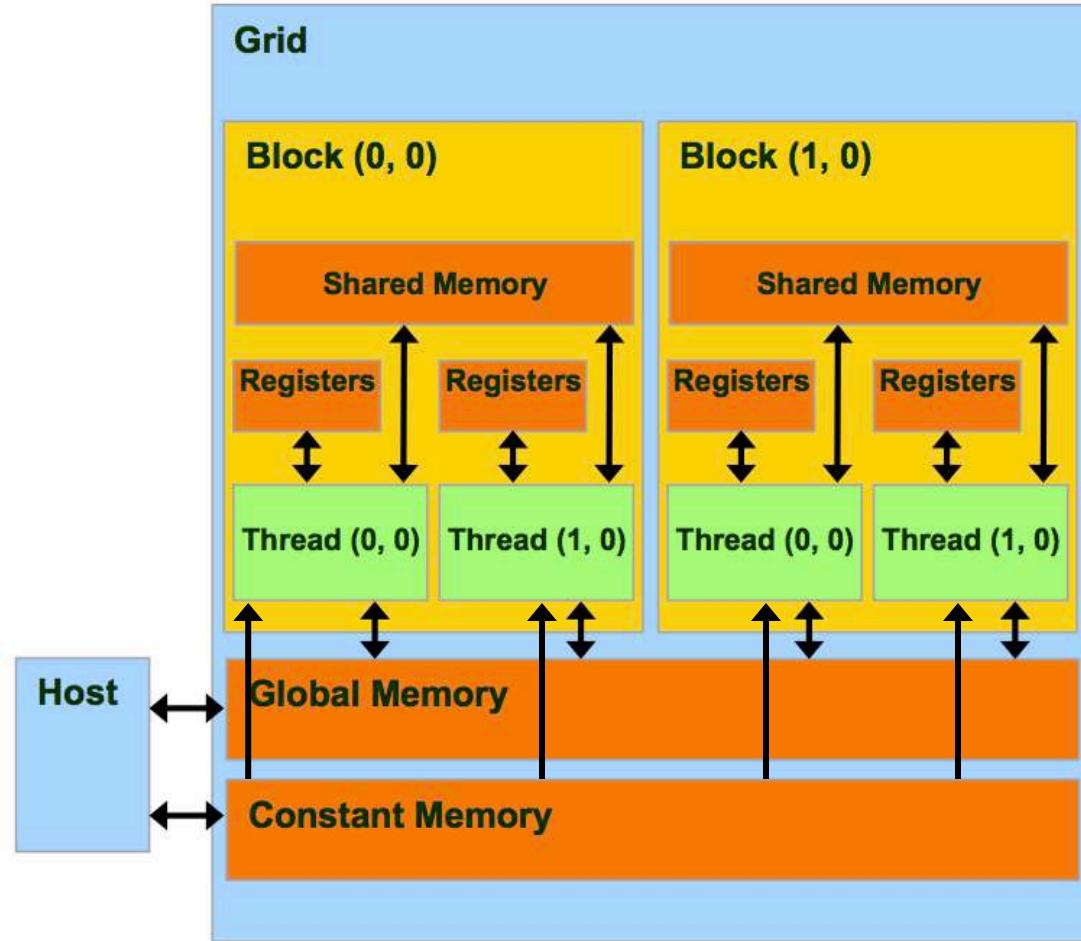
- Use **_shared_** to declare a variable / array in shared memory
 - Data is shared between threads in a block
 - Not visible to threads in other blocks
- Use **_syncthreads()** as a barrier
 - Required to prevent data hazards / race conditions

Constant memory

- Read-only during kernel execution
- Located off-chip in global memory but accessed via dedicated hardware
 - broadcasts to all threads in a half-warp (16 threads), saving bandwidth
 - cached
- Define constant memory
 - `__constant__ int c_a[dimension];`
- Copy data into constant memory
 - `cudaMemcpyToSymbol(c_a, h_a, size);`

CUDA memories

- Each thread can
 - read/write per-thread **registers**
 - read/write per-thread **local memory**
 - read/write per-block **shared memory**
 - read/write per-grid **global memory**
 - read-only per-grid **constant memory**



General programming strategy

- Global memory resides in device memory (DRAM)
 - much slower access than shared memory
- Take advantage of fast shared memory by tiling data
 - Partition data into subsets that fit into shared memory
 - Handle each data subset with one thread block
 - Load the subset from global to shared memory using multiple threads to exploit parallelism in memory access
 - perform computation on data subset in shared memory, (each thread can access data multiple times)
 - copy results from shared memory to global memory

General programming strategy

- Use constant memory for data that is accessed by all threads within a block (half-warp, actually) at the same time
 - this reduces memory bandwidth requirements
- Do not use constant memory if threads access different elements of the data
 - half-warps can place only a single read-request at a time
 - if threads need different data from constant memory, these reads get serialized
- Finally, there is texture memory (skipped here)

Avoiding race conditions with atomic operations

Atomic operations?

- An atomic operation cannot be divided into several operations
- What happens when we increment a counter?
`i++;`
- This consists of three steps
 - 1) Read the value stored at the address of `i`
 - 2) Add 1 to the value read in step 1)
 - 3) Write the result back to the address of `i`
- What happens if multiple threads increment the counter?

