# Programming Parallel Computers 

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Part 4C:
Memory access patterns in CUDA programs

## Sample application: cheapest 2-hop path

$d$ (input):

$d[]=\{0,8,2$,
1, 0, 9,
$4,5,0\}$
r (output):


$$
\left.r[]=\begin{array}{lll}
0, & 7, & 2 \\
1, & 0, & 3 \\
4, & 5, & 0
\end{array}\right\}
$$

void step(float* $r$, const float* d, int $n$ ) \{ for (int $i=0 ; i<n ;++i)\{$ for (int $j=0 ; j<n ;++j)\{$ float $v=i n f i n i t y ;$ for (int $k=0 ; k<n ;++k)\{$ float $x=d[n * i+k]$; float $y=d[n * k+j]$; float $z=x+y$; $\mathrm{v}=\min (\mathrm{v}, \mathrm{z})$;

$$
\}
$$

$$
r[n * i+j]=v ;
$$

\}
\}

## Splitting work

- Work to do:
- need to compute $n \times n$ results
- computing one result takes $n$ steps
- How do we split this in blocks and threads?
- Natural idea:
- one thread computes one result
- one block computes $b \times b$ results, for some suitable $b$
- if we choose e.g. $b=16$, then a block consists of 8 warps


## Splitting work

- Example: input dimensions are $1600 \times 1600$ :
- we want to create $100 \times 100$ blocks
- each block consists of $16 \times 16$ threads
- Create 10000 blocks with 256 threads:
- blocks numbered 0 ... 9999
- threads numbered 0 ... 255
- Convert block \& thread index to $(i, j)$ pair:
- thread number 123 in block number 4567 computes the result for $i=$ ??? and $j=$ ???


## Splitting work

- Example: input dimensions are $1600 \times 1600$ :
- we want to create $100 \times 100$ blocks
- each block consists of $16 \times 16$ threads
- Create 10000 blocks with 256 threads:
- blocks numbered 0 ... 9999
- threads numbered 0 ... 255
- Convert block \& thread index to $(i, j)$ pair:
- thread number $123=7 \cdot 16+11$ in block number $4567=45 \cdot 100+67$ computes the result for $i=67 \cdot 16+11$ and $j=45 \cdot 16+7$


## Splitting work: using 2D indexes

- Example: input dimensions are $1600 \times 1600$ :
- we want to create $100 \times 100$ blocks
- each block consists of $16 \times 16$ threads
- Create 10000 blocks with 256 threads using 2D indexes:
- blocks numbered ( 0,0 ) ... $(99,99)$
- threads numbered $(0,0)$... $(15,15)$
- Convert block \& thread coordinates to $(i, j)$ pair:
- thread number $(11,7)$ in block number $(67,45)$ computes the result for $i=67 \cdot 16+11$ and $j=45 \cdot 16+7$


## Splitting work: rounding

- Example: input dimensions are $1601 \times 1601$ :
- we want to create $101 \times 101$ blocks
- each block consists of $16 \times 16$ threads
- Create 10000 blocks with 256 threads using 2D indexes:
- blocks numbered $(0,0)$... $(100,100)$
- threads numbered $(0,0)$... $(15,15)$
- There will be some threads with $i \geq 1601$ and/or $j \geq 1601$, they will do nothing

```
__global__ void mykernel(float* r, const float* d, int n) {
    int i = threadIdx.x + blockIdx.x * blockDim.x;
    int j = threadIdx.y + blockIdx.y * blockDim.y;
    if (i >= n || j >= n)
        return;
    float v = HUGE_VALF;
for (int k = 0; k < n; ++k) {
            float x = d[n*i + k];
        float y = d[n*k + j];
        float z = x + y;
        v = min(v, z);
    }
    r[n*i + j] = v;
}
```


## What if n is not a multiple of 16

blockDim.x = 16
blockDim. $\mathrm{y}=16$

float* dGPU = NULL;
cudaMalloc((void**)\&dGPU, $n$ * $n$ * sizeof(float));
float* rGPU = NULL;
cudaMalloc((void**)\&rGPU, $n * n * \operatorname{sizeof(float));~}$
cudaMemcpy(dGPU, d, n * n * sizeof(float), cudaMemcpyHostToDevice);
n/16, rounded up
dim3 dimBlock(16, 16);
dim3 dimGrid(divup(n, dimBlock.x), divup(n, dimBlock.y)); mykernel<<<dimGrid, dimBlock>>>(rGPU, dGPU, n);
cudaMemcpy(r, rGPU, $n$ * $n$ * sizeof(float), cudaMemcpyDeviceToHost);
cudaFree(dGPU); cudaFree(rGPU);

## Performance

- Test input: $\boldsymbol{n}=\mathbf{6 3 0 0}$
- Maari computers:
- baseline CPU solution: 397 s
- best CPU solution: 2.3 s
- current GPU solution: 42 s
- What is the bottleneck?


## Memory

- A key challenge in CPU code: getting data fast enough from the CPU memory
- A key challenge in GPU code: getting data fast enough from the GPU memory


## Memory access pattern

- Blocks are divided in warps
- warp = 32 threads
- Entire warp executes synchronously
- If one thread reads some memory, all threads of the warp read some memory








## Memory access pattern

- One memory read in kernel: entire warp of threads reads memory simultaneously
- Threads access small continuous parts of memory: need to load few cache lines $\rightarrow$ good
- Threads access 32 different locations far from each other: need to load many cache lines $\rightarrow$ bad

First warp:
thread $0: i=0, j=0$
thread 1: $i=1, j=0$
thread 2: $i=2, j=0$
thread 3: $i=3, j=0$

```
```

int i = threadIdx.x + ...

```
```

int i = threadIdx.x + ...
int j = threadIdx.y + ...
int j = threadIdx.y + ...
for (... ++k) {
for (... ++k) {
float x = d[n*i + k];
float x = d[n*i + k];
float y = d[n*k + j];
float y = d[n*k + j];
}

```
}
```

```
    ...
```

```
    ...
```

thread 31: $\mathbf{i}=15, \mathrm{j}=1$


First warp, first iteration:

```
int i = threadIdx.x + ...
int i = threadIdx.x + ...
```

threads 0 \& 16: read d[0] for (... ++k) \{
threads $1 \& 17$ : read d[1000]
threads 2 \& 18: read d[2000]
threads 3 \& 19: read d[3000]

First warp, first iteration:

$$
\begin{aligned}
\text { int } i & =\text { threadIdx.x }+\ldots \\
\text { int } j & =\text { threadIdx. } y+\ldots
\end{aligned}
$$

threads 0 \& 16: read d[0] for (... ++k) \{

First warp, second iteration:

$$
\begin{aligned}
& \text { int } \mathbf{i}=\text { threadIdx.x + } \ldots \\
& \text { int } \mathbf{j}=\text { threadIdx.y }+\ldots
\end{aligned}
$$

threads 0 \& 16: read d[1] for (... ++k) \{

First warp, third iteration:

```
int i = threadIdx.x + ...
int j = threadIdx.y + ...
```

threads 0 \& 16: read d[2] for (... ++k) \{
threads $1 \& 17$ : read d[1002]
threads 2 \& 18: read d[2002]
threads $3 \& 19$ : read d[3002]
threads 0-15: read d[2000]
threads 16-31: read d[2001]

```
int i = threadIdx.x + ...
int j = threadIdx.y + ...
for (... ++k) {
        float x =-d[nci + k];
        float y = d[n\k + j];
        float x = d[n*j + k];
        float y = d[n*k + i];
    ...
}
```



```
\[
r[n * j+i]=v ;
\]
```

First warp, first iteration:

$$
\begin{aligned}
& \text { int } i=\text { threadIdx.x }+\ldots \\
& \text { int } j=\text { threadIdx.y }+\ldots \\
& \text { for }(\ldots++k)\{
\end{aligned}
$$

$$
\text { threads } 0-15: \text { read d[0] float } x=d[n * j+k] \text {; }
$$

threads 16-31: read d[1000]

First warp, first iteration:
threads 16-31: read d[1000]

$$
\begin{aligned}
& \text { int } \mathbf{i}=\text { threadIdx. } x+\ldots \\
& \text { int } \mathbf{j}=\text { threadIdx. } y+\ldots \\
& \text { for }(\ldots++k)\{ \\
& \text { float } x=d[n * j+k] ; \\
& \text { float } y=d[n * k+i] ;
\end{aligned}
$$

$$
\text { threads } 0-15: \text { read } d[0] \quad \text { float } x=d[n * j+k] ;
$$

threads 0 \& 16: read d[0]
threads $1 \& 17$ : read d[1]
threads 2 \& 18: read d[2]

First warp, second iteration:

$$
\begin{aligned}
& \text { int } \mathbf{i}=\text { threadIdx. } x+\ldots \\
& \text { int } \mathbf{j}=\text { threadIdx. } y+\ldots \\
& \text { for }(\ldots++k)\{ \\
& \text { float } x=d[n * j+k] ; \\
& \text { float } y=d[n * k+i] ;
\end{aligned}
$$

threads 0-15: read d[1] float $x=d[n * j+k]$;
threads 16-31: read d[1001]
threads 0 \& 16: read d[1000] threads $1 \& 17$ : read d[1001] threads 2 \& 18: read d[1002]

First warp, third iteration:

$$
\begin{aligned}
& \text { int } i=\text { threadIdx. } x+\ldots \\
& \text { int } j=\text { threadIdx. } y+\ldots \\
& \text { for }(\ldots++k)\{
\end{aligned}
$$

$$
\text { threads 0-15: read d[2] float } x=d[n * j+k] ;
$$

$$
\text { threads 16-31: read d[1002] float } y=d[n * k+i] ;
$$

threads 0 \& 16: read d[2000] threads $1 \& 17$ : read d[2001] threads 2 \& 18: read d[2002]

## Performance

- V0: baseline - 42 s
- V1: better memory access pattern - 8 s
- But we can do much better by applying familiar ideas:
- reuse data in registers
- reuse data in "cache" (here: shared memory)


## Performance

V0: baseline
V1: memory access
V2: registers
V3: shared memory


