

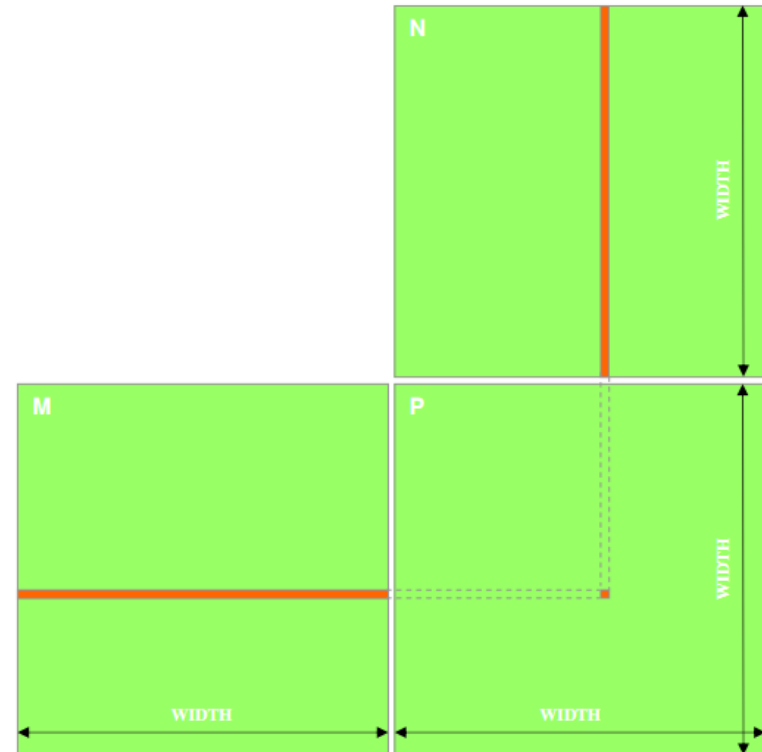
CUDA编程(2)

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我们来重新分析 matrix multiply

Matrix Multiply: CPU 实现

```
void MatrixMulOnHost(float* M, float* N, float* P, int width)
{
    for (int i = 0; i < width; ++i)
        for (int j = 0; j < width; ++j)
        {
            float sum = 0;
            for (int k = 0; k < width; ++k)
            {
                float a = M[i * width + k];
                float b = N[k * width + j];
                sum += a * b;
            }
            P[i * width + j] = sum;
        }
}
```



Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{
    // 2D Thread ID
    int tx = threadIdx.x;
    int ty = threadIdx.y;

    // Pvalue stores the Pd element that is computed by the thread
    float Pvalue = 0;

    for (int k = 0; k < Width; ++k)
    {
        float Mdelement = Md[ty * Md.width + k];
        float Ndelement = Nd[k * Nd.width + tx];
        Pvalue += Mdelement * Ndelement;
    }

    // Write the matrix to device memory each thread writes one element
    Pd[ty * Width + tx] = Pvalue;
}
```

访问矩阵，所以用二维block

Matrix Multiply: CUDA Kernel

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// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
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    // 2D Thread ID
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    for (int k = 0; k < Width; ++k)
    {
        float Mdelement = Md[ty * Md.width + k];
        float Ndelement = Nd[k * Nd.width + tx];
        Pvalue += Mdelement * Ndelement;
    }

    // Write the matrix to device memory each thread writes one element
    Pd[ty * Width + tx] = Pvalue;
}
```

每个kernel计算一个输出结果

Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{
    // 2D Thread ID
    int tx = threadIdx.x;
    int ty = threadIdx.y;

    // Pvalue stores the Pd element that is computed by the thread
    float Pvalue = 0;

    for (int k = 0; k < Width; ++k)
    {
        float Mdelement = Md[ty * Md.width + k];
        float Ndelement = Nd[k * Nd.width + tx];
        Pvalue += Mdelement * Ndelement;
    }

    // Write the matrix to device memory each thread writes one element
    Pd[ty * Width + tx] = Pvalue;
}
```

CPU 版本的2个外层循环去哪儿了？

Matrix Multiply: CUDA Kernel