Atomic operations

- If multiple threads modify an address, the result is unpredictable
- Atomic operations are performed without interference from other threads
- Atomic operations are available on newer GPUs (efficient since Kepler chips) and can operate on global or shared memory
 - `atomicAdd()` , `atomicSub()` , `atomicMin()`
 - etc. see programming guide for full list
- Use wisely – code execution will be serialized

Example: Histogram

- Assume data set of 8-bit (1 byte) values
- Compute occurrence of each (256) possible value
- Serial CPU code:

```
#define SIZE (100*1024*1024)
int main(void){
    unsigned char buffer[SIZE];
    unsigned int histo[256];
    get_data(buffer,SIZE);           //read data
    for (int i=0; i<256; i++)      //initialize to zero
        histo[i] = 0;
    for (int i=0; i<SIZE; i++) {    //compute histogram
        histo[buffer[i]]++;
    }
    return 0;
}
```

Histogram on a GPU

- Using atomic add operation to avoid data races

```
#define SIZE (100*1024*1024)

// histogram kernel
__global__ histo_kernel(unsigned char *buffer,
                        int size, unsigned int *histo) {

    int tid = threadIdx.x + blockIdx.x * blockDim.x;
    int stride = blockDim.x * gridDim.x;

    while (tid < size) {
        atomicAdd( &(histo[buffer[i]]), 1 );
        tid += stride;
    }
}
```

- This will work – but with terrible performance

Histogram on a GPU

- This kernel will have a terrible performance compared to the CPU because
 - the kernel does very little work
 - thousands of threads access few (256) memory locations with atomic add operations
- We can improve the performance by using shared memory
 - write operations to shared memory are fast
 - fewer threads will try to access the same memory locations with the atomic add operation

Histogram on a GPU

- Histogram kernel with shared memory

```
#define SIZE (100*1024*1024)

// histogram kernel
__global__ histo_kernel(unsigned char *buffer,
                        int size, unsigned int *histo) {

    // shared memory, assume 256 threads per block
    __shared__ unsigned int temp[256];
    temp[threadIdx.x] = 0;
    __syncthreads();

    int tid = threadIdx.x + blockIdx.x * blockDim.x;
    int stride = blockDim.x * gridDim.x;

    // compute histogram in shared memory for this block
```

Histogram on a GPU

```
// compute histogram in shared memory for this block
while (tid < size) {
    atomicAdd( &(temp[buffer[i]]), 1 );
    tid += stride;
}
__syncthreads();

// now merge each block's histogram
// again assuming 256 threads per block
atomicAdd( &(histo[threadIdx.x]),
           temp[threadIdx.x] );
}
```

Histogram on a GPU

- Our main program

```
int main(void) {  
  
    // host and device memory / pointers  
    unsigned char h_buffer[SIZE], *d_buffer;  
    unsigned int h_hist[256], *d_hist;  
  
    // get our input data  
    get_data(buffer,SIZE);  
  
    // allocate device memory  
    cudaMalloc( (void**)&d_buffer, SIZE);  
    cudaMalloc( (void**)&d_hist, 256 * sizeof(int) );  
  
    // copy data to device  
    cudaMemcpy( d_buffer, h_buffer, SIZE,  
               cudaMemcpyHostToDevice);
```

Histogram on a GPU

```
// initialize histogram to zero
cudaMemset(d_histo, 0, 256);

// launch kernel
histo_kernel<<<32,256>>>(d_buffer,SIZE,d_histo);

// copy results back
cudaMemcpy( h_histo, d_histo, 256*sizeof(int) ,
            cudaMemcpyDeviceToHost);

// free memory
cudaFree(d_buffer); cudaFree(d_histo);

// print our histogram
print_histogram(h_histo);

return 0;
}
```

Device management etc

Coordinating host & device

- Kernel launches are asynchronous
 - Control returns to CPU immediately
 - This is great since the CPU can do work while the GPU is busy
- CPU needs to synchronize before using results
 - **cudaMemcpy()**
Blocks the CPU until the copy is complete; copy begins when all preceding CUDA calls have completed
 - **cudaMemcpyAsync()**
Asynchronous, does not block the CPU
 - **cudaDeviceSynchronize()**
Blocks CPU until all preceding CUDA calls completed

Error management

- All CUDA API calls return an error code (`cudaError_t`)
 - Error in the API call itself
 - Error in an earlier asynchronous operation (e.g. kernel)
- Get error code for last error and handle error

```
// do some stuff on the GPU, now check status
cudaError_t error = cudaGetLastError();
// and handle error
if (error != cudaSuccess) {
    // print CUDA error message and exit
    printf("CUDA error: %s\n",
           cudaGetString(error));
    exit(MYERRCODE);
}
```

Query device properties

- Application can query and select GPUs

- how many GPUs do we have

`cudaGetDeviceCount(int *count)`

- choose device for execution

`cudaSetDevice(int device)`

- which device am I currently running on?

