

Hands-on CUDA

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How to use the GPU

- 1) Libraries (ex. Physics) : ready to use
- 2) Compiler Directives (ex. OpenACC)
- 3) Programming Language (CUDA, OpenCL)



Work Proposal: OpenACC



Libraries

Linear Algebra FFT, BLAS, SPARSE, Matrix				
Numerical & Math RAND, Statistics				
Data Struct. & AI Sort, Scan, Zero Sum				
Visual Processing Image & Video				

- Don't require any GPU knowledge or even parallel computing experience

Compiler directives

```
#pragma acc parallel loop
copyin(input1[0:inputLength],input2[0:inputLength]),
copyout(output[0:inputLength])
for(i = 0; i < inputLength; ++i) {
    output[i] = input1[i] + input2[i];
}
```

Don't requires GPU knowledge, but a little bit of parallel programming



Programming Language

More Efficient

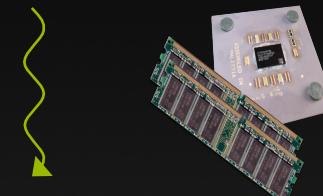
Flexible: may be better optimized for specific platforms

Verbose: express more details

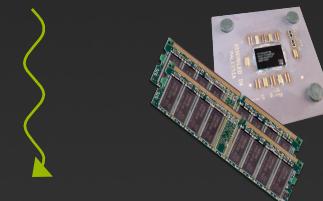
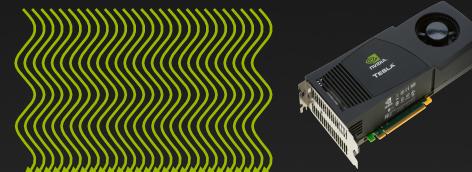


Latency devices (CPU) x Throughput devices (GPU)

CPU is much more faster when latency matters



GPU is much more faster when throughput matters



Paradigmas de GPU Programming

3 coisas que voce deve saber
de cor!



#1 – Estamos falando de computação heterogênea

- *Host* CPU e sua memória (host memory)
- *Device* GPU e sua memória (Global memory)



Host



Device

Heterogeneous Computing

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

using namespace std;

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

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

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

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

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

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

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

int main(void) {
    int *in, *out;           // host copies of a, b, c
    int *d_in, *d_out;       // device copies of a, b, c
    int size = (N + 2*RADIUS) * sizeof(int);

    // Alloc space for host copies and setup values
    in = (int *)malloc(size); fill_ints(in, N + 2*RADIUS);
    out = (int *)malloc(size); fill_ints(out, N + 2*RADIUS);

    // Alloc space for device copies
    cudaMalloc((void **)&d_in, size);
    cudaMalloc((void **)&d_out, size);

    // Copy to device
    cudaMemcpy(d_in, in, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_out, out, size, cudaMemcpyHostToDevice);

    // Launch stencil_1d() kernel on GPU
    stencil_1d<<<NBLOCK_SIZE,BLOCK_SIZE>>>(d_in + RADIUS,
d_out + RADIUS);

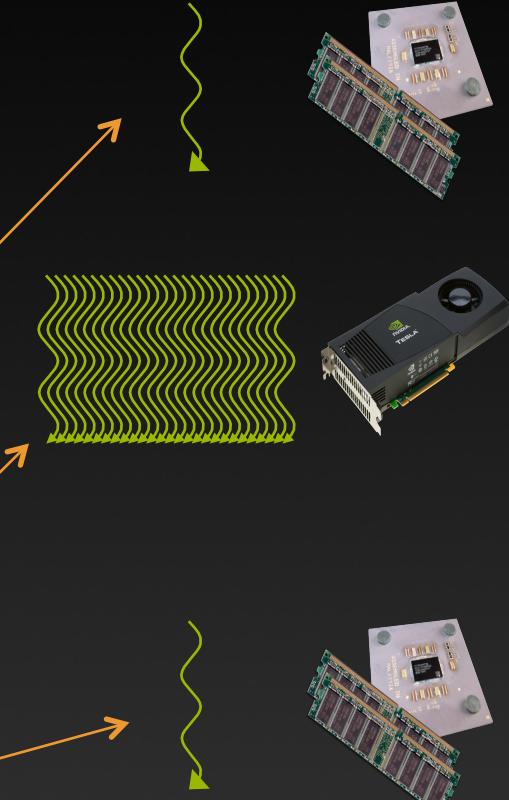
    // Copy result back to host
    cudaMemcpy(out, d_out, size, cudaMemcpyDeviceToHost);

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

parallel fn

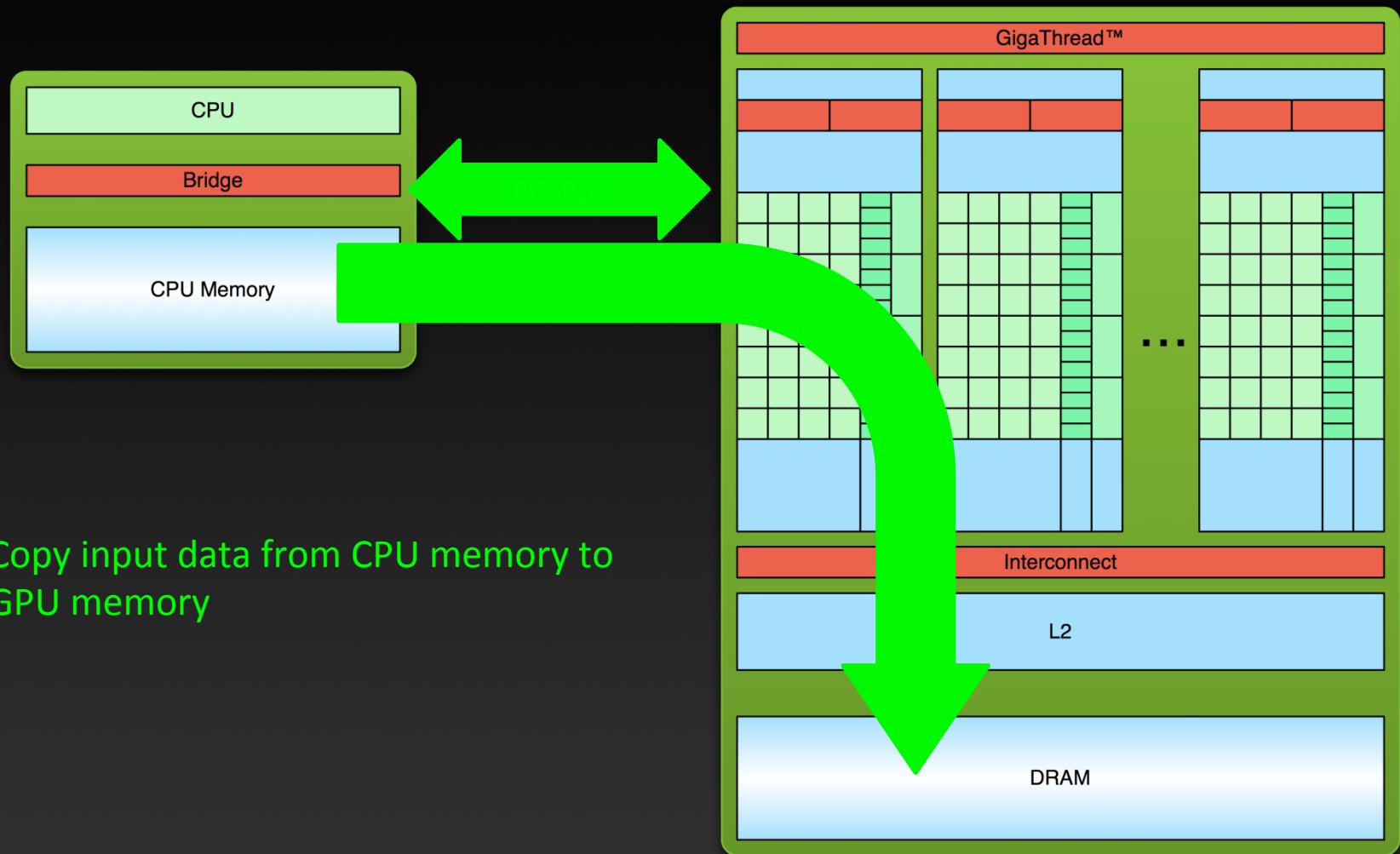
serial code

parallel code
serial code



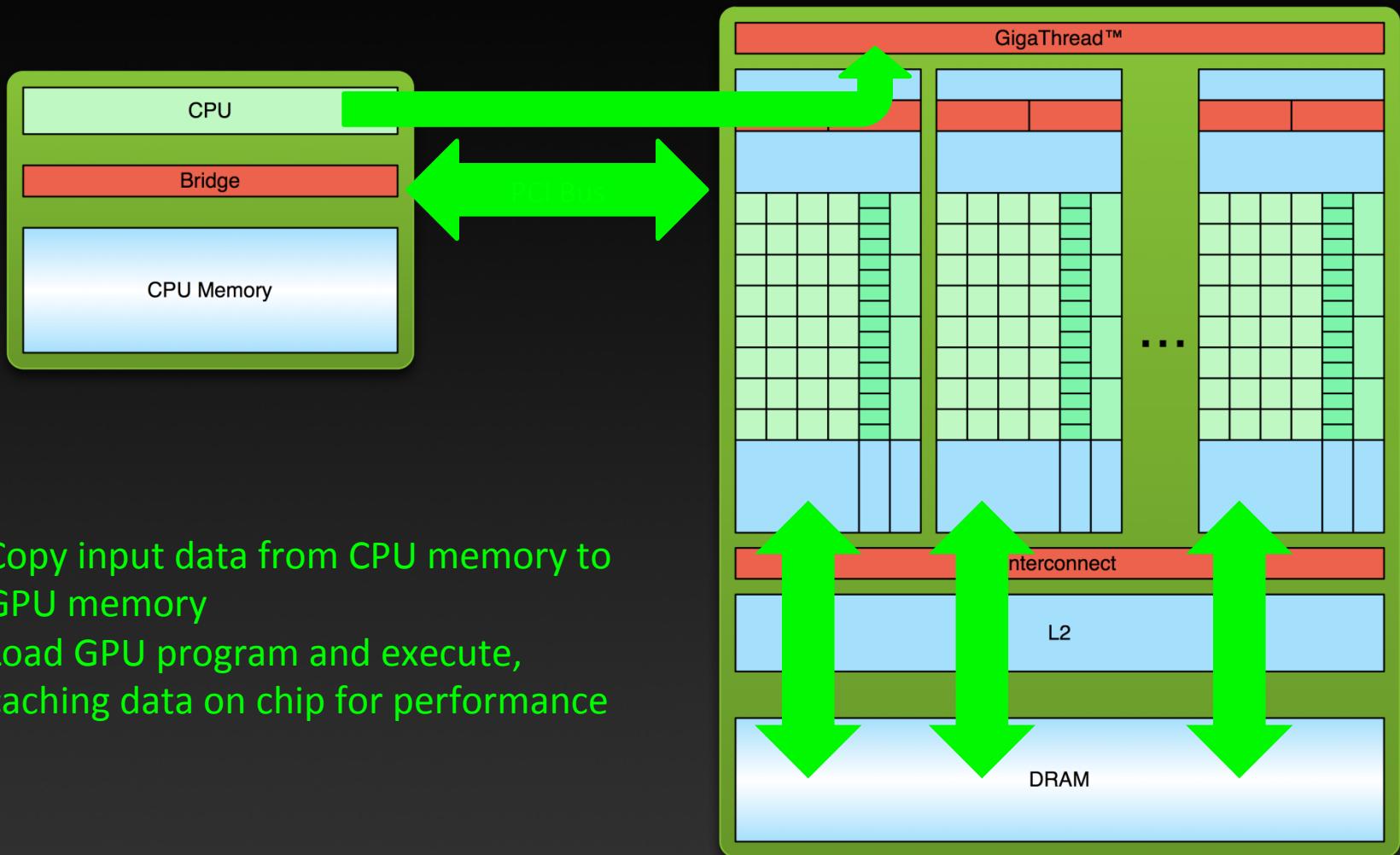
#2 – Tráfego de memória importa muito!...