```
// Matrix multiplication kernel – thread specification
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{
    // 2D Thread ID
    int tx = threadIdx.x;
    int ty = threadIdx.y;

    // Pvalue stores the Pd element that is computed by the thread
    float Pvalue = 0;

    for (int k = 0; k < Width; ++k)
    {
        float Mdelement = Md[ty * Md.width + k];
        float Ndelement = Nd[k * Nd.width + tx];
        Pvalue += Mdelement * Ndelement;
    }

    // Write the matrix to device memory each thread writes one element
    Pd[ty * Width + tx] = Pvalue;
}
```

不用锁或同步，为什么？

▶ 问题

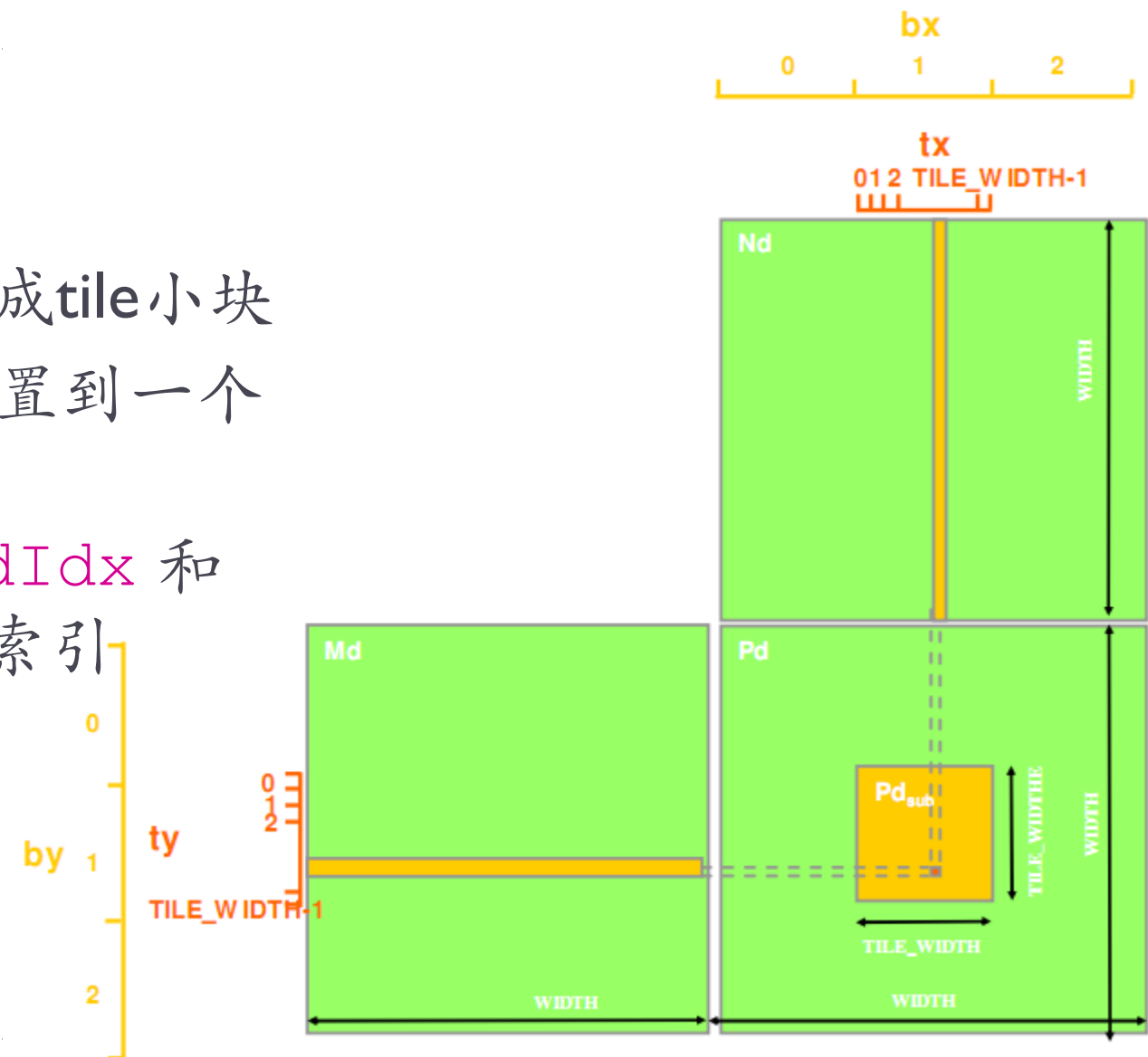
▶ 矩阵长度限制

- ▶ 仅用一个block

- ▶ **G80 和 GT200 – 最多512 个线程/block**

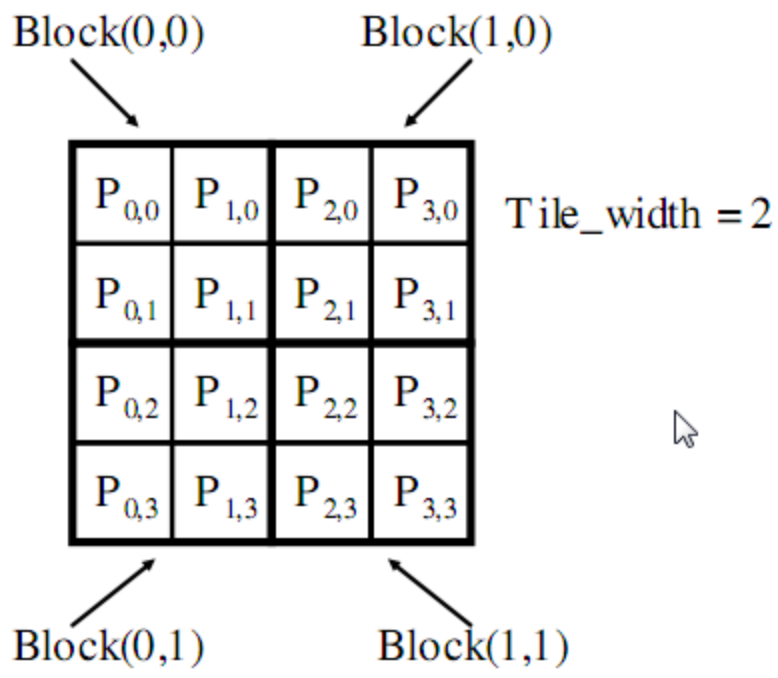
- ▶ 很多 global memory 读写访问

- ▶ 去除长度限制
 - ▶ 将Pd 矩阵拆成tile小块
 - ▶ 把一个tile 布置到一个block
 - ▶ 通过 threadIdx 和 blockIdx 索引

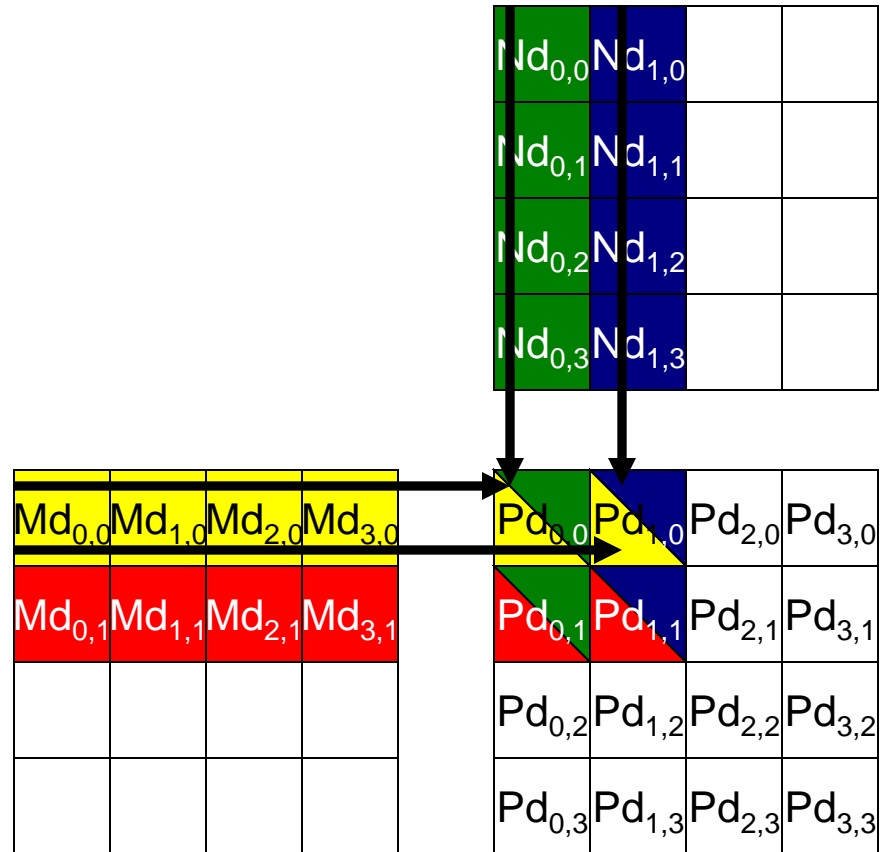


▶ 例如

- ▶ 矩阵: 4x4
- ▶ TILE_WIDTH = 2
- ▶ Block 尺寸: 2x2



- ▶ 例如
- ▶ 矩阵: 4×4
- ▶ $\text{TILE_WIDTH} = 2$
- ▶ Block 尺寸: 2×2



