GPU Teaching Kit

Accelerated Computing

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..

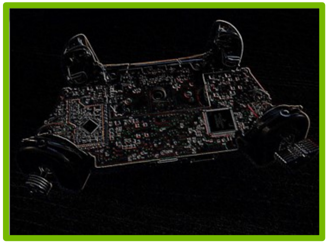
Gaussian Blur

$$\frac{1}{273}\begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$

Convolution as a Edge Detection

-1	0	1
-2	0	2
-1	0	1

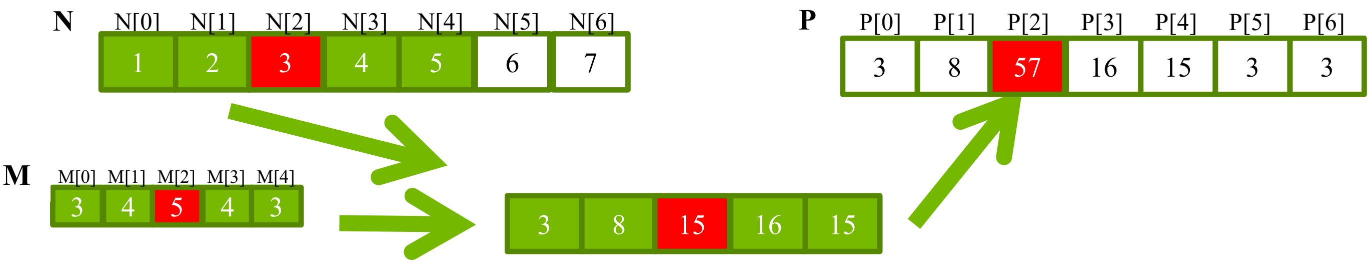
0	-1	2
-1	0	1
-2	-1	0



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.

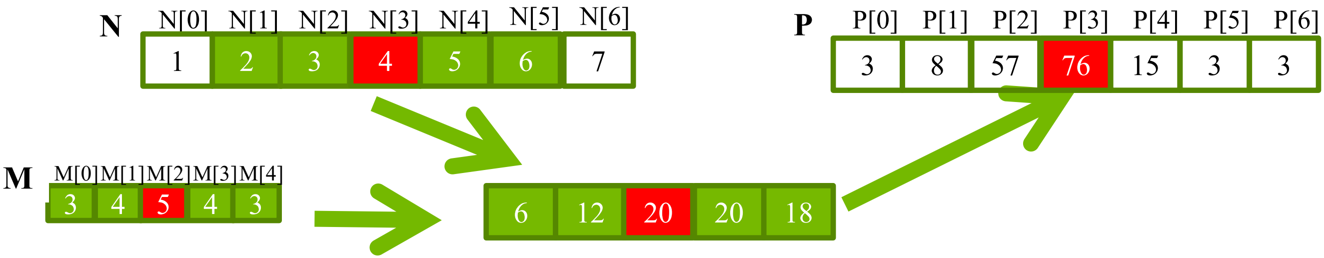
1D Convolution Example



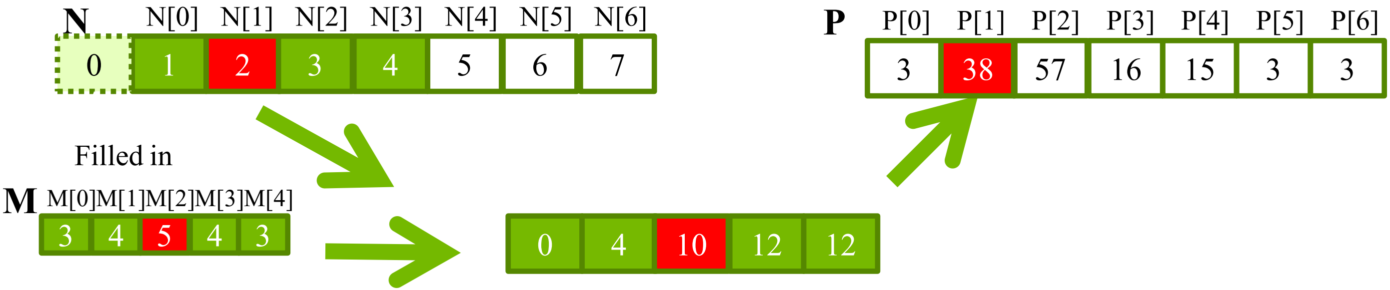
- Commonly used for audio processing
  - Mask size is usually an odd number of elements for symmetry (5 in this example)
- The figure shows calculation of P[2]