GPU Computing Flow



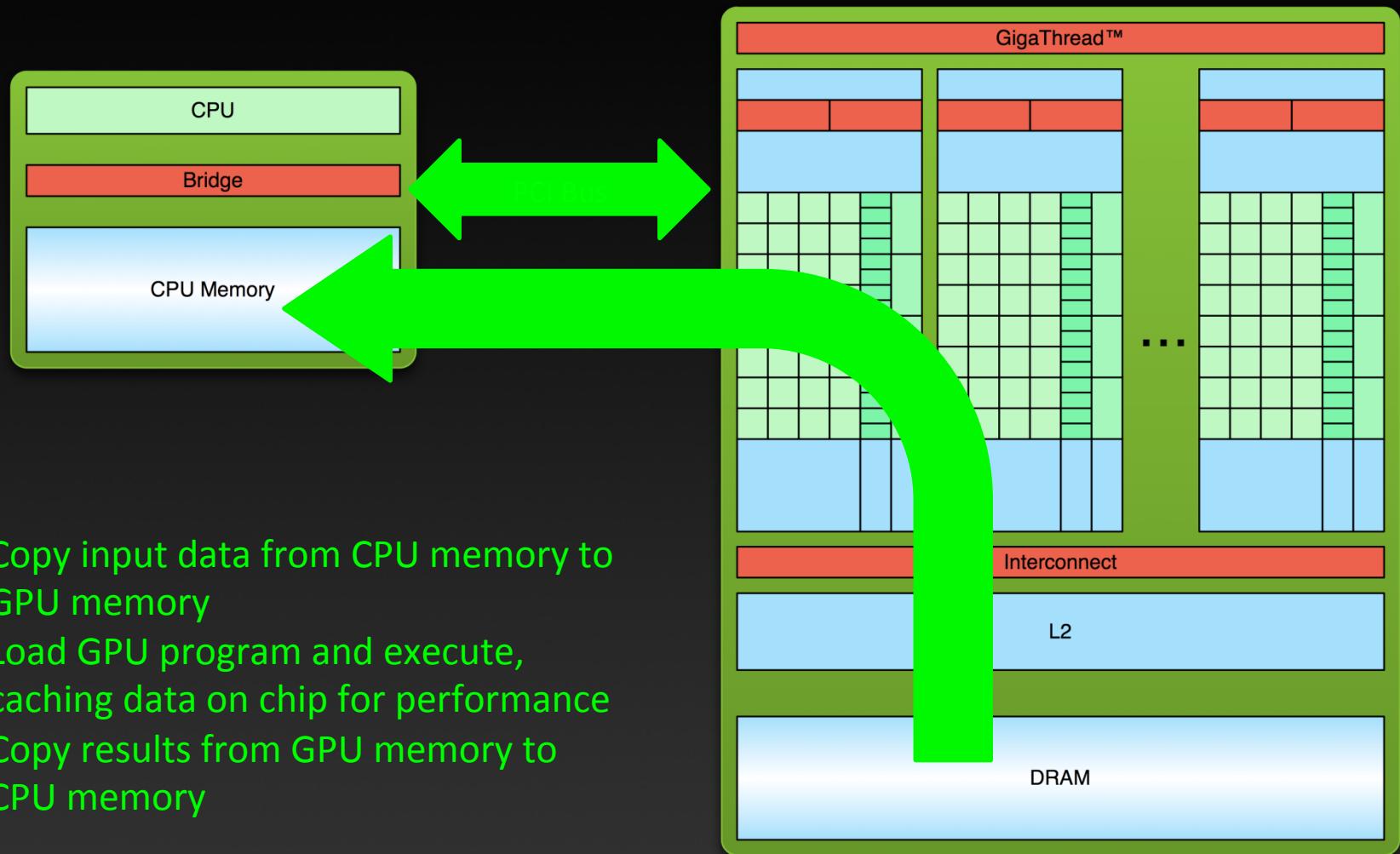
This slide is credited to Mark Harris (nvidia)

GPU Computing Flow



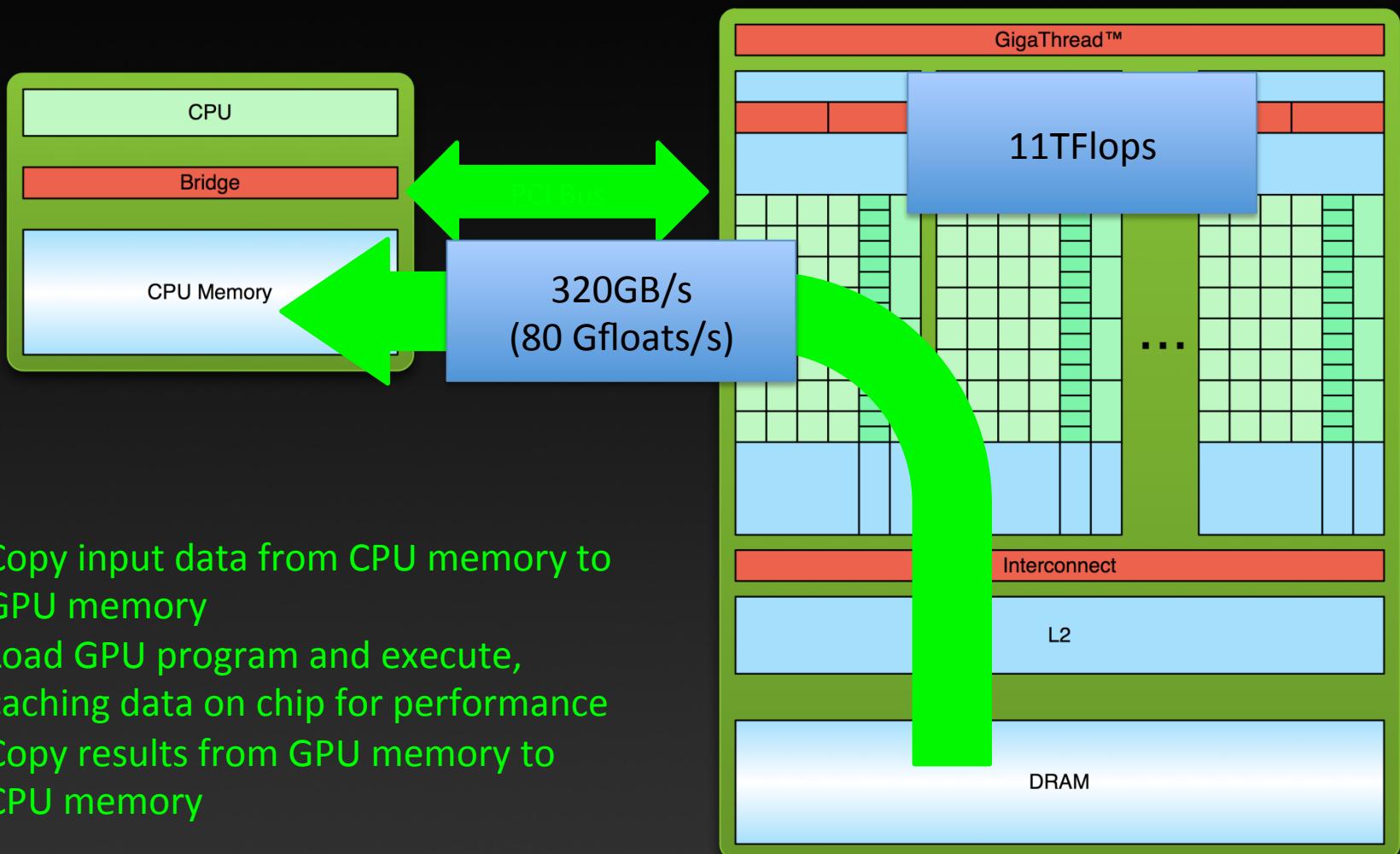
1. Copy input data from CPU memory to GPU memory
2. Load GPU program and execute, caching data on chip for performance

GPU Computing Flow

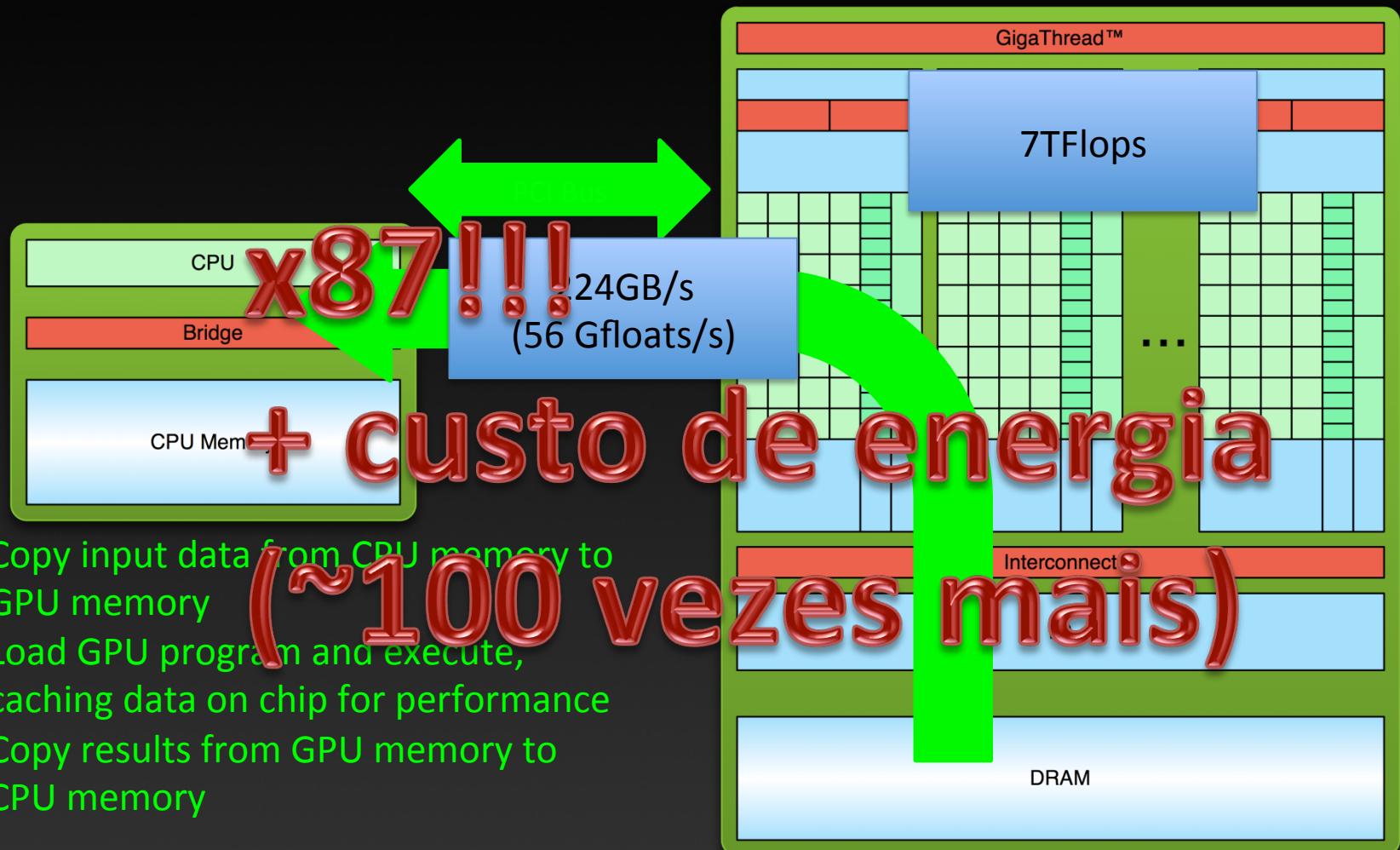


This slide is credited to Mark Harris (nvidia)

