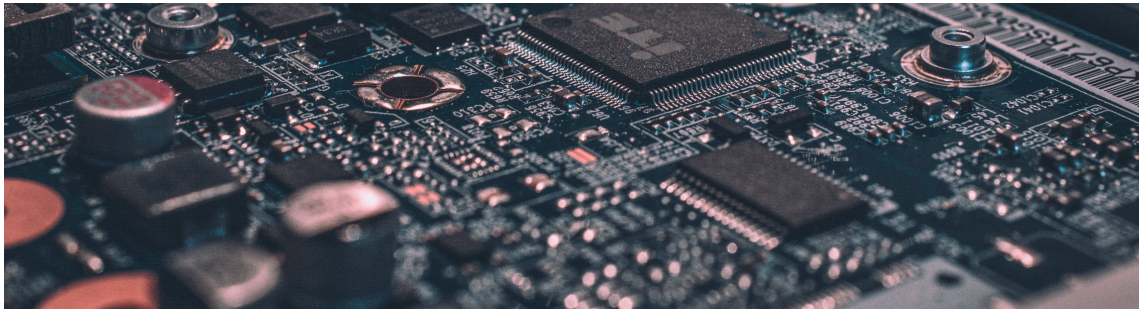




GPU ACCELERATORS AT JSC OF THREADS AND KERNELS

28 May 2018 | Andreas Herten | Forschungszentrum Jülich

Outline

GPUs at JSC

GPU Architecture

- Empirical Motivation

- Comparisons

- 3 Core Features

 - Memory

 - Asynchronicity

 - SIMT

- High Throughput

- Summary

Programming GPUs

- Libraries

- OpenACC/ OpenMP

- CUDA C/C++

- Performance Analysis

- Advanced Topics

- Using GPUs on JURECA

- Compiling

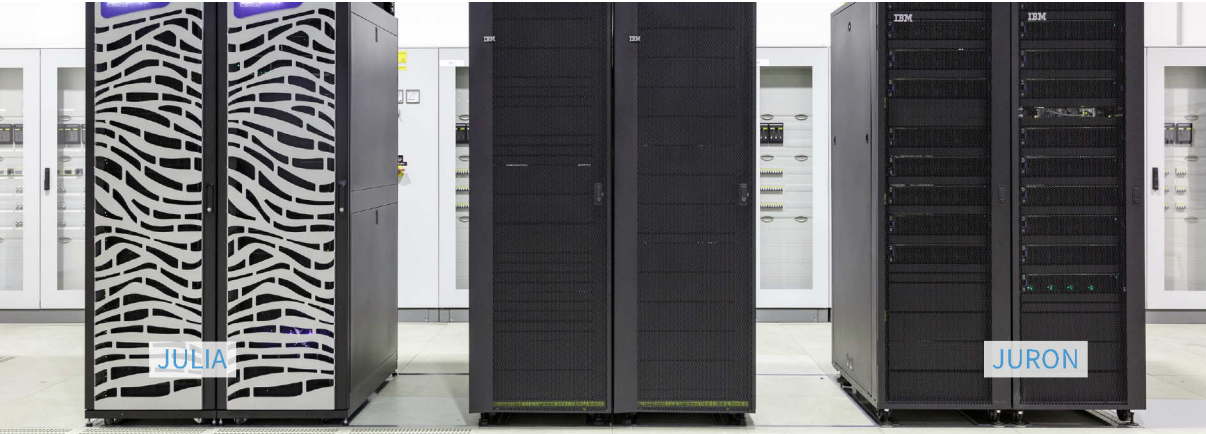
- Resource Allocation





JURECA – Jülich's Multi-Purpose Supercomputer

- 1872 nodes with Intel Xeon E5 2680 v3 Haswell CPUs (2×12 cores)
- 75 nodes with 2 NVIDIA Tesla K80 cards (look like 4 GPUs); each 2×12 GB RAM
- JURECA Booster: 1640 nodes with Intel Xeon Phi *Knights Landing*
- 1.8 (CPU) + 0.44 (GPU) + 5 (KNL) PFLOP/s peak performance (#29)



JURON – A Human Brain Project *Prototype*

- 18 nodes with IBM POWER8NVL CPUs (2×10 cores)
- Per Node: 4 NVIDIA Tesla P100 cards (16 GB HBM2 memory), connected via NVLink
- GPU: 0.38 PFLOP/s peak performance



JUWELS – Jülich's New Large System *currently under construction*

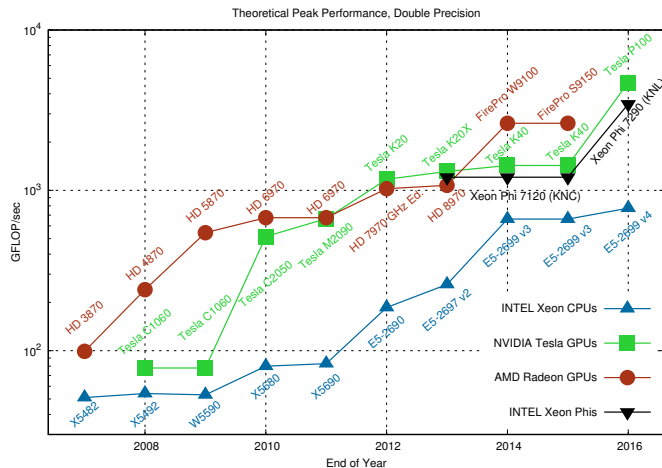
- 2500 nodes with Intel Xeon CPUs (2×24 cores)
- 48 nodes with 4 NVIDIA Tesla V100 cards (16 GB HBM2 memory)
- 10.4 (CPU) + 1.6 (GPU) + PFLOP/s peak performance

GPU Architecture

Why?