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

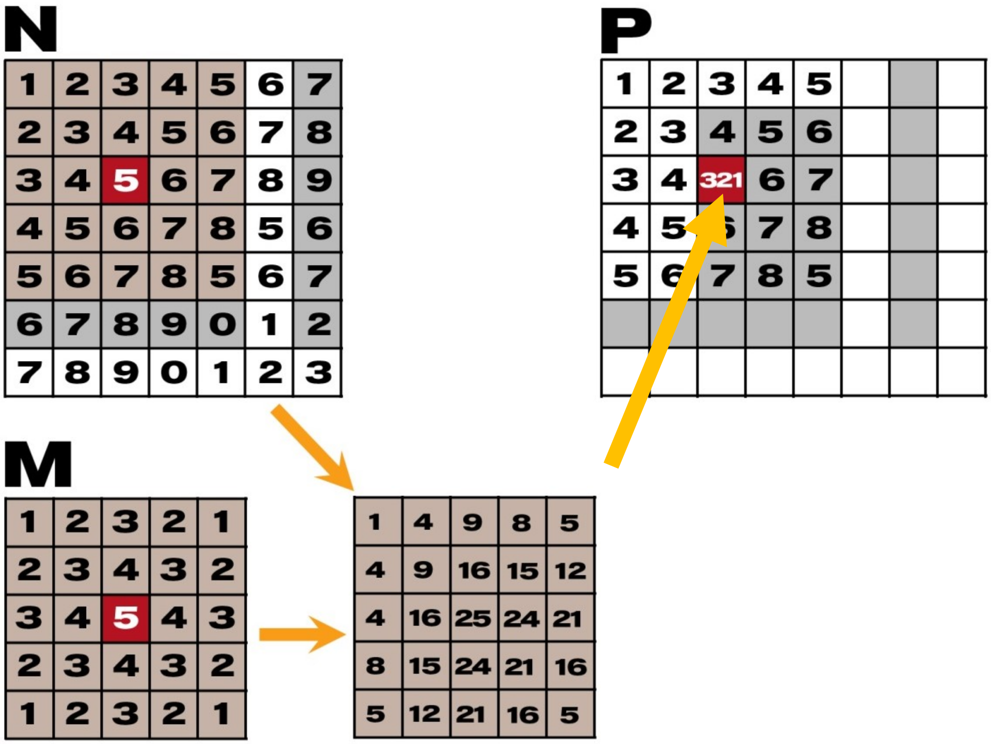
```
__global__ void convolution_1D_basic_kernel(float *N, float *M,
            float *P, int Mask_Width, int Width)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;

    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

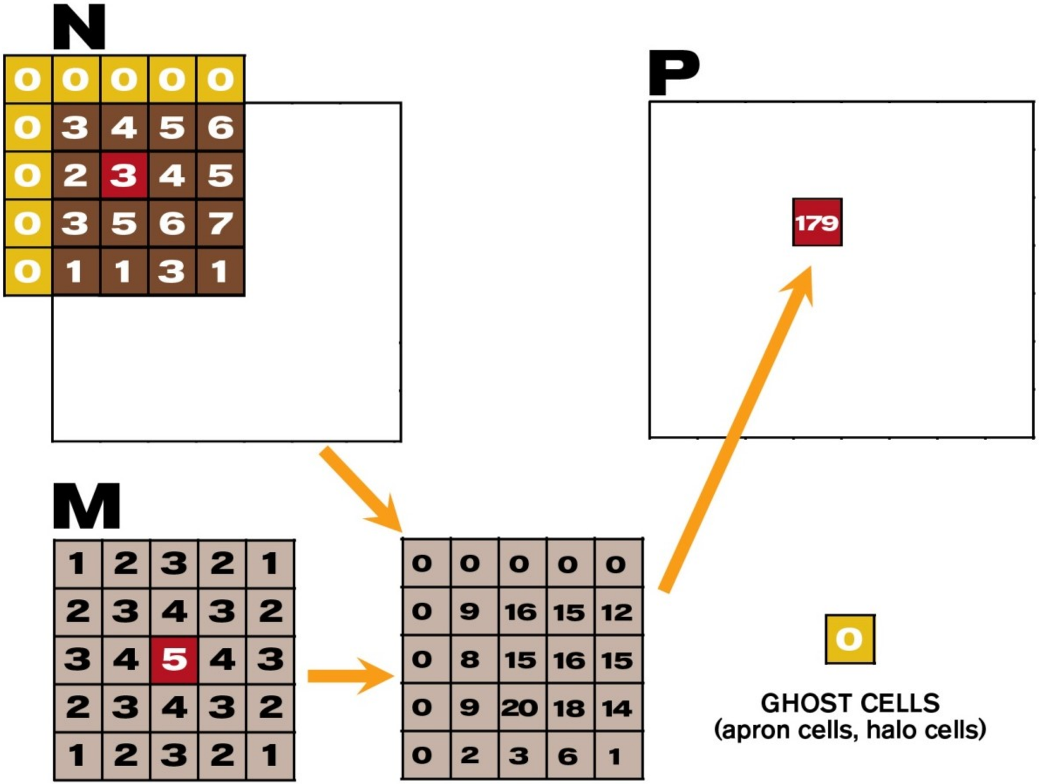
– This kernel forces all elements outside the valid input range to 0