`cudaGetDevice(int *device)`

- get hardware information

`cudaGetDeviceProperties(`
`cudaDeviceProp *prop, int device)`

Query device properties

- Examples of CUDA device properties
 - `char name[256]`
 - `int major, int minor`
 - `size_t totalGlobalMem, size_t totalConstMem`
 - `int maxThreadsDim[3], int maxGridSize[3]`
 - `int multiProcessorCount`
- E.g. launch number of blocks depending on HW

```
cudaDeviceProp prop;  
cudaGetDeviceProperties(&prop, 0);  
int blocks = 4 * prop.multiProcessorCount;  
my_kernel<<<blocks, threads>>>();
```

Measuring performance

- CUDA events can record GPU time stamps

```
// event timers
cudaEvent_t start, stop;
float elapsedTime;

// create start and stop events
cudaEventCreate(&start); cudaEventCreate(&stop);

// get start time stamp
cudaEventRecord(start, 0);

// do some work on the GPU (call a kernel)

// get stop time stamp and synchronize
cudaEventRecord(stop, 0); cudaEventSynchronize(stop);

// get elapsed time, in milliseconds
cudaEventElapsedTime(&elapsedTime, start, stop);

// destroy events
cudaEventDestroy(start); cudaEventDestroy(stop);
```

Page-locked host memory

- Allocate page-locked (pinned) host memory
 - will never be paged out to disk
 - GPU can use DMA to copy data (bypass CPU)
 - DMA copies are usually faster than regular memory copies (depends on PCIE, FSB speed)
 - don't overuse – RAM needs to be available

```
int *h_a;
```

```
cudaHostAlloc( (void**) &a, size, cudaHostAllocDefault );
```

```
cudaFreeHost( a );
```

CUDA streams

- Up to now we have exploited data parallelism
- CUDA streams is about task parallelism, that is executing different operations simultaneously
- CUDA streams represent a queue of GPU operations that get executed in a specific order
 - kernel launches
 - memory copies
 - event starts / stops

CUDA streams

- Create a stream and add work to its queue

```
int *d_a, *h_a;

// initialize the stream
cudaStream_t stream;
cudaStreamCreate( &stream );

// allocate memory
cudaHostAlloc( (void**) &h_a, SIZE, cudaHostAllocDefault );
cudaMalloc( (void**) &d_a, SIZE );

// asynchronous memory copy - needs pinned memory
cudaMemcpyAsync( d_a, h_a, SIZE,
                 cudaMemcpyHostToDevice, stream );
```

CUDA streams

```
// launch a kernel for this stream
my_kernel<<<grid,block,stream>>>(d_a,SIZE) ;

// asynchronous memory copy - needs pinned memory
cudaMemcpyAsync(h_a, d_a, SIZE,
                cudaMemcpyDeviceToHost, stream) ;

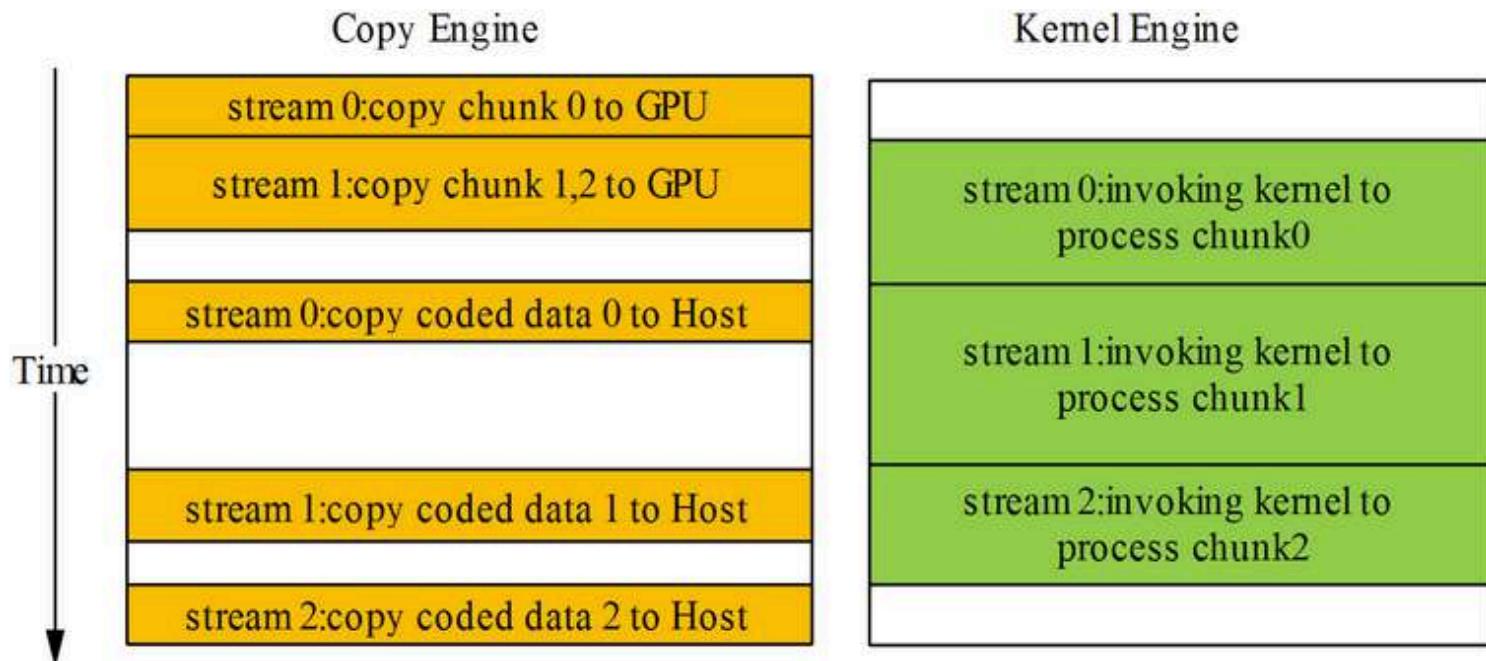
// host does other stuff
do_some_work();

// synchronize with host, destroy stream
cudaStreamSynchronize(stream);
cudaStreamDestroy(stream);

// now it's safe to do some stuff with h_a
do_more_work(h_a);
```