Status Quo Across Architectures

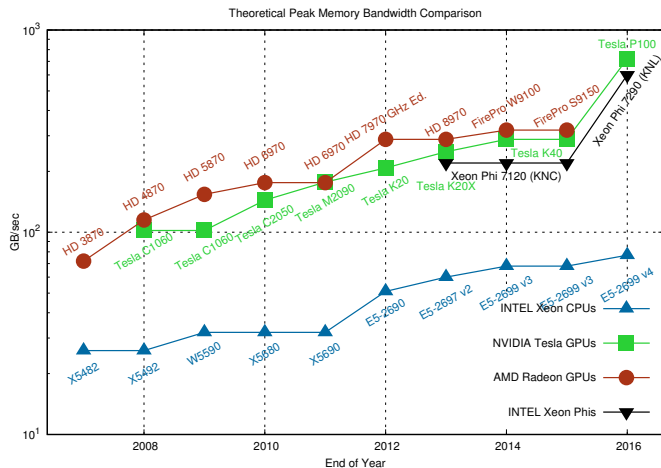
Performance



Graphic: Rupp [2]

Status Quo Across Architectures

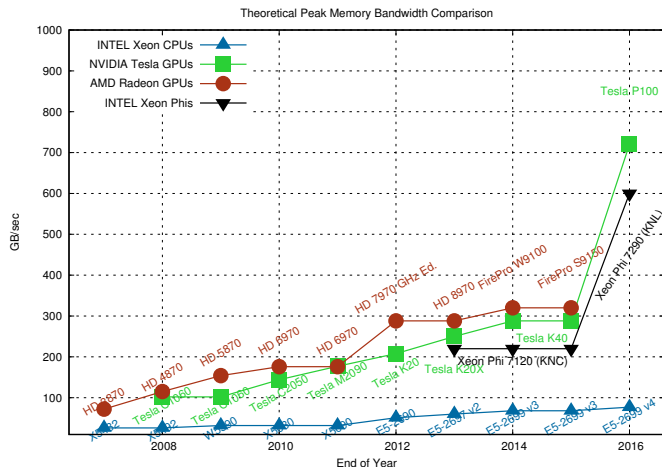
Memory Bandwidth



Graphic: Rupp [2]

Status Quo Across Architectures

Memory Bandwidth



Graphic: Rupp [2]

CPU vs. GPU

A matter of specialties



CPU vs. GPU

A matter of specialties



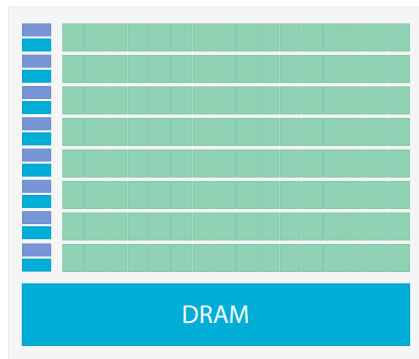
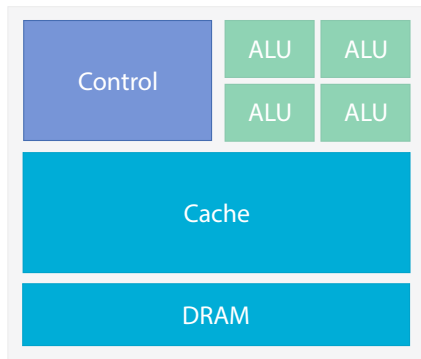
Transporting one



Transporting many

CPU vs. GPU

Chip



GPU Architecture

Overview

Aim: Hide Latency
Everything else follows

GPU Architecture

Overview

Aim: Hide Latency
Everything else follows

SIMT

Asynchronicity

Memory



GPU Architecture

Overview

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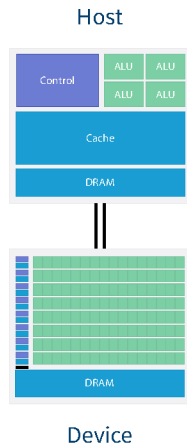
Asynchronicity

Memory

Memory

GPU memory ain't no CPU memory

- GPU: accelerator / extension card
- Separate device from CPU

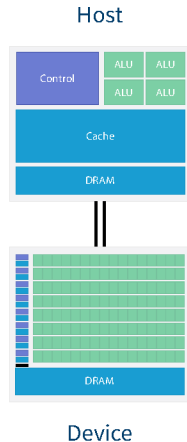


Memory

GPU memory ain't no CPU memory

Unified Virtual Addressing

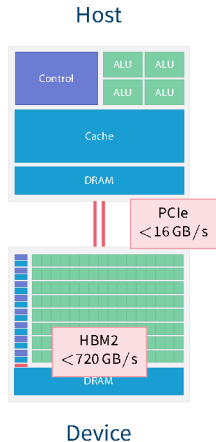
- GPU: accelerator / extension card
- Separate device from CPU
↓
Separate memory, but UVA



Memory

GPU memory ain't no CPU memory

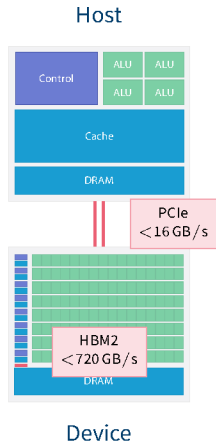
- GPU: accelerator / extension card
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Memory

GPU memory ain't no CPU memory

- GPU: accelerator / extension card
- Separate device from CPU
 - Separate memory, but UVA**
- Memory transfers need special consideration!
Do as little as possible!