GPU Computing Flow



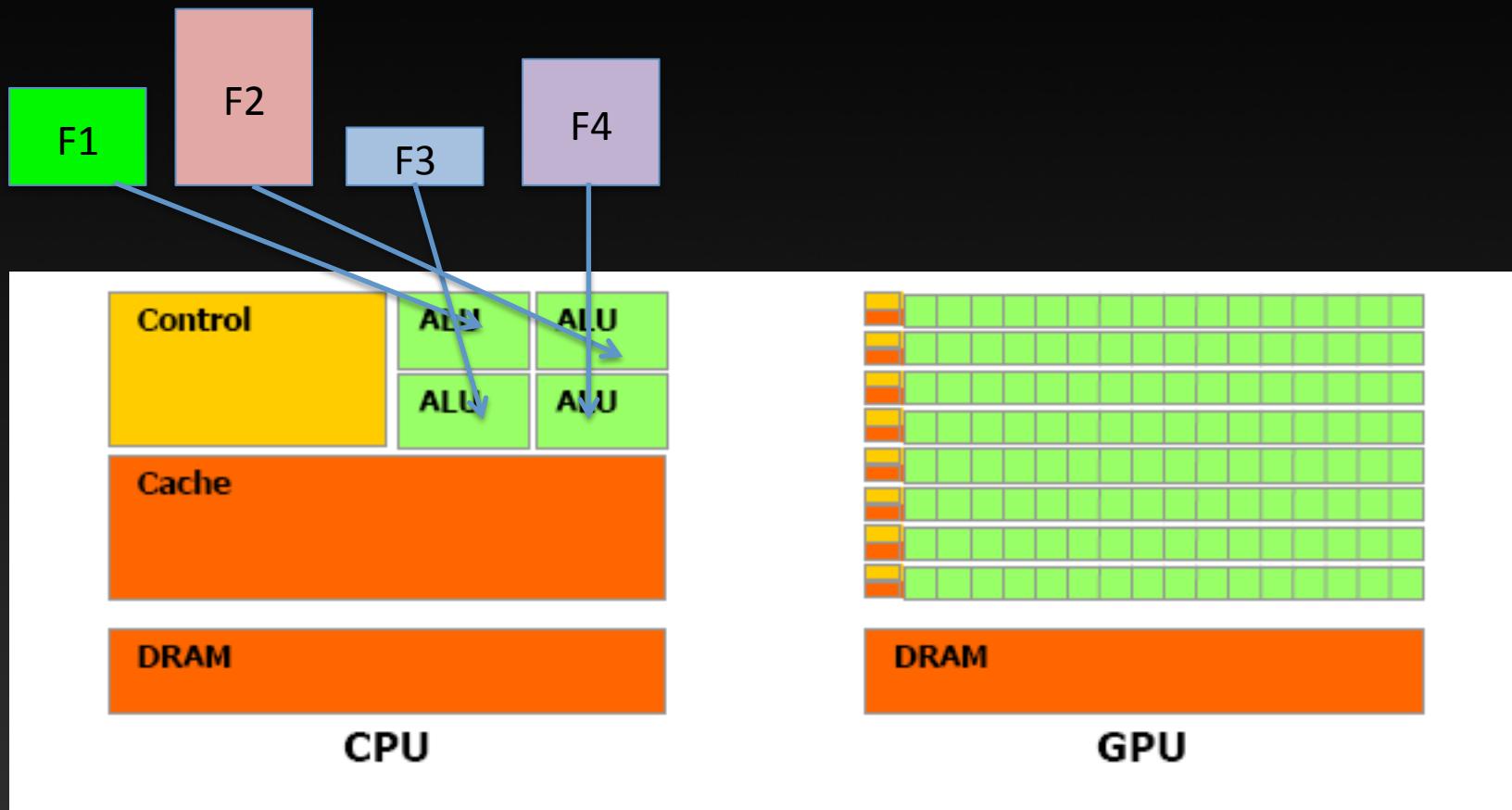
GPU Computing Flow



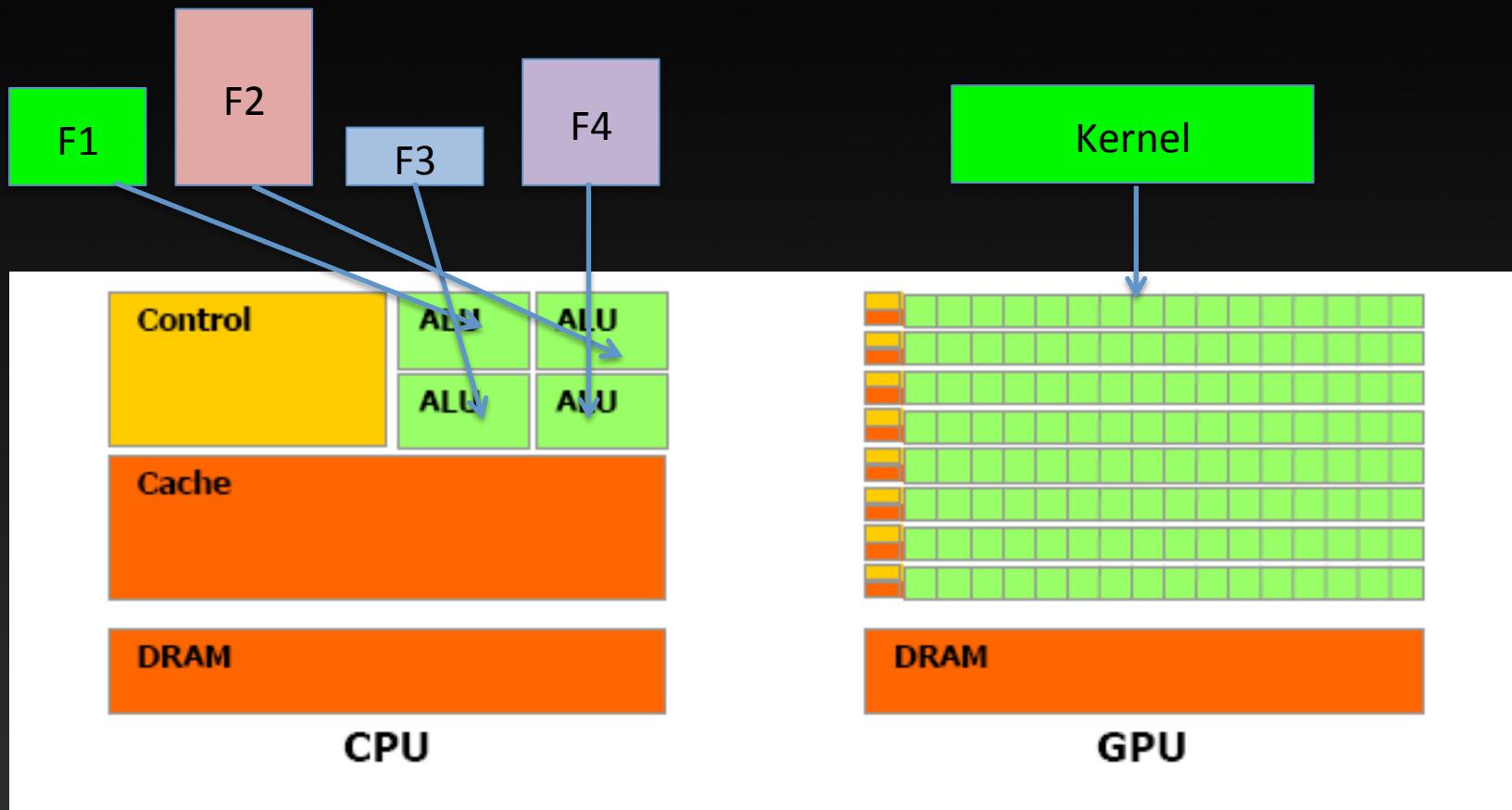
#3 – 1 kernels, muitos threads...



