NVIDIA

GPU Teaching Kit

Accelerated Computing

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Module 8.1 – Parallel Computation Patterns (Stencil)

Convolution

Objective

- To learn convolution, an important method
  - Widely used in audio, image and video processing
  - Foundational to stencil computation used in many science and engineering applications
  - Basic 1D and 2D convolution kernels

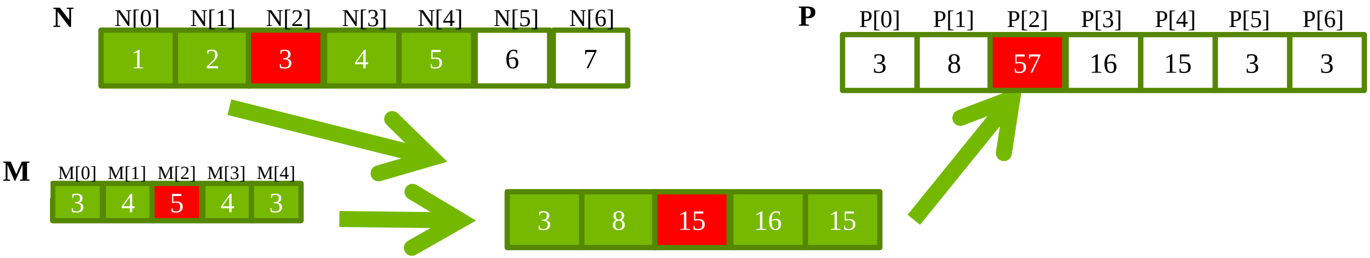
Convolution as a Filter

- Often performed as a filter that transforms signal or pixel values into more desirable values.
  - Some filters smooth out the signal values so that one can see the big-picture trend
  - Others like Gaussian filters can be used to sharpen boundaries and edges of objects in images..

Convolution – a computational definition

- An array operation where each output data element is a weighted sum of a collection of neighboring input elements
- The weights used in the weighted sum calculation are defined by an input mask array, commonly referred to as the *convolution kernel*
  - We will refer to these mask arrays as convolution masks to avoid confusion.
  - The value pattern of the mask array elements defines the type of filtering done
  - Our image blur example in Module 3 is a special case where all mask elements are of the same value and hard coded into the source code.

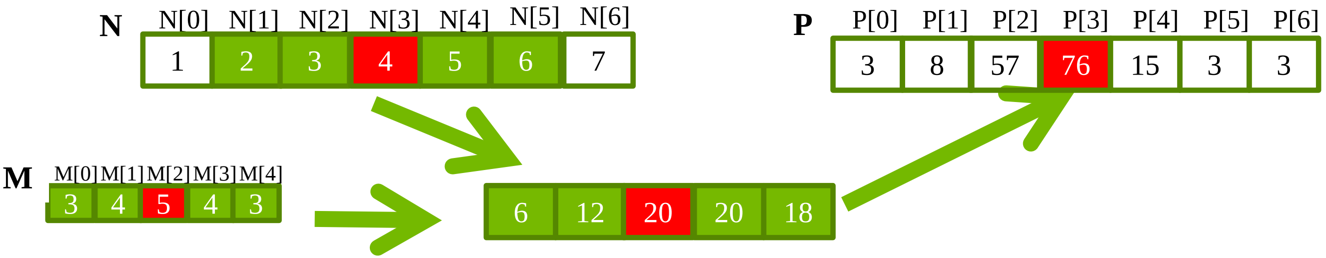
1D Convolution Example



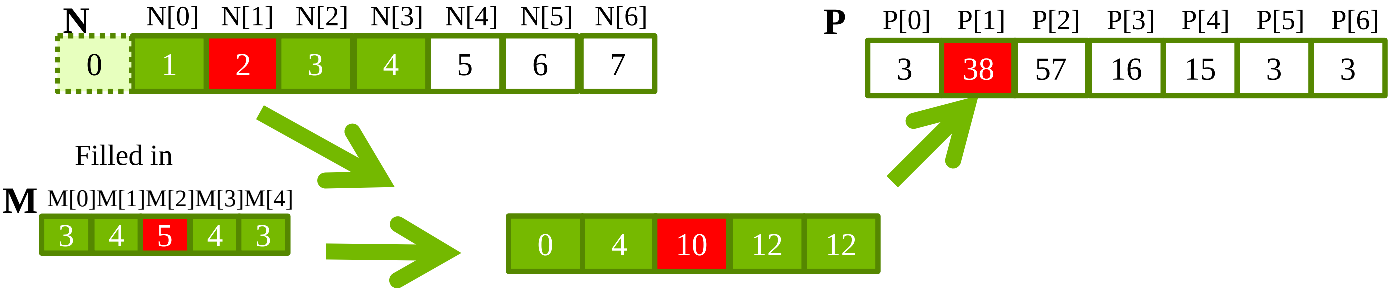
- Commonly used for audio processing
  - Mask size is usually an odd number of elements for symmetry (5 in this example)
- The figure shows calculation of P[2]

P[2] = N[0]*M[0] + N[1]*M[1] + N[2]*M[2] + N[3]*M[3] + N[4]*M[4]

Calculation of P[3]



Convolution Boundary Condition



- Calculation of output elements near the boundaries (beginning and end) of the array need to deal with "ghost" elements
  - Different policies (0, replicates of boundary values, etc.)

