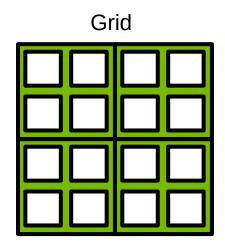
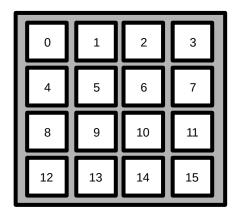
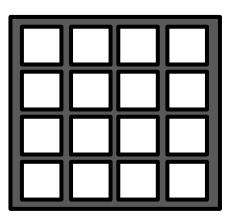
Using Shared Memory to Support Coalesced Memory Access

We will examine a matrix transpose to demonstrate how shared memory can be used to promote coalesced data transfers to and from global memory

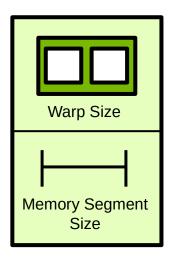


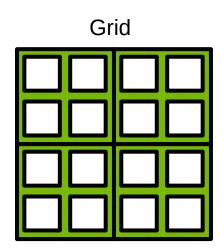
Here we have a (2,2) grid, with each block containing (2,2) threads as well as (4,4) input and output matrices



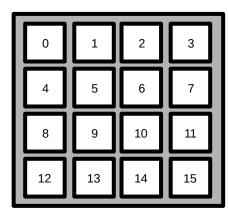


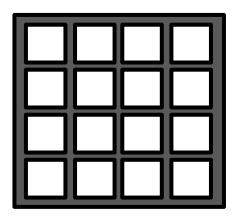




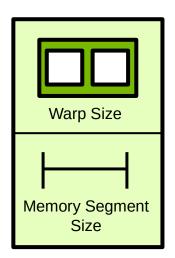


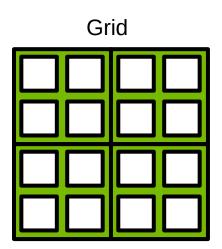
For these slides we will define a warp as 2 threads, and a memory segment as 2 data elements wide



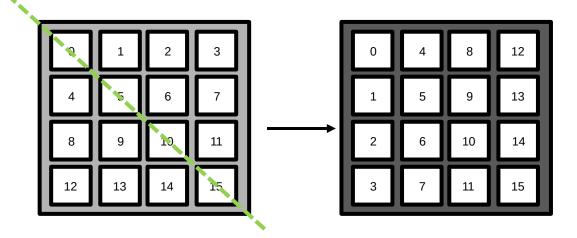








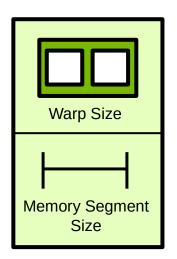
Our goal is to transpose the input by rotating all elements around the diagonal, writing the transposed elements to output

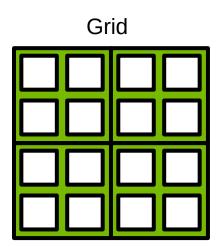


Output

Input

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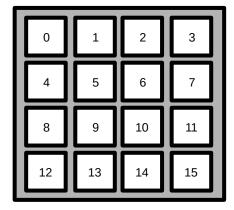


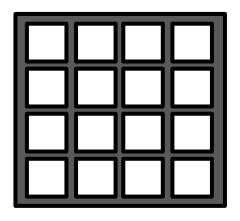


A naïve approach is to launch a grid with threads equal to input elements, and to have each thread read 1 element, then write it to output in the transposed location

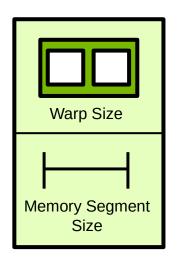
```
x, y = cuda.grid(2)

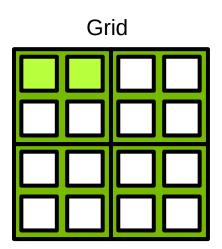
out[x][y] = in[y][x]
```







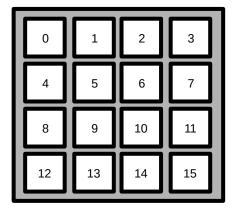


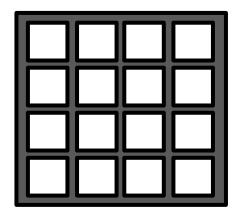


Observing the behavior of a single warp, is it the case that memory reads are coalesced? Let's dig into answering that question

