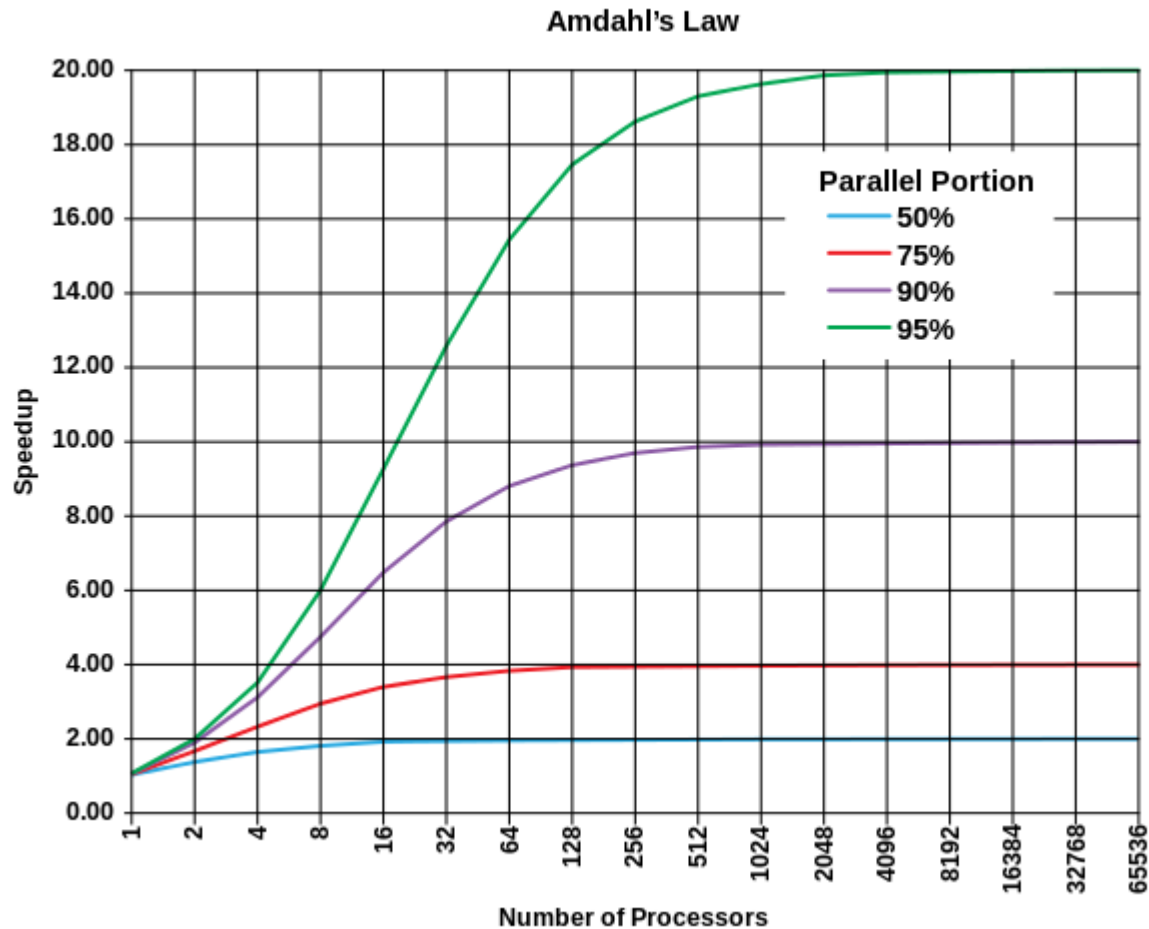


# Parallel Computing

Some basic ideas

# Amdahl's Law (Gene Amdahl 1967)



Evolution according to Amdahl's law of the theoretical speedup of the execution of a program in function of the number of processors executing it, for different values of  $p$ . The speedup is limited by the serial part of the program. For example, if 95% of the program can be parallelized, the theoretical maximum speedup using parallel computing would be 20 times.

## Calculate Amdahl's Law:

Let  $X$  be the part of my program (in terms of computing time) which can be parallelised. The sequential computing time  $T_{seq}$  is normalized to unity (1), and can be expressed as:

$$T_{seq} = 1 = X + (1-X)$$

The parallel computing time  $T_{par}$  under ideal conditions (ideal load balancing, ultrafast communication):

$$T_{par} = X/p + (1-X) \quad \text{with processor number (core number) } p$$

Then the speed-up of the program  $S = T_{seq} / T_{par}$  :

$$S = 1 / (1-X+X/p) \quad ; \quad \text{Note: } T_{par}/T_{seq} = 1/S \text{ (sometimes also plotted)}$$