Threads em GPU x CPU



Threads em GPU x CPU

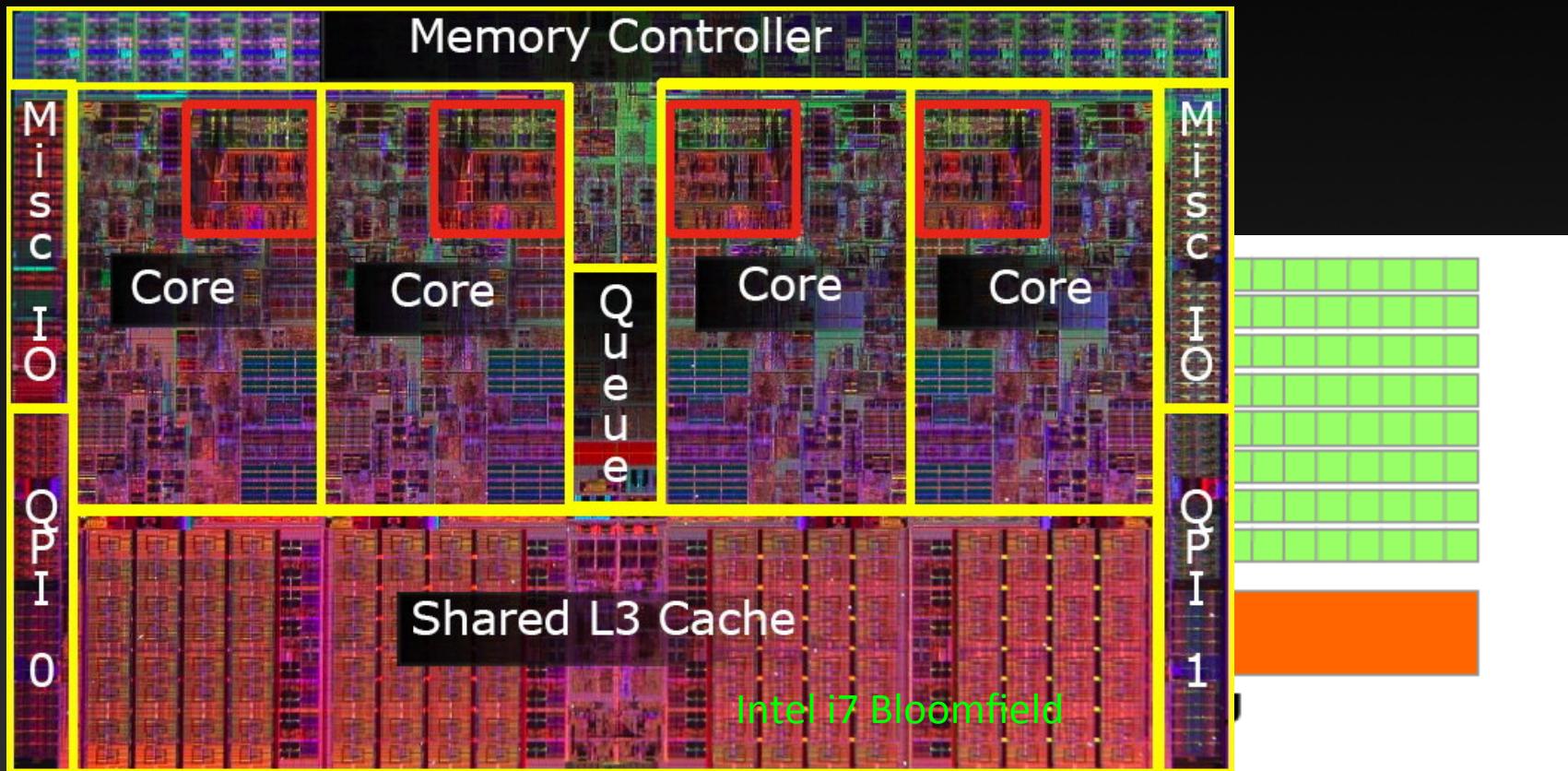


Modelo SIMT

SIMT
means
Single Instruction
Multiple Thread
...
by allacronyms.com

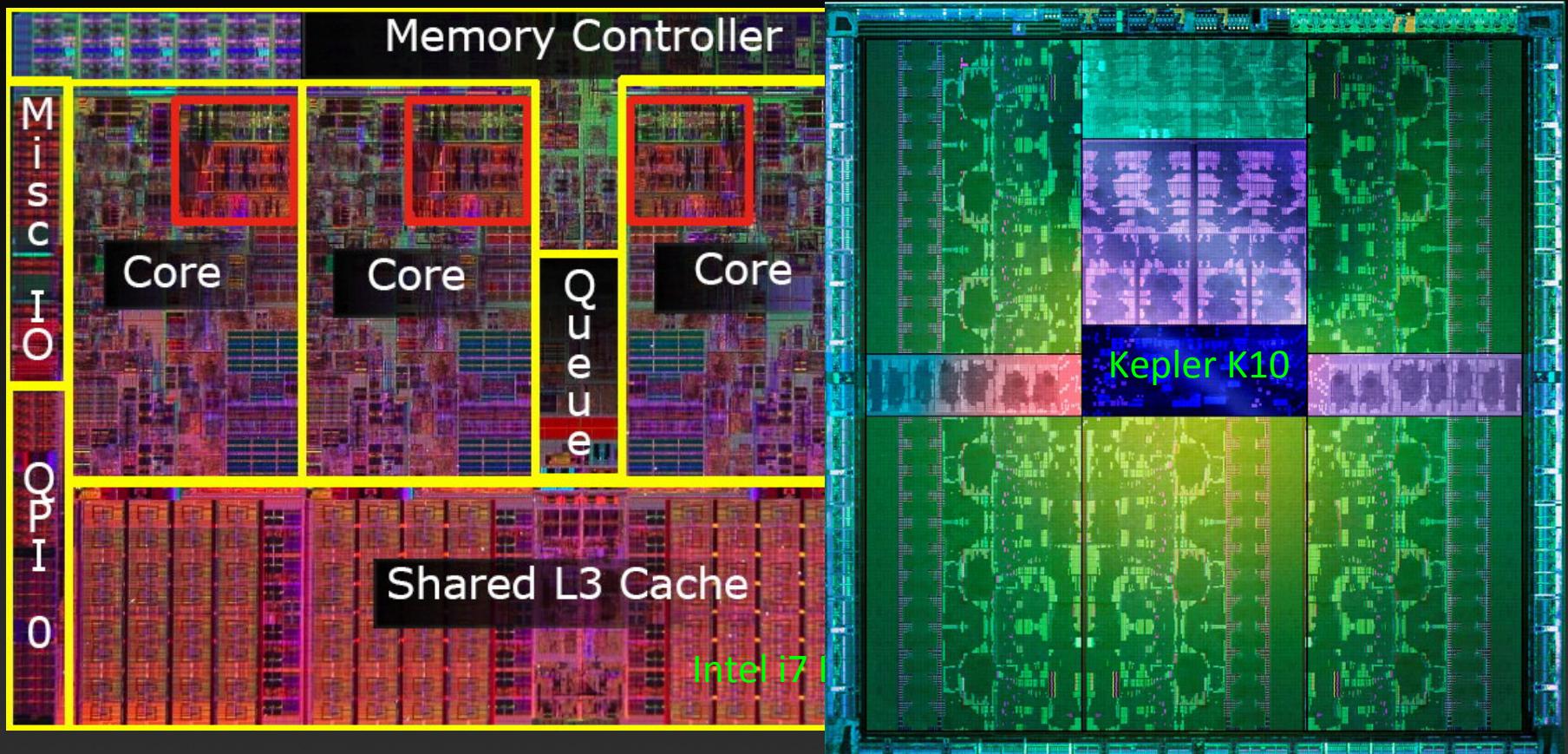


GPU x CPU



Only ~1% of CPU is dedicated to computation,
99% to moving/storing data to combat latency.

GPU x CPU



Only ~1% of CPU is dedicated to computation,
99% to moving/storing data to combat latency.

GRID



Principais conceitos de CUDA

Device: a GPU

Host: a CPU

Kernel – Programa que vai para a GPU

Thread – Instâncias do kernel

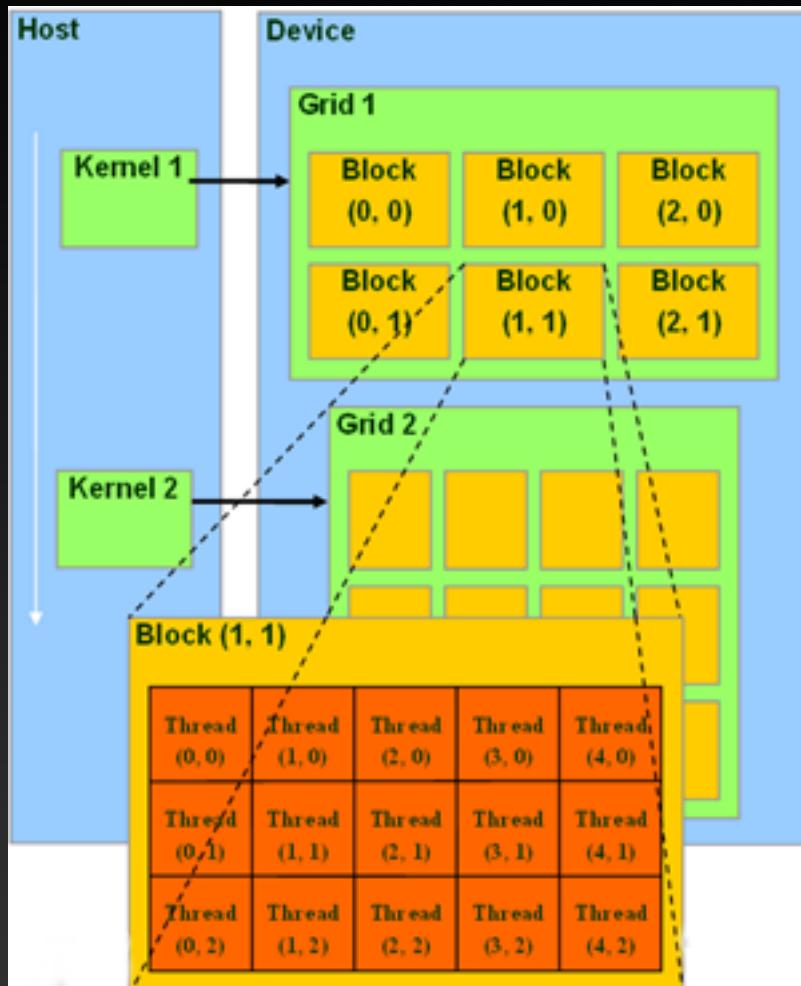
Global Memory: memória principal da GPU

Main memory: memória principal da CPU

CUDA, PTX and Cubin



Threads, Blocks e Grids



Um kernel é executado numa GRID

Cada bloco é composto por threads (1024)

Todas as threads de um bloco podem usar a mesma shared memory

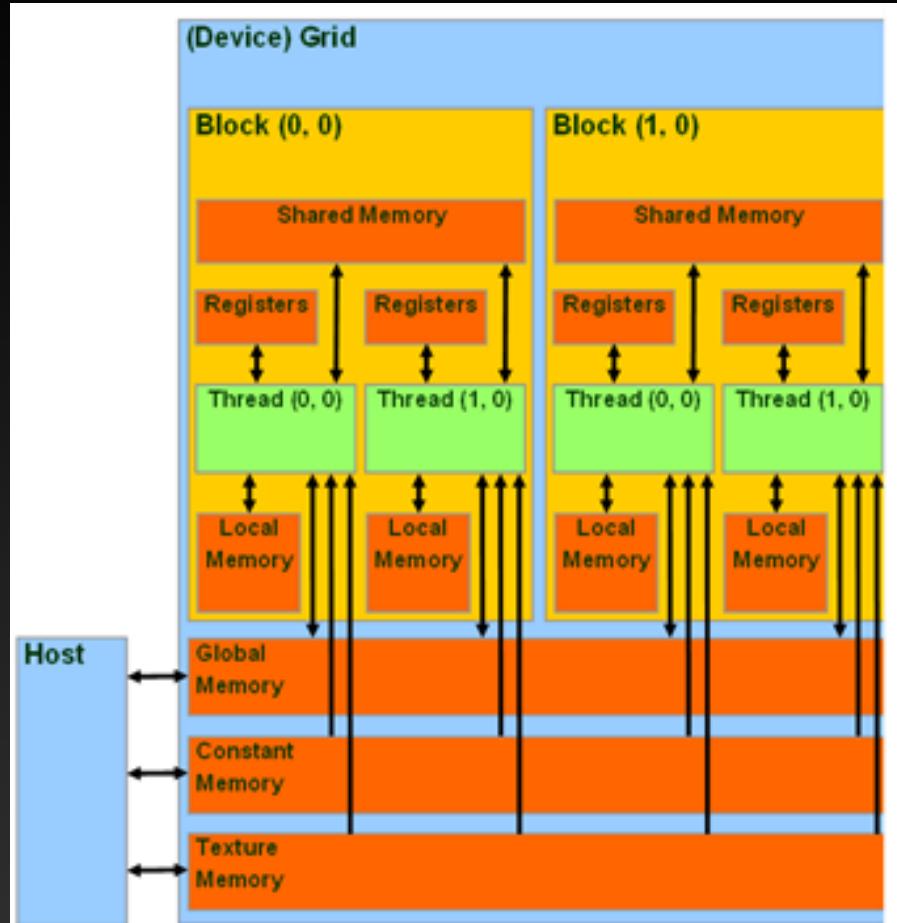
Threads de blocos diferentes não podem compartilhar a mesma shared memory, mas podem compartilhar dados pela memória global

Kernel, Threads e Warps



Memórias...

- Hierarquia de memória
- Local
- Cache L1 and L2
- shared
- Constant
- Texture
- Global



Hello World

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



GPU



CPU



Hello World

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



Alimentando a GPU com dados...

- **Malloc ()** ~ `cudaMalloc()`
- **Free ()** ~ `cudaFree()`
- **cudaMemcpy ()** ~ `memcpy()`



Alimentando a GPU com dados...

```
int main(void) {  
    int a, b, c;                      // CPU  
    int *d_a, *d_b, *d_c;            // GPU  
    int size = sizeof(int);  
  
    // Allocate space for device  
    cudaMalloc((void **) &d_a, size);  
    cudaMalloc((void **) &d_b, size);  
    cudaMalloc((void **) &d_c, size);  
  
    // Setup input values  
    a = 10;  
    b = 20;
```



Alimentando a GPU com dados...

```
// CPU -> GPU
cudaMemcpy(d_a, &a, size, cudaMemcpyHostToDevice);
cudaMemcpy(d_b, &b, size, cudaMemcpyHostToDevice);

// kernel execution: 1 thread
add<<<1,1>>>(d_a, d_b, d_c);

// GPU -> CPU
cudaMemcpy(&c, d_c, size, cudaMemcpyDeviceToHost);

// Clean memory
cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
```



Memoria unificada

`cudaMallocManaged()` → igual a `cudaMalloc()`, porém permite unificar as duas memórias de forma conceitual.

```
cudaMallocManaged ((void **) &a, size);  
cudaMallocManaged ((void **) &b, size);  
cudaMallocManaged ((void **) &c, size);  
  
// kernel execution: 1 thread  
add<<<1,1>>>(a, b, c);  
  
// Syncrhonize  
cudaDeviceSynchronize();  
  
// Clean memory  
cudaFree(a); cudaFree(b); cudaFree(c);
```



Memoria unificada

Global Variable

__managed__

```
__device__ __managed__ int a[1000];
__device__ __managed__ int b[1000];
__device__ __managed__ int c[1000];

// kernel execution: 1 thread
add<<<10,100>>>();

// Syncrhonize
cudaDeviceSynchronize();
```



Para compilar os programas



Acesso Remoto a máquinas com Suporte CUDA

Instruções para uso das máquinas remotas para programação em
CUDA.



Instruções Importantes.

- Você irá utilizar a máquina remota somente para compilar e executar o programa.
- Existe um diretório chamado **Alunos** na raiz do usuário, onde cada um deve criar uma pasta para si.
- Criar um diretório com o seu nome e renomeá-lo.
- A criação dessas pastas individuais será necessária pois existem várias pessoas da mesma turma utilizando a mesma conta.



Instruções Importantes

- Para compilar o projeto, digite o comando **make**
- Para limpar os códigos de máquina gerados digite o comando **make clean**.
- Manual CUDA está disponível neste link-
<http://docs.nvidia.com/cuda/cuda-c-programming-guide/>



Usuário e senha

u: cudateaching

p: teachingCUDA2018

Esta conta é uma conta temporária, e será suspensa ao final do curso.



Divisão de Acceso da máquina

- Devem se conectar à máquina:
 - 200.20.15.153 – Porta: 22
- Para utilizar uma determinada GPU é preciso escrever na frente do comando de execução a variável de ambiente seguinte:

CUDA_VISIBLE_DEVICES=1

- No caso anterior o 1 é o índice da GPU 1, sendo que a DGX tem 8 GPUs, portanto:
 - Grupo 01 devem rodar os seus testes na GPU 1
 - Grupo 02 devem rodar os seus testes na GPU 2
 - Grupo 03 devem rodar os seus testes na GPU 3



Orientações Importantes

- Devido a esta conta ser uma conta compartilhada, você deve criar uma pasta sua ou para sua equipe dentro da pasta **Alunos**, para que assim os arquivos de cada um fiquem organizados.
- A pasta **NVIDIA_CUDA-9.0_Samples** que está na raiz da máquina, é a pasta da NVIDIA contendo todos os exemplos de desenvolvimento do SDK. Você não deve modificar esta pasta!
- Sempre que quiser utilizar algum código desta pasta, faça uma cópia para sua pasta que você criou.



Rodando um Hello World em CUDA 01

- Baixe PARA SUA PASTA o seguinte programa através do link
[https://www.dropbox.com/s/3qay3sp2wpfhull/
vectorAddSample.zip](https://www.dropbox.com/s/3qay3sp2wpfhull/vectorAddSample.zip)
- Esse código nada mais é que o exemplo padrão da NVIDIA de soma de dois vetores em paralelo.