A 1D Convolution Kernel with Boundary Condition Handling

– This kernel forces all elements outside the valid input range to 0

```
__global__ void convolution_1D_basic_kernel(float *N, float *M,
              float *P, int Mask_Width, int Width)
{
   int i = blockIdx.x*blockDim.x + threadIdx.x;

   float Pvalue = 0;
   int N_start_point = i – (Mask_Width/2);

   for (int j = 0; j < Mask_Width; j++) {
      if (N_start_point + j >= 0 && N_start_point + j < Width) {
         Pvalue += N[N_start_point + j]*M[j];
      }
   }

   P[i] = Pvalue;
}
```

A 1D Convolution Kernel with Boundary Condition Handling

– This kernel forces all elements outside the valid input range to 0

```
__global__ void convolution_1D_basic_kernel(float *N, float *M,
            float *P, int Mask_Width, int Width)
{
  int i = blockIdx.x*blockDim.x + threadIdx.x;

  float Pvalue = 0;
  int N_start_point = i – (Mask_Width/2);

  if (i < Width) {

    for (int j = 0; j < Mask_Width; j++) {
      if (N_start_point + j >= 0 && N_start_point + j < Width) {
        Pvalue += N[N_start_point + j]*M[j];
      }
    }

    P[i] = Pvalue;
  }
}
```

2D Convolution

N

1	2	3	4	5	6	7
2	3	4	5	6	7	8
3	4	5	6	7	8	9
4	5	6	7	8	5	6
5	6	7	8	5	6	7
6	7	8	9	0	1	2
7	8	9	0	1	2	3

M

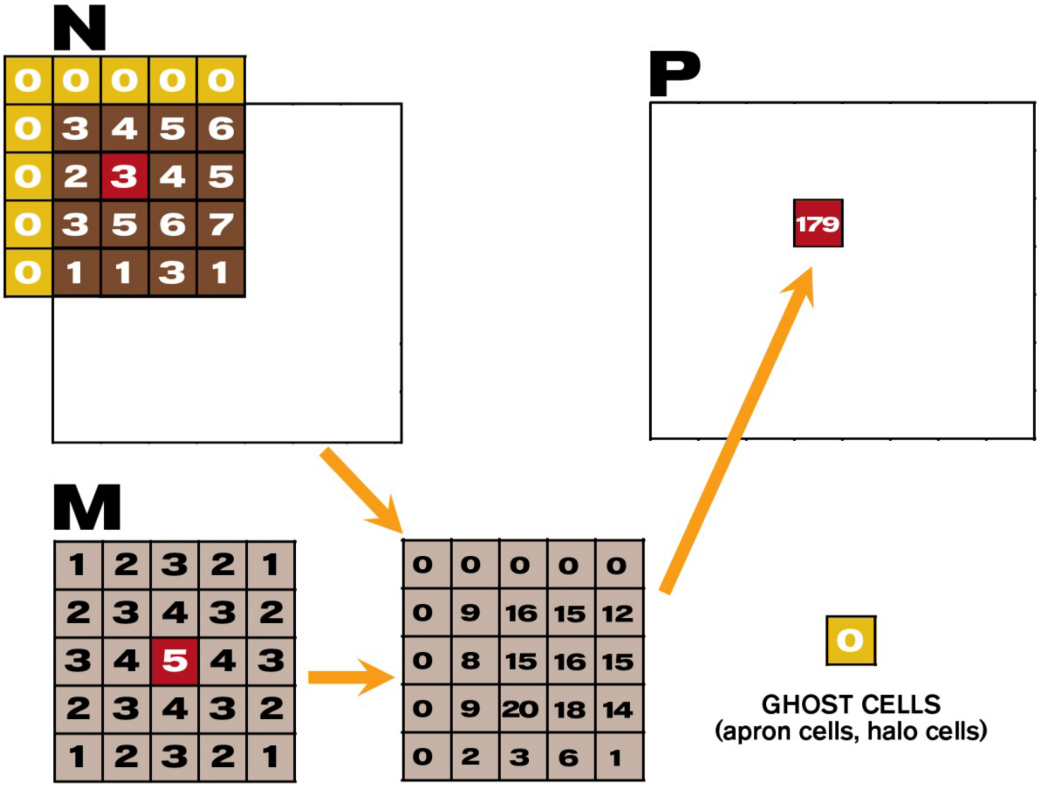
1	2	3	2	1
2	3	4	3	2
3	4	5	4	3
2	3	4	3	2
1	2	3	2	1