```
__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;
   }
}
```

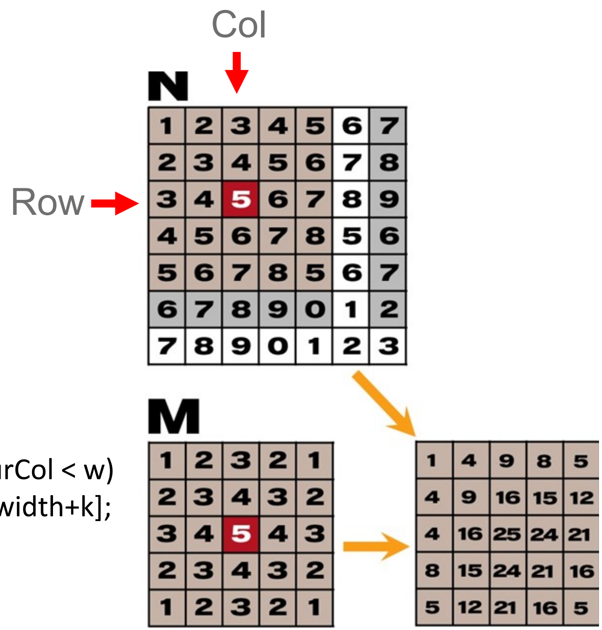
2D Convolution



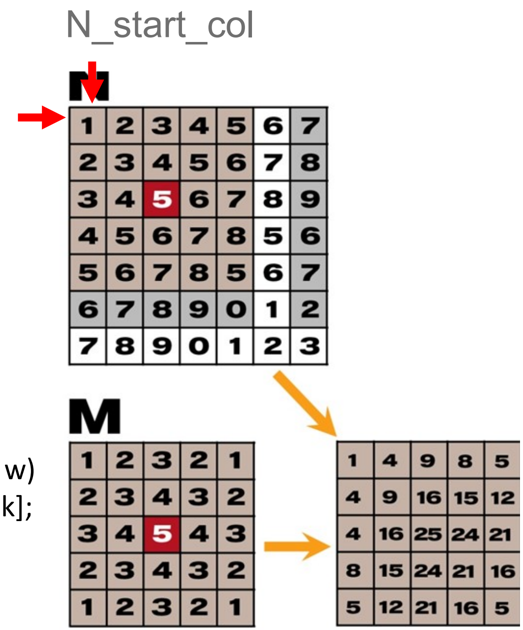
2D Convolution – Ghost Cells



```
__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 && curCol < w)
                pixVal += in[curRow * w + curCol] * mask[j*maskwidth+k];
             }
          }
       }