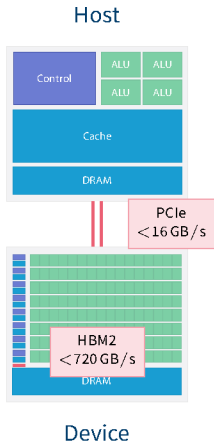


Memory

GPU memory ain't no CPU memory

Unified Memory

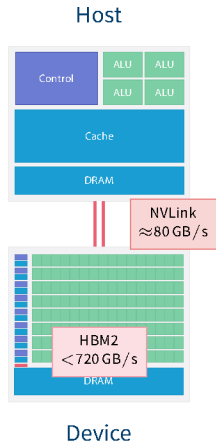
- GPU: accelerator / extension card
- Separate device from CPU
- **Separate memory, but UVA and UM**
- Memory transfers need special consideration!
Do as little as possible!
- Formerly: Explicitly copy data to/from GPU
Now: Done automatically (performance...?)



Memory

GPU memory ain't no CPU memory

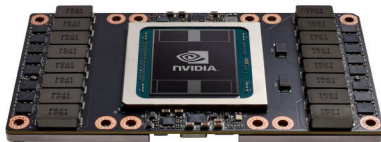
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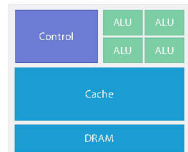
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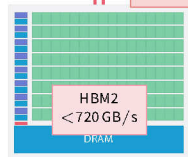
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- Memory transfers need special consideration!
Do as little as possible!
- Formerly: Explicitly copy data to/from GPU
Now: Done automatically (performance...?)
- P100: 16 GB RAM, 720 GB/s; V100: 16 (32) GB RAM, 900 GB/s



Host



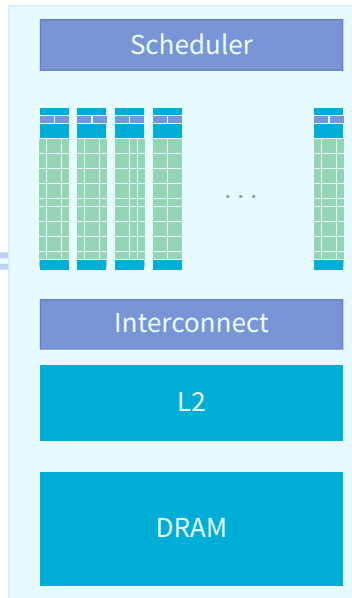
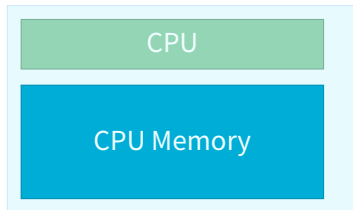
NVLink
≈ 80 GB/s