```
__global__ void MatrixMulKernel(  
    float* Md, float* Nd, float* Pd, int Width)  
{  
    int Row = blockIdx.y * blockDim.y + threadIdx.y;  
    int Col = blockIdx.x * blockDim.x + threadIdx.x;  
  
    float Pvalue = 0;  
    for (int k = 0; k < Width; ++k)  
        Pvalue += Md[Row * Width + k] * Nd[k * Width +  
            Col];  
  
    Pd[Row * Width + Col] = Pvalue;  
}
```

计算矩阵Pd 和M的行索引

```
__global__ void MatrixMulKernel(  
    float* Md, float* Nd, float* Pd, int Width)  
{  
    int Row = blockIdx.x * blockDim.x + threadIdx.x;  
    int Col = blockIdx.y * blockDim.y + threadIdx.y;  
  
    float Pvalue = 0;  
    for (int k = 0; k < Width; ++k)  
        Pvalue += Md[Col * Width + k] * Nd[k * Width + Row];  
  
    Pd[Row * Width + Col] = Pvalue;  
}
```

计算矩阵Pd和N的列索引

```
__global__ void MatrixMulKernel(  
    float* Md, float* Nd, float* Pd, int Width)  
{  
    int Row = blockIdx.y * blockDim.y + threadIdx.y;  
    int Col = blockIdx.x * blockDim.x + threadIdx.x;  
  
    float Pvalue = 0;  
    for (int k = 0; k < Width; ++k)  
        Pvalue += Md[Row * Width + k] * Nd[k * Width + Col];  
  
    Pd[Row * Width + Col] = Pvalue;  
}
```

每个线程计算块内子矩阵的一个元素

```
__global__ void MatrixMulKernel(  
    float* Md, float* Nd, float* Pd, int Width)  
{  
    int Row = blockIdx.y * blockDim.y + threadIdx.y;  
    int Col = blockIdx.x * blockDim.x + threadIdx.x;  
  
    float Pvalue = 0;  
    for (int k = 0; k < Width; ++k)  
        Pvalue += Md[Row * Width + k] * Nd[k * Width + Col];  
  