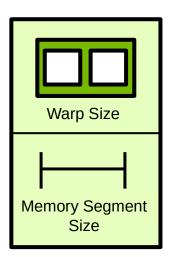
```
x, y = cuda.grid(2)

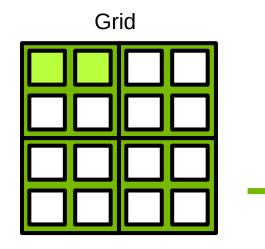
out[x][y] = in[y][x]
```



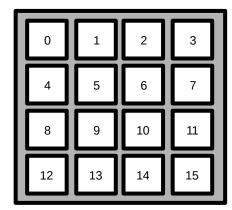


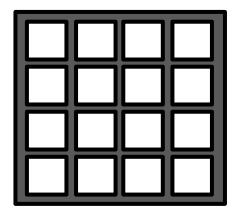




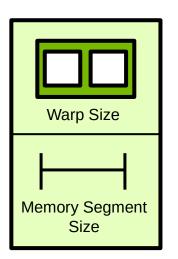


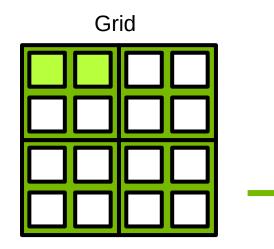
Rewriting the creation of the indexing variables, it is clearer that contiguous threads in the same warp are adjacent along the x axis



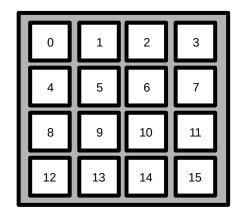


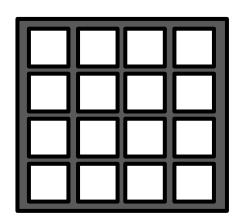






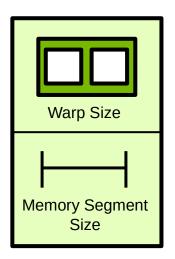
Furthermore, these contiguous threads will read elements from the rows of input where data elements are contiguous

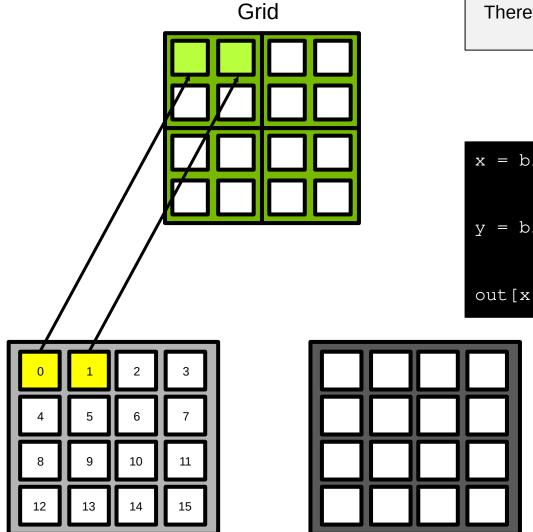










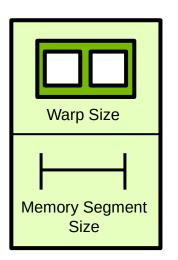


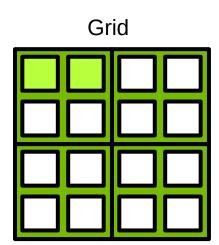
Therefore, it makes sense that reads from input are coalesced

Output

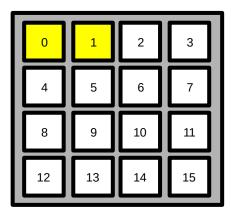
Input

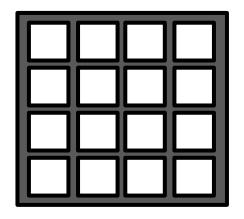




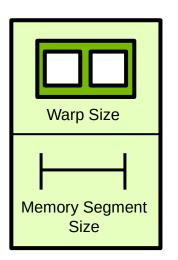


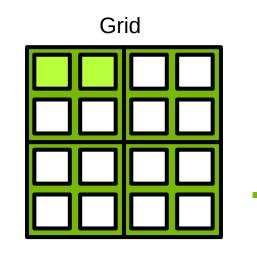
What about this warp's writes to output, will they be coalesced?