Device

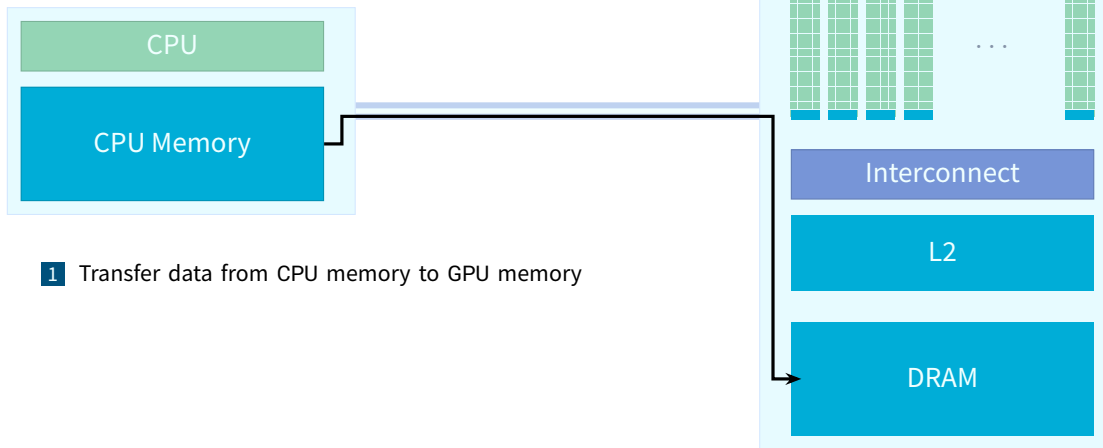
Processing Flow

CPU → GPU → CPU



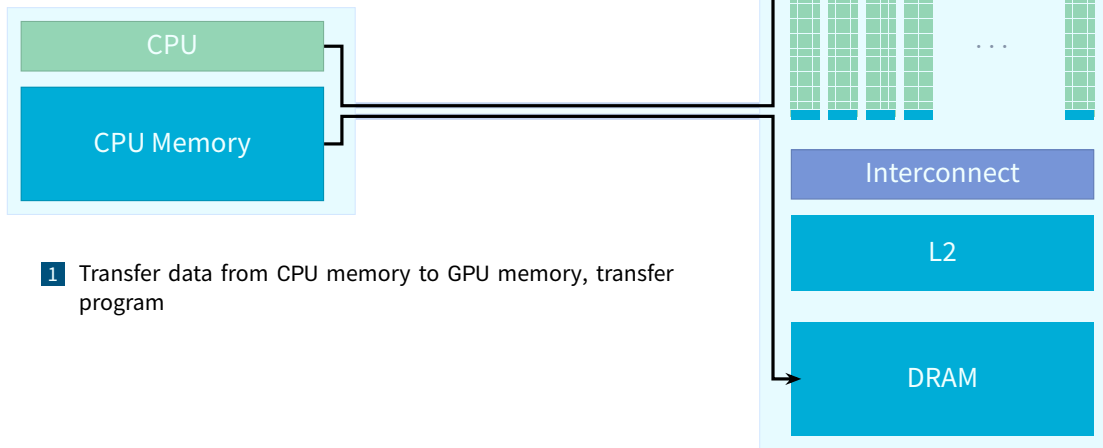
Processing Flow

CPU → GPU → CPU



Processing Flow

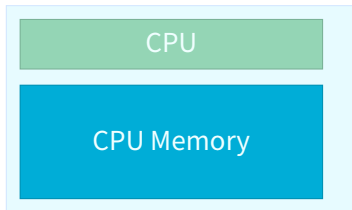
CPU → GPU → CPU



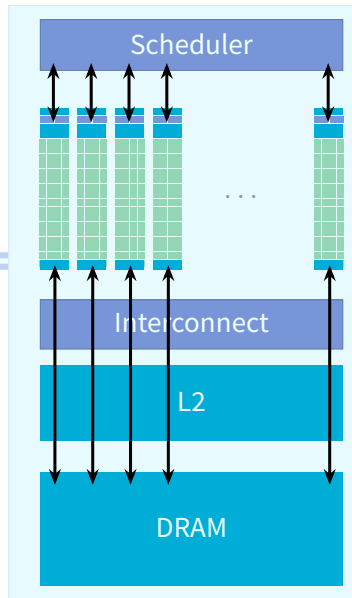
- 1 Transfer data from CPU memory to GPU memory, transfer program

Processing Flow

CPU → GPU → CPU

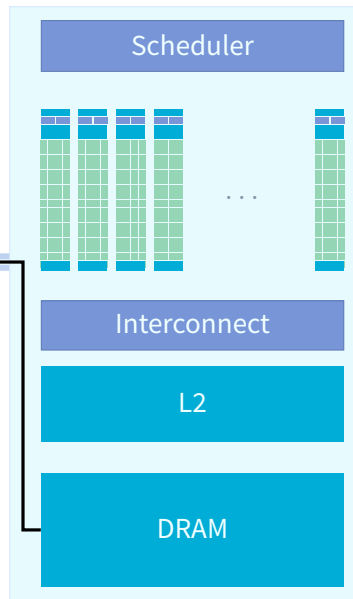
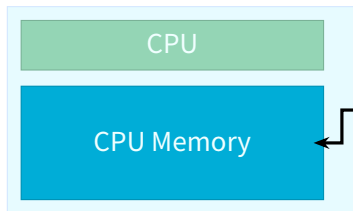


- 1 Transfer data from CPU memory to GPU memory, transfer program
- 2 Load GPU program, execute on SMs, get (cached) data from memory; write back



Processing Flow

CPU → GPU → CPU



- 1 Transfer data from CPU memory to GPU memory, transfer program
- 2 Load GPU program, execute on SMs, get (cached) data from memory; write back
- 3 Transfer results back to host memory

GPU Architecture

Overview

Aim: Hide Latency
Everything else follows

SIMT

Asynchronicity

Memory

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Async

Following different streams

- Problem: Memory transfer is comparably slow
Solution: Do something else in meantime (**computation**)!

→ Overlap tasks

- Copy and compute engines run separately (*streams*)



- GPU needs to be fed: Schedule many computations
- CPU can do other work while GPU computes; synchronization

GPU Architecture

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Aim: Hide Latency
Everything else follows

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GPU Architecture

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Aim: Hide Latency
Everything else follows

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SIMT

$$\text{SIMT} = \text{SIMD} \oplus \text{SMT}$$

- CPU:
 - Single Instruction, Multiple Data (SIMD)

Scalar

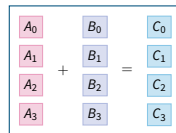
A_0	+	B_0	=	C_0
A_1	+	B_1	=	C_1
A_2	+	B_2	=	C_2
A_3	+	B_3	=	C_3

SIMT

$$\text{SIMT} = \text{SIMD} \oplus \text{SMT}$$

- CPU:
 - Single Instruction, Multiple Data (SIMD)

Vector

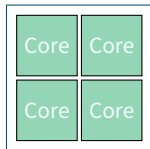
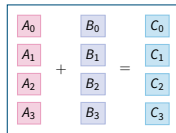


SIMT

$$\text{SIMT} = \text{SIMD} \oplus \text{SMT}$$

- CPU:
 - Single Instruction, Multiple Data (SIMD)
 - Simultaneous Multithreading (SMT)

Vector

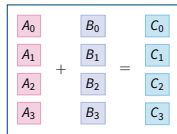


SIMT

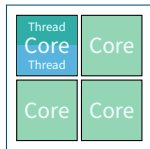
$$\text{SIMT} = \text{SIMD} \oplus \text{SMT}$$

- CPU:
 - Single Instruction, Multiple Data (SIMD)
 - Simultaneous Multithreading (SMT)

Vector



SMT

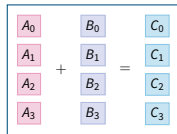


SIMT

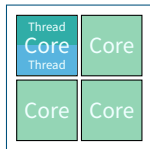
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- CPU:
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 - Simultaneous Multithreading (SMT)
- GPU: Single Instruction, Multiple Threads (SIMT)

Vector



SMT

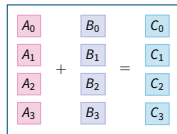


SIMT

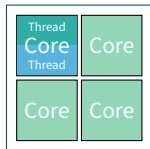
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- CPU:
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 - Simultaneous Multithreading (SMT)
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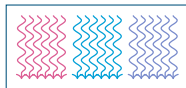
Vector



SMT



SIMT

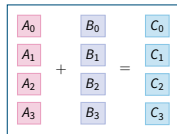


SIMT

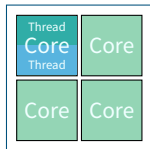
$$\text{SIMT} = \text{SIMD} \oplus \text{SMT}$$