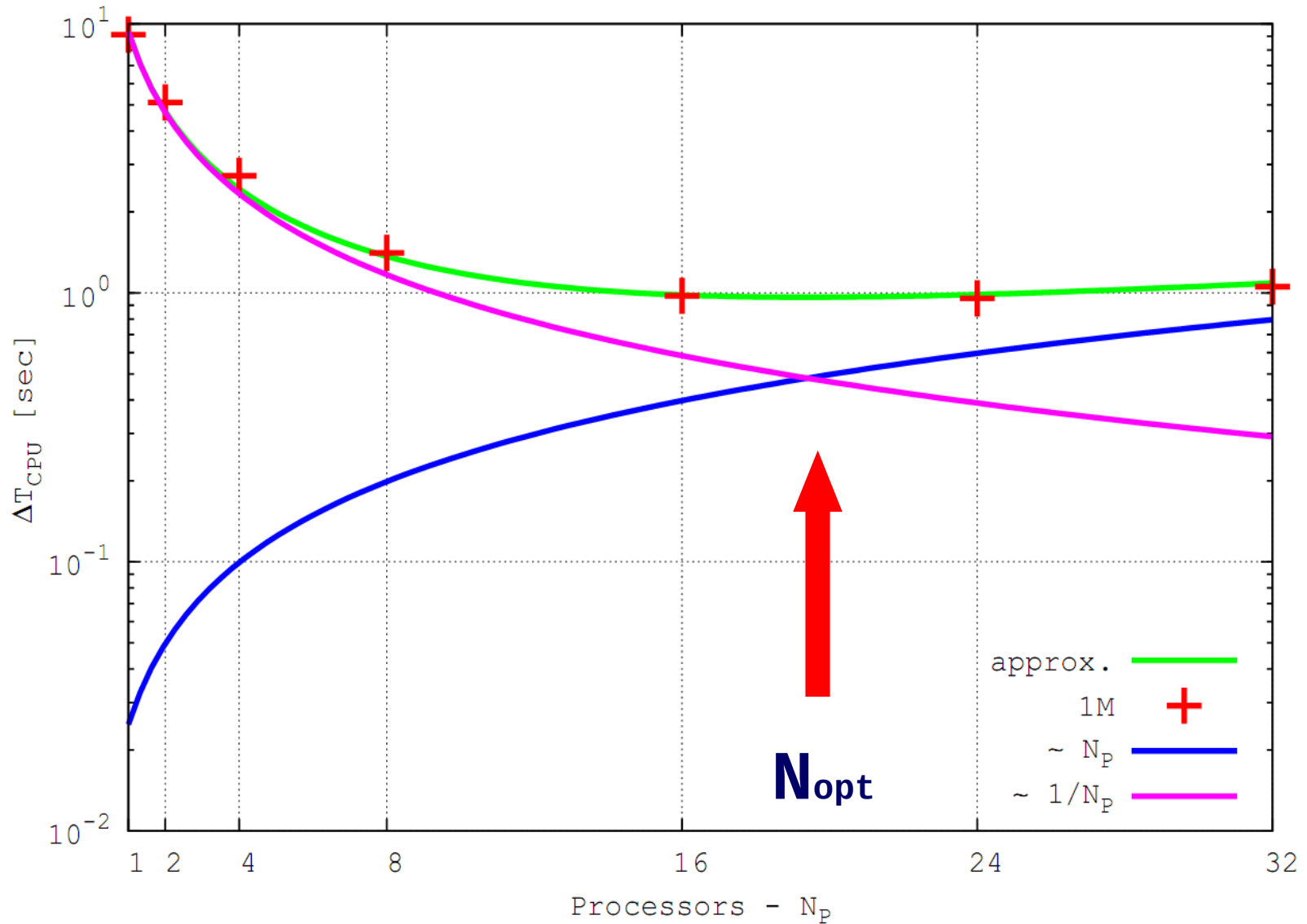
Note the limit if  $p$  is very large:  $S = 1/(1-X)$ . And if  $X \sim 1$ :  $S \sim p$

With communication overhead:

$$T_{par} = X/p + (1-X) + T_{comm} \quad \rightarrow \quad S = 1 / (1-X+X/p+T_{comm})$$

If  $T_{comm}$  independent of  $p$  we have for large  $p$ :  $S = 1 / (1-X + T_{comm}) = \text{const.}$

# Parallel code on cluster



## Strong and Soft Scaling

- Strong Scaling: Fixed Problem size, increase  $p$
- Soft Scaling: Increase Problem size, increase  $p$   
(constant amount of work per processing element)

Ansatz for Soft Scaling:

- $T_{\text{seq}} = p = p (X + (1-X))$
- $T_{\text{par}} = X + p (1-X)$
- $S = T_{\text{seq}}/T_{\text{par}} = p / (X+p (1-X))$   
If  $X \sim 1$ :  $S = p$  ;  $T_{\text{par}} = X = \text{const.}$