1	4	9	8	5
4	9	16	15	12
4	16	25	24	21
8	15	24	21	16
5	12	21	16	5

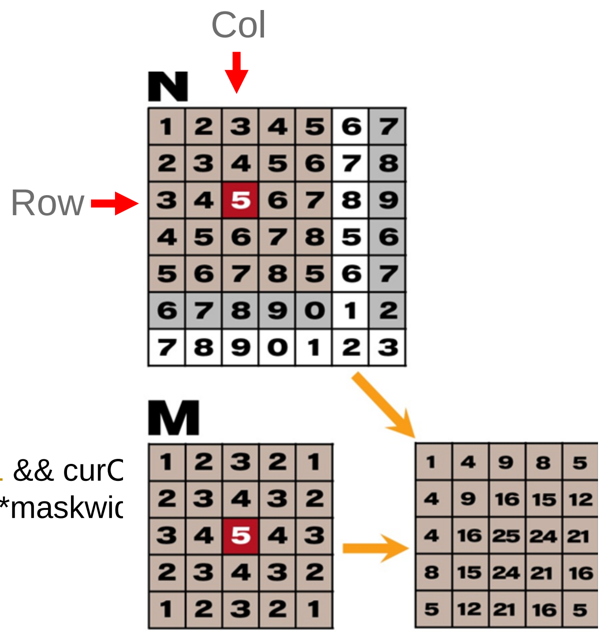
P

1	2	3	4	5			
2	3	4	5	6			
3	4	321	6	7			
4	5	6	7	8			
5	6	7	8	5			

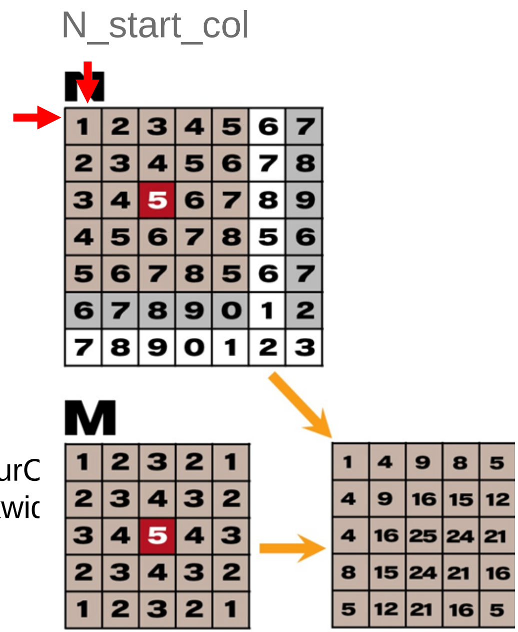
2D Convolution – Ghost Cells



```
__global__
 void convolution_2D_basic_kernel(unsigned char * in, unsigned char * mask, unsigned char * out,
                    int maskwidth, int w, int h) {
    int Col  =   blockIdx.x * blockDim.x + threadIdx.x;
    int Row  = blockIdx.y * blockDim.y + threadIdx.y;

    if (Col < w && Row < h) {
        int pixVal = 0;

        N_start_col  = Col –   (maskwidth/2);
        N_start_row = Row – (maskwidth/2);

        // Get the of the surrounding box
        for(int j = 0; j < maskwidth; ++j) {
            for(int k = 0; k < maskwidth; ++k) {

                int curRow = N_Start_row + j;
                int curCol =   N_start_col  + k;
                // Verify we have a valid image pixel
                if(curRow > -1 && curRow < h && curCol > -1 && curC
                    pixVal += in[curRow * w + curCol] * mask[j*maskwic
                }
            }
        }

        // Write our new pixel value out
        out[Row * w + Col] = (unsigned char)(pixVal);
 }
}
```



```
__global__
 void convolution_2D_basic_kernel(unsigned char * in, unsigned char * mask, unsigned char * out,
                    int maskwidth, int w, int h) {
    int Col  =   blockIdx.x * blockDim.x + threadIdx.x;
    int Row  = blockIdx.y * blockDim.y + threadIdx.y;

    if (Col < w && Row < h) {
       int pixVal = 0;

       N_start_col  = Col –   (maskwidth/2);
       N_start_row = Row – (maskwidth/2);

       // Get the of the surrounding box
       for(int j = 0; j < maskwidth; ++j) {
          for(int k = 0; k < maskwidth; ++k) {

             int curRow = N_Start_row + j;
             int curCol =   N_start_col  + k;
             // Verify we have a valid image pixel
             if(curRow > -1 && curRow < h && curCol > -1 && curC
                pixVal += in[curRow * w + curCol] * mask[j*maskwic
             }
          }
       }

       // Write our new pixel value out
       out[Row * w + Col] = (unsigned char)(pixVal);
}
```



```
__global__
 void convolution_2D_basic_kernel(unsigned char * in, unsigned char * mask, unsigned char * out,
                     int maskwidth, int w, int h) {
    int Col  =   blockIdx.x * blockDim.x + threadIdx.x;
    int Row  = blockIdx.y * blockDim.y + threadIdx.y;

    if (Col < w && Row < h) {
       int pixVal = 0;

       N_start_col  = Col –   (maskwidth/2);
       N_start_row = Row – (maskwidth/2);

       // Get the of the surrounding box
       for(int j = 0; j < maskwidth; ++j) {
          for(int k = 0; k < maskwidth; ++k) {

             int curRow = N_Start_row + j;
             int curCol =   N_start_col  + k;
             // Verify we have a valid image pixel
             if(curRow > -1 && curRow < h && curCol > -1 && curCol < w) {
                pixVal += in[curRow * w + curCol] * mask[j*maskwidth+k];
             }
          }
       }

       // Write our new pixel value out
       out[Row * w + Col] = (unsigned char)(pixVal);
    }
}
```

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Module 8.2 – Parallel Computation Patterns (Stencil)

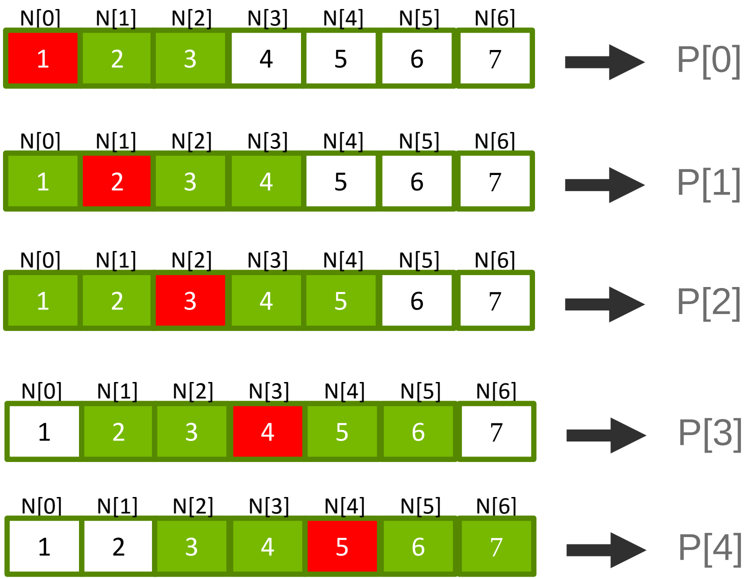
Tiled Convolution

Objective

- To learn about tiled convolution algorithms
  - Some intricate aspects of tiling algorithms
  - Output tiles versus input tiles

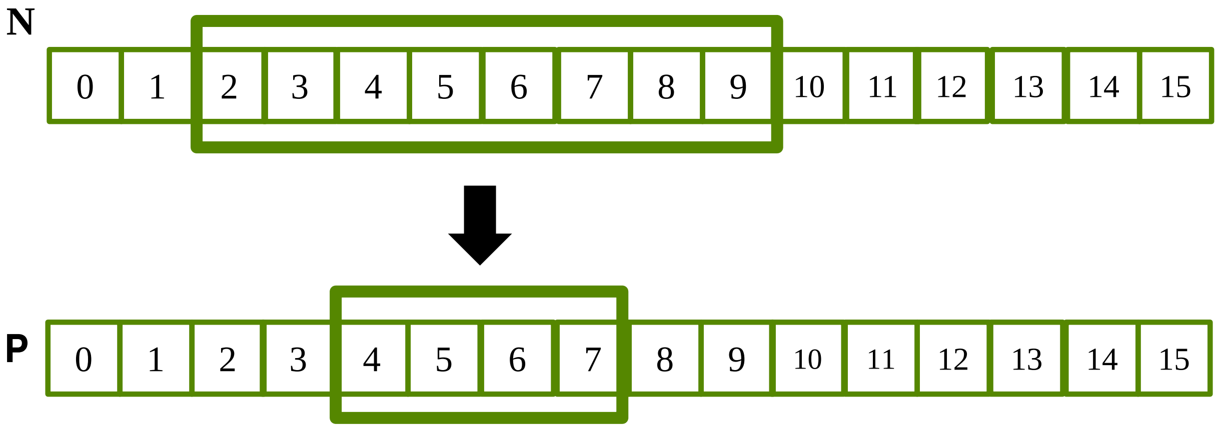
Tiling Opportunity Convolution

- Calculation of adjacent output elements involve shared input elements
  - E.g., N[2] is used in calculation of P[0], P[1], P[2]. P[3 and P[5] assuming a 1D convolution Mask_Width of width 5
- We can load all the input elements required by all threads in a block into the shared memory to reduce global memory accesses