       // 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);
    }
}
```



```
__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);
   }
}
```

CONSTANT MEMORY AND CACHING

– There are three interesting properties of the way the mask array M is used in convolution.
– First, the size of the M array is typically small. Most convolution masks are less than 10 elements in each dimension. Even in the case of a 3D convolution, the mask typically contains only less than 1000 elements.
– Second, the contents of M are not changed throughout the execution of the kernel.
– Third, all threads need to access the mask elements.
– Even better, all threads access the M elements in the same order, starting from M[0] and move by one element a time.
– These two properties make the mask array an excellent candidate for constant memory and caching.

CONSTANT MEMORY AND CACHING

- Like global memory variables, constant memory variables are also visible to all thread blocks.
- The main difference is that a constant memory variable cannot be changed by threads during kernel execution.
- Furthermore, the size of the constant memory is quite small, currently at 64KB.
- To declare an M array in constant memory, the host code declares it as a global variable as follows:

```
#define MAX_MASK_WIDTH 10
__constant__ float M[MAX_MASK_WIDTH];
```

- This is a global variable declaration and should be outside any function in the source file.

CONSTANT MEMORY AND CACHING

– Assume that the host code has already allocated and initialized the mask in a mask M_h array in the host memory with Mask_Width elements.
– The contents of the M_h can be transferred to M in the device constant memory as follows:

```
cudaMemcpyToSymbol(M, M_h, Mask_Width*sizeof(float));
```

– Note that this is a special memory copy function that informs the CUDA runtime that the data being copied into the constant memory will not be changed during kernel execution.

```
cudaMemcpyToSymbol(dest, src, size)
```

CONSTANT MEMORY AND CACHING

```
__global__ void convolution_1D_ba sic_kernel(float *N, 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;