# ΦGPU – NBODY Code

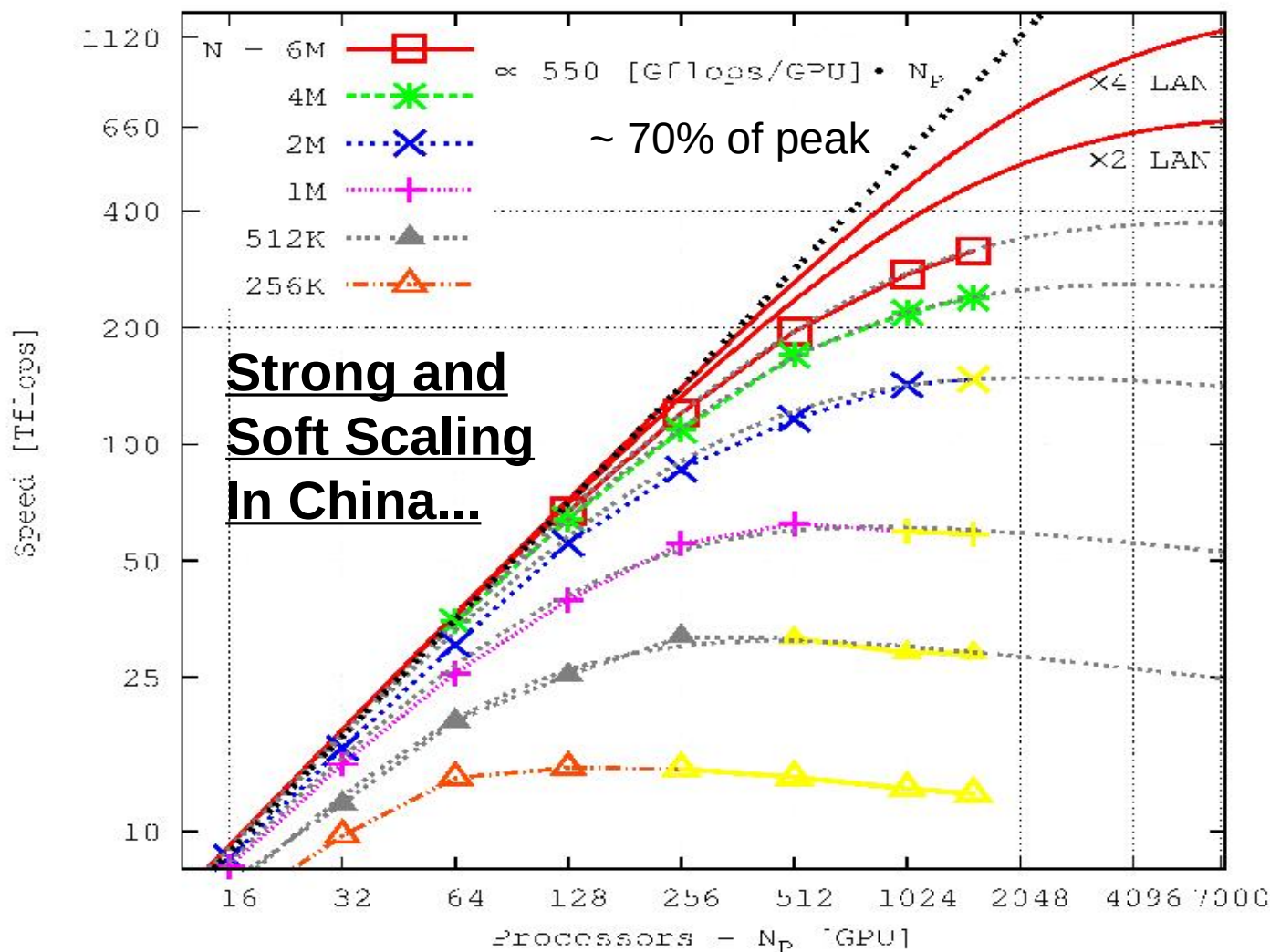
中国科学院国家天文台

National Astronomical Observatories, CAS

350 Teraflop/s  
1600 GPUs .  
440 cores  
= 704.000  
GPU-Cores

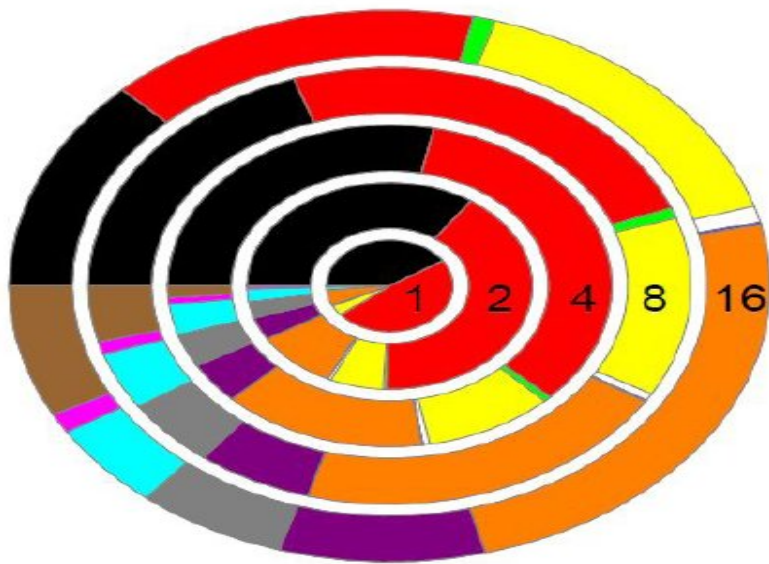
Using  
Mole-8.5  
of  
IPE/CAS  
Beijing