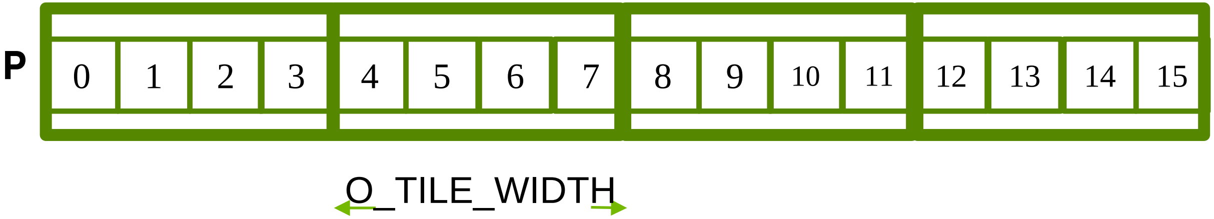


Input Data Needs

- Assume that we want to have each block to calculate T output elements
  - T + Mask_Width -1 input elements are needed to calculate T output elements
  - T + Mask_Width -1 is usually not a multiple of T, except for small T values
  - T is usually significantly larger than Mask_Width



Definition – output tile



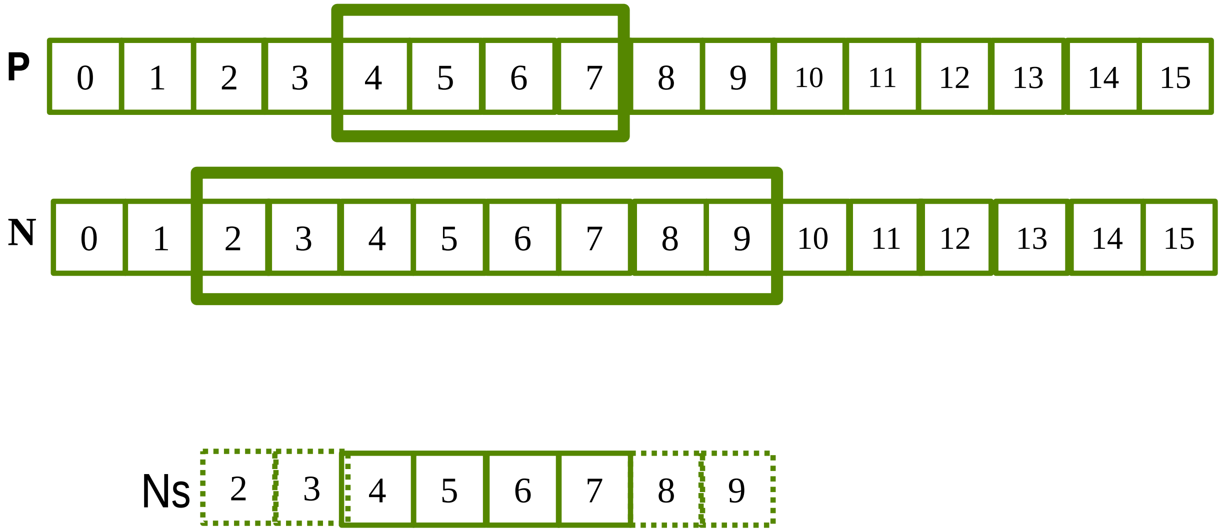
Each thread block calculates an output tile

Each output tile width is O_TILE_WIDTH

For each thread,

O_TILE_WIDTH is 4 in this example

Definition - Input Tiles

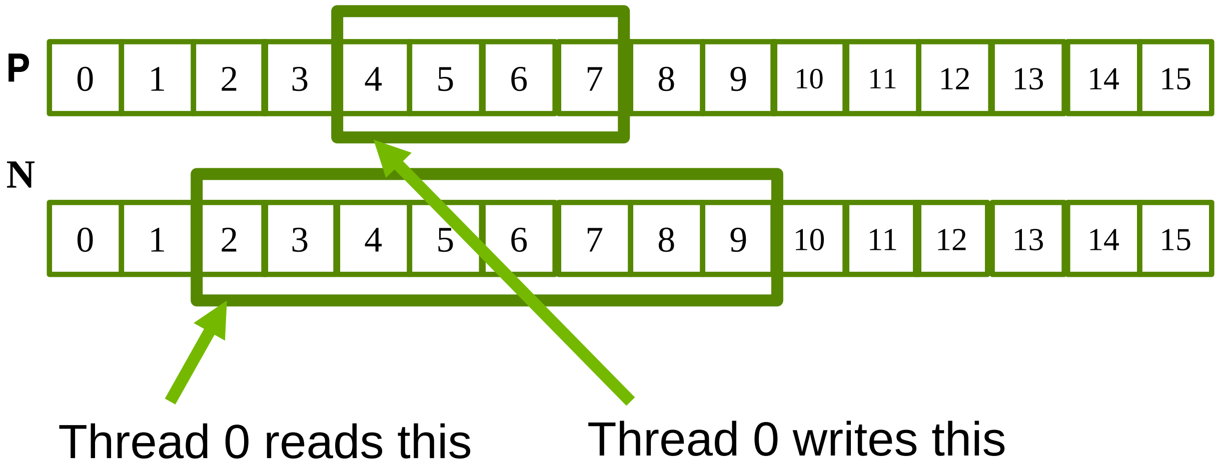


Each input tile has all values needed to calculate the corresponding output tile.