}
```

GPU Teaching Kit

Accelerated Computing

Module 8.2 – Parallel Computation Patterns (Stencil)

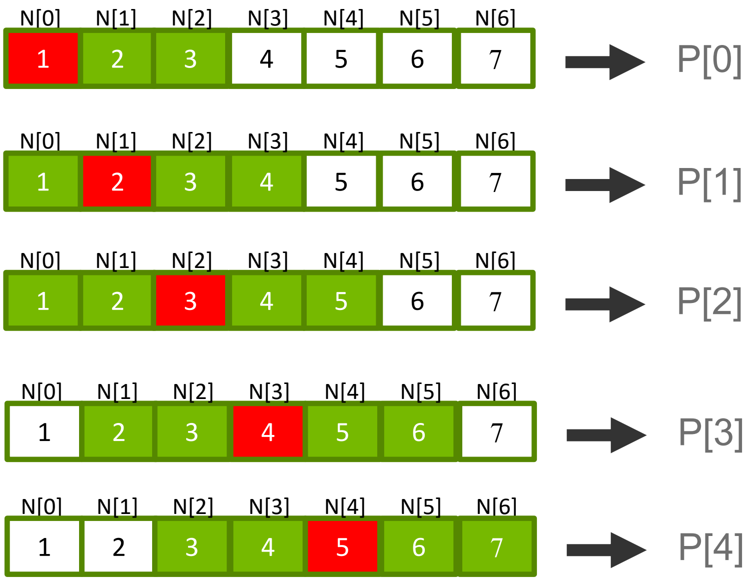
Tiled Convolution

Objective

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

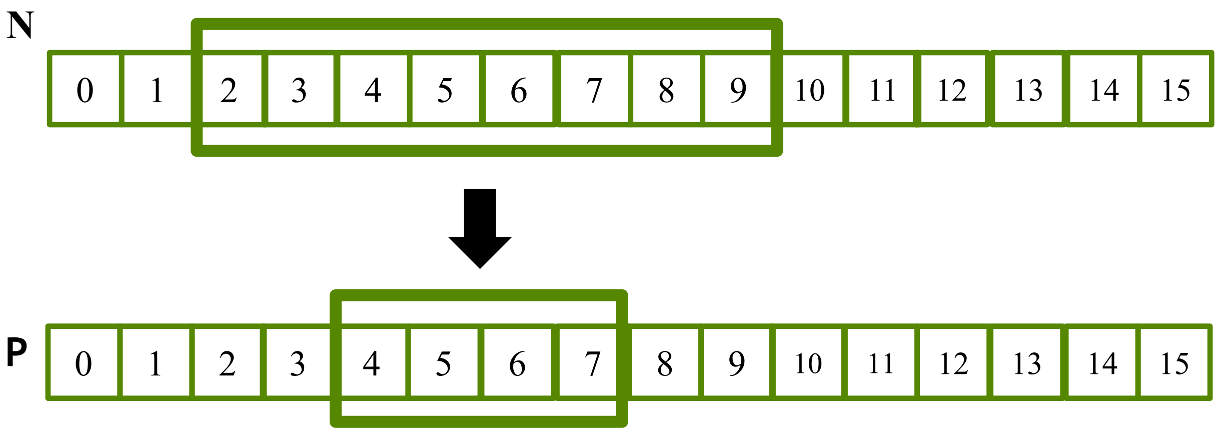
Tiling Opportunity Convolution

- 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[4] 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

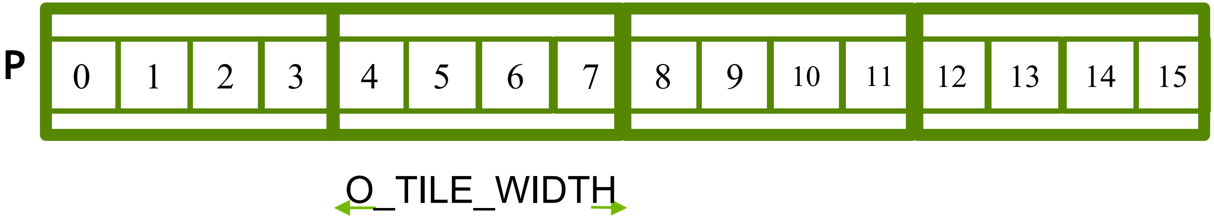