CUDA streams

- Using multiple CUDA streams
 - for example divide problem into small chunks and overlap memory copies in one stream with computation in a second stream



CUDA streams

- Using two streams

```
int *d_a0, *d_a1, *h_a;

// initialize the stream
cudaStream_t stream0; cudaStream_t stream1;
cudaStreamCreate(&stream0); cudaStreamCreate(&stream1);

// allocate memory
cudaHostAlloc((void**)&h_a, SIZE, cudaHostAllocDefault);
cudaMalloc((void**)&d_a0, SIZE/2);
cudaMalloc((void**)&d_a1, SIZE/2);

// asynchronous memory copy - needs pinned memory
cudaMemcpyAsync(d_a0, h_a, SIZE/2,
                cudaMemcpyHostToDevice, stream0);
```

CUDA streams

```
cudaMemcpyAsync(d_a1, h_a+SIZE/2, SIZE/2,  
                cudaMemcpyHostToDevice, stream1);  
  
// launch kernels for both streams  
my_kernel<<<grid,block,stream0>>>(d_a0,SIZE/2);  
my_kernel<<<grid,block,stream1>>>(d_a1,SIZE/2);  
  
// asynchronous memory copy - needs pinned memory  
cudaMemcpyAsync(h_a, d_a0, SIZE/2,  
                cudaMemcpyDeviceToHost, stream0);  
cudaMemcpyAsync(h_a+SIZE/2, d_a1, SIZE/2,  
                cudaMemcpyDeviceToHost, stream1);  
  
// do stuff on the host, synchronize streams,  
// destroy streams etc
```

GPU Computing with OpenACC Directives

based on material by
Mark Harris - NVIDIA corporation

PGI Community Edition

- <https://developer.nvidia.com/openacc-toolkit>
- PGI Accelerator Fortran/C/C++ compilers
 - OpenACC 2.5 on Nvidia GPUs
 - OpenACC 2.5, CUDA Fortran, OpenMP 3.1 on CPU host
- PGPROF Performance Profiler
- GPU-enabled libraries
- OpenACC Code Samples
- See also openacc.org and the PGI website.

A Very Simple Exercise: SAXPY

SAXPY in C

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

...
// Perform SAXPY on 1M elements
saxpy(1<<20, 2.0, x, y);
...
```

SAXPY in Fortran

```
subroutine saxpy(n, a, x, y)
    real :: x(:), y(:), a
    integer :: n, i
 !$acc kernels
    do i=1,n
        y(i) = a*x(i)+y(i)
    enddo
 !$acc end kernels
end subroutine saxpy
...
! Perform SAXPY on 1M elements
call saxpy(2**20, 2.0, x_d, y_d)
...
```

Directive Syntax

- Fortran

```
!$acc directive [clause [,] clause] ...]
```

Often paired with a matching end directive surrounding a structured code block

```
!$acc end directive
```

- C

```
#pragma acc directive [clause [,] clause] ...]
```

Often followed by a structured code block

*kernel*s: Your first OpenACC Directive

Each loop executed as a separate *kernel* on the GPU.

```
!$acc kernels
do i=1,n
    a(i) = 0.0
    b(i) = 1.0
    c(i) = 2.0
end do
}
do i=1,n
    a(i) = b(i) + c(i)
end do
}
 !$acc end kernels
```

kernel 1

kernel 2

Kernel:
A parallel
function that runs
on the GPU

*kernel*s Construct

Fortran

```
!$acc kernels [clause ...]
      structured block
 !$acc end kernels
```

C

```
#pragma acc kernels [clause ...]
{ structured block }
```

Clauses

```
if( condition )
async( expression )
```

Also, any data clause (more later)

Complete SAXPY example code

- Trivial first example
 - Apply a loop directive
 - Learn compiler commands

```
#include <stdlib.h>

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

```
int main(int argc, char **argv)
{
    int N = 1<<20; // 1 million floats

    float *x = (float*)malloc(N * sizeof(float));
    float *y = (float*)malloc(N * sizeof(float));

    for (int i = 0; i < N; ++i)
    {
        x[i] = 2.0f;
        y[i] = 1.0f;
    }

    saxpy(N, 3.0f, x, y);

    return 0;
}
```

Compile and run

- C:

```
pgcc -acc -Minfo=accel -o saxpy_acc saxpy.c
```

- Fortran:

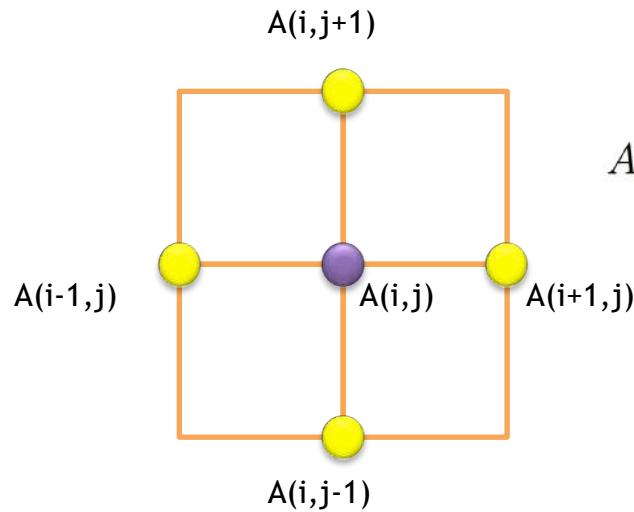
```
pgf90 -acc -Minfo=accel -o saxpy_acc saxpy.f90
```