Two Design Options

- Design 1: The size of each thread block matches the size of an output tile
  - All threads participate in calculating output elements
  - blockDim.x would be 4 in our example
  - Some threads need to load more than one input element into the shared memory
- Design 2: The size of each thread block matches the size of an input tile
  - Some threads will not participate in calculating output elements
  - blockDim.x would be 8 in our example
  - Each thread loads one input element into the shared memory
- We will present Design 2 and leave Design 1 as an exercise.

Thread to Input and Output Data Mapping



For each thread,
Index_i = index_o – n

were n is Mask_Width /2
n is 2 in this example

All Threads Participate in Loading Input Tiles

```
float output = 0.0f;

if((index_i >= 0) && (index_i < Width)) {
  Ns[tx] = N[index_i];
}
else{
  Ns[tx] = 0.0f;
}
```

Some threads do not participate in calculating output

```
if (threadIdx.x < O_TILE_WIDTH){
   output = 0.0f;
   for(j = 0; j < Mask_Width; j++) {
       output += M[j] * Ns[j+threadIdx.x];
   }
   P[index_o] = output;
}
```

– index_o = blockIdx.x*O_TILE_WIDTH + threadIdx.x

– Only Threads 0 through O_TILE_WIDTH-1 participate in calculation of output.

Setting Block Size

```
#define O_TILE_WIDTH 1020
#define BLOCK_WIDTH (O_TILE_WIDTH + 4)

dim3 dimBlock(BLOCK_WIDTH,1, 1);

dim3 dimGrid((Width-1)/O_TILE_WIDTH+1, 1, 1)
```

The Mask_Width is 5 in this example

In general, block width should be

`output tile width + (mask width-1)`

Shared Memory Data Reuse

N_ds

Mask_Width is 5

Element 2 is used by thread 4 (1X)

Element 3 is used by threads 4, 5 (2X)

Element 4 is used by threads 4, 5, 6 (3X)

Element 5 is used by threads 4, 5, 6, 7 (4X)

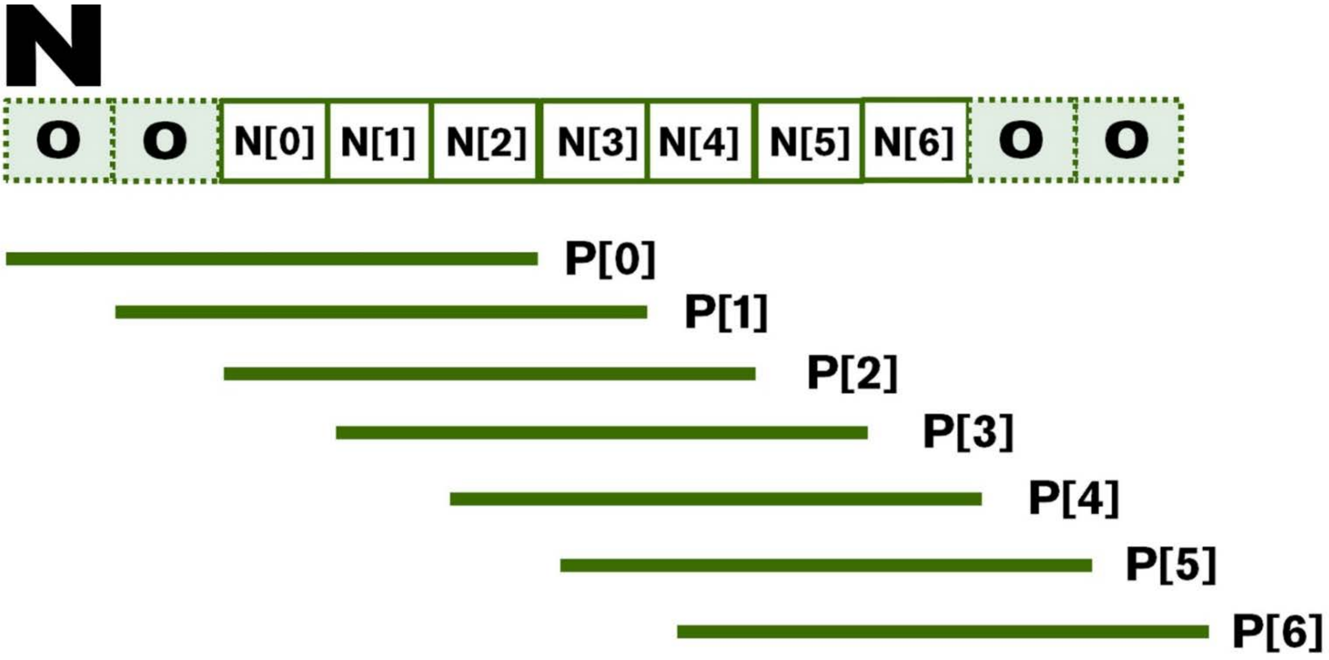
Element 6 is used by threads 4, 5, 6, 7 (4X)

Element 7 is used by threads 5, 6, 7 (3X)

Element 8 is used by threads 6, 7 (2X)

Element 9 is used by thread 7 (1X)

Ghost Cells



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Module 8.3 – Parallel Computation Patterns (Stencil)

Tile Boundary Conditions

Objective

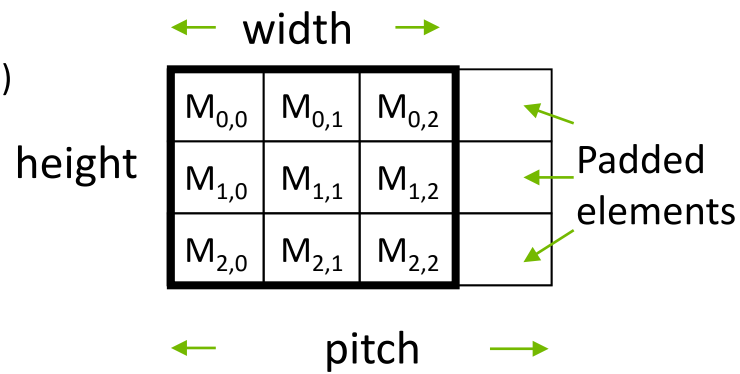
- To learn to write a 2D convolution kernel
  - 2D Image data types and API functions
  - Using constant caching
  - Input tiles vs. output tiles in 2D
  - Thread to data index mapping
  - Handling boundary conditions