Input Data Needs

- 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



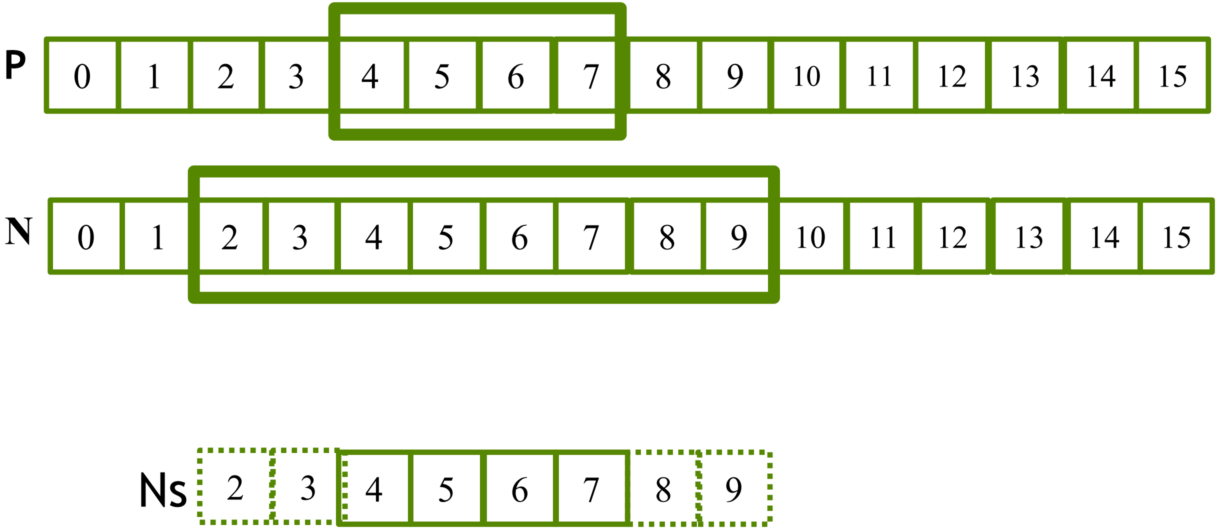
Each thread block calculates an output tile

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.

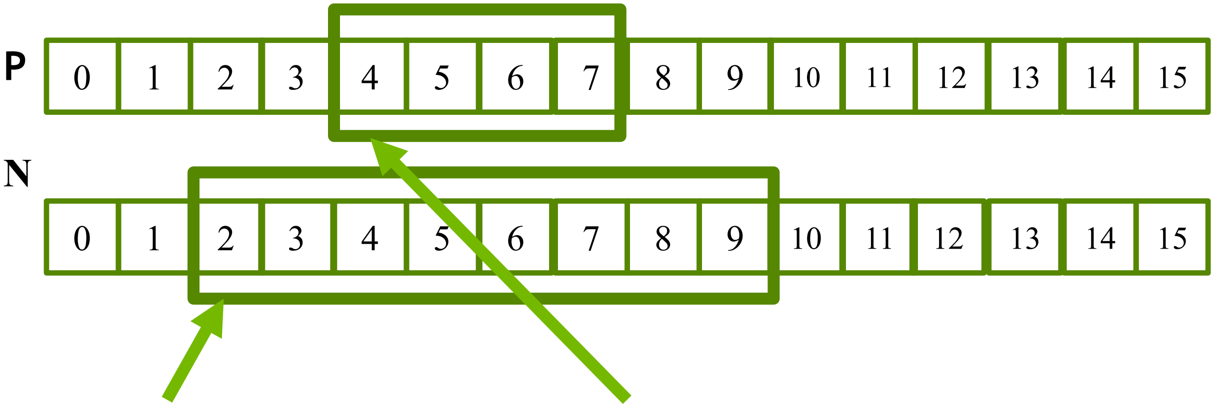
Two Design Options

- 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



Thread 0 reads this

Thread 0 writes this

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;
}
```