- Compiler output:

```
pgcc saxpy.c -acc -Minfo=accel -o saxpy-gpu.x
saxpy:
  8, Generating copyin(x[:n])
      Generating copy(y[:n])
  9, Loop is parallelizable
      Accelerator kernel generated
      Generating Tesla code
      9, #pragma acc loop gang, vector(128) /* blockIdx.x
threadIdx.x */
```

Example: Jacobi Iteration

- Iteratively converges to correct value (e.g. Temperature), by computing new values at each point from the average of neighboring points.
 - Common, useful algorithm
 - Example: Solve Laplace equation in 2D: $\Delta\varphi(x, y) = 0$



$$A_{k+1}(i, j) = \frac{A_k(i - 1, j) + A_k(i + 1, j) + A_k(i, j - 1) + A_k(i, j + 1)}{4}$$

Jacobi Iteration C Code

```
while ( error > tol && iter < iter_max )
{
    error=0.0;

    for( int j = 1; j < n-1; j++) {
        for(int i = 1; i < m-1; i++) {

            Anew[j][i] = 0.25 * (A[j][i+1] + A[j][i-1] +
                                  A[j-1][i] + A[j+1][i]);

            error = max(error, abs(Anew[j][i] - A[j][i]));
        }
    }

    for( int j = 1; j < n-1; j++) {
        for( int i = 1; i < m-1; i++ ) {
            A[j][i] = Anew[j][i];
        }
    }

    iter++;
}
```

Iterate until converged

Iterate across matrix elements

Calculate new value from neighbors

Compute max error for convergence

Swap input/output arrays

Jacobi Iteration Fortran Code

```
do while ( err > tol .and. iter < iter_max )  
  err=0._fp_kind
```



Iterate until converged

```
do j=1,m  
  do i=1,n
```



Iterate across matrix elements

```
  Anew(i,j) = .25_fp_kind * (A(i+1, j ) + A(i-1, j ) + &  
                               A(i , j-1) + A(i , j+1))
```



Calculate new value from neighbors

```
  err = max(err, Anew(i,j) - A(i,j))  
 end do  
end do
```



Compute max error for convergence

```
do j=1,m-2  
  do i=1,n-2  
    A(i,j) = Anew(i,j)  
  end do  
end do
```



Swap input/output arrays

```
iter = iter +1  
end do
```

OpenMP C Code

```
while ( error > tol && iter < iter_max ) {  
    error=0.0;  
  
#pragma omp parallel for shared(m, n, Anew, A)  
    for( int j = 1; j < n-1; j++) {  
        for(int i = 1; i < m-1; i++) {  
  
            Anew[j][i] = 0.25 * (A[j][i+1] + A[j][i-1] +  
                                  A[j-1][i] + A[j+1][i]);  
  
            error = max(error, abs(Anew[j][i] - A[j][i]));  
        }  
    }  
  
#pragma omp parallel for shared(m, n, Anew, A)  
    for( int j = 1; j < n-1; j++) {  
        for( int i = 1; i < m-1; i++ ) {  
            A[j][i] = Anew[j][i];  
        }  
    }  
  
    iter++;  
}
```

Parallelize loop across
CPU threads

Parallelize loop across
CPU threads

OpenMP Fortran Code

```
do while ( err > tol .and. iter < iter_max )
  err=0._fp_kind

 !$omp parallel do shared(m,n,Anew,A) reduction(max:err)
  do j=1,m
    do i=1,n

      Anew(i,j) = .25_fp_kind * (A(i+1, j ) + A(i-1, j ) + &
                                   A(i , j-1) + A(i , j+1))

      err = max(err, Anew(i,j) - A(i,j))
    end do
  end do

 !$omp parallel do shared(m,n,Anew,A)
  do j=1,m-2
    do i=1,n-2
      A(i,j) = Anew(i,j)
    end do
  end do

  iter = iter +1
end do
```

Parallelize loop across
CPU threads

Parallelize loop across
CPU threads

GPU startup overhead

- If no other GPU process running, GPU driver may be swapped out
 - Linux specific
 - Starting it up can take 1-2 seconds
- Two options
 - Run `nvidia-smi -pm 1` in persistence mode (requires root permissions)
 - Run “`nvidia-smi -q -l 30`” in the background
 - Any well configured supercomputer should be running the driver in persistence mode.
- If your running time is off by ~2 seconds from results in these slides, suspect this
 - Nvidia-smi should be running in persistent mode for these exercises

First Attempt: OpenACC C

```
while ( error > tol && iter < iter_max ) {
    error=0.0;

#pragma acc kernels
    for( int j = 1; j < n-1; j++) {
        for(int i = 1; i < m-1; i++) {

            Anew[j][i] = 0.25 * (A[j][i+1] + A[j][i-1] +
                                  A[j-1][i] + A[j+1][i]);

            error = max(error, abs(Anew[j][i] - A[j][i]));
        }
    }

#pragma acc kernels
    for( int j = 1; j < n-1; j++) {
        for( int i = 1; i < m-1; i++ ) {
            A[j][i] = Anew[j][i];
        }
    }

    iter++;
}
```