Rodando um Hello World em CUDA 02

- Voce pode baixar este software através do comando "wget
[https://www.dropbox.com/s/3qay3sp2wpfhull/
vectorAddSample.zip](https://www.dropbox.com/s/3qay3sp2wpfhull/vectorAddSample.zip)"
- Depois deve descompactar o arquivo com o comando "unzip vectorAddSample.zip"



Rodando um Hello World em CUDA 03

- Para compilar o projeto basta digitar **make** e pressionar enter.
- Para executar lembre-se sempre de adicionar a variável de ambiente para selecionar a GPU do seu grupo (por exemplo para os alunos do Grupo 2):

```
CUDA_VISIBLE_DEVICES=2 ./vectorAdd
```

- Para limpar o projeto basta digitar **make clean** e pressionar enter.



Rodando um Hello World em CUDA 04

- Fique à vontade para modificar a cópia do projeto da maneira que lhe for mais conveniente.
- Alternativamente este mesmo software que soma dois vetores, também está disponível na pasta **NVIDIA_CUDA-9.0_Samples** na subpasta **0_Simple**, na pasta **vectorAdd**.
- Você pode copiar esta pasta com o código fonte para a pasta pessoal sua que você criou.

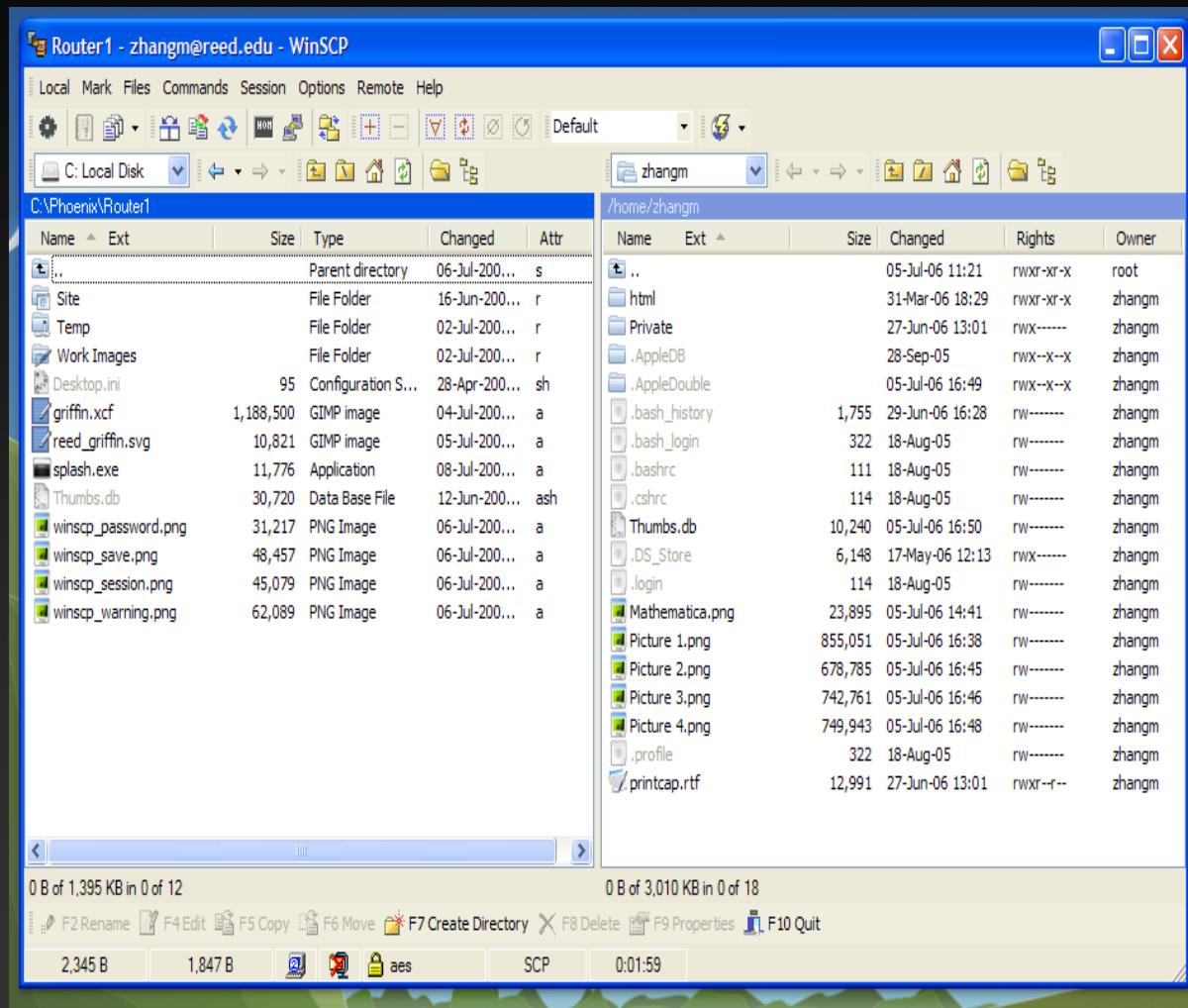


Programas sugeridos para acessar a máquina remota a partir de Windows

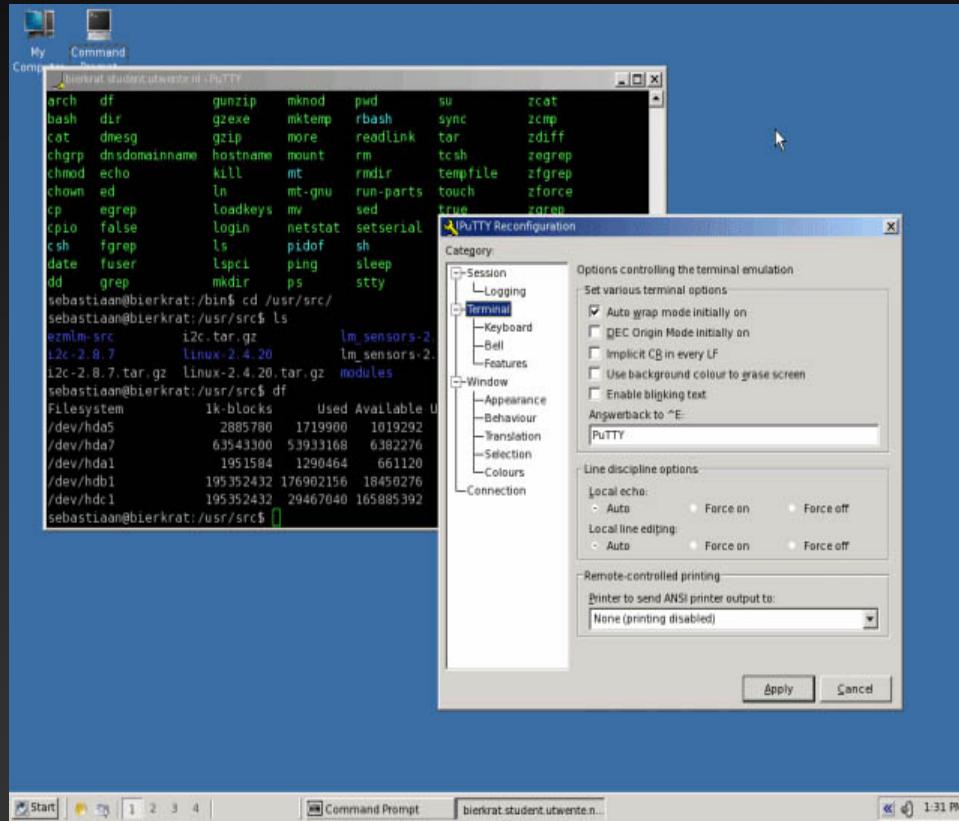
- MOBAXTERM - <http://mobaxterm.mobatek.net/>
- Através desse software voce se conecta a maquina desejada, e ele dispoe de todas as ferramentas necesarias, desde transferencia de arquivo através de interface, até terminal e editor de texto.



winSCP- Troca de Arquivos- http://winscp.net/



Putty - Terminal de acesso remoto – SSH Client -www.putty.org – para Windows



Terminal (MAC)

ssh cudateaching@200.20.15.153



Compiling a GPU program

Name file as .cu

Nvcc name.cu

./a.out

Voilá! . . .



Errors types

https://www.cs.cmu.edu/afs/cs/academic/class/15668-s11/www/cuda-doc/html/group__CUDART__TYPES_q3f51e3575c2178246db0a94a430e0038.html

CUDA error types

Enumerator:

cudaSuccess

The API call returned with no errors. In the case of query calls, this can also mean that the operation being queried is complete (see `cudaEventQuery()` and `cudaStreamQuery()`).

cudaErrorMissingConfiguration

The device function being invoked (usually via `cudaLaunch()`) was not previously configured via the `cudaConfigureCall()` function.

cudaErrorMemoryAllocation

The API call failed because it was unable to allocate enough memory to perform the requested operation.

cudaErrorInitializationError

The API call failed because the CUDA driver and runtime could not be initialized.

cudaErrorLaunchFailure

An exception occurred on the device while executing a kernel. Common causes include dereferencing an invalid device pointer and accessing out of bounds shared memory. The device cannot be used until `cudaThreadExit()` is called. All existing device memory allocations are invalid and must be reconstructed if the program is to continue using CUDA.

cudaErrorPriorLaunchFailure

This indicated that a previous kernel launch failed. This was previously used for device emulation of kernel launches.

Deprecated:

This error return is deprecated as of CUDA 3.1. Device emulation mode was removed with the CUDA 3.1 release.

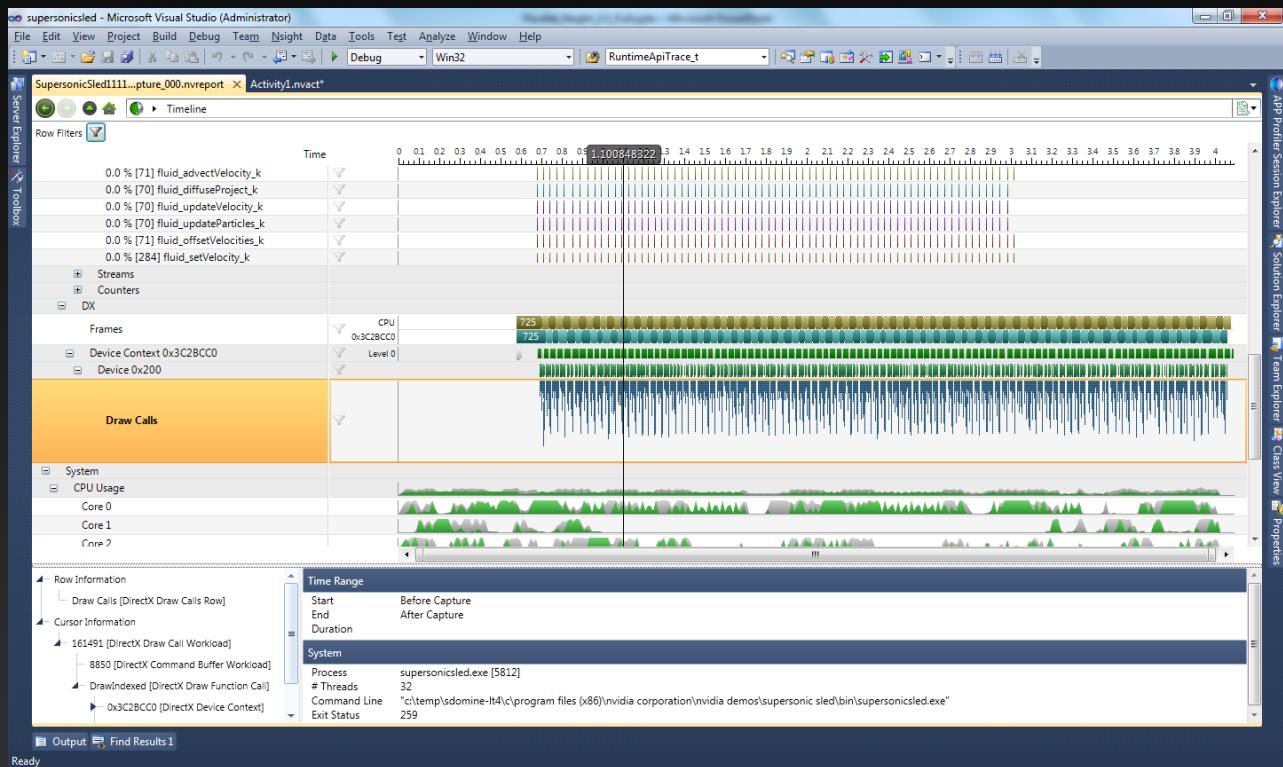
cudaErrorLaunchTimeout

This indicates that the device kernel took too long to execute. This can only occur if timeouts are enabled - see the device property `kernelExecTimeoutEnabled` for more information. The device cannot be used until `cudaThreadExit()` is called. All existing device memory allocations are invalid and must be reconstructed if the program is to continue using CUDA.