Berczik et al.  
2013



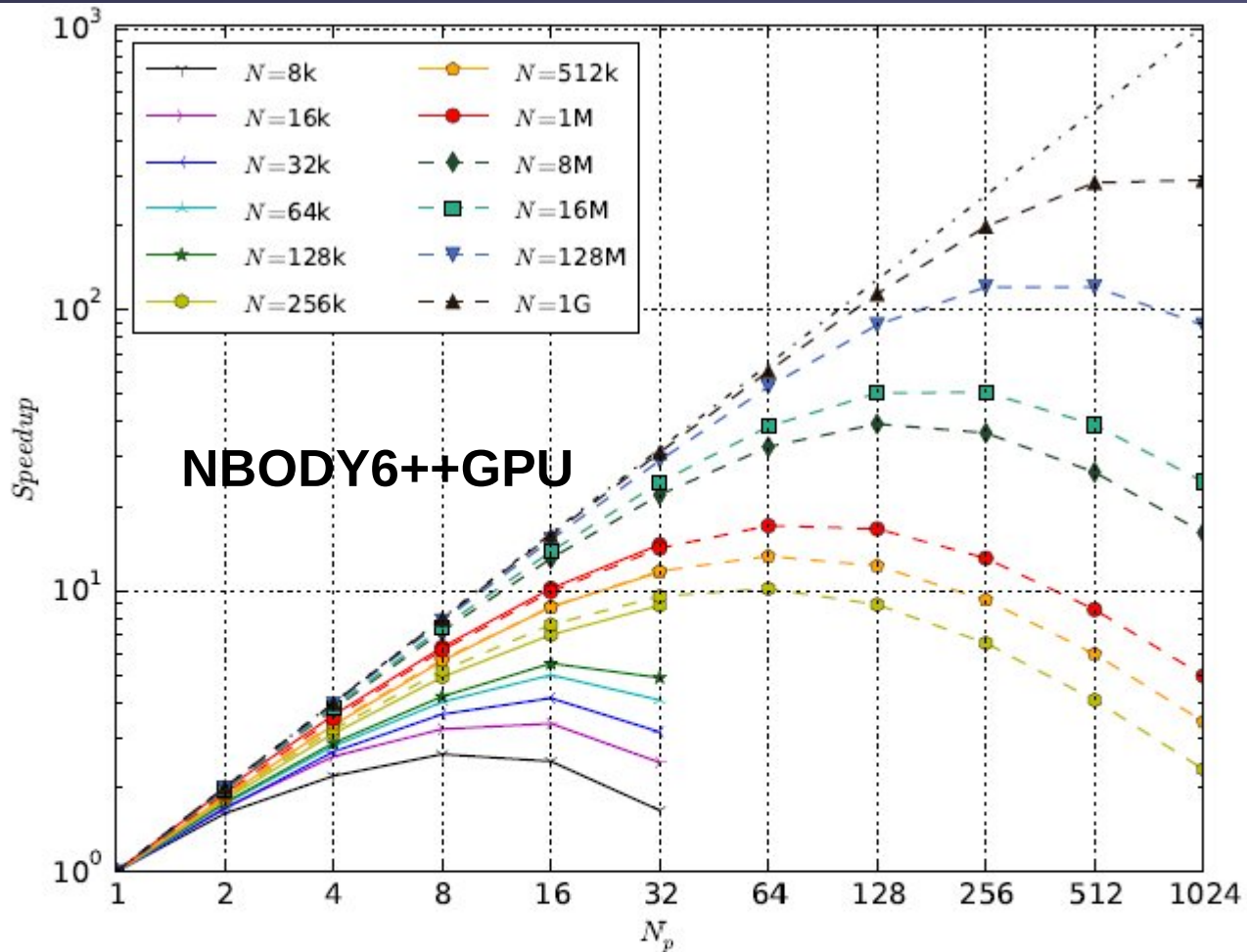
中国科学院过程工程研究所

Institute Of Process Engineering, Chinese Academy Of Sciences



**Table 1** Main components of NBODY6++

Description	Timing variable	Expected scaling		Fitting value [sec]
		$N$	$N_p$	
Regular force computation	$T_{\text{reg}}$	$\mathcal{O}(N_{\text{reg}} \cdot N)$	$\mathcal{O}(N_p^{-1})$	$(2.2 \cdot 10^{-9} \cdot N^{2.11} + 10.43) \cdot N_p^{-1}$
Irregular force computation	$T_{\text{irr}}$	$\mathcal{O}(N_{\text{irr}} \cdot \langle N_{nb} \rangle)$	$\mathcal{O}(N_p^{-1})$	$(3.9 \cdot 10^{-7} \cdot N^{1.76} - 16.47) \cdot N_p^{-1}$
Prediction	$T_{\text{pre}}$	$\mathcal{O}(N^{kn_p})$	$\mathcal{O}(N_p^{-kp_p})$	$(1.2 \cdot 10^{-6} \cdot N^{1.51} - 3.58) \cdot N_p^{-0.5}$
Data moving	$T_{\text{mov}}$	$\mathcal{O}(N^{kn_{m1}})$	$\mathcal{O}(1)$	$2.5 \cdot 10^{-6} \cdot N^{1.29} - 0.28$
MPI communication (regular)	$T_{\text{mcr}}$	$\mathcal{O}(N^{kn_{cr}})$	$\mathcal{O}(kp_{cr} \cdot \frac{N_p-1}{N_p})$	$(3.3 \cdot 10^{-6} \cdot N^{1.18} + 0.12)(1.5 \cdot \frac{N_p-1}{N_p})$
MPI communication (irregular)	$T_{\text{mci}}$	$\mathcal{O}(N^{kn_{ci}})$	$\mathcal{O}(kp_{ci} \cdot \frac{N_p-1}{N_p})$	$(3.6 \cdot 10^{-7} \cdot N^{1.40} + 0.56)(1.5 \cdot \frac{N_p-1}{N_p})$
Synchronization	$T_{\text{syn}}$	$\mathcal{O}(N^{kn_s})$	$\mathcal{O}(N_p^{kp_s})$	$(4.1 \cdot 10^{-8} \cdot N^{1.34} + 0.07) \cdot N_p$
Sequential parts on host	$T_{\text{host}}$	$\mathcal{O}(N^{kn_h})$	$\mathcal{O}(1)$	$4.4 \cdot 10^{-7} \cdot N^{1.49} + 1.23$



*Huang, Berczik, Spurzem, Res. Astron. Astroph. 2016, 16, 11.*

**Fig. 2** The speed-up ( $S$ ) of NBODY6++ as a function of particle number ( $N$ ) and processor number ( $N_p$ ). Solid points are the measured speed-up ratio between sequential and parallel wall-clock time, dash lines predict the performance of larger scale simulations further. The symbols used in figure have the magnitudes:  $1k = 1,024$ ,  $1M = 1k^2$  and  $1G = 1k^3$ .