Execute GPU kernel for
loop nest

Execute GPU kernel for
loop nest

First Attempt: OpenACC Fortran

```
do while ( err > tol .and. iter < iter_max )
  err=0._fp_kind

 !$acc kernels
 do j=1,m
   do i=1,n

     Anew(i,j) = .25_fp_kind * (A(i+1, j    ) + A(i-1, j    ) + &
                                 A(i    , j-1) + A(i    , j+1))

     err = max(err, Anew(i,j) - A(i,j))
   end do
 end do
 !$acc end kernels

 !$acc kernels
 do j=1,m-2
   do i=1,n-2
     A(i,j) = Anew(i,j)
   end do
 end do
 !$acc end kernels
 iter = iter +1
end do
```

Generate GPU kernel
for loop nest



Generate GPU kernel
for loop nest



First Attempt: Compiler output (C)

```
pgf90 -acc -ta=nvidia -Minfo=accel -o jacobi-pgf90-acc-v1.x jacobi-acc-v1.f90
laplace:
 44, Generating copyout(anew(1:4094,1:4094))
    Generating copyin(a(0:4095,0:4095))
 45, Loop is parallelizable
 46, Loop is parallelizable
    Accelerator kernel generated
    Generating Tesla code
 45, !$acc loop gang ! blockidx%y
 46, !$acc loop gang, vector(128) ! blockidx%x threadidx%x
 49, Max reduction generated for error
 57, Generating copyin(anew(1:4094,1:4094))
    Generating copyout(a(1:4094,1:4094))
 58, Loop is parallelizable
 59, Loop is parallelizable
    Accelerator kernel generated
    Generating Tesla code
 58, !$acc loop gang ! blockidx%y
 59, !$acc loop gang, vector(128) ! blockidx%x threadidx%x
```

First Attempt: Performance

SDSC Comet

CPU: Intel Xeon E5-2680 v3

GPU: NVIDIA Tesla K80
(using single GPU)

Execution	Time (s)	Speedup
CPU 1 OpenMP thread	71	--
CPU 2 OpenMP threads	41	1.73x
CPU 4 OpenMP threads	26	2.73x
CPU 6 OpenMP threads	24	2.96x
OpenACC GPU	501	0.05x FAIL

**Speedup vs.
1 CPU core**

**Speedup vs.
6 CPU cores**

What went wrong?

```
export PGI_ACC_TIME=1      ! Activate profiling, then run again
```

Accelerator Kernel Timing data

/server-home1/agoetz/UCSD_Phys244/2017/openacc-samples/laplace-2d/jacobi-acc-v1.f90

laplace NVIDIA devicenum=0

time(us): 89,612,134

..... <snip – some lines cut>

44: data region reached 2000 times

44: data copyin transfers: 8000

device time(us): total=22,587,486 max=2,898 min=2,799 avg=2,823

52: data copyout transfers: 8000

device time(us): total=20,278,262 max=2,612 min=2,497 avg=2,534

57: compute region reached 1000 times

59: kernel launched 1000 times

grid: [128x1024] block: [32x4]