    Pd[Row * Width + Col] = Pvalue;  
}
```

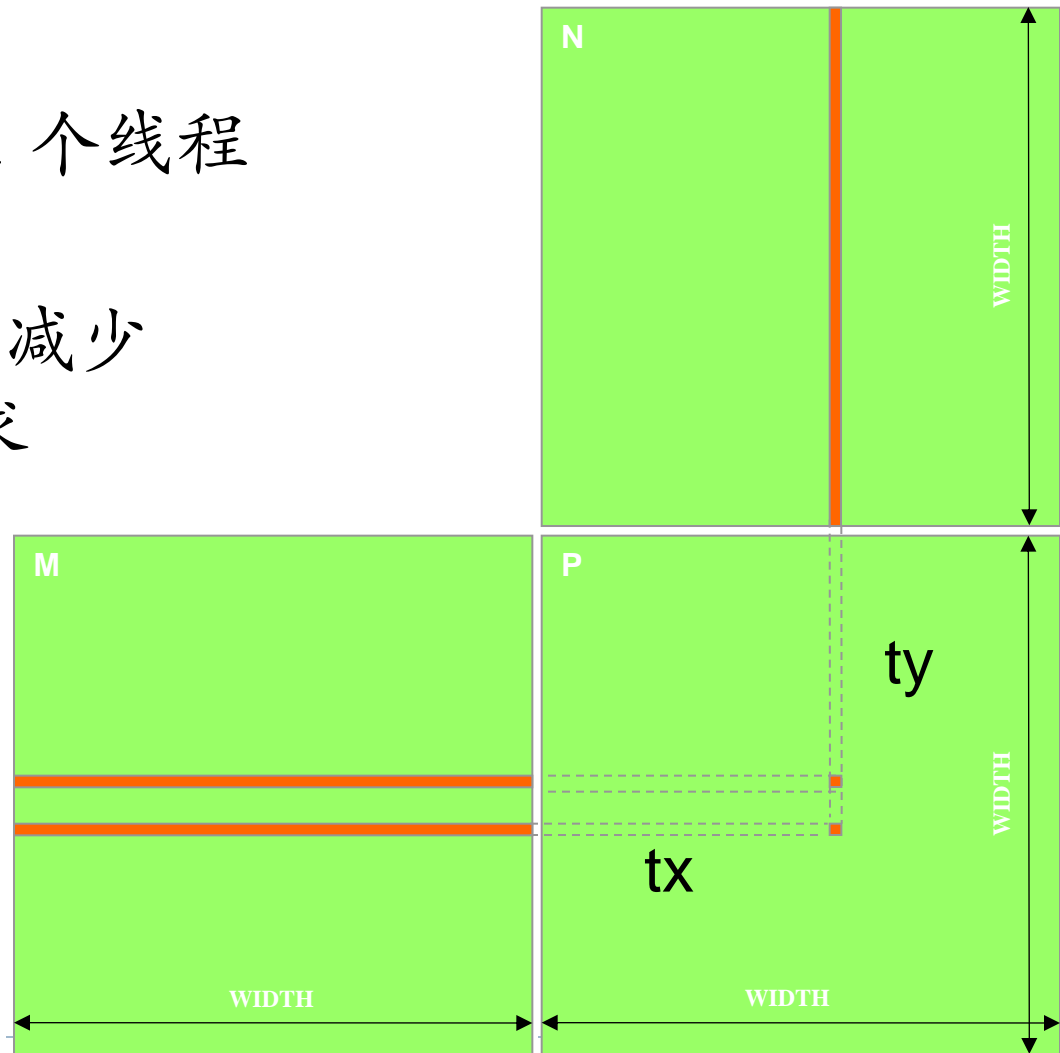
► 调用 kernel:

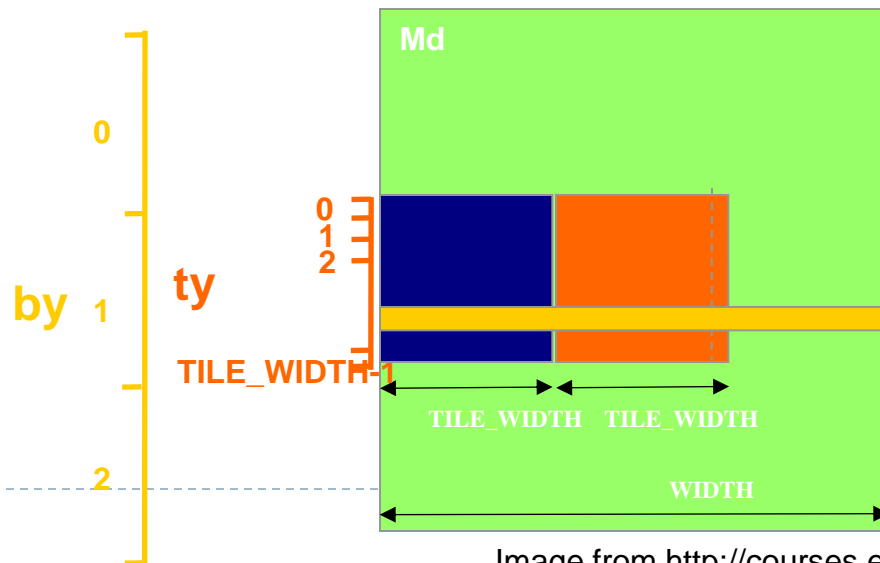
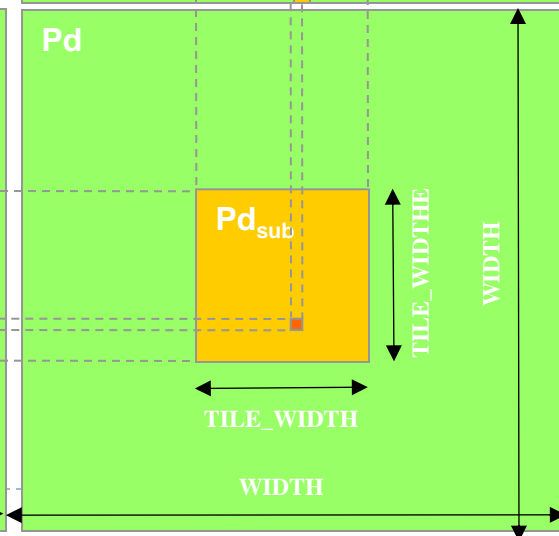
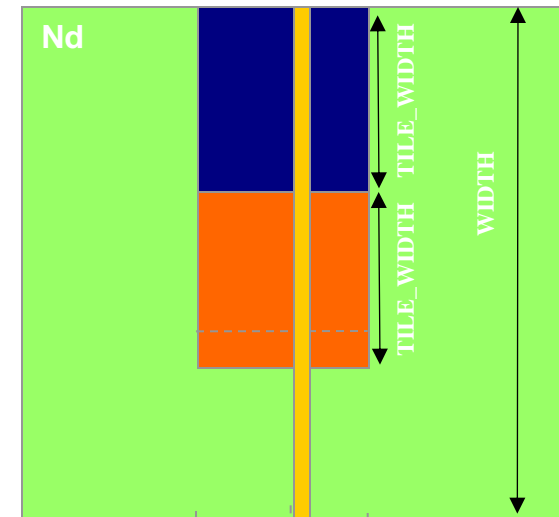
```
dim3 dimGrid(Width / TILE_WIDTH, Height / TILE_WIDTH);  
dim3 dimBlock(TILE_WIDTH, TILE_WIDTH);  
  