- CPU:
 - Single Instruction, Multiple Data (SIMD)
 - Simultaneous Multithreading (SMT)
- GPU: Single Instruction, Multiple Threads (SIMT)
 - CPU core $\approx$ GPU multiprocessor (SM)
 - Working unit: set of threads (32, a *warp*)
 - Fast switching of threads (large register file)
 - Branching 

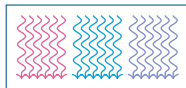
Vector



SMT



SIMT



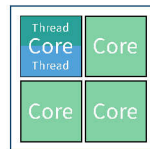
SIMT



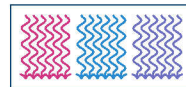
Vector

$$\begin{bmatrix} A_0 \\ A_1 \\ A_2 \\ A_3 \end{bmatrix} + \begin{bmatrix} B_0 \\ B_1 \\ B_2 \\ B_3 \end{bmatrix} = \begin{bmatrix} C_0 \\ C_1 \\ C_2 \\ C_3 \end{bmatrix}$$

SMT



SIMT



Graphics: Nvidia Corporation [5]

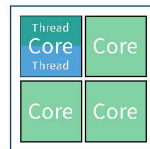
SIMT



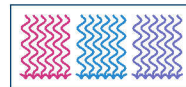
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SMT



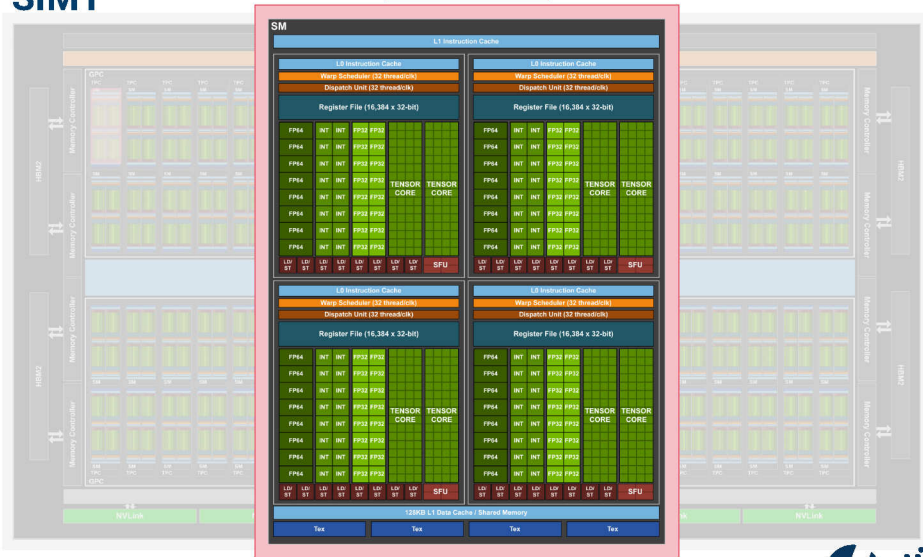
SIMT



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SIMT

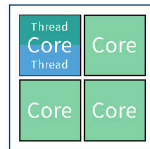
Multiprocessor



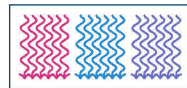
Vector

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SMT



SIMT



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Low Latency vs. High Throughput

Maybe GPU's ultimate feature

CPU Minimizes latency within each thread

GPU Hides latency with computations from other thread warps

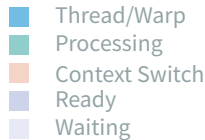
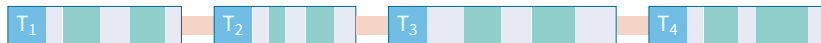
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CPU Core: Low Latency



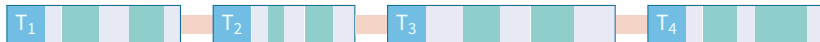
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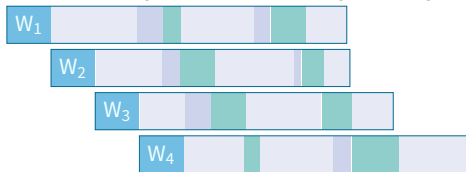
CPU Minimizes latency within each thread

GPU Hides latency with computations from other thread warps

CPU Core: Low Latency



GPU Streaming Multiprocessor: High Throughput



- Thread/Warp
- Processing
- Context Switch
- Ready
- Waiting

CPU vs. GPU

Let's summarize this!



Optimized for **low latency**

- + Large main memory
- + Fast clock rate
- + Large caches
- + Branch prediction
- + Powerful ALU
- Relatively low memory bandwidth
- Cache misses costly
- Low performance per watt



Optimized for **high throughput**

- + High bandwidth main memory
- + Latency tolerant (parallelism)
- + More compute resources
- + High performance per watt
- Limited memory capacity
- Low per-thread performance
- Extension card

Programming GPUs

Preface: CPU

A simple CPU program!

SAXPY: $\vec{y} = a\vec{x} + \vec{y}$, with single precision

Part of **LAPACK BLAS** Level 1

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

```
float a = 42;  
int n = 10;  
float x[n], y[n];  
// fill x, y
```

```
saxpy(n, a, x, y);
```



Programming GPUs

Libraries

Libraries

Programming GPUs is easy: **Just don't!**

Libraries

Programming GPUs is easy: **Just don't!**

Use applications & libraries!

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Libraries

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cuBLAS



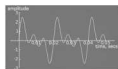
cuSPARSE



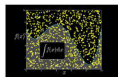
cuDNN



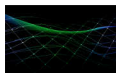
Numba



cuFFT



cuRAND



CUDA Math

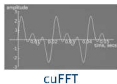


theano

Libraries

Programming GPUs is easy: **Just don't!**

Use applications & libraries!