device time(us): total=1,456,273 max=1,465 min=1,452 avg=1,456

elapsed time(us): total=1,498,877 max=1,524 min=1,492 avg=1,498

57: data region reached 2000 times

57: data copyin transfers: 8000

device time(us): total=22,664,227 max=2,902 min=2,802 avg=2,833

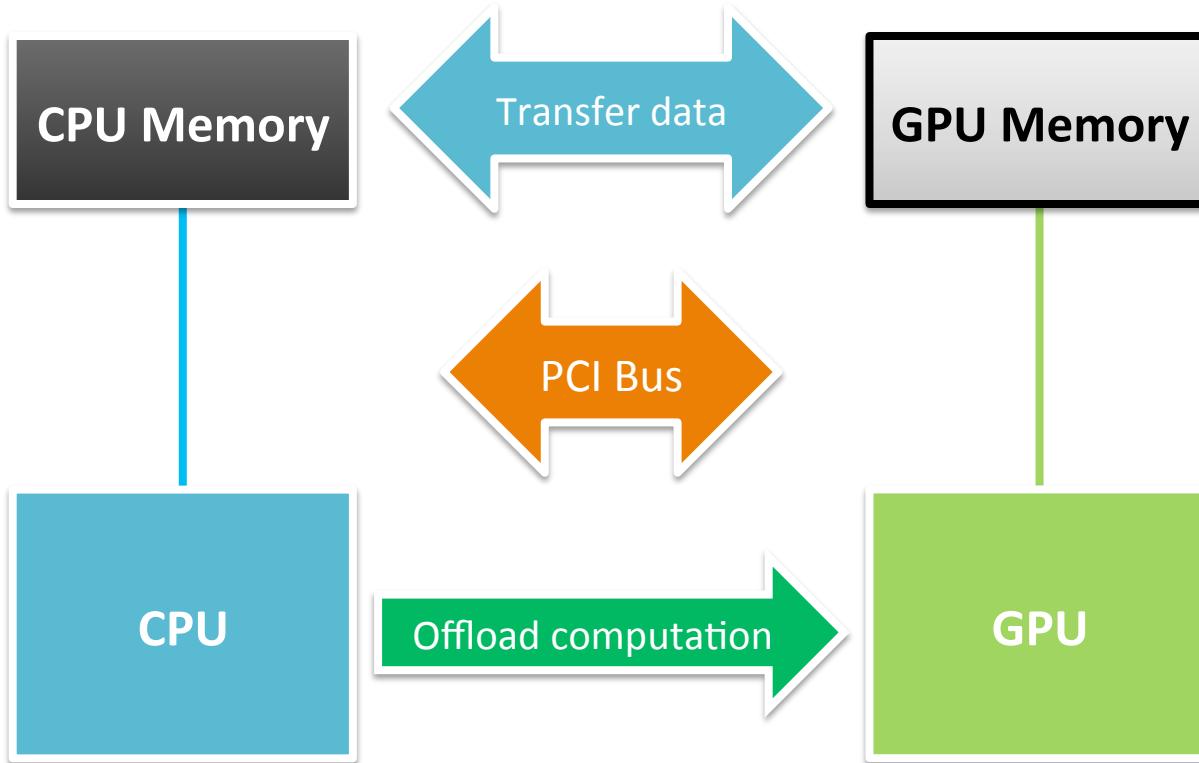
63: data copyout transfers: 8000

device time(us): total=20,278,000 max=2,618 min=2,498 avg=2,534

22.5 seconds

1.5 seconds

Basic Concepts



For efficiency, decouple data movement and compute off-load

Excessive Data Transfers

```
while ( error > tol && iter < iter_max )  
{  
    error=0.0;
```

A, Anew resident on host

Copy

#pragma acc kernels

A, Anew resident on accelerator

These copies
happen every
iteration of the
outer while loop!*

```
for( int j = 1; j < n-1; j++) {  
    for( int i = 1; i < m-1; i++) {  
        Anew[j][i] = 0.25 * (A[j][i+1] + A[j][i-1] +  
                               A[j-1][i] + A[j+1][i]);  
        error = max(error, abs(Anew[j][i] - A[j][i]));  
    }  
}
```

A, Anew resident on accelerator

Copy

A, Anew resident on host

...

*Note: there are two #pragma acc kernels, so there are 4 copies per while loop iteration!

DATA MANAGEMENT

DATA CONSTRUCT

Fortran

```
!$acc data [clause ...]  
    structured block  
!$acc end data
```

C

```
#pragma acc data [clause ...]  
    { structured block }
```

General Clauses

```
if( condition )  
    async( expression )
```

- Data regions are different than compute regions
 - E.g. data region for outer loop and kernels region for inner loop

DATA CLAUSES

- copy (list)** Allocates memory on GPU and copies data from host to GPU when entering region and copies data to the host when exiting region.
 - copyin (list)** Allocates memory on GPU and copies data from host to GPU when entering region.
 - copyout (list)** Allocates memory on GPU and copies data to the host when exiting region.
 - create (list)** Allocates memory on GPU but does not copy.
 - present (list)** Data is already present on GPU from another containing data region.
- and **present_or_copy[in|out]**, **present_or_create**, **deviceptr**.

ARRAY SHAPING

- Compiler sometimes cannot determine size of arrays
 - Must specify explicitly using data clauses and array “shape”; compiler will tell
- C

```
#pragma acc data copyin(a[0:size-1]), copyout(b[s/4:3*s/4])
```
- Fortran

```
!$pragma acc data copyin(a(1:size)), copyout(b(s/4:3*s/4))
```
- Note: data clauses can be used on data, kernels or parallel

UPDATE CONSTRUCT

Fortran

```
!$acc update [clause ...]
```

C

```
#pragma acc update [clause ...]
```

Clauses

host(list)

if(expression)

device(list)

async(expression)

Used to update existing data after it has changed in its corresponding copy (e.g. update device copy after host copy changes)

Move data from GPU to host, or host to GPU.
Data movement can be conditional, and asynchronous.

Second Attempt: OpenACC C

```
#pragma acc data copy(A), create(Anew)
while ( error > tol && iter < iter_max ) {
    error=0.0;

#pragma acc kernels
    for( int j = 1; j < n-1; j++ ) {
        for(int i = 1; i < m-1; i++) {

            Anew[j][i] = 0.25 * (A[j][i+1] + A[j][i-1] +
                                  A[j-1][i] + A[j+1][i]);

            error = max(error, abs(Anew[j][i] - A[j][i]));
        }
    }

#pragma acc kernels
    for( int j = 1; j < n-1; j++ ) {
        for( int i = 1; i < m-1; i++ ) {
            A[j][i] = Anew[j][i];
        }
    }

    iter++;
}
```

Copy A in at beginning of loop, out at end. Allocate Anew on accelerator



Second Attempt: OpenACC Fortran

```
!$acc data copy(A) , create(Anew)
do while ( err > tol .and. iter < iter_max )
    err=0._fp_kind
    !$acc kernels
    do j=1,m
        do i=1,n
            Anew(i,j) = .25_fp_kind * (A(i+1, j ) + A(i-1, j ) + &
                                         A(i , j-1) + A(i , j+1))
            err = max(err, Anew(i,j) - A(i,j))
        end do
    end do
    !$acc end kernels
    ...
iter = iter +1
end do
!$acc end data
```

Copy A in at beginning of loop,
out at end. Allocate Anew on
accelerator

Second Attempt: Performance

SDSC Comet

CPU: Intel Xeon E5-2680 v3

GPU: NVIDIA Tesla K80
(using single GPU)

Execution	Time (s)	Speedup
CPU 1 OpenMP thread	71	--
CPU 2 OpenMP threads	41	1.73x
CPU 4 OpenMP threads	26	2.73x
CPU 6 OpenMP threads	24	2.96x
OpenACC GPU	5	4.8x