MatrixMulKernel<<<dimGrid, dimBlock>>>(  
    Md, Nd, Pd, TILE_WIDTH);
```

global memory
读写怎么办?

-
- ▶ 受限于global memory 带宽
 - ▶ G80 峰值GFLOPS: 346.5
 - ▶ 需要 1386 GB/s 的带宽来达到
 - ▶ G80 存储器实际带宽: 86.4 GB/s
 - ▶ 限制代码 21.6 GFLOPS
 - ▶ 实际上，代码运行速度是 15 GFLOPS
 - ▶ 必须大幅减少对 global memory 的访问

- ▶ 每个输入元素被Width 个线程读取
- ▶ 使用 shared memory 来减少 global memory 带宽需求



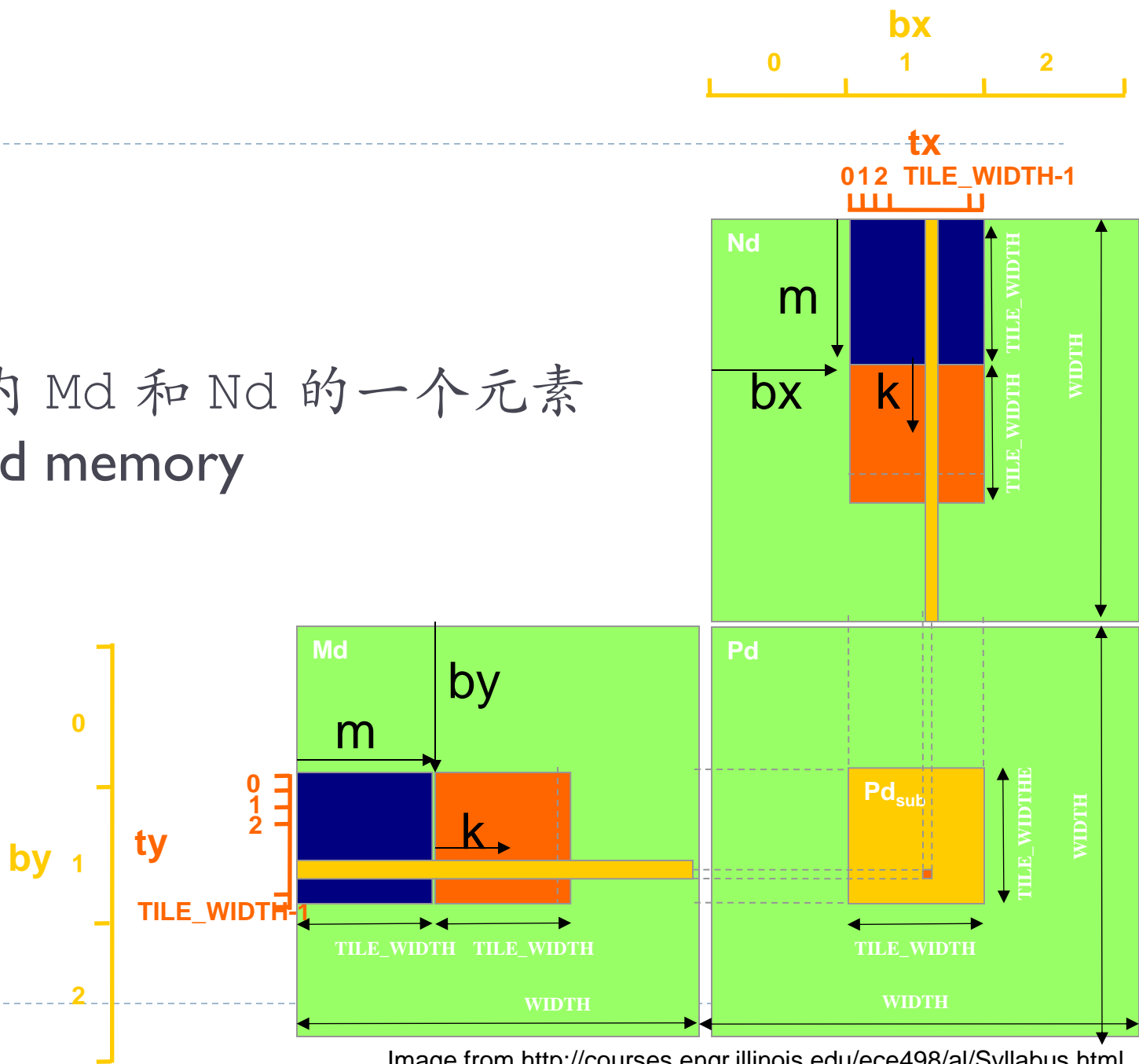


把 kernel 拆分成多个阶段

- 每个阶段用 Md 和 Nd 的子集累加 Pd
- 每个阶段有很好的数据局部性

每个线程

- 读入瓦片内 Md 和 Nd 的一个元素存入 shared memory