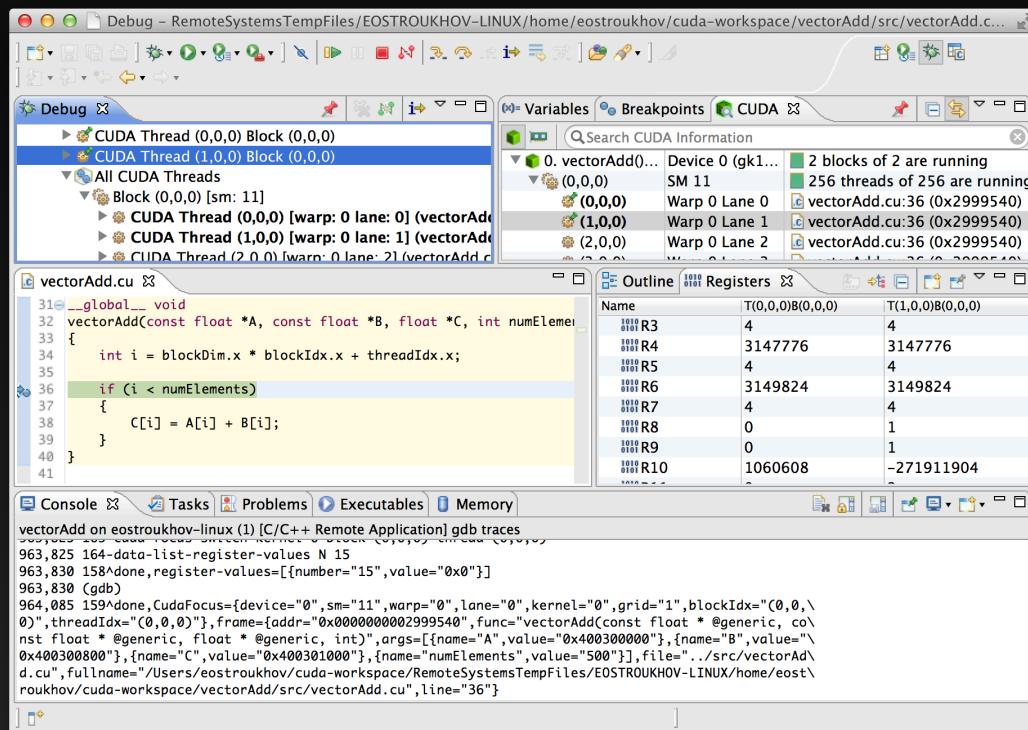
Debuggers

NSight



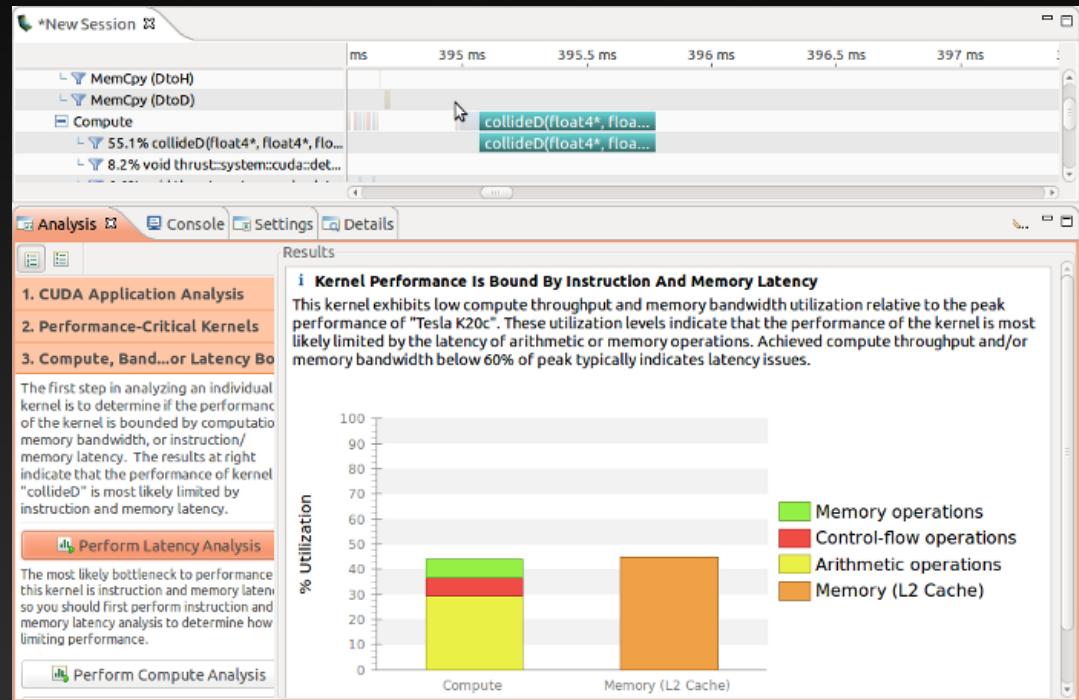
Debuggers

CUDA GDB



Debuggers

CUDA Memcheck



Profiler tools

NSIGHT

NVPP

NVPROF



NVIDIA NVProf

```
Nvprof ./a.out
```

```
Make some tests... Changing vector size...
```



Finalmente... O paralelismo

```
__global__ void vecAdd(int *d_a, int *d_b, int *d_c) {
    int i = threadIdx;
    d_c[i] = d_a[i] + d_b[i]
}

int main()
{
    ...
    vecAdd<<<1, N>>>(d_a, d_b, d_c);
}
```



Pequeno concerto..

```
__global__ void add(int *d_a, int *d_b, int *d_c) {
    int i = threadIdx.x;
    d_c[i] = d_a[i] + d_b[i]
}

int main()
{
    ...
    vecAdd<<<1, N>>>(d_a, d_b, d_c); // blockDim.x = N
}
```



Explorando o paralelismo: Threads

```
__global__ void add(int *d_a, int *d_b, int *d_c) {  
    int i = threadIdx.x;  
    d_c[i] = d_a[i] + d_b[i]  
}
```

At the same time...

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

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

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

...

c[N-1] = a[N-1] + b[N-1];



Há um limite de threads... Por bloco...

Technical specifications	Compute capability (version)														
	1.0	1.1	1.2	1.3	2.x	3.0	3.5	3.7	5.0	5.2					
Maximum dimensionality of grid of thread blocks	2				3										
Maximum x-dimension of a grid of thread blocks	65535						$2^{31}-1$								
Maximum y-, or z-dimension of a grid of thread blocks	65535														
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			32							
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	128 K	256 K	64 K						
Maximum number of 32-bit registers per thread	128				63	255									
Maximum amount of shared memory per multiprocessor	16 KB				48 KB	112 KB	64 KB	96 KB							
Number of shared memory banks	16				32										
Amount of local memory per thread	16 KB				512 KB										



If $N > 1024$???



If N > 1024 ???

```
__global__ void add(int *d_a, int *d_b, int *d_c) {  
    int i = threadIdx.x;  
    While (i < N)  
    {  
        d_c[i] = d_a[i] + d_b [i];  
        i += blockDim.x;  
    }  
}
```

c[0] = a[0] + b[0];
c[1024]= a[1024]+ b[1024];
c[2048]= a[2048]+ b[2048];
...

c[1] = a[1] + b[1];
c[1025]= a[1025]+ b[1025];
c[2049]= a[2049]+ b[2049];
...

...



Apenas estamos usando 1 SM!...



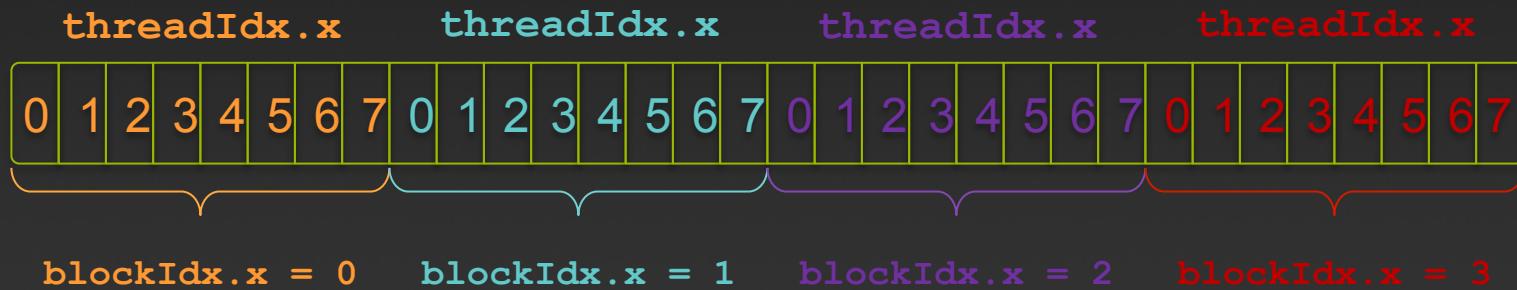
Blocos

```
__global__ void add(int *d_a, int *d_b, int *d_c) {  
    int i= threadIdx.x + blockIdx.x * blockDim.x;  
  
    d_c[i] = d_a[i] + d_b[i];  
}  
  
int main()  
{  
    vecAdd <<<K,M>>>(A, B, C);  
}
```



Blocos

```
__global__ void add(int *d_a, int *d_b, int *d_c) {  
    int i = threadIdx.x + blockIdx.x * blockDim.x;  
  
    d_c[i] = d_a[i] + d_b[i];  
}  
  
int main()  
{  
    vecAdd <<<K,M>>>(A, B, C);  
}
```



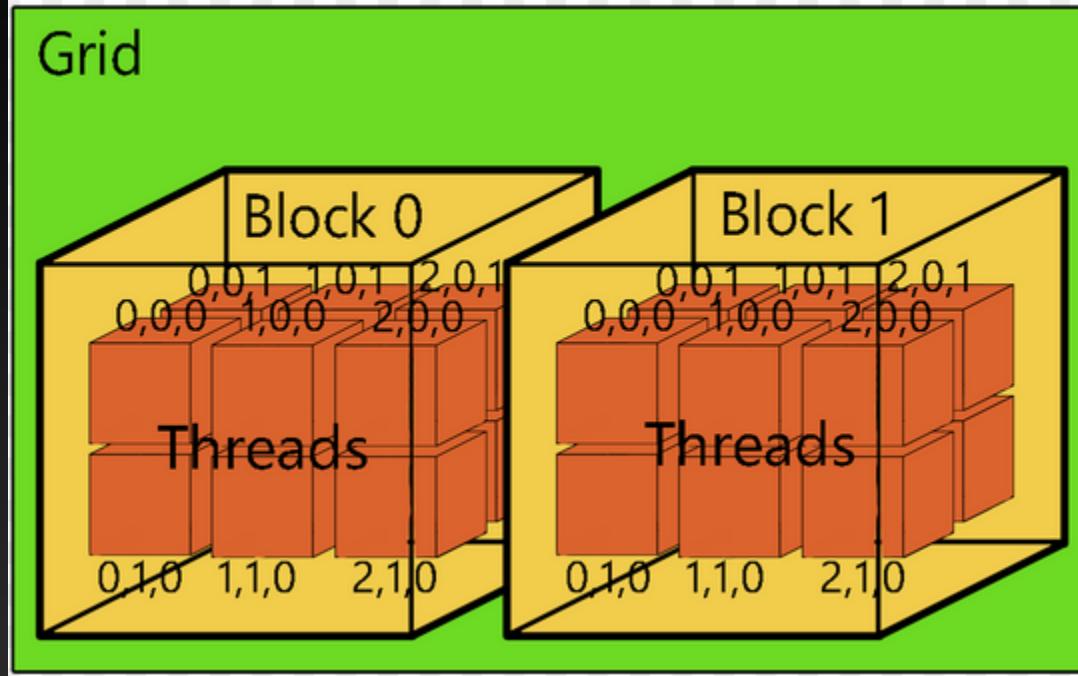
Perigo: indices não referenciados...

```
__global__ void add(int *d_a, int *d_b, int *d_c) {
    int i = threadIdx.x + blockIdx.x * blockDim.x;
    if (i < N)
        d_c[i] = d_a[i] + d_b[i];
}

int main()
{
    vecAdd <<<K,M>>>(A, B, C);      // K*M >= N
}
```