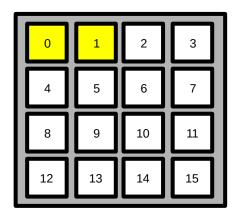


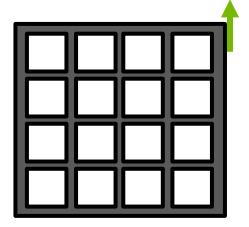




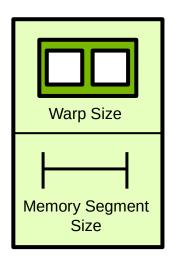


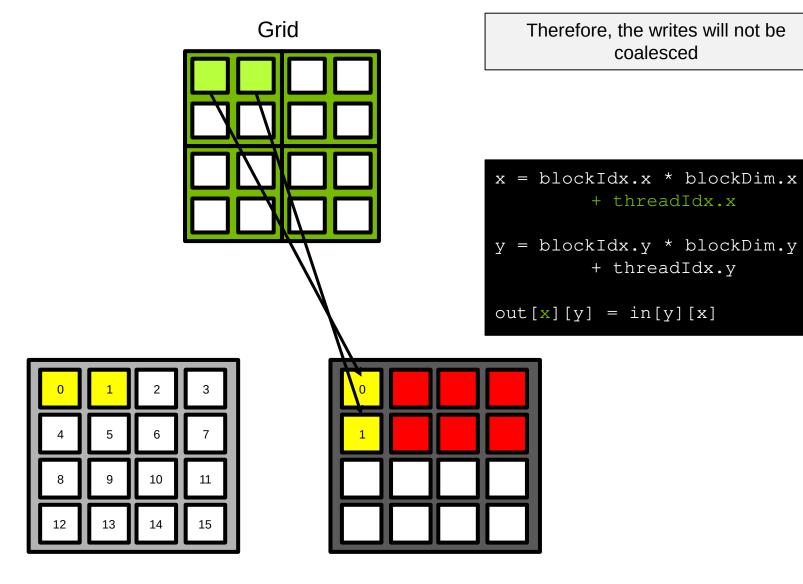
Here we see that contiguous threads in the same warp will be writing along a column in output



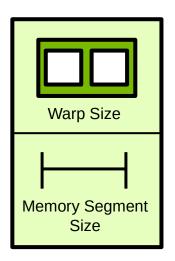


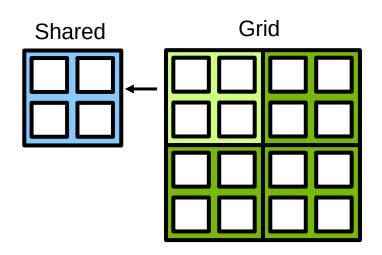






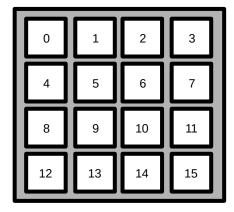


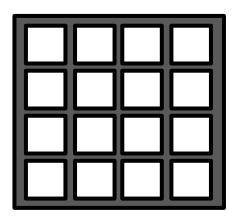




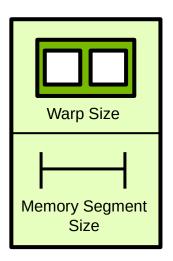
We can use shared memory to make coalesced reads and writes. Here, each block will allocate a (2,2) shared memory tile

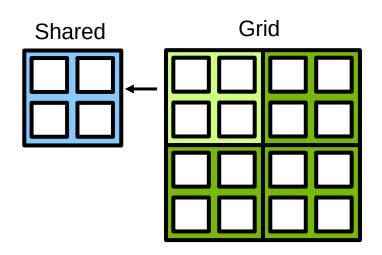
tile = cuda.shared.array(2,2)





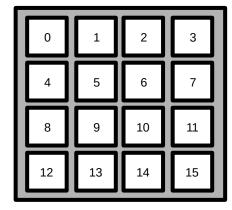


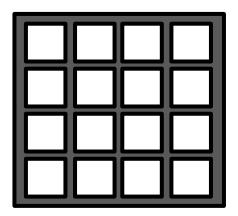




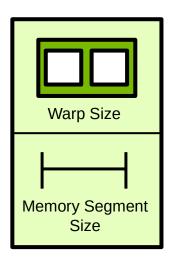
(It is worth reminding that in our slides, to preserve space, 2 threads is a warp length. A real warp is 32 threads)