2D Image Matrix with Automated Padding

- It is sometimes desirable to pad each row of a 2D matrix to multiples of DRAM bursts
  - So each row starts at the DRAM burst boundary
  - Effectively adding columns
  - This is usually done automatically by matrix allocation function
  - Pitch can be different for different hardware

- Example: a 3X3 matrix padded into a 3X4 matrix

Height is 3
Width is 3
Channels is 1 (See MP Description)
Pitch is 4



Row-Major Layout with Pitch

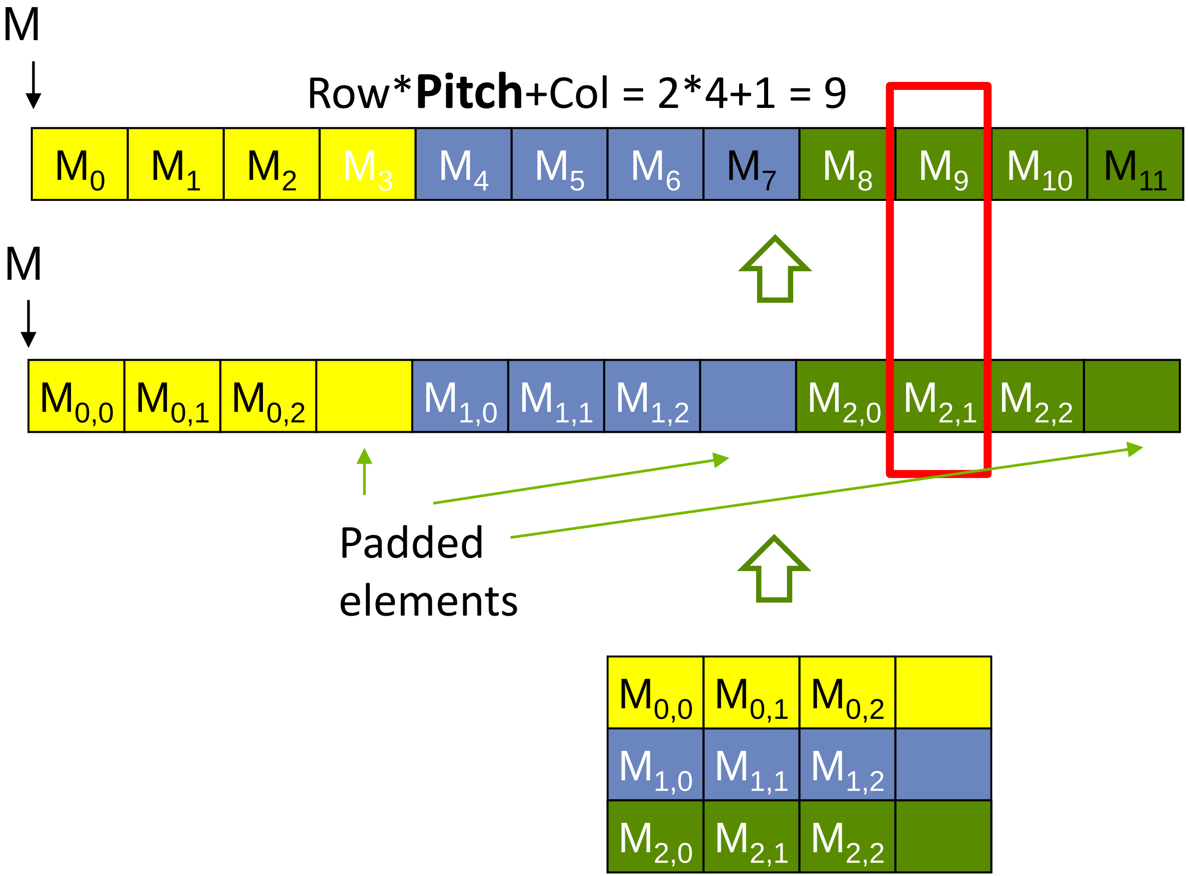


Image Matrix Type in this Course

```
// Image Matrix Structure declaration
//
typedef struct {
   int width;
   int height;
   int pitch;
   int channels;
   float* data;
} * wbImage_t;
```

This type will only be used in the host code of the MP.

wbImage_t API Function for Your Lab

```
wbImage_t  wbImage_new(int height, int
width, int channels)
wbImage_t  wbImport(char * File);

void wbImage_delete(wbImage_t img)

int wbImage_getWidth(wbImage_t img)
int wbImage_getHeight(wbImage_t img)
int wbImage_getChannels(wbImage_t img)
int wbImage_getPitch(wbImage_t img)

float *wbImage_getData(wbImage_t img)
```

For simplicity, the pitch of all matrices are set to be width * channels (no padding) for our labs.

The use of all API functions has been done in the provided host code.

Setting Block Size

```
#define O_TILE_WIDTH 12
#define BLOCK_WIDTH (O_TILE_WIDTH + 4)

dim3 dimBlock(BLOCK_WIDTH,BLOCK_WIDTH);
dim3 dimGrid((wbImage_getWidth(N)-1)/O_TILE_WIDTH+1,
          (wbImage_getHeight(N)-1)/O_TILE_WIDTH+1, 1)
```

```
In general, BLOCK_WIDTH should be
        O_TILE_WIDTH + (MASK_WIDTH-1)
```