**CPU Speedup
vs.
1 CPU core**

**GPU Speedup
vs.
6 CPU cores**

Further speedups

- OpenACC gives us more detailed control over parallelization
 - Via **gang**, **worker**, and **vector** clauses
- By understanding more about OpenACC execution model and GPU hardware organization, we can get higher speedups on this code
- By understanding bottlenecks in the code via profiling, we can reorganize the code for higher performance

Finding Parallelism in your code

- (Nested) for loops are best for parallelization
- Large loop counts needed to offset GPU/memcpy overhead
- Iterations of loops must be independent of each other
 - To help compiler: restrict keyword (C), independent clause
- Compiler must be able to figure out sizes of data regions
 - Can use directives to explicitly control sizes
- Pointer arithmetic should be avoided if possible
 - Use subscripted arrays, rather than pointer-indexed arrays.
- Function calls within accelerated region must be inlineable.

Tips and Tricks

- (PGI) Use time option to learn where time is being spent
 - ta=nvidia,time
- Eliminate pointer arithmetic
- Inline function calls in directives regions
 - (PGI): -Minline or -Minline=levels:N
- Use contiguous memory for multi-dimensional arrays
- Use data regions to avoid excessive memory transfers
- Conditional compilation with `_OPENACC` macro

OpenACC Learning Resources

- OpenACC info, specification, FAQ, samples, and more
 - <http://openacc.org>
- PGI OpenACC resources
 - <http://www.pgroup.com/resources/accel.htm>

COMPLETE OPENACC API

Kernels Construct

Fortran

```
!$acc kernels [clause ...]  
    structured block  
!$acc end kernels
```

C

```
#pragma acc kernels [clause ...]  
    { structured block }
```

Clauses

```
if( condition )  
async( expression )
```

Also any data clause

Kernels Construct

Each loop executed as a separate kernel on the GPU.

```
!$acc kernels
do i=1,n
    a(i) = 0.0
    b(i) = 1.0
    c(i) = 2.0
end do
}
kernel 1

do i=1,n
    a(i) = b(i) + c(i)
end do
}
kernel 2
!$acc end kernels
```

Parallel Construct

Fortran

```
!$acc parallel [clause ...]  
    structured block  
!$acc end parallel
```

Clauses

```
if( condition )  
async( expression )  
num_gangs( expression )  
num_workers( expression )  
vector_length( expression )
```

C

```
#pragma acc parallel [clause ...]  
    { structured block }
```

```
private( list )  
firstprivate( list )  
reduction( operator:list )
```

Also any data clause

Parallel Clauses

`num_gangs (expression)`

Controls how many parallel gangs are created (CUDA `gridDim`).

`num_workers (expression)`

Controls how many workers are created in each gang (CUDA `blockDim`).

`vector_length (list)`

Controls vector length of each worker (SIMD execution).

`private(list)`

A copy of each variable in list is allocated to each gang.

`firstprivate (list)`

private variables initialized from host.

`reduction(operator:list)`

private variables combined across gangs.

Loop Construct

Fortran

```
!$acc loop [clause ...]  
    loop  
!$acc end loop
```

C

```
#pragma acc loop [clause ...]  
{ loop }
```

Combined directives

```
!$acc parallel loop [clause ...] !$acc parallel loop [clause  
!$acc kernels loop [clause ...] ...]  
                      !$acc kernels loop [clause ...]
```

Detailed control of the parallel execution of the following loop.

Loop Clauses

`collapse(n)`

Applies directive to the following `n` nested loops.

`seq`

Executes the loop sequentially on the GPU.

`private(list)`

A copy of each variable in `list` is created for each iteration of the loop.

`reduction(operator:list)`

`private` variables combined across iterations.

Loop Clauses Inside parallel Region

gang

Shares iterations across the gangs of the parallel region.

worker

Shares iterations across the workers of the gang.

vector

Execute the iterations in SIMD mode.

Loop Clauses Inside kernels Region

gang [(*num_gangs*)]

Shares iterations across across at most *num_gangs* gangs.

worker [(*num_workers*)]

Shares iterations across at most *num_workers* of a single gang.

vector [(*vector_length*)]

Execute the iterations in SIMD mode with maximum *vector_length*.

independent

Specify that the loop iterations are independent.

OTHER SYNTAX

Other Directives

`cache` construct

Cache data in software managed data cache (CUDA shared memory).

`host_data` construct

Makes the address of device data available on the host.

`wait` directive

Waits for asynchronous GPU activity to complete.

`declare` directive

Specify that data is to be allocated in device memory for the duration of an implicit data region created during the execution of a subprogram.

Runtime Library Routines

Fortran

```
use openacc  
#include "openacc_lib.h"
```

```
acc_get_num_devices  
acc_set_device_type  
acc_get_device_type  
acc_set_device_num  
acc_get_device_num  
acc_async_test  
acc_async_test_all
```

C

```
#include "openacc.h"  
  
acc_async_wait  
acc_async_wait_all  
acc_shutdown  
acc_on_device  
acc_malloc  
acc_free
```

Environment and Conditional Compilation

`ACC_DEVICE device`

Specifies which device type to connect to.

`ACC_DEVICE_NUM num`

Specifies which device number to connect to.

`_OPENACC`

Preprocessor directive for conditional compilation. Set to OpenACC version