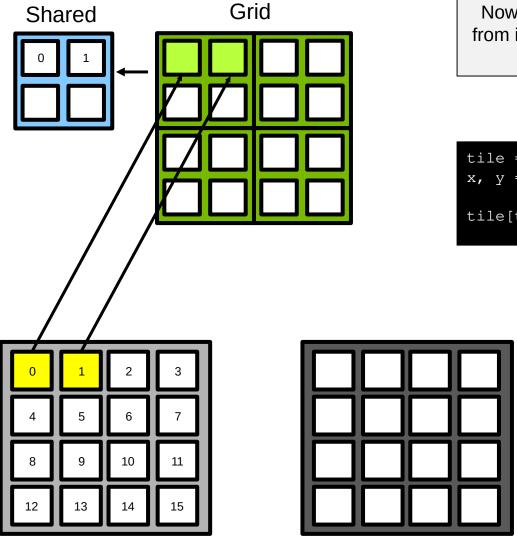
tile = cuda.shared.array(2,2)





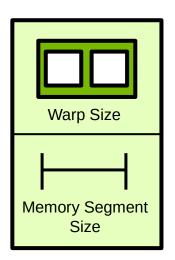


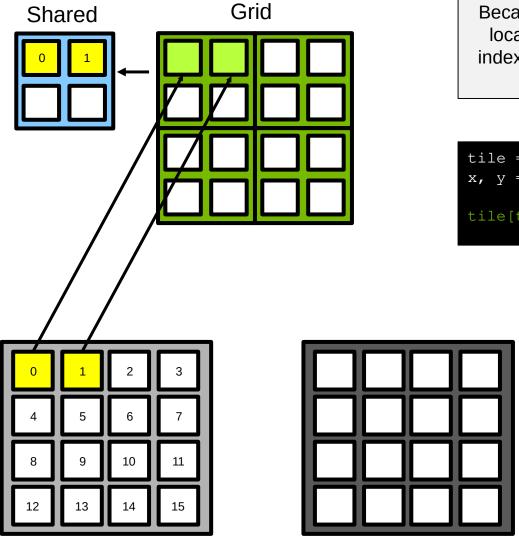




Now we can make coalesced reads from input, and write the values to the block's shared memory tile

tile = cuda.shared.array(2,2) x, y = cuda.grid(2)tile[tIdx.y][tIdx.x] = in[y][x]

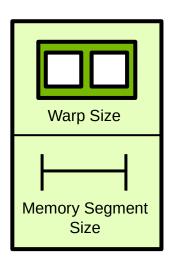


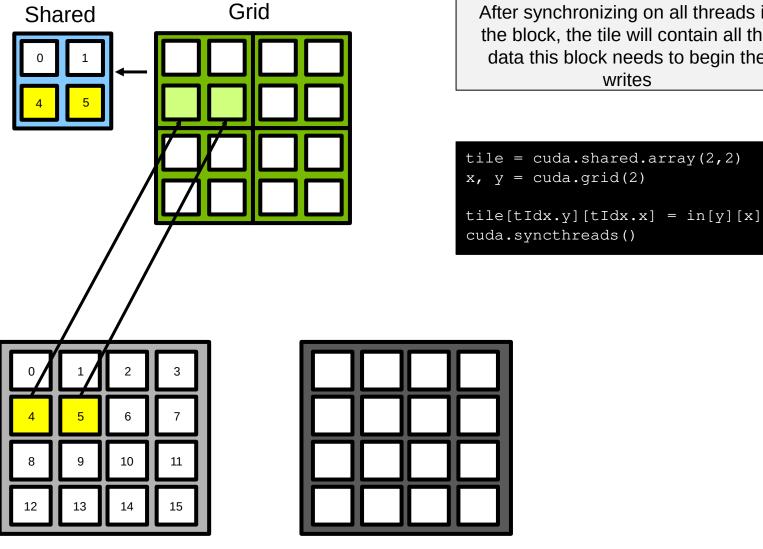


Because each shared memory tile is local to the block (not the grid) we index into it using thread indices, not grid indices

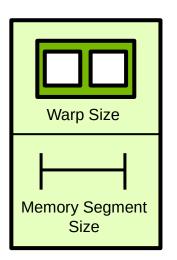
tile = cuda.shared.array(2,2)
x, y = cuda.grid(2)
tile[tIdx.y][tIdx.x] = in[y][x]