Using constant memory and caching for Mask

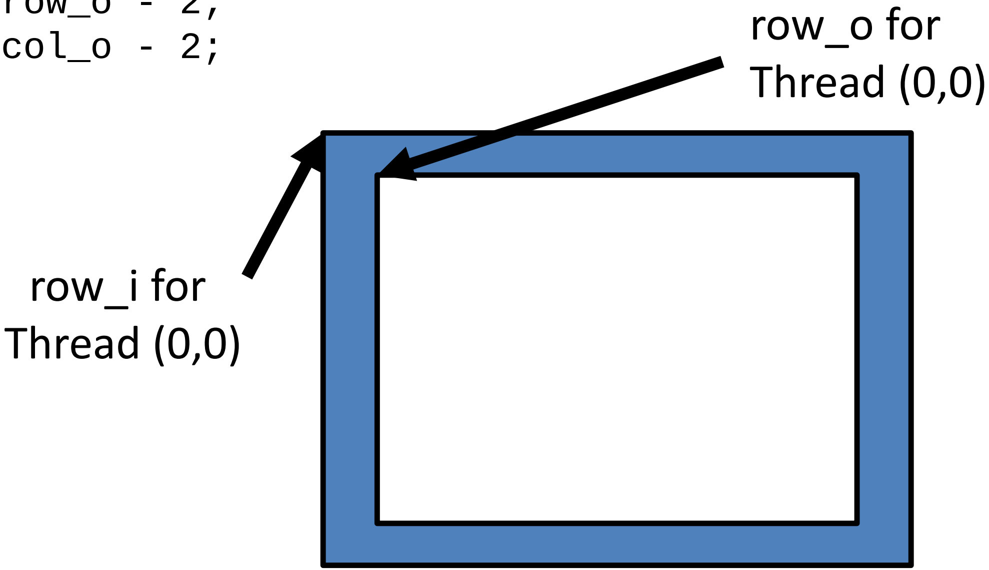
- Mask is used by all threads but not modified in the convolution kernel
  - All threads in a warp access the same locations at each point in time
- CUDA devices provide constant memory whose contents are aggressively cached
  - Cached values are broadcast to all threads in a warp
  - Effectively magnifies memory bandwidth without consuming shared memory
- Use of const __restrict__ qualifiers for the mask parameter informs the compiler that it is eligible for constant caching, for example:

```
__global__ void convolution_2D_kernel(float *P,
    float *N, height, width, channels,
    const float __restrict__ *M) {
```

Shifting from output coordinates to input coordinate

```
int tx = threadIdx.x;
int ty = threadIdx.y;
int row_o = blockIdx.y*O_TILE_WIDTH + ty;
int col_o = blockIdx.x*O_TILE_WIDTH + tx;

int row_i = row_o - 2;
int col_i = col_o - 2;
```



Taking Care of Boundaries (1 channel example)

```
if((row_i >= 0) && (row_i < height) &&
   (col_i >= 0)  && (col_i < width)) {
  Ns[ty][tx] = data[row_i * width + col_i];
} else{
  Ns[ty][tx] = 0.0f;
}
```

Use of width here is OK since pitch is set to width for this MP.

Some threads do not participate in calculating output. (1 channel example)

```
float output = 0.0f;
if(ty < O_TILE_WIDTH && tx < O_TILE_WIDTH){
   for(i = 0; i < MASK_WIDTH; i++) {
     for(j = 0; j < MASK_WIDTH; j++) {
       output += M[i][j] * Ns[i+ty][j+tx];
   }
}
```

Some threads do not write output (1 channel example)

```
if(row_o < height && col_o < width)
  data[row_o*width + col_o] = output;
```

You need to write the kernel for a 3-channel (RGB) image.
See more details in the Lab MP Description.

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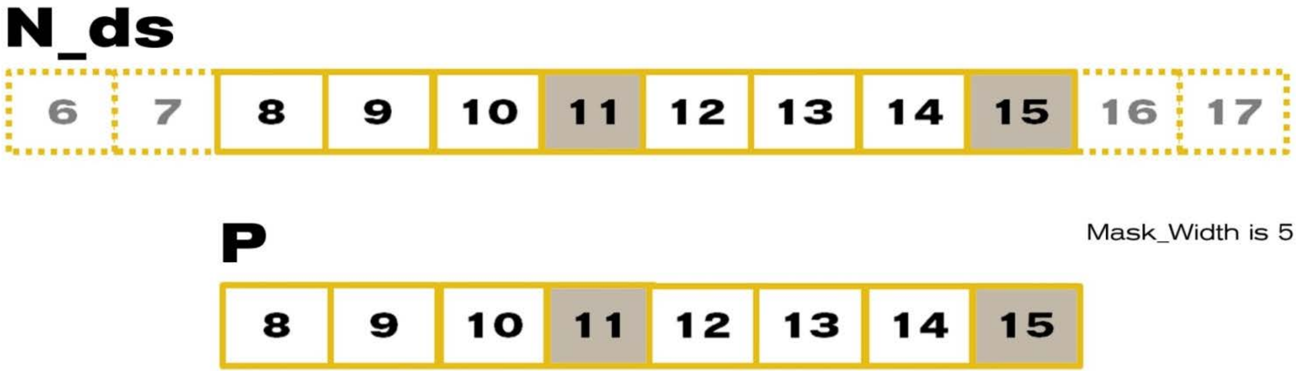
Module 8.4 – Parallel Computation Patterns (Stencil)

Analyzing Data Reuse in Tiled Convolution

Objective

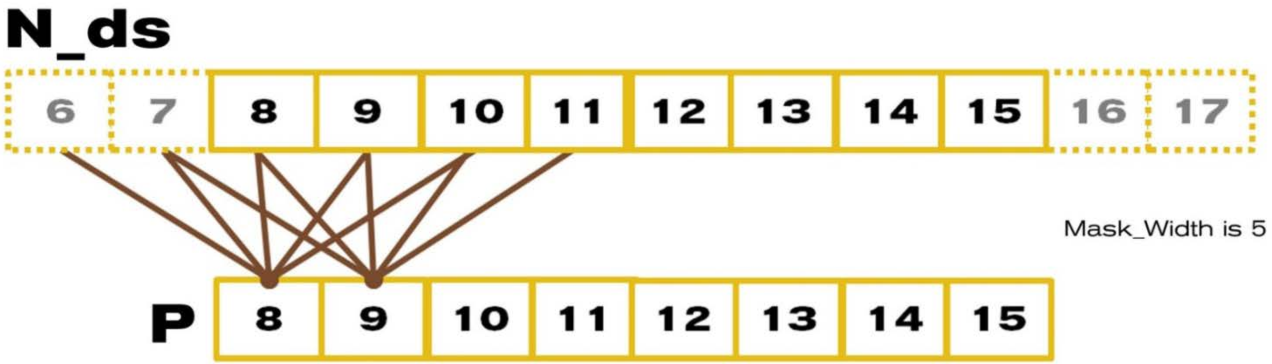
- To learn to analyze the cost and benefit of tiled parallel convolution algorithms
  - More complex reuse pattern than matrix multiplication
  - Less uniform access patterns