Numba



theano



- GPU-parallel BLAS (all 152 routines)
- Single, double, complex data types
- Constant competition with Intel's MKL
- Multi-GPU support

→ <https://developer.nvidia.com/cublas>
<http://docs.nvidia.com/cuda/cublas>

cuBLAS

Code example

```
float a = 42;  int n = 10;
float x[n], y[n];
// fill x, y

cublasHandle_t handle;
cublasCreate(&handle);

float * d_x, * d_y;
cudaMallocManaged(&d_x, n * sizeof(x[0]));
cudaMallocManaged(&d_y, n * sizeof(y[0]));
cublasSetVector(n, sizeof(x[0]), x, 1, d_x, 1);
cublasSetVector(n, sizeof(y[0]), y, 1, d_y, 1);

cublasSaxpy(n, a, d_x, 1, d_y, 1);

cublasGetVector(n, sizeof(y[0]), d_y, 1, y, 1);

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

cuBLAS

Code example

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float a = 42; int n = 10;  
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```

```
cublasHandle_t handle;  
cublasCreate(&handle);
```

Initialize

```
float * d_x, * d_y;  
cudaMallocManaged(&d_x, n * sizeof(x[0]));  
cudaMallocManaged(&d_y, n * sizeof(y[0]));  
cublasSetVector(n, sizeof(x[0]), x, 1, d_x, 1);  
cublasSetVector(n, sizeof(y[0]), y, 1, d_y, 1);
```

```
cublasSaxpy(n, a, d_x, 1, d_y, 1);
```

```
cublasGetVector(n, sizeof(y[0]), d_y, 1, y, 1);
```

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float * d_x, * d_y;  
cudaMallocManaged(&d_x, n * sizeof(x[0]));  
cudaMallocManaged(&d_y, n * sizeof(y[0]));  
cublasSetVector(n, sizeof(x[0]), x, 1, d_x, 1);  
cublasSetVector(n, sizeof(y[0]), y, 1, d_y, 1);
```

Allocate GPU memory

```
cublasSaxpy(n, a, d_x, 1, d_y, 1);
```

```
cublasGetVector(n, sizeof(y[0]), d_y, 1, y, 1);
```

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

cuBLAS

Code example

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Finalize

Programming GPUs

OpenACC/ OpenMP

GPU Programming with Directives

Keepin' you portable

- Annotate serial source code by directives

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#pragma acc loop  
for (int i = 0; i < 1; i++) {};
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- Compiler interprets directives, creates according instructions

GPU Programming with Directives

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Pro

- Portability
 - Other compiler? No problem! To it, it's a serial program
 - Different target architectures from same code
- Easy to program

Con

- Only few compilers
- Not all the raw power available
- Harder to debug
- Easy to program wrong

OpenACC

Code example

```
void saxpy_acc(int n, float a, float * x, float * y) {  
    #pragma acc kernels  
    for (int i = 0; i < n; i++)  
        y[i] = a * x[i] + y[i];  
}  
  
float a = 42;  
int n = 10;  
float x[n], y[n];  
// fill x, y  
  
saxpy_acc(n, a, x, y);
```



OpenACC

Code example

```
void saxpy_acc(int n, float a, float * x, float * y) {  
    #pragma acc parallel loop copy(y) copyin(x)  
    for (int i = 0; i < n; i++)  
        y[i] = a * x[i] + y[i];  
}
```

```
float a = 42;  
int n = 10;  
float x[n], y[n];  
// fill x, y
```

```
saxpy_acc(n, a, x, y);
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Programming GPUs

CUDA C/C++

Programming GPU Directly

Finally...

- Two solutions:

Programming GPU Directly

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- OpenCL Open Computing Language by Khronos Group (Apple, IBM, NVIDIA, ...) 2009

- Platform: Programming language (OpenCL C/C++), API, and compiler
 - Targets CPUs, GPUs, FPGAs, and other many-core machines
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- Platform: Drivers, programming language (CUDA C/C++), API, compiler, debuggers, profilers, ...
 - Only NVIDIA GPUs
 - Compilation with `nvcc` (free, but not open)
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- Choose what flavor you like, what colleagues/collaboration is using

- **Hardest: Come up with parallelized algorithm**



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CUDA's Parallel Model

In software: Threads, Blocks

- Methods to exploit parallelism:

CUDA's Parallel Model

In software: Threads, Blocks

- Methods to exploit parallelism:

- Thread



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CUDA's Parallel Model

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- Methods to exploit parallelism:

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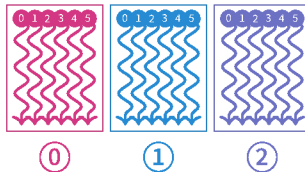
CUDA's Parallel Model

In software: Threads, Blocks

- Methods to exploit parallelism:

- Threads → Block

- Blocks



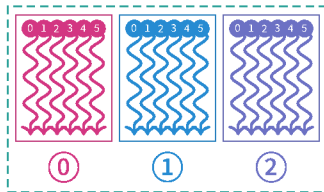
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CUDA's Parallel Model

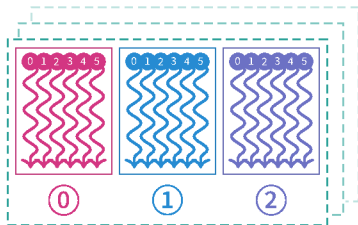
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- Blocks → Grid

- Threads & blocks in 3D



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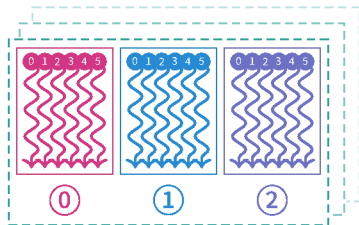
In software: Threads, Blocks

- Methods to exploit parallelism:

- Threads → Block

- Blocks → Grid

- Threads & blocks in 3D



- Parallel function: **kernel**

- `__global__ kernel(int a, float * b) { }`

- Access own ID by global variables `threadIdx.x`, `blockIdx.y`, ...

- Execution entity: **threads**

- Lightweight → fast switching!

- 1000s threads execute simultaneously → order non-deterministic!

CUDA SAXPY

With runtime-managed data transfers

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