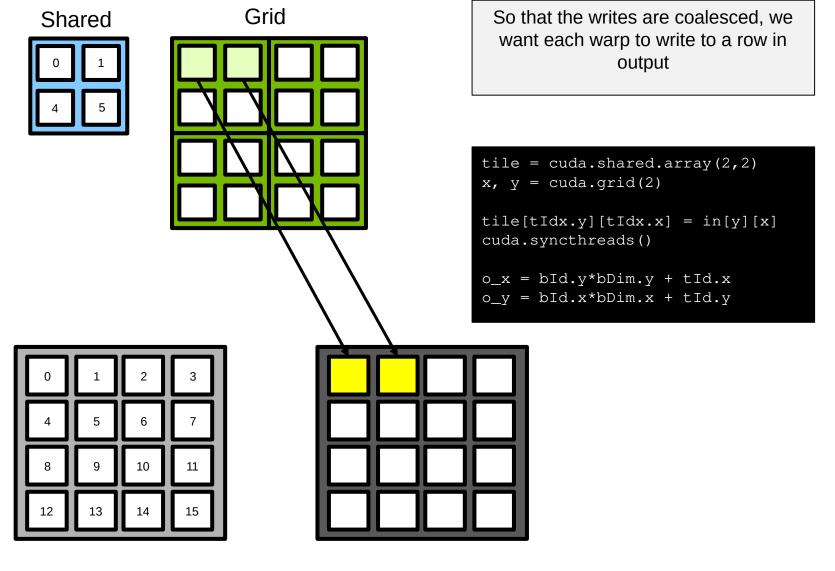




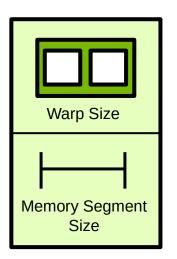


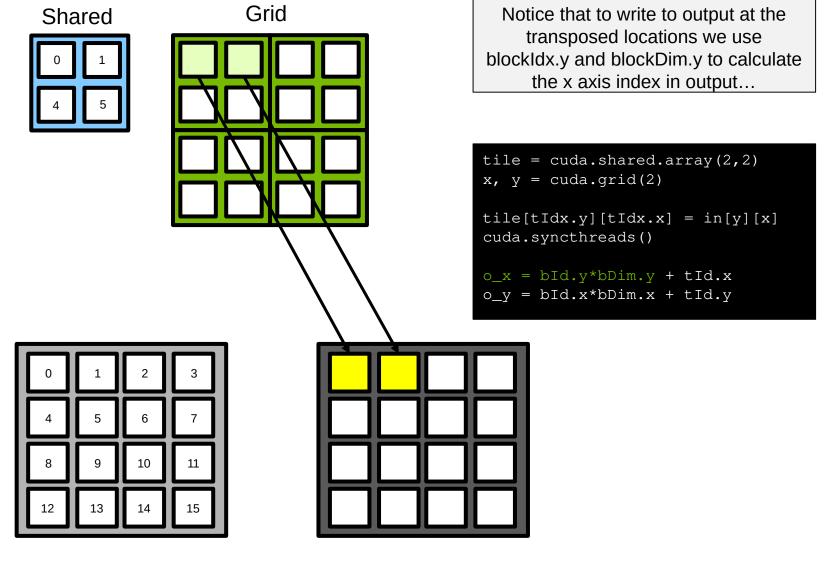
After synchronizing on all threads in the block, the tile will contain all the data this block needs to begin the writes