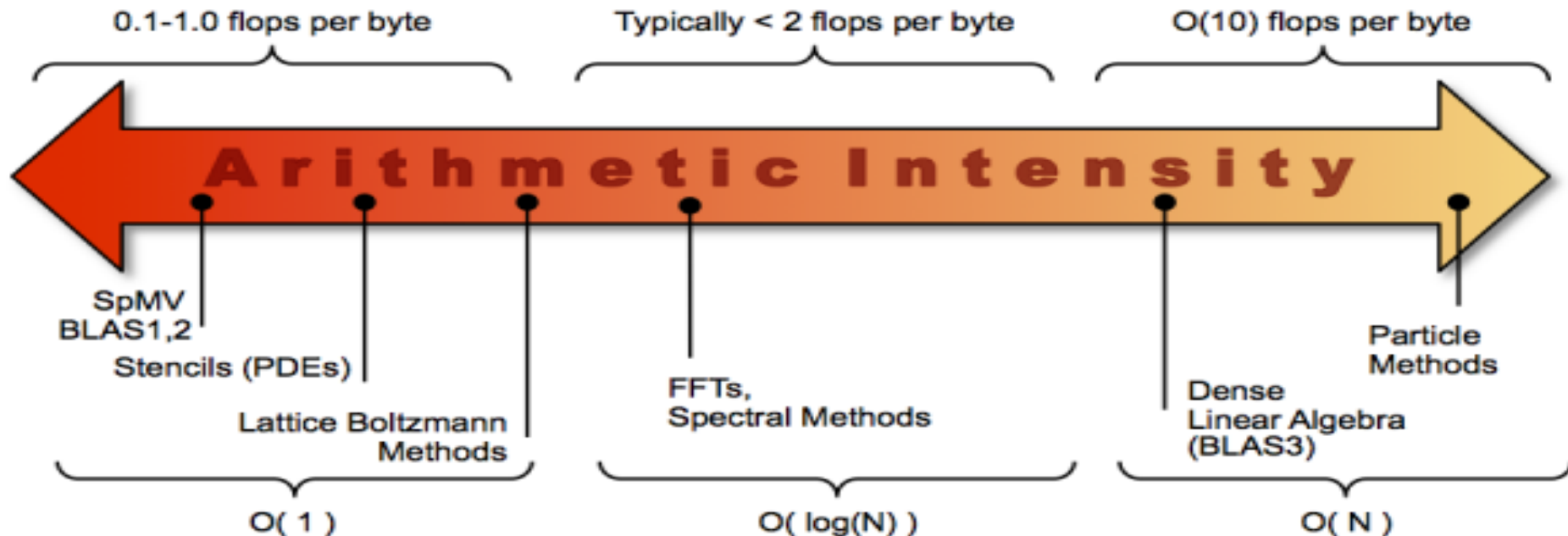


# Roofline Performance Model (LBL)

<http://crd.lbl.gov/departments/computer-science/PAR/research/roofline>

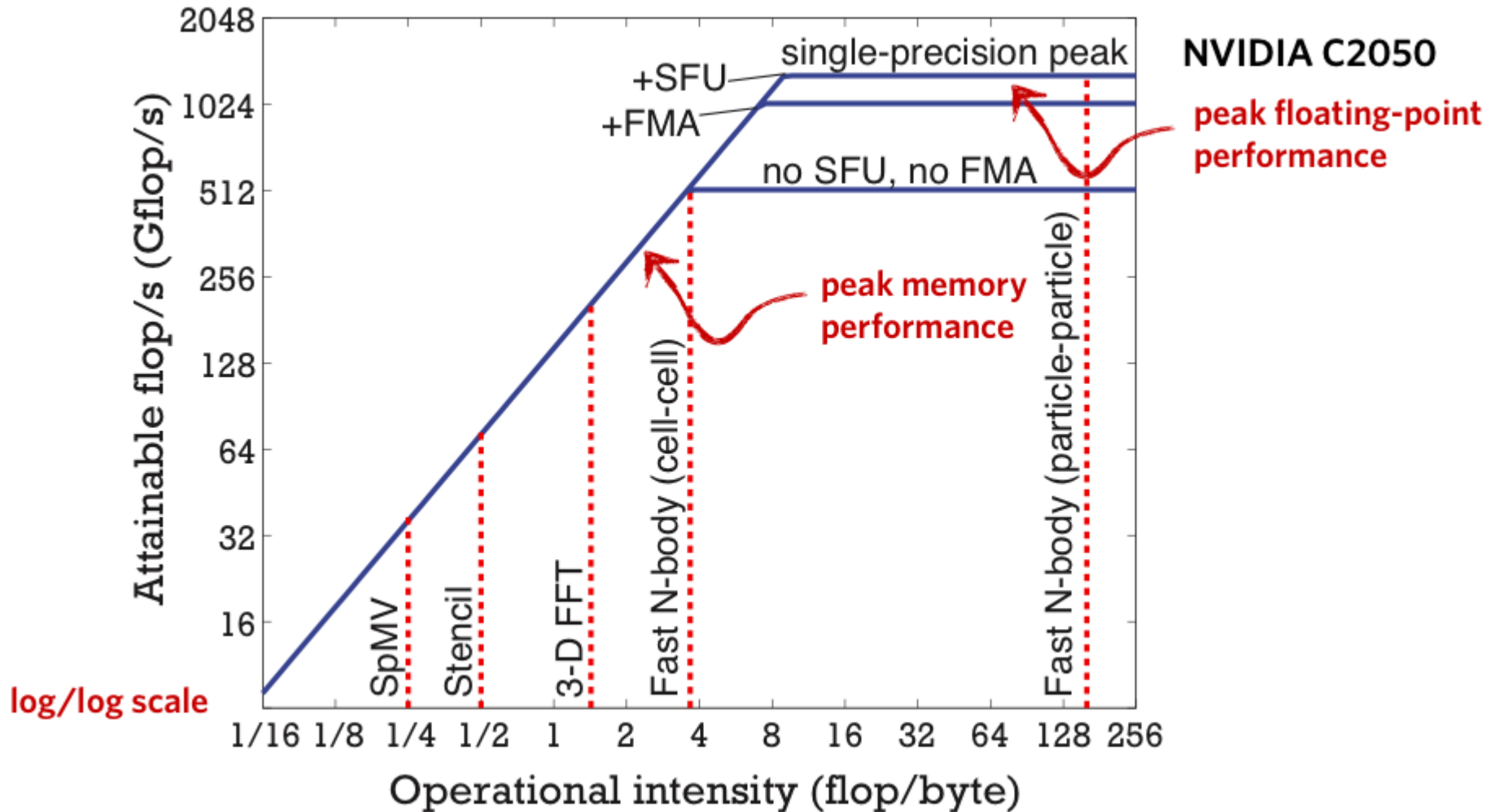
## Arithmetic Intensity

The core parameter behind the Roofline model is Arithmetic Intensity. Arithmetic Intensity is the ratio of total floating-point operations to total data movement (bytes).



# Roofline Performance Model (LBL)

[http://lorenabarba.com/wp-content/uploads/2012/01/roofline\\_slide.png](http://lorenabarba.com/wp-content/uploads/2012/01/roofline_slide.png)



# Parallel Computing

## Matrix Multiply and Debugging

# Timing with CUDA Event API

```
int main ()
{
    cudaEvent_t start, stop;
    float time;

    cudaEventCreate (&start);
    cudaEventCreate (&stop);

    cudaEventRecord (start, 0);

    someKernel <<<grids, blocks, 0, 0>>> (...);

    cudaEventRecord (stop, 0);
    cudaEventSynchronize (stop);
    cudaEventElapsedTime (&time, start, stop);

    cudaEventDestroy (start);
    cudaEventDestroy (stop);

    printf ("Elapsed time %f sec\n", time*.001);

    return 1;
}
```