An 8-element Convolution Tile



For Mask_Width=5, we load 8+5-1=12 elements
(12 memory loads)

Each output P element uses 5 N elements



P[8] uses N[6], N[7], N[8], N[9], N[10]
P[9] uses N[7], N[8], N[9], N[10], N[11]
P[10] use N[8], N[9], N[10], N[11], N[12]
…
P[14] uses N[12], N[13], N[14], N[15], N[16]
P[15] uses N[13], N[14], N[15], N[16], N[17]

A simple way to calculate tiling benefit

– (8+5-1)=12 elements loaded
– 8*5 global memory accesses replaced by shared memory accesses
– This gives a bandwidth reduction of 40/12=3.3

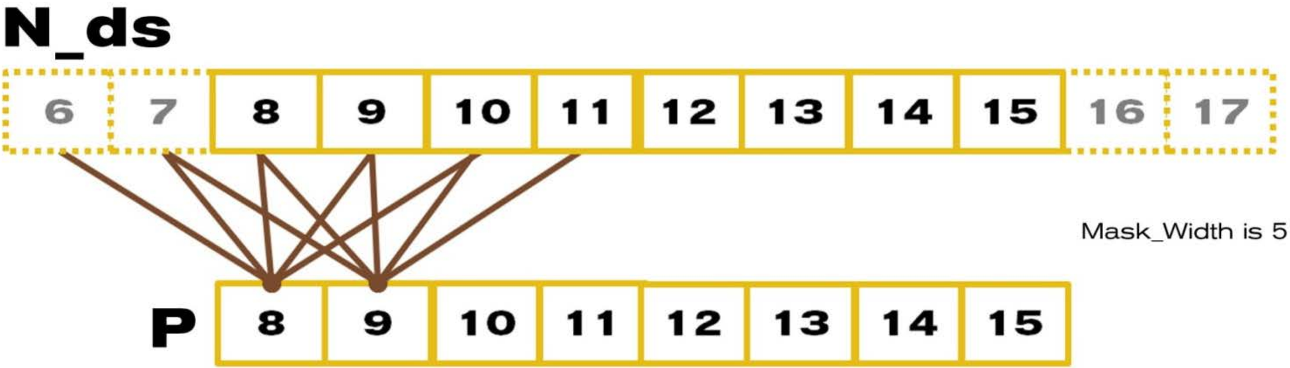
In General, for 1D TILED CONVOLUTION

- `O_TILE_WIDTH+MASK_WIDTH -1` elements loaded for each input tile
- `O_TILE_WIDTH*MASK_WIDTH` global memory accesses replaced by shared memory accesses
- This gives a reduction factor of

`(O_TILE_WIDTH*MASK_WIDTH)/(O_TILE_WIDTH+MASK_WIDTH-1)`

This ignores ghost elements in edge tiles.

Another Way to Look at Reuse



N[6] is used by P[8] (1X)
N[7] is used by P[8], P[9] (2X)
N[8] is used by P[8], P[9], P[10] (3X)
N[9] is used by P[8], P[9], P[10], P[11] (4X)
N10 is used by P[8], P[9], P[10], P[11], P[12] (5X)
… (5X)
N[14] is used by P[12], P[13], P[14], P[15] (4X)
N[15] is used by P[13], P[14], P[15] (3X)

Another Way to Look at Reuse

The total number of global memory accesses (to the (8+5-1)=12 N elements) replaced by shared memory accesses is:

$$1 + 2 + 3 + 4 + 5 * (8\text{-}5\text{+}1) + 4 + 3 + 2 + 1$$
$$= 10 + 20 + 10$$
$$= 40$$

So the reduction is:

$$40/12 = 3.3$$

In General, for 1D

– The total number of global memory accesses to the input tile can be calculated as

1 + 2+…+ MASK_WIDTH-1 + MASK_WIDTH*(O_TILE_WIDTH-MASK_WIDTH+1) + MASK_WIDTH-1 + …+ 2 + 1

= MASK_WIDTH * (MASK_WIDTH-1) + MASK_WIDTH * (O_TILE_WIDTH-MASK_WIDTH+1)

= MASK_WIDTH * O_TILE_WIDTH

For a total of O_TILE_WIDTH + MASK_WIDTH -1 input tile elements

Examples of Bandwidth Reduction for 1D

The reduction ratio is:

MASK_WIDTH * (O_TILE_WIDTH)/(O_TILE_WIDTH+MASK_WIDTH-1)

O_TILE_WIDTH	16	32	64	128	256
MASK_WIDTH= 5	4.0	4.4	4.7	4.9	4.9
MASK_WIDTH = 9	6.0	7.2	8.0	8.5	8.7

For 2D Convolution Tiles

– $(O\_TILE\_WIDTH+MASK\_WIDTH-1)^2$ input elements need to be loaded into shared memory
– The calculation of each output element needs to access $MASK\_WIDTH^2$ input elements
– $O\_TILE\_WIDTH^2 * MASK\_WIDTH^2$ global memory accesses are converted into shared memory accesses
– The reduction ratio is

$$O\_TILE\_WIDTH^2 * MASK\_WIDTH^2 / (O\_TILE\_WIDTH+MASK\_WIDTH-1)^2$$

Bandwidth Reduction for 2D

The reduction ratio is:

$O\_TILE\_WIDTH^2 * MASK\_WIDTH^2 / (O\_TILE\_WIDTH+MASK\_WIDTH-1)^2$

O_TILE_WIDTH	**8**	**16**	**32**	**64**
MASK_WIDTH = 5	11.1	16	19.7	22.1
MASK_WIDTH = 9	20.3	36	51.8	64

Tile size has significant effect on of the memory bandwidth reduction ratio.

This often argues for larger shared memory size.

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