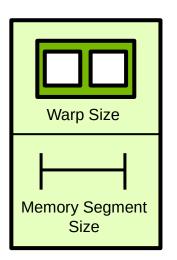


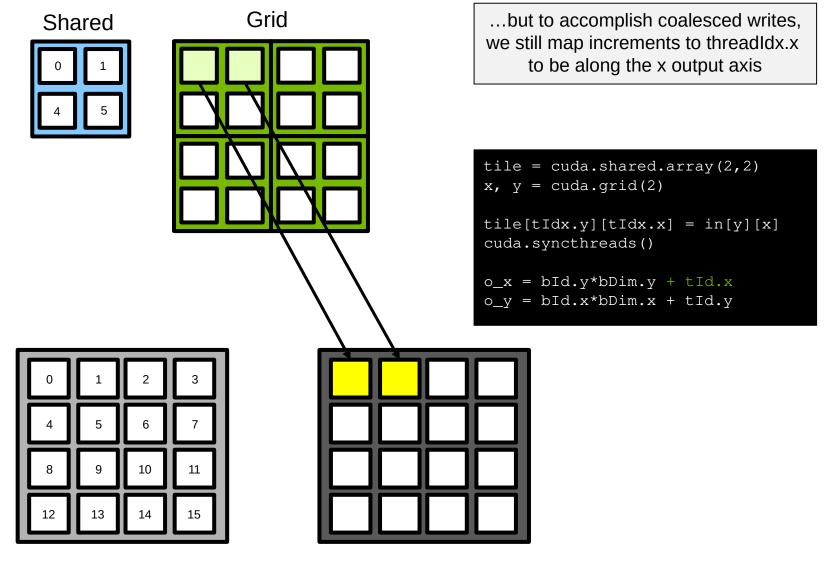




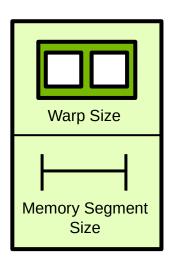


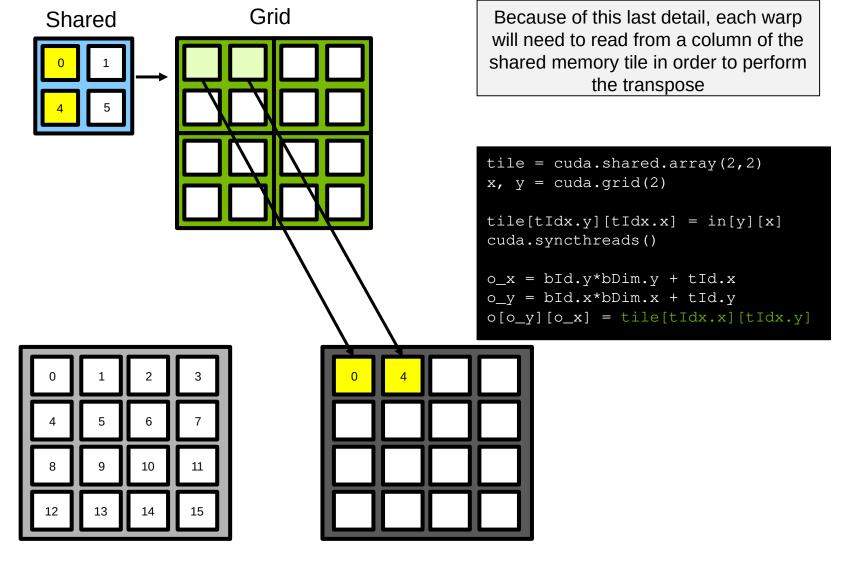




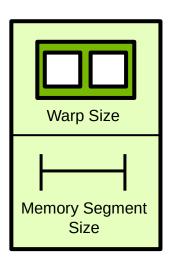


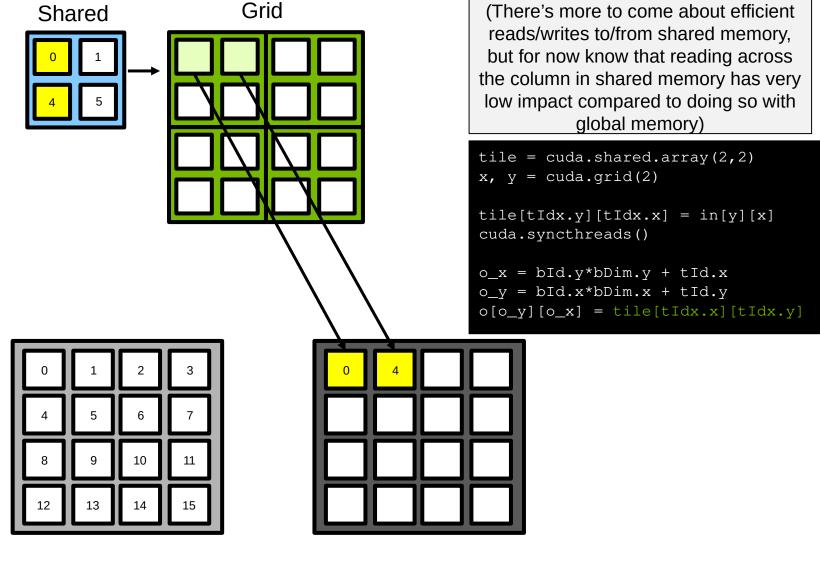




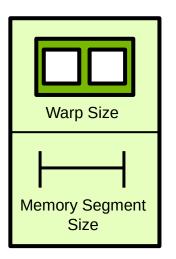


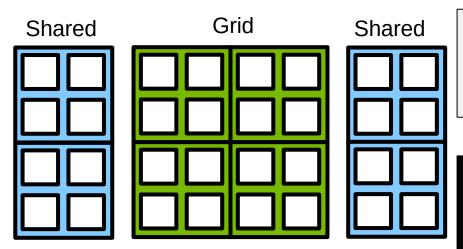










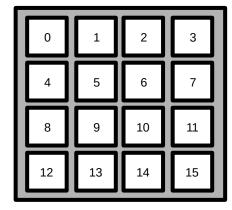