```
float a = 42;  
int n = 10;  
float x[n], y[n];  
// fill x, y  
cudaMallocManaged(&x, n * sizeof(float));  
cudaMallocManaged(&y, n * sizeof(float));
```

```
saxpy_cuda<<<2, 5>>>(n, a, x, y);
```

```
cudaDeviceSynchronize();
```



Programming GPUs

Performance Analysis

GPU Tools

The helpful helpers helping helpless (and others)

- NVIDIA

- `cuda-gdb` GDB-like command line utility for debugging

- `cuda-memcheck` Like Valgrind's memcheck, for checking errors in memory accesses

- `Nsight` IDE for GPU developing, based on Eclipse (Linux, OS X) or Visual Studio (Windows)

- `nvprof` Command line profiler, including detailed performance counters

- `Visual Profiler` Timeline profiling and annotated performance experiments

- OpenCL: `CodeXL` (Open Source, GPUOpen/AMD) – debugging, profiling.

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nvprof

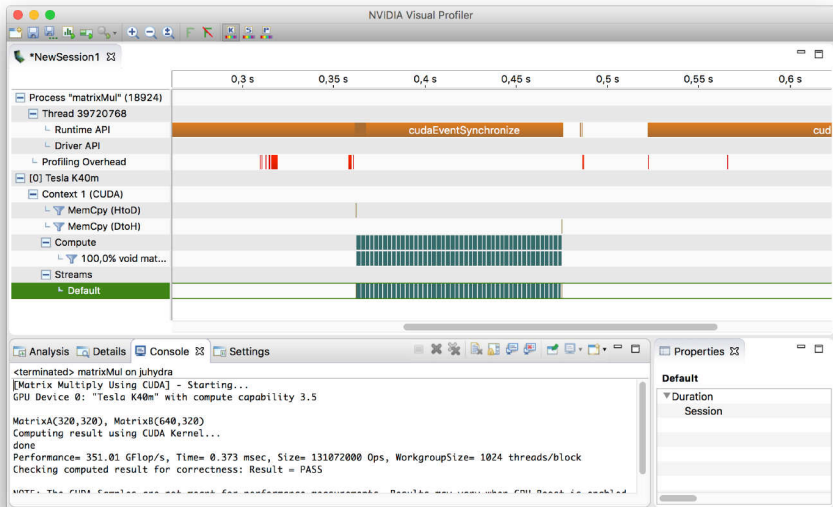
Command that line

```
$ nvprof ./matrixMul -wA=1024 -hA=1024 -wB=1024 -hB=1024
==37064== Profiling application: ./matrixMul -wA=1024 -hA=1024 -wB=1024 -hB=1024
==37064== Profiling result:
Time(%)      Time      Calls      Avg      Min      Max      Name
99.19%    262.43ms      301    871.86us    863.88us    882.44us    void matrixMulCUDA<int=32>(float*, float*, float*, int, int)
 0.58%    1.5428ms        2    771.39us    764.65us    778.12us    [CUDA memcpy HtoD]
 0.23%    599.40us        1    599.40us    599.40us    599.40us    [CUDA memcpy DtoH]
```

==37064== API calls:

Time(%)	Time	Calls	Avg	Min	Max	Name
61.26%	258.38ms	1	258.38ms	258.38ms	258.38ms	cudaEventSynchronize
35.68%	150.49ms	3	50.164ms	914.97us	148.65ms	cudaMalloc
0.73%	3.0774ms	3	1.0258ms	1.0097ms	1.0565ms	cudaMemcpy
0.62%	2.6287ms	4	657.17us	655.12us	660.56us	cuDeviceTotalMem
0.56%	2.3408ms	301	7.7760us	7.3810us	53.103us	cudaLaunch
0.48%	2.0111ms	364	5.5250us	235ns	201.63us	cuDeviceGetAttribute
0.21%	872.52us	1	872.52us	872.52us	872.52us	cudaDeviceSynchronize
0.15%	612.20us	1505	406ns	361ns	1.1970us	cudaSetupArgument
0.12%	499.01us	3	166.34us	140.45us	216.16us	cudaFree

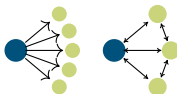
Visual Profiler



Advanced Topics

So much more interesting things to show!

- Optimize memory transfers to reduce overhead
- Optimize applications for GPU architecture
- Drop-in BLAS acceleration with NVBLAS (`$LD_PRELOAD`)
- Tensor Cores for Deep Learning
- Use multiple GPUs
 - On one node
 - Across many nodes → MPI
- ...
- Most of that: Addressed at **dedicated training courses**



Using GPUs on JURECA

Compiling on JURECA

CUDA

- Module: `module load CUDA/9.1.85`
- Compile: `nvcc file.cu`
Default host compiler: `g++`; use `nvcc_pgc++` for PGI compiler
- cuBLAS: `g++ file.cpp -I$CUDA_HOME/include -L$CUDA_HOME/lib64 -lcublas -lcudart`

OpenACC

- Module: `module load PGI/17.10-GCC-5.5.0`
- Compile: `pgc++ -acc -ta=tesla file.cpp`

MPI

- Module: `module load MVAPICH2/2.3a-GDR`
Enabled for CUDA (*CUDA-aware*); no need to copy data to host before transfer

Running on JURECA

- Dedicated GPU partitions: gpus and develgpus (+ vis)
 - `--partition=develgpus` Total 4 nodes (Job: <2 h, ≤ 2 nodes)
 - `--partition=gpus` Total 70 nodes (Job: <1 d, ≤ 32 nodes)
 - Needed: Resource configuration with `--gres`
 - `--gres=gpu:2`
 - `--gres=gpu:4`
 - `--gres=mem1024,gpu:2 --partition=vis`
- See [online documentation](#)

Example

- 96 tasks in total, running on 4 nodes
- Per node: 4 GPUs