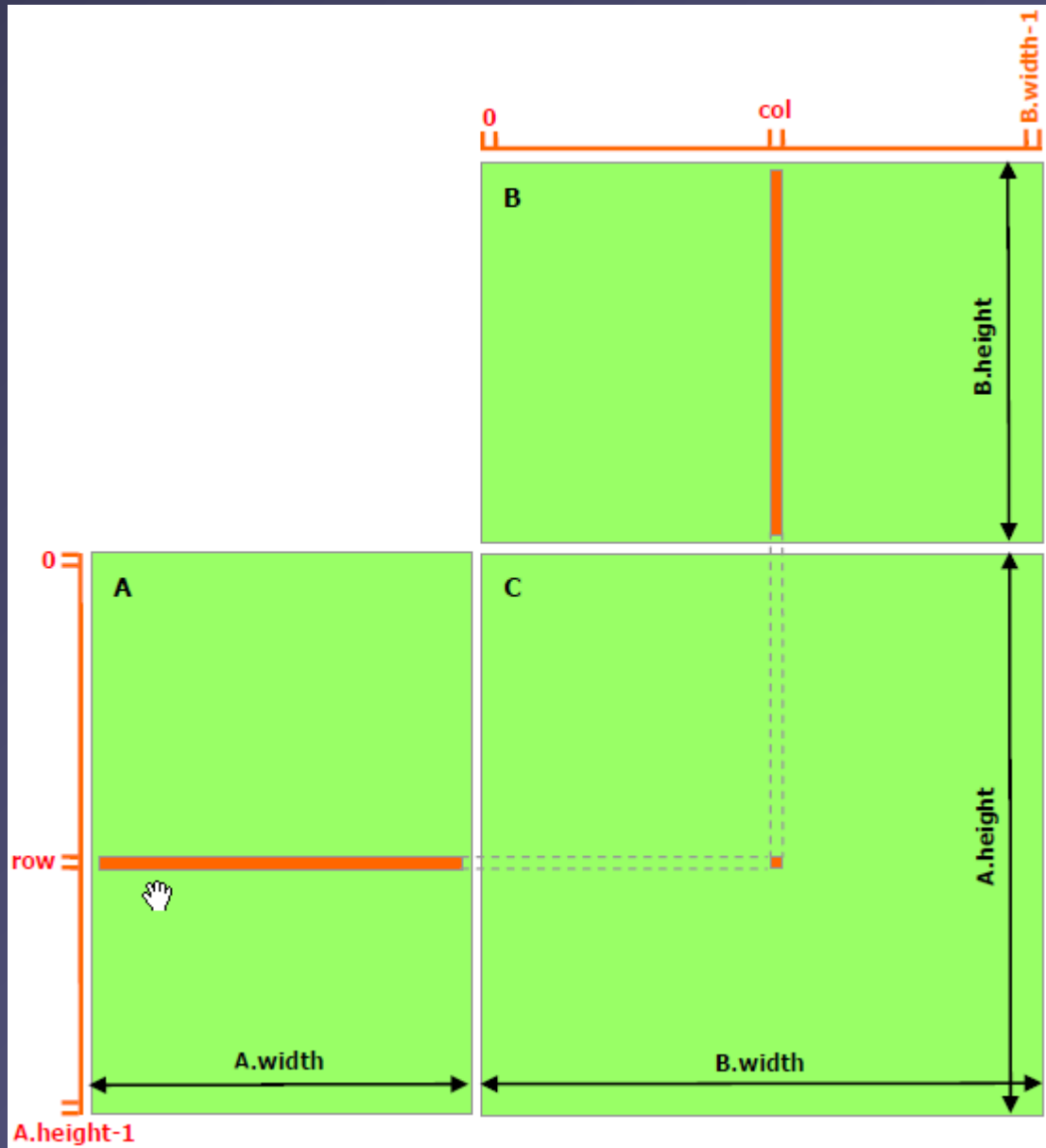
CUDA Event API Timer are,

- OS independent
- High resolution
- Useful for timing asynchronous calls

← Ensures kernel execution has completed

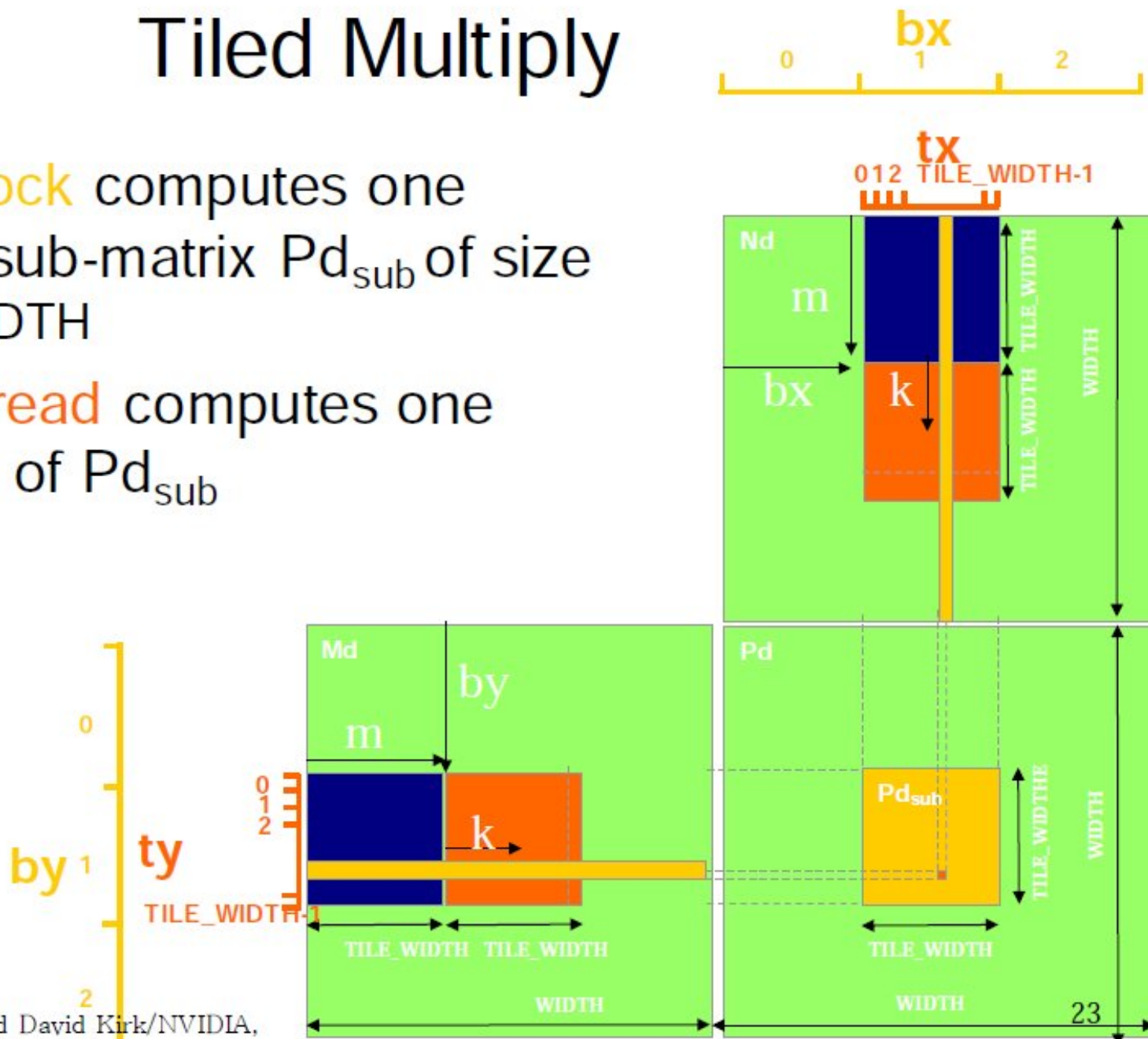
Standard CPU timers will not measure the timing information of the device.