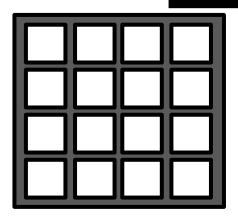
In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

```
tile = cuda.shared.array(2,2)
x, y = cuda.grid(2)

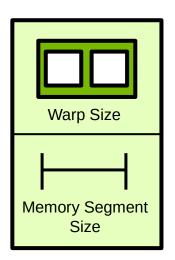
tile[tIdx.y][tIdx.x] = in[y][x]
cuda.syncthreads()

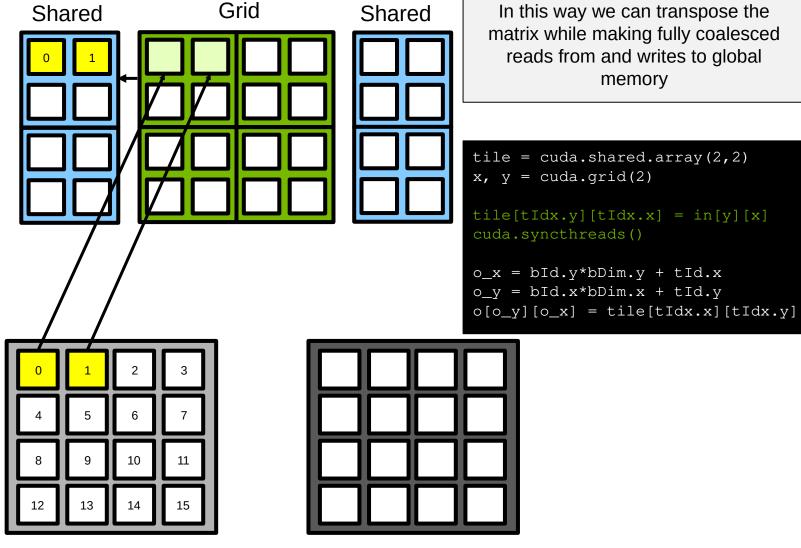
o_x = bId.y*bDim.y + tId.x
o_y = bId.x*bDim.x + tId.y
o[o_y][o_x] = tile[tIdx.x][tIdx.y]
```