Threads podem ser indexados em 1, 2 ou 3 dimensões



(`threadIdx.x`, `threadIdx.y`, `threadIdx.z`)

Threads podem ser indexados em 1, 2 ou 3 dimensões

```
__global__ void MatAdd(int *d_a, int *d_b, int *d_c) {  
    int i= threadIdx.x;  
    int j= threadIdx.y;  
  
    d_c[i][j] = d_a[i][j] + d_b[i][j];  
}  
  
int main()  
{  
    dim3 threadsPerBlock (N,M)                      // N*M < 1024  
    vecAdd <<<1,threadsPerBlock>>>(A, B, C);  
}
```



Multiplicação de Matrizes

b_{00}	b_{01}	b_{02}	b_{03}
b_{10}	b_{11}	b_{12}	b_{13}
b_{20}	b_{21}	b_{22}	b_{23}
b_{30}	b_{31}	b_{32}	b_{33}
b_{40}	b_{41}	b_{42}	b_{43}
b_{50}	b_{51}	b_{52}	b_{53}

a_{00}	a_{01}	a_{02}	a_{03}	a_{04}	a_{05}
a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}

c_{00}	c_{01}	c_{02}	c_{03}
c_{10}	c_{11}	c_{12}	c_{13}
c_{20}	c_{21}	c_{22}	c_{23}

tid_{00}	tid_{01}	tid_{02}	tid_{03}
tid_{10}	tid_{11}	tid_{12}	tid_{13}
tid_{20}	tid_{21}	tid_{22}	tid_{23}

bid₀₀

$$A * B = C = \begin{bmatrix} \sum_{i=1}^m a_{1i} * b_{i1} & \sum_{i=1}^m a_{1i} * b_{i2} & \dots & \sum_{i=1}^m a_{1i} * b_{ir} \\ \sum_{i=1}^m a_{2i} * b_{i1} & \sum_{i=1}^m a_{2i} * b_{i2} & \dots & \sum_{i=1}^m a_{2i} * b_{ir} \\ \vdots & \ddots & \ddots & \vdots \\ \sum_{i=1}^m a_{ni} * b_{i1} & \sum_{i=1}^m a_{ni} * b_{i2} & \dots & \sum_{i=1}^m a_{ni} * b_{ir} \end{bmatrix}$$

Multiplicação de Matrizes

(implementação trivial)

```
__global__ void add(int *d_a, int *d_b, int *d_c, int K) {  
    int col= threadIdx.x + blockIdx.x * blockDim.x;  
    int row= threadIdx.y + blockIdx.y * blockDim.y;  
    cValue = 0.0f;  
  
    for (int k = 0; k < K; k++)  
        cValue += d_a[col][k] * d_b[k][row];  
  
    d_c[col][row]= cValue  
}
```



Multiplicação de Matrizes

(implementação trivial)

```
__global__ void add(int *d_a, int *d_b, int *d_c, int K) {  
    int i= threadIdx.x + blockIdx.x * blockDim.x;  
    int j= threadIdx.y + blockIdx.y * blockDim.y;  
    cValue = 0;  
  
    for (int k = 0; k < K; k++)  
        cValue += d_a[i][k] * d_b[k][j];  
  
    d_c[i][j]= cValue  
}
```

PORQUE NÃO É UMA BOA
SOLUÇÃO???



Divergencia de Threads

```
__global__ void add(int *d_a) {  
    int i = threadIdx.x + blockIdx.x * blockDim.x;  
  
    if ((i%2) != 0)                      // i is odd  
        d_a[i] *=2;  
    else                                // i is even  
        d_a[i] /=2;  
}
```



Warps

Independent of the Architecture, it consists on 32 threads per warp. Thread multiple of 32 will optimize the occupancy rate

Coalescence is strong in the same warp

Thread Divergence is also strong in the same warp



Aviso importante

Respect the amount of register size for each Warp

Technical specifications	Compute capability (version)													
	1.0	1.1	1.2	1.3	2.x	3.0	3.5	3.7	5.0	5.2				
Maximum dimensionality of grid of thread blocks	2				3									
Maximum x-dimension of a grid of thread blocks	65535						$2^{31}-1$							
Maximum y-, or z-dimension of a grid of thread blocks	65535													
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			32						
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	128 K	64 K							
Maximum number of 32-bit registers per thread	128				63	255								
Maximum amount of shared memory per multiprocessor	16 KB				48 KB		112 KB	64 KB	96 KB					
Number of shared memory banks	16				32									
Amount of local memory per thread	16 KB				512 KB									

Kernels concorrentes

```
1 cudaMalloc ( &dA, sizeA ) ;
2 cudaMalloc ( &dB, sizeB ) ;
3 ...
4 cudaMemcpy ( dA, A, size, H2D ) ;
5 cudaMemcpy ( dB, B, size, H2D ) ;
6 ...
7 kernelA <<< gridA, blockA>>> ( ..., dA, ... ) ;
8 kernelB <<< gridB, blockB>>> ( ..., dB, ... ) ;
9 ...
```

Shared Memory

- Available for a complete Block. Can only be manipulated by the Device...
- Kepler support banks of 8 bytes of shared memory. Previous architectures accepted 4.



Shared Memory

```
__global__ void copy_vector(float *data)
{
    int index = threadIdx.x;

    __shared__ float temp_data[256];
    temp_data[index] = data[index];

    ...
}
```



Shared Memory

```
__global__ void copy_vector(float *data)
{
    int index = threadIdx.x;

    __shared__ float temp_data[256];
    temp_data[index] = data[index];

    __syncthread();

    ...
}
```

Is this code more efficient than only using the global memory???



Analisando a eficiência da Shared Memory

```
__global__ void copy_vector(float *data)
{
    int index = threadIdx.x;
    int i, aux=0;

    __shared__ float temp_data[256];
    temp_data[index] = data[index];

    __syncthread();

    for (i=0; i<25; i++)
    {
        aux += temp_data[i];
    }
    data[index] = aux;
}
```

...



Aviso importante

Respect the amount of shared memory available for each Block

Technical specifications	Compute capability (version)													
	1.0	1.1	1.2	1.3	2.x	3.0	3.5	3.7	5.0	5.2				
Maximum dimensionality of grid of thread blocks	2				3									
Maximum x-dimension of a grid of thread blocks	65535						$2^{31}-1$							
Maximum y-, or z-dimension of a grid of thread blocks	65535													
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			32						
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	128 K	64 K							
Maximum number of 32-bit registers per thread	128				63	255								
Maximum amount of shared memory per multiprocessor	16 KB				48 KB		112 KB	64 KB	96 KB					
Number of shared memory banks	16				32									
Amount of local memory per thread	16 KB				512 KB									

Implementando o Parallel Reduce (Shared Memory)

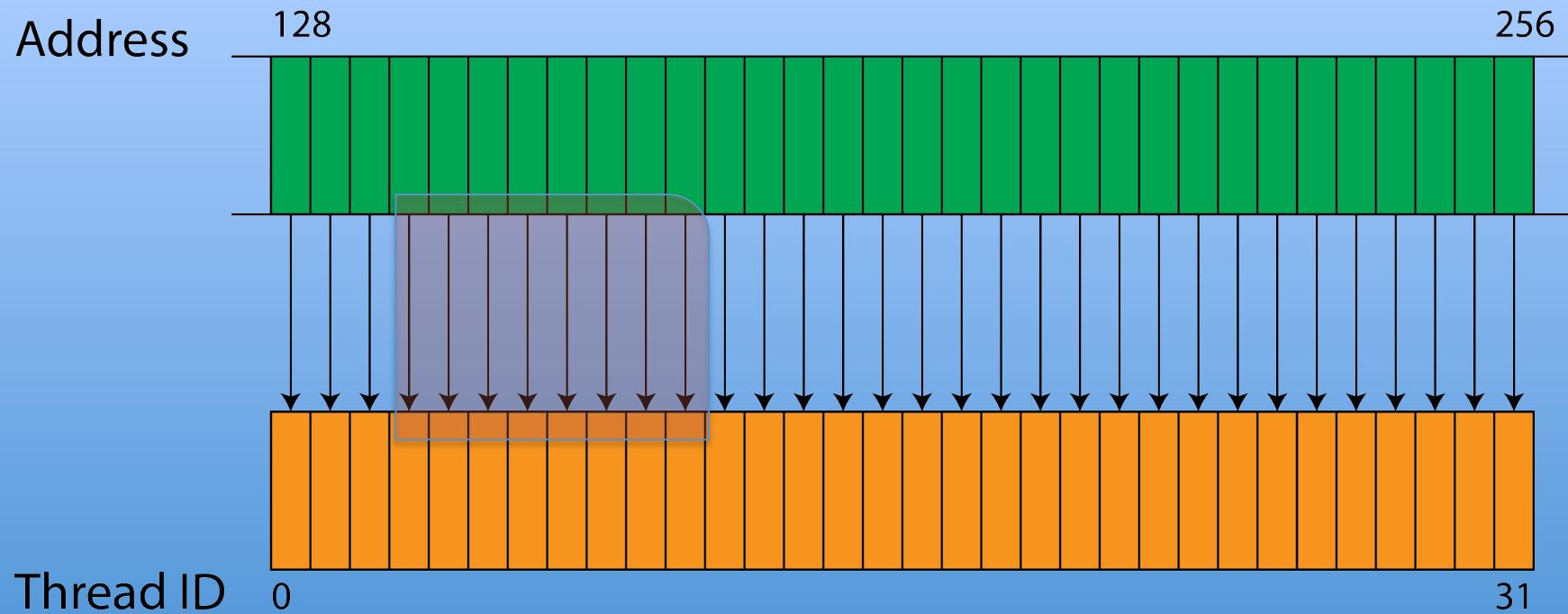
```
__global__ void reduceShared (float *d_In, *d_Out)
{
    external __shared__ s_data[];
    int index = blockIdx.x*blockDim.x + threadIdx.x;
    int tid = threadIdx.x;

    s_data = d_In[index]
    __syncthread();

    for (int stride = blockDim.x/2; stride > 0; stride >>=1) {
        if (tid < stride){
            s_data [index] += s_data[index+s];
        }
        __syncthread();
    if (tid == 0){
        d_Out[blockIdx.x] = s_data[0];
    }
}
```



Coalescencia



Otimizando o código

Each SM fetches 128 bytes per memory access.

Good optimization is obtained when reading 32 bytes .
Reading 64 bits requires one fetch finish for making another.



Exemplo de Coalescence

Array of Structures

```
1 struct st_particle{
2     float3 p;
3     float3 v;
4     float3 a;
5 };
6
7 __global__ void K_Particle_01(st_particle *vet){
8
9     int i = blockDim.x * blockIdx.x + threadIdx.x;
10    vet[i].p.x = vet[i].p.x + vet[i].v.x * vet[i].a.x;
11    vet[i].p.y = vet[i].p.y + vet[i].v.y * vet[i].a.y;
12    vet[i].p.z = vet[i].p.z + vet[i].v.z * vet[i].a.z;
13
14 }
```

Data of particle #0 begins in position 0 of the memory, the attributes of particle #2 starts in position 96 bytes of memory and so on.



Exemplo de Coalescência

```
1 __global__ void K_Particle_02(float *vet_px, float *vet_py, float *vet_pz,
2                                 float *vet_vx, float *vet_vy, float *vet_vz,
3                                 float *vet_ax, float *vet_ay, float *vet_az){
4
5     int i = blockDim.x * blockIdx.x + threadIdx.x;
6     vet_px[i] = vet_px[i] + vet_vx[i] * vet_ax[i];
7     vet_py[i] = vet_py[i] + vet_vy[i] * vet_ay[i];
8     vet_pz[i] = vet_pz[i] + vet_vz[i] * vet_az[i];
9
10
11 }
12 }
```

Structure of Arrays



Atomic Operations



Exercício: o que acontece com este código???

```
#define BLOCKS 1000
#define THREADSPERBLOCK 1000
#define size 10

__global__ void incrementVector (float *data)
{
    int index = blockIdx.x*blockDim.x + threadIdx.x;
    data[index] = data[index] + 1;
}
```



E agora?

```
#define BLOCKS 1000
#define THREADSPERBLOCK 1000
#define size 10

__global__ void incrementVector (float *data)
{
    int index = blockIdx.x*blockDim.x + threadIdx.x;
    index = index % size;
    data[index] = data[index] + 1;
}
```



Exercicio: corrigir usando barreiras...

```
#define BLOCKS 1000
#define THREADSPERBLOCK 1000
#define size 10

__global__ void incrementVector (float *data)
{
    int index = blockIdx.x*blockDim.x + threadIdx.x;
    index = index % size;
    data[index] = data[index] + 1;
}
```



Atomic Operation

```
#define BLOCKS 1000
#define THREADSPERBLOCK 1000
#define size 10

__global__ void incrementVector (float *data)
{
    int index = blockIdx.x*blockDim.x + threadIdx.x;
    index = index % size;
    atomicAdd(&data[index], 1);
}
```



Lista de Atomic Operation

```
int atomicAdd(int* address, int val);  
  
int atomicSub(int* address, int val);  
  
int atomicExch(int* address, int val);  
  
int atomicMin(int* address, int val);  
  
int atomicMax(int* address, int val);  
  
unsigned int atomicInc(unsigned int* address, unsigned int val); // old >= val ? 0 : (old+1)  
  
unsigned int atomicDec(unsigned int* address, unsigned int val);  
  
int atomicAnd(int* address, int val); // Or and Xor also available
```

Works fine for int . Only add and exchange work for float and double



Limitações de Atomic Operation

1. only a set of operations are supported
2. Restricted to data types
3. Random order in operation
4. Serialize access to the memory (there is no magic!)