# Intuitive multiply



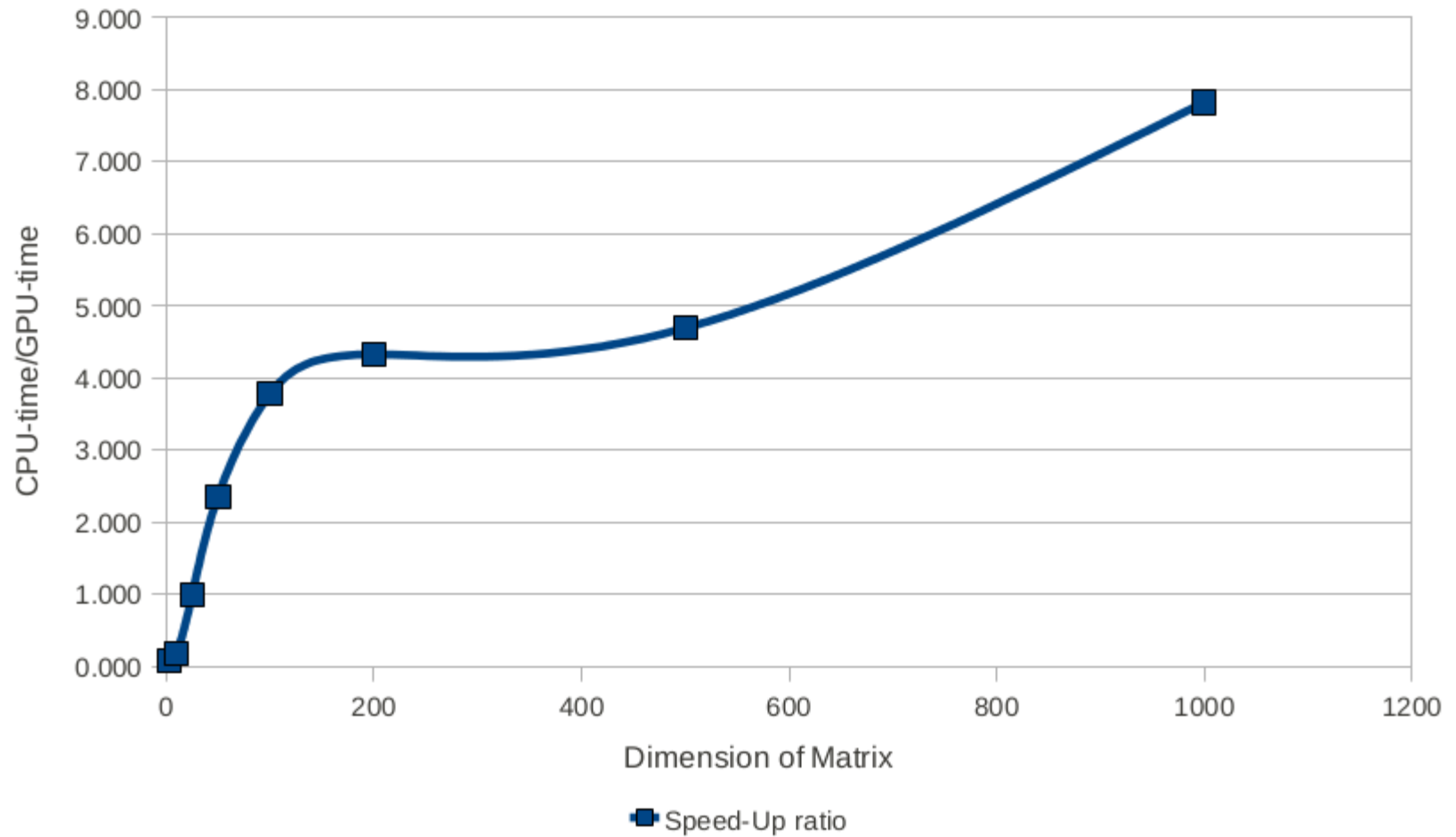
# Tiled Multiply

- Each **block** computes one square sub-matrix  $Pd_{sub}$  of size  $TILE\_WIDTH$
- Each **thread** computes one element of  $Pd_{sub}$



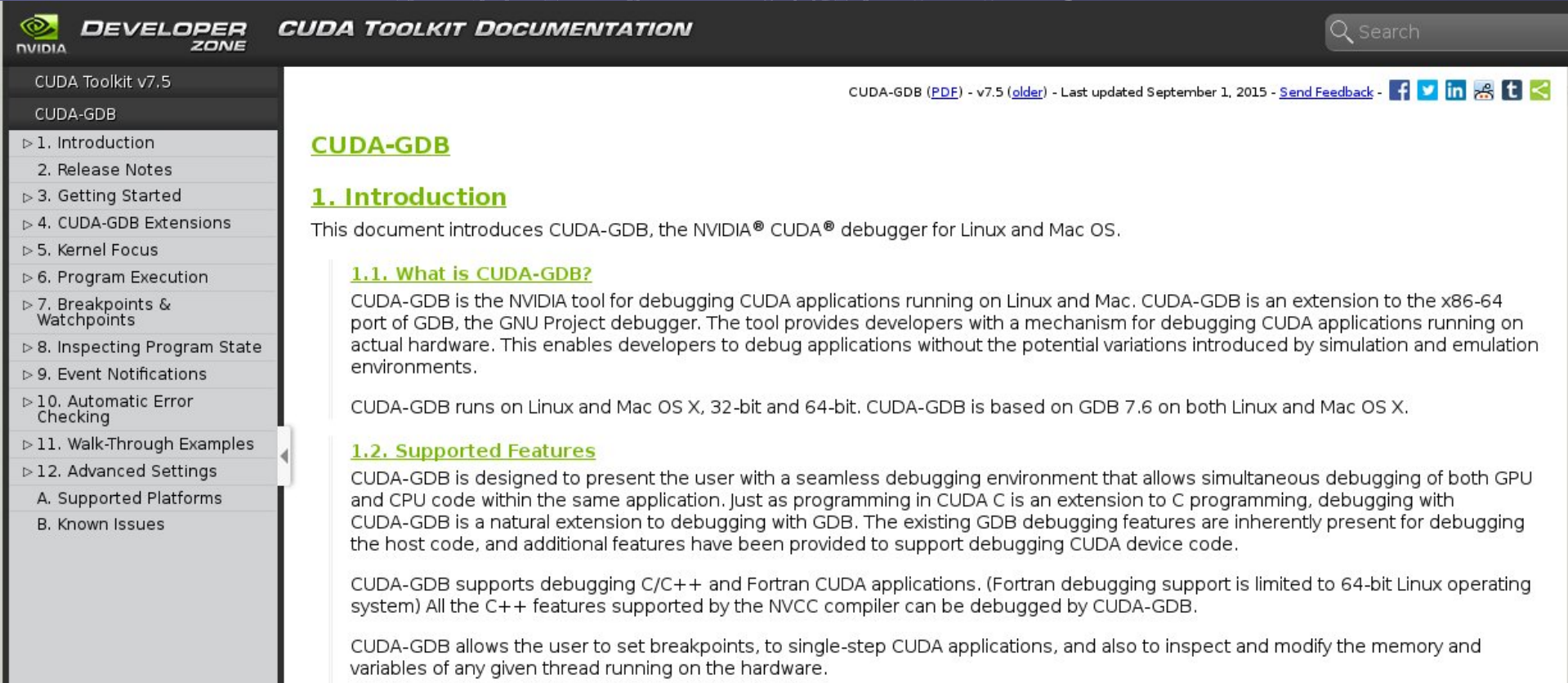
# Speed-Up Ratio

## GPU speed-up over CPU



# CUDA – GNU Debugger – CUDA-gdb

<http://docs.nvidia.com/cuda/cuda-gdb/index.html>



The screenshot shows the NVIDIA Developer Zone documentation page for CUDA-GDB. The page has a dark header with the NVIDIA logo, 'DEVELOPER ZONE', and 'CUDA TOOLKIT DOCUMENTATION'. A search bar is on the right. A left sidebar contains a navigation menu with items like 'CUDA Toolkit v7.5', 'CUDA-GDB', and a list of sections from 1 to 12. The main content area is white and contains the following text:

CUDA-GDB (PDF) - v7.5 (older) - Last updated September 1, 2015 - [Send Feedback](#) - [f](#) [t](#) [in](#) [d](#) [t](#) [v](#)

## CUDA-GDB

### 1. Introduction

This document introduces CUDA-GDB, the NVIDIA® CUDA® debugger for Linux and Mac OS.

#### 1.1. What is CUDA-GDB?

CUDA-GDB is the NVIDIA tool for debugging CUDA applications running on Linux and Mac. CUDA-GDB is an extension to the x86-64 port of GDB, the GNU Project debugger. The tool provides developers with a mechanism for debugging CUDA applications running on actual hardware. This enables developers to debug applications without the potential variations introduced by simulation and emulation environments.

CUDA-GDB runs on Linux and Mac OS X, 32-bit and 64-bit. CUDA-GDB is based on GDB 7.6 on both Linux and Mac OS X.

#### 1.2. Supported Features

CUDA-GDB is designed to present the user with a seamless debugging environment that allows simultaneous debugging of both GPU and CPU code within the same application. Just as programming in CUDA C is an extension to C programming, debugging with CUDA-GDB is a natural extension to debugging with GDB. The existing GDB debugging features are inherently present for debugging the host code, and additional features have been provided to support debugging CUDA device code.

CUDA-GDB supports debugging C/C++ and Fortran CUDA applications. (Fortran debugging support is limited to 64-bit Linux operating system) All the C++ features supported by the NVCC compiler can be debugged by CUDA-GDB.

CUDA-GDB allows the user to set breakpoints, to single-step CUDA applications, and also to inspect and modify the memory and variables of any given thread running on the hardware.



Click the image to shrink it.



**Debug**

- vectorAdd {0} [device: gk110 (0)] (Breakpoint)
  - CUDA Thread (0,0,0) Block (0,0,0)
  - CUDA Thread (1,0,0) Block (0,0,0)**
- All CUDA Threads
  - Block (0,0,0) [sm: 11]
    - CUDA Thread (0,0,0) [warp: 0 lane: 0] (vectorAdd.cu:36)

**Variables Breakpoints CUDA Modules**

Search CUDA Information

(0,0,0)	SM 11	256 threads of 256 are running
(0,0,0)	Warp 0 Lane 0	vectorAdd.cu:36 (0x9a6530)
(1,0,0)	Warp 0 Lane 1	vectorAdd.cu:36 (0x9a6530)

```

32 vectorAdd(const float *A, const float *B, float *C, int numE
33 {
34     int i = blockDim.x * blockIdx.x + threadIdx.x;
35
36     if (i < numElements)
37     {
38         C[i] = A[i] + B[i];
39     }
40 }
41
  
```

**Outline Registers**

Name	T(0,0,0)B(0,0,0)	T(1,0,0)B(0,0,0)
R5	4	4
R6	3149824	3149824
R7	4	4
R8	0	1
R9	0	1
R10	1060608	-271911904
R11	0	2

vectorAdd [C/C++ Application] gdb traces

```

0x400300800"}, {name="C", value="0x400301000"}, {name="numElements", value="500"}], file="../src/vectorAd
d.cu", fullname="/home/eostroukhov/cuda-workspace/vectorAdd/src/vectorAdd.cu", line="36"}
470,340 (gdb)
470,340 157^done, register-values=[{number="15", value="0x0"}]
470,340 (gdb)
470,340 158^done, register-values=[{number="15", value="0"}]
470,340 (gdb)
  
```

# Wrapping Up 1

## Exercises (CUDA Lectures in afternoon)

1. hello, device- first kernel call, hello world, GPU properties
2. add - vector addition using one thread in one block only
3. add-index - vector addition using blocks in parallel, one thread per block only.
4. add-parallel - vector addition using all blocks and threads in parallel
5. dot - scalar product using shared memory of one block only for reduction
6. dot-full - scalar product using shared memory and atomic add across blocks
7. histo - histogram using fat threads and atomic add on shared and global memory, timing
8. dot-perfect - scalar product using fat threads, shared memory, final reduction on host.
9. matmul - matrix multiplication with tiled access shared memory

# Wrapping Up 2

## Elements of CUDA C learnt:

threadIdx.x , blockIdx.x, blockDim.x, gridDim.x  
(threadIdx.y, blockIdx.y, blockDim.y, gridDim.y  
kernel<<<n,m>>> (...)  
\_\_device\_\_ \_\_global\_\_  
\_\_shared\_\_  
cudaMalloc / cudaFree  
cudaMemcpy / cudaMemcpy  
cudaGetDeviceProperties  
cudaEventCreate, cudaEventRecord,  
cudaEventSynchronize, cudaEventElapsedTime,  
cudaEventDestroy  
AtomicAdd

Threads, Blocks  
work with 2D grids)  
kernel calls  
device code  
shared memory on GPU  
manage global memory of GPU  
copy/set to or from memory  
get device properties in program

CUDA profiling  
atomic functions

## Wrapping Up 3

### What we have not yet learnt...

\_\_constant\_\_

cudaBindTexture

fat threads for 2D and 3D stencils

cudaStreamCreate, cudaStreamDestroy

constant memory on GPU

using texture memory

thread coalescence opt.

working with CUDA streams