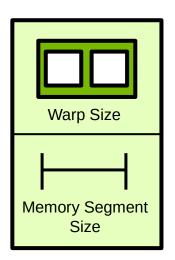


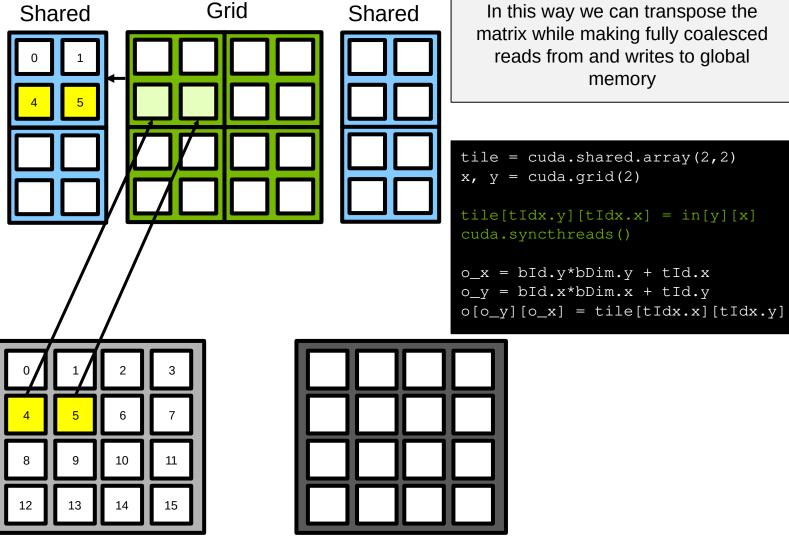




Output

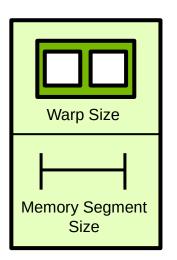
memory

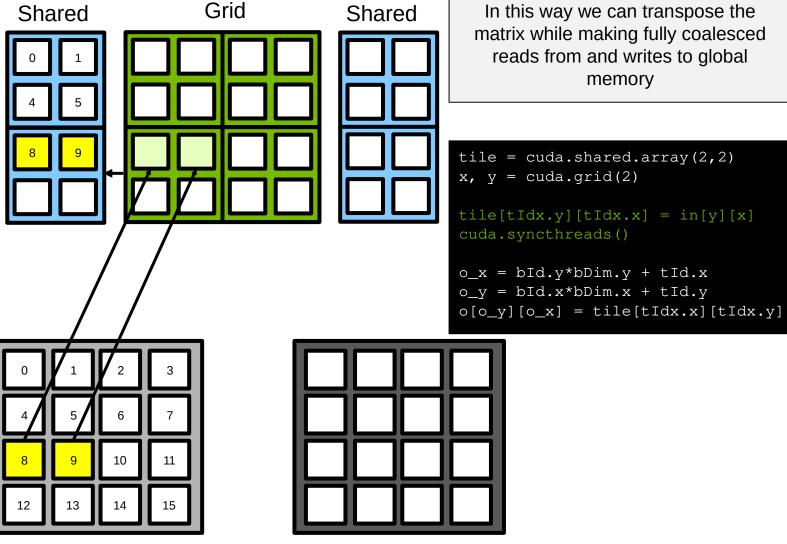




In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

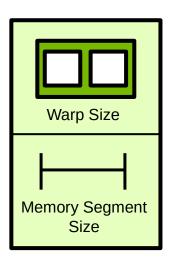


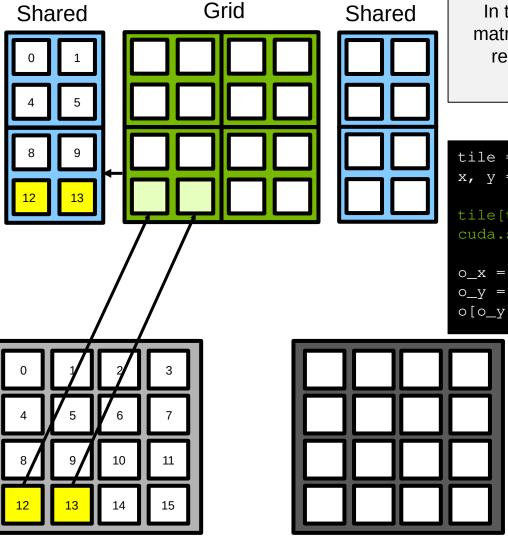




In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory







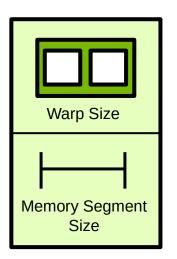
In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

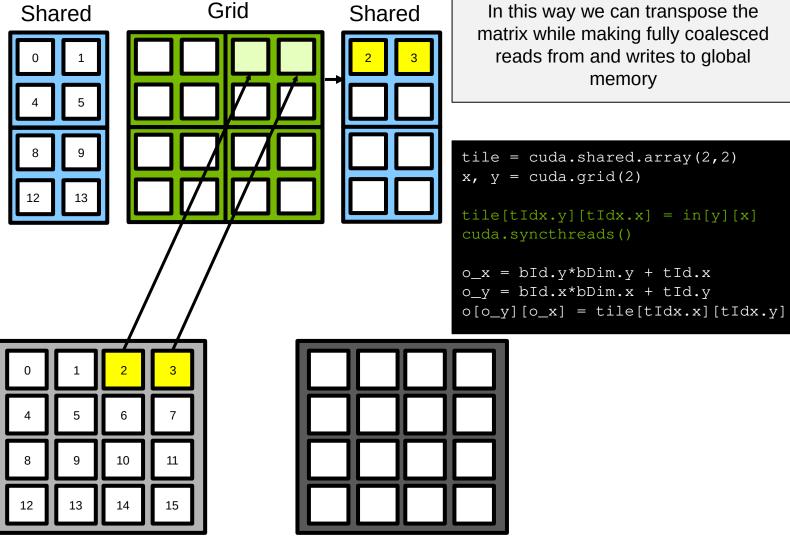
```
tile = cuda.shared.array(2,2)
x, y = cuda.grid(2)

tile[tIdx.y][tIdx.x] = in[y][x]
cuda.syncthreads()

o_x = bId.y*bDim.y + tId.x
o_y = bId.x*bDim.x + tId.y
o[o_y][o_x] = tile[tIdx.x][tIdx.y]
```

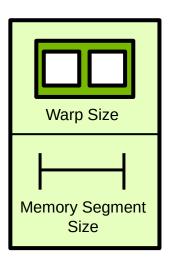