```
#!/bin/bash -x
#SBATCH --nodes=4
#SBATCH --ntasks=96
#SBATCH --ntasks-per-node=24
#SBATCH --output=gpu-out.%j
#SBATCH --error=gpu-err.%j
#SBATCH --time=00:15:00
```

```
#SBATCH --partition=gpus
#SBATCH --gres=gpu:4
```

```
srun ./gpu-prog
```

Conclusion, Resources

- GPUs provide highly-parallel computing power
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**Thank you
for your attention!**
a.herten@fz-juelich.de



APPENDIX

Appendix

Glossary

References

Glossary I

API A programmatic interface to software by well-defined functions. Short for application programming interface. [71](#), [72](#), [73](#), [74](#), [75](#)

CUDA Computing platform for [GPUs](#) from NVIDIA. Provides, among others, CUDA C/C++. [2](#), [70](#), [71](#), [72](#), [73](#), [74](#), [75](#), [76](#), [77](#), [78](#), [79](#), [80](#), [81](#), [82](#), [83](#), [84](#), [85](#), [93](#), [96](#), [97](#), [98](#), [99](#), [100](#), [103](#)

JSC Jülich Supercomputing Centre, the supercomputing institute of Forschungszentrum Jülich, Germany. [2](#), [96](#), [97](#), [98](#), [99](#), [100](#), [103](#)

JURECA A multi-purpose supercomputer with 1800 nodes at JSC. [2](#), [3](#), [92](#), [93](#), [94](#)

JURON One of the two HBP pilot system in Jülich; name derived from Juelich and Neuron. [4](#)

Glossary II

JUWELS Jülich's new supercomputer, the successor of JUQUEEN. [5](#)

MPI The Message Passing Interface, a API definition for multi-node computing. [91](#), [93](#)

NVIDIA US technology company creating [GPUs](#). [3](#), [4](#), [5](#), [71](#), [72](#), [73](#), [74](#), [75](#), [87](#), [88](#), [96](#), [97](#), [98](#), [99](#), [100](#), [103](#)

NVLink **NVIDIA**'s communication protocol connecting [CPU](#) ↔ [GPU](#) and [GPU](#) ↔ [GPU](#) with high bandwidth. [4](#), [103](#)

OpenACC Directive-based programming, primarily for many-core machines. [2](#), [64](#), [65](#), [66](#), [67](#), [68](#), [69](#), [93](#), [96](#), [97](#), [98](#), [99](#), [100](#)

OpenCL The *Open Computing Language*. Framework for writing code for heterogeneous architectures ([CPU](#), [GPU](#), DSP, FPGA). The alternative to [CUDA](#). [71](#), [72](#), [73](#), [74](#), [75](#), [87](#), [88](#)

Glossary III

OpenMP Directive-based programming, primarily for multi-threaded machines. 2, 64, 65, 66, 67

P100 A large GPU with the Pascal architecture from NVIDIA. It employs NVLink as its interconnect and has fast HBM2 memory. 4

Pascal GPU architecture from NVIDIA (announced 2016). 103

POWER CPU architecture from IBM, earlier: PowerPC. See also POWER8. 103

POWER8 Version 8 of IBM's POWER processor, available also under the OpenPOWER Foundation. 4, 103

SAXPY Single-precision $A \times X + Y$. A simple code example of scaling a vector and adding an offset. 49, 85

Glossary IV

Tesla The GPU product line for general purpose computing computing of NVIDIA. 3, 4, 5

CPU Central Processing Unit. 3, 4, 5, 11, 12, 13, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 49, 71, 72, 73, 74, 75, 103

GPU Graphics Processing Unit. 2, 3, 4, 5, 6, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 48, 50, 51, 52, 53, 54, 55, 56, 64, 65, 66, 67, 70, 71, 72, 73, 74, 75, 86, 87, 88, 91, 92, 94, 95, 96, 97, 98, 99, 100, 103

HBP Human Brain Project. 103

SIMD Single Instruction, Multiple Data. 34, 35, 36, 37, 38, 39, 40, 41, 42, 43

Glossary V

SIMT Single Instruction, Multiple Threads. [14](#), [15](#), [16](#), [29](#), [30](#), [32](#), [33](#), [34](#), [35](#), [36](#), [37](#), [38](#), [39](#), [40](#), [41](#), [42](#), [43](#)

SM Streaming Multiprocessor. [34](#), [35](#), [36](#), [37](#), [38](#), [39](#), [40](#), [41](#), [42](#), [43](#)

SMT Simultaneous Multithreading. [34](#), [35](#), [36](#), [37](#), [38](#), [39](#), [40](#), [41](#), [42](#), [43](#)

References I

- [2] Karl Rupp. *Pictures: CPU/GPU Performance Comparison*. URL: <https://www.karlrupp.net/2013/06/cpu-gpu-and-mic-hardware-characteristics-over-time/> (pages 8–10).
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- [5] Nvidia Corporation. *Pictures: Volta GPU*. Volta Architecture Whitepaper. URL: <https://images.nvidia.com/content/volta-architecture/pdf/Volta-Architecture-Whitepaper-v1.0.pdf> (pages 41–43).