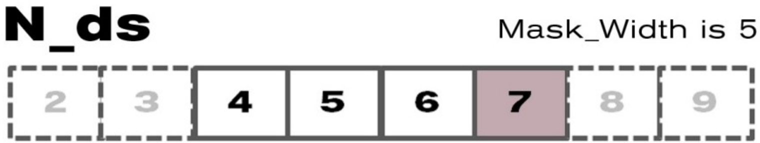
Some threads do not participate in calculating output

```
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

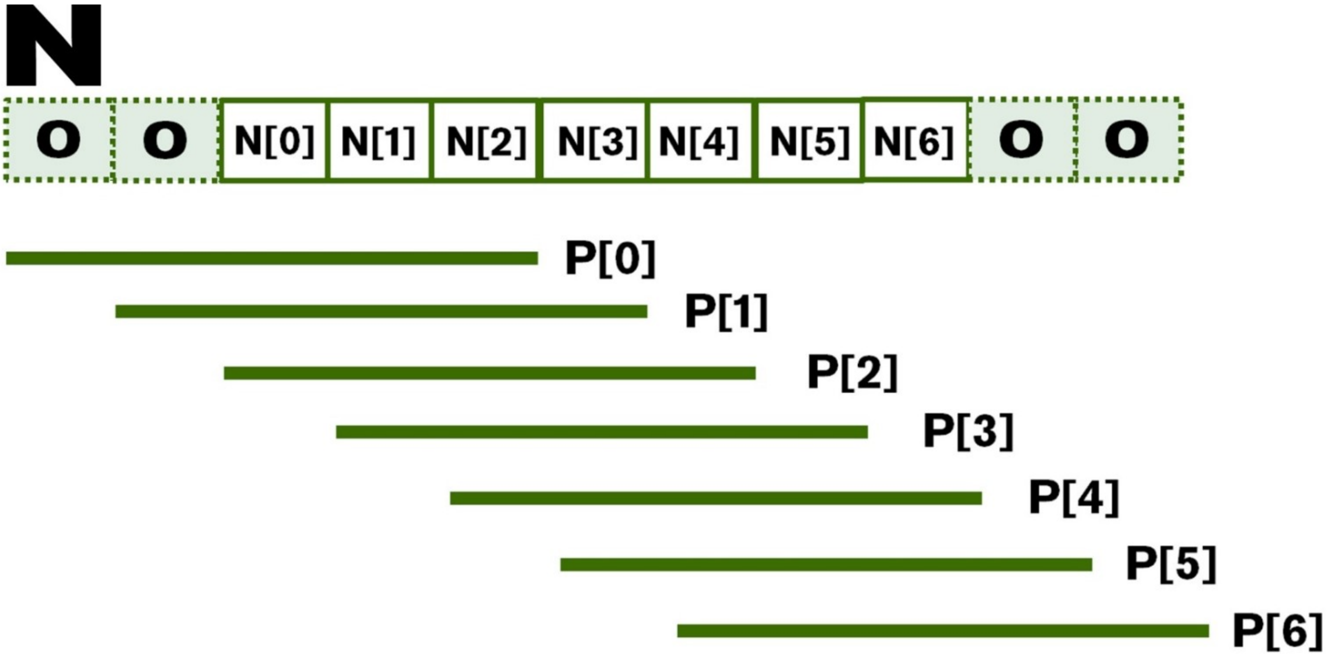
– Only Threads 0 through O_TILE_WIDTH-1 participate in calculation of output.

Shared Memory Data Reuse

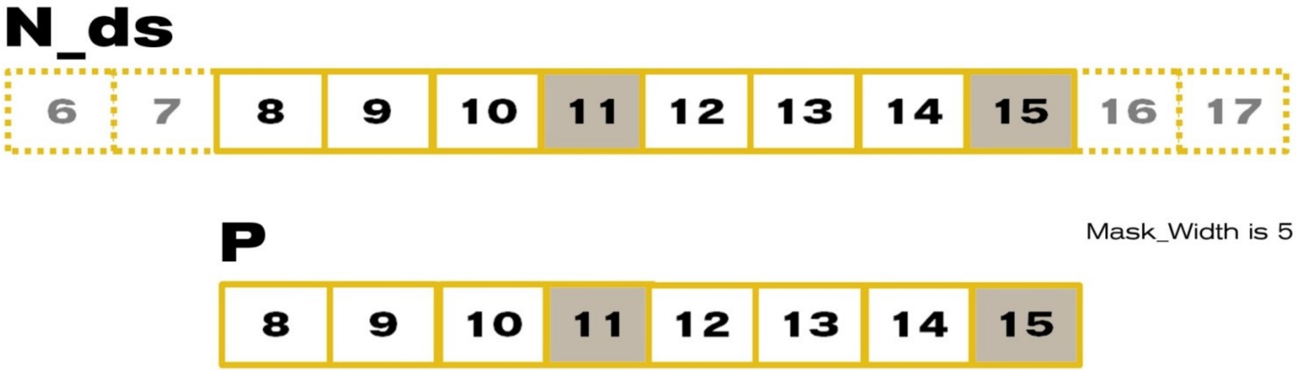


Element 2 is used by thread 4 (1X)
Element 3 is used by threads 4, 5 (2X)
Element 4 is used by threads 4, 5, 6 (3X)
Element 5 is used by threads 4, 5, 6, 7 (4X)
Element 6 is used by threads 4, 5, 6, 7 (4X)
Element 7 is used by threads 5, 6, 7 (3X)
Element 8 is used by threads 6, 7 (2X)
Element 9 is used by thread 7 (1X)

Ghost Cells

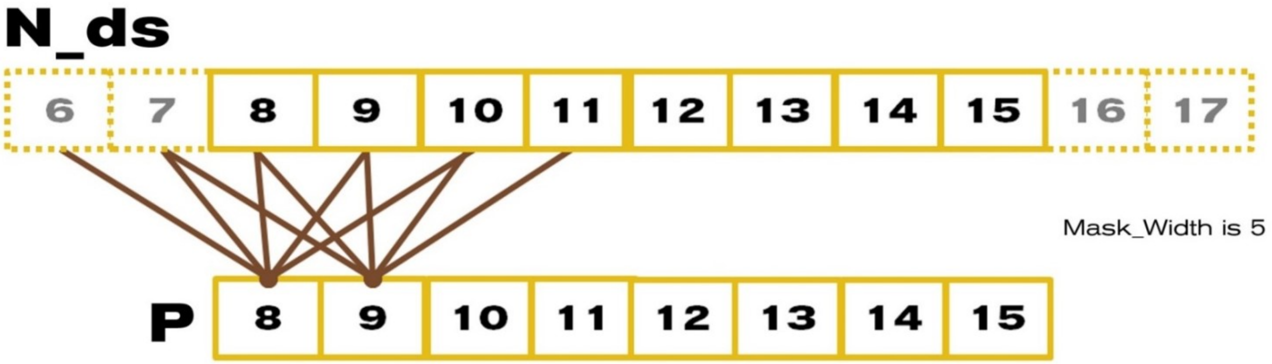


An 8-element Convolution Tile



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

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

GPU Teaching Kit

Accelerated Computing