```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
    __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

    int bx = blockIdx.x;  int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
    __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

    int bx = blockIdx.x; int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

Shared memory 存储
Md 和 Nd 的子集

```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
    __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

    int bx = blockIdx.x; int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

Width/TILE_WIDTH
 • 阶段数目
 m
 • 当前阶段的索引


```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
    __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

    int bx = blockIdx.x; int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

从Md 和 Nd 各取一个元素
存入 shared memory



```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
    __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

    int bx = blockIdx.x;  int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

等待block内所有线程, 即,
等到整个瓦片存入 shared
memory

```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
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    int bx = blockIdx.x;  int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

累加点乘的子集

```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
    __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

    int bx = blockIdx.x;  int by = blockIdx.y;
    int tx = threadIdx.x; int ty = threadIdx.y;

    int Row = by * TILE_WIDTH + ty;
    int Col = bx * TILE_WIDTH + tx;

    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

为什么?

```

__global__ void MatrixMulKernel(
    float* Md, float* Nd, float* Pd, int Width)
{
    __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
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    int bx = blockIdx.x;  int by = blockIdx.y;
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    int Row = by * TILE_WIDTH + ty;
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    float Pvalue = 0;
    for (int m = 0; m < Width/TILE_WIDTH; ++m) {
        Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
        Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
        __syncthreads();

        for (int k = 0; k < TILE_WIDTH; ++k)
            Pvalue += Mds[ty][k] * Nds[k][tx];
        __syncthreads();
    }
    Pd[Row*Width+Col] = Pvalue;
}

```

把最终结果写入
global memory

Matrix Multiply

- ▶ 如何选取 `TILE_WIDTH` 的数值?
 - ▶ 如果太大的话会怎样?

-
- ▶ 如何选取 TILE_WIDTH 的数值?
 - ▶ 如果太大的话会怎样?
 - ▶ 超出一个块允许的最大线程数
 - G80 and GT200 – 512
 - Fermi – 1024
 - Kerpler – 1024
 - 可疑的, 依据不同的计算能力, 请查表

▶ 如何选取 TILE_WIDTH 的数值?

▶ 如果太大的话会怎样?

▶ 超出一个块允许的最大线程数

→ G80 and GT200 – 512

→ Fermi – 1024

▶ 超出 shared memory 极限

→ G80: 16KB / SM 并且 8 blocks / SM

→ 2 KB / block

→ 1 KB 给 Nds , 1 KB 给 Mds ($16 * 16 * 4$)

→ TILE_WIDTH = 16

→ 更大的 TILE_WIDTH 将导致更少的块数

- ▶ Shared memory 瓦片化的好处

- ▶ global memory 访问次数减少 `TILE_WIDTH` 倍

- ▶ 16x16 瓦片 减少16倍

- ▶ G80

- ▶ 现在 global memory 支持 345.6 GFLOPS

- ▶ 接近峰值 346.5 GFLOPS

G80 线程尺寸的考虑

- 每个 thread block 有许多个线程
 - TILE_WIDTH 为 16 时: $16 * 16 = 256$ 个线程
- 需要许多个 thread blocks
 - 一个 $1024 * 1024$ Pd 需要: $64 * 64 = 4K$ Thread Blocks
- 每个 thread block 执行 $2 * 256 = 512$ 次 global memory 的 float 读入, 为了供应 $256 * (2 * 16) = 8K$ mul/add 操作.
 - 存储带宽不再是限制因素

Atomic Functions 原子函数

■ 许多原子操作:

// 算术运算

`atomicAdd()`

`atomicSub()`

`atomicExch()`

`atomicMin()`

`atomicMax()`

`atomicAdd()`

`atomicDec()`

// 位运算

`atomicAnd()`

`atomicOr()`

`atomicXor()`

Atomic Functions 原子函数

- 不同块里面的线程如何协作？
- 尽量少用原子操作，为什么？