Great improvements on latest architectures



Streams

Task Parallelism: two or more completely different tasks in parallel



Streams

cudaHostAlloc: malloc memory in the Host

Differs from traditional malloc() since it guarantees that the memory will be page-locked, i.e., it will never be paged to memory out to disk (assures that data will always be resident at physical memory)

Constraint: doing so the memory may run out much faster than when using malloc...



Streams

Knowing the physical address buffer allows the GPU to use the DMA (Direct Memory Access), which proceeds without the intervention of the CPU



Streams

```
...  
int *a, *dev_a;  
  
a = (int*)malloc(size*sizeof(*a));  
cudaMalloc ( (void**)&dev_a, size * sizeof (*dev_a));  
  
cudaMemcpy (dev_a, a, size * sizeof(*dev_a), cudaMemcpyHostToDevice));  
  
...
```



Streams

```
...  
int *a, *dev_a;  
  
cudaHostAlloc ( (void**)&a , size * sizeof (*a) , cudaHostAllocDefault );  
cudaMalloc     ( (void**)&dev_a, size * sizeof (*dev_a));  
  
cudaMemcpy (dev_a, a, size * sizeof(*dev_a) , cudaMemcpyHostToDevice));  
  
cudaFreeHost ( a );  
cudaFree     (dev_a);  
  
...
```



Streams

GPU allow to create specific order of operations using streams. In some situations it allows to create parallel tasks.



Streams

```
...  
int *a, *dev_a;  
cudaStream_t stream;  
  
cudaStreamCreate(&stream);  
  
cudaMalloc  ( (void**)&dev_a, size * sizeof (*dev_a));  
cudaHostAlloc ( (void**)&a      , size * sizeof (*a), cudaHostAllocDefault );  
  
cudaMemcpyAsync (dev_a, a, size * sizeof(*dev_a) , cudaMemcpyHostToDevice,  
stream));  
  
// A stream operation is Asynchronous. Each stram opeartion only starts  
// after the previous stream operation have finished  
  
Kernel <<<GridDim, BlockDim, stream>>> (dev_a);  
  
cudaMemcpyAsync (dev_a, a, size * sizeof(*dev_a) , cudaMemcpyHostToDevice,  
stream));  
  
cudaStreamDEstroy (stream);
```



Streams

```
...  
int *a, *dev_a;  
cudaStream_t stream;  
  
cudaStreamCreate(&stream);  
  
cudaMalloc  ( (void**)&dev_a, size * sizeof (*dev_a));  
cudaHostAlloc ( (void**)&a      , size * sizeof (*a), cudaHostAllocDefault );  
  
cudaMemcpyAsync (dev_a, a, size * sizeof(*dev_a), cudaMemcpyHostToDevice,  
stream); // Async copy only works with page locked memory  
  
// A stream operation is Asynchronous. Each stram opeartion only starts  
// after the previous stream operation have finished  
  
Kernel <<<GridDim, BlockDim, stream>>> (dev_a);  
  
cudaMemcpyAsync (dev_a, a, size * sizeof(*dev_a), cudaMemcpyHostToDevice,  
stream));  
cudaStreamDEstroy (stream);
```



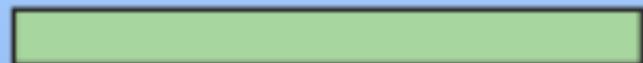
Streams

```
...  
int *a, *dev_a;  
cudaStream_t stream;  
  
cudaStreamCreate(&stream);  
  
cudaMalloc  ( (void**)&dev_a, size * sizeof (*dev_a));  
cudaHostAlloc ( (void**)&a      , size * sizeof (*a), cudaHostAllocDefault );  
  
cudaMemcpyAsync (dev_a, a, size * sizeof(*dev_a), cudaMemcpyHostToDevice,  
stream);  
  
// A stream operation is Asynchronous. Each stram opeartion only starts  
// after the previous stream operation have finished  
  
Kernel <<<GridDim, BlockDim, stream>>> (dev_a);  
  
cudaMemcpyAsync (dev_a, a, size * sizeof(*dev_a), cudaMemcpyHostToDevice,  
stream);  
  
cudaStreamDEstroy (stream);
```



Optimizing code with Asynchronous operations

Copy data



Execute



Copy data



Execute



Stream overlaps

```
...  
#define N (1024 * 1024)  
#define TOTAL_SIZE (N*20)  
  
Int *h_a, *h_b, *h_c;  
  
Int *d_a0, *d_b0, *d_c0;  
Int *d_a1, *d_b1, *d_c1;  
  
cudaStream_t stream0, stream1;  
cudaStreamCreate(&stream0);  
cudaStreamCreate(&stream1);  
  
cudaMalloc ( (void**)&d_a0, N*sizeof (int));  
cudaMalloc ( (void**)&d_b0, N*sizeof (int));  
cudaMalloc ( (void**)&d_c0, N*sizeof (int));  
cudaMalloc ( (void**)&d_a1, N*sizeof (int));  
cudaMalloc ( (void**)&d_b1, N*sizeof (int));  
cudaMalloc ( (void**)&d_c1, N*sizeof (int));
```



Stream overlaps

...

```
cudaHostAlloc ( (void**)&h_a, TOTAL_SIZE*sizeof (int), cudaHostAllocDefault );
cudaHostAlloc ( (void**)&h_b, TOTAL_SIZE*sizeof (int), cudaHostAllocDefault );
cudaHostAlloc ( (void**)&h_c, TOTAL_SIZE*sizeof (int), cudaHostAllocDefault );

For (int i=0; i<TOTAL_SIZE; i++) {
    h_a[i] = rand();
    h_b[i] = rand();
}
```



Stream overlaps

```
For (int i=0; i < TOTAL_SIZE ; i+=N*2)
{

    cudaMemcpyAsync (dev_a0, h_a+i, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream0));
    cudaMemcpyAsync (dev_b0, h_b+i, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream0));
    kernel<<<N/256, 256, 0, stream0>>> (d_a0, d_b0, d_c0);

    cudaMemcpyAsync (h_c+i, dc_0, N* sizeof(int), cudaMemcpyDeviceToHost,
                    stream0));

    cudaMemcpyAsync (dev_a1, h_a+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream1));
    cudaMemcpyAsync (dev_b1, h_b+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream1));
    kernel<<<N/256, 256, 0, stream0>>> (d_a1, d_b1, d_c1);

    cudaMemcpyAsync (h_c+i+N, dc_1, N* sizeof(int), cudaMemcpyDeviceToHost,
                    stream1));
}

}
```



Stream overlaps

```
cudaMemcpyAsync (dev_a1, h_a+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                 stream1));
cudaMemcpyAsync (dev_b1, h_b+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                 stream1));
kernel<<<N/256, 256, 0, stream0>>> (d_a1, d_b1, d_c1);

cudaMemcpyAsync (h_c+i+N, dc_1, N* sizeof(int), cudaMemcpyDeviceToHost,
                 stream1));
}

cudaStreamSynchronize (stream0);
cudaStreamSynchronize (stream1);

// frees and destroys...
```



Stream overlaps

```
cudaMemcpyAsync (dev_a1, h_a+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                 stream1));
cudaMemcpyAsync (dev_b1, h_b+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                 stream1));
kernel<<<N/256, 256, 0, stream0>>> (d_a1, d_b1, d_c1);

cudaMemcpyAsync (h_c+i+N, dc_1, N* sizeof(int), cudaMemcpyDeviceToHost,
                 stream1));
}

cudaStreamSynchronize (stream0);
cudaStreamSynchronize (stream1);

// frees and destroys...
```

Esta versão ainda não traz otimizações:
Sobrecarga do engine de memória e kernel



Improving Stream

```
For (int i=0; i < TOTAL_SIZE ; i+=N*2)
{

    cudaMemcpyAsync (dev_a0, h_a+i, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream0);

    cudaMemcpyAsync (dev_b0, h_b+i, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream0);

    cudaMemcpyAsync (dev_a1, h_a+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream1);

    cudaMemcpyAsync (dev_b1, h_b+i+N, N* sizeof(int), cudaMemcpyHostToDevice,
                    stream1);

    kernel<<<N/256, 256, 0, stream0>>> (d_a0, d_b0, d_c0);
    kernel<<<N/256, 256, 0, stream0>>> (d_a1, d_b1, d_c1);

    cudaMemcpyAsync (h_c+i, dc_0, N* sizeof(int), cudaMemcpyDeviceToHost,
                    stream0);

    cudaMemcpyAsync (h_c+i+N, dc_1, N* sizeof(int), cudaMemcpyDeviceToHost,
                    stream1));
}
```



Optimizing with compiler directives

CUDA capability	Features
2.0	Fermi architecture
3.0	Kepler architecture
3.2	Unified memory programming
3.5	Dynamic parallelism
5.0, 5.2 and 5.3	Maxwell

Directives

```
nvcc -arch=compute_20 -code=sm_20,sm_32, sm_35,  
sm_50,sm_52,sm_53 foo.cu -o foo
```

```
nvcc -arch=compute_35 -code=sm_35 foo.cu -o foo
```

```
nvcc -use_fast_math foo.cu -o foo
```



Last advices...

- Find ways to parallelize sequential code,
- Minimize data transfers between the host and the device,
- Adjust kernel launch configuration to maximize device utilization,
- Ensure global memory accesses are coalesced,
- Minimize redundant accesses to global memory whenever possible,
- Avoid different execution paths within the same warp.

Read more at: <http://docs.nvidia.com/cuda/kepler-tuning-guide/index.html#ixzz3jGmjoXLj>



NVLink



Mixed Precision

“Deep learning have found that deep neural network architectures have a natural resilience to errors due to the backpropagation algorithm used in training them, and some developers have argued that 16-bit floating point (half precision, or FP16) is sufficient for training neural networks.”

P100: 21.2 Tflops for Half precision

half a, b ...



GPU Educational Kit

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GPU-accelerated computing is the use of a graphics processing unit (GPU) together with a CPU to accelerate scientific, analytics, engineering, consumer, and enterprise applications. Pioneered in 2007 by NVIDIA®, GPU accelerators now power energy-efficient datacenters in government labs, universities, enterprises, and small-and-medium businesses around the world. GPUs are accelerating applications in platforms ranging from cars, to mobile phones and tablets, to drones and robots.

HOW GPUs ACCELERATE APPLICATIONS

GPU-accelerated computing offers unprecedented application performance by offloading compute-intensive portions of the application to the GPU, while the remainder of the code still runs on the CPU. From a user's perspective, applications simply run significantly faster.

How GPU Acceleration Works

Application Code

VISIT CUDA ZONE

GET STARTED TODAY

There are three basic approaches to adding GPU acceleration to your applications:

- ✓ Dropping in GPU-optimized libraries
- ✓ Adding compiler "hints" to auto-parallelize your code
- ✓ Using extensions to standard languages like C and Fortran

Learning how to use GPUs with the CUDA parallel programming model is easy.

For free online classes and developer resources visit CUDA zone.



GPU Educational Kit

Curso completo de Programação em GPUs:
(legendado para Português)

<http://www2.ic.uff.br/~gpu/kit-de-ensino-gpgpu/>

<http://www2.ic.uff.br/~gpu/learn-gpu-computing/deep-learning/>



esteban@ic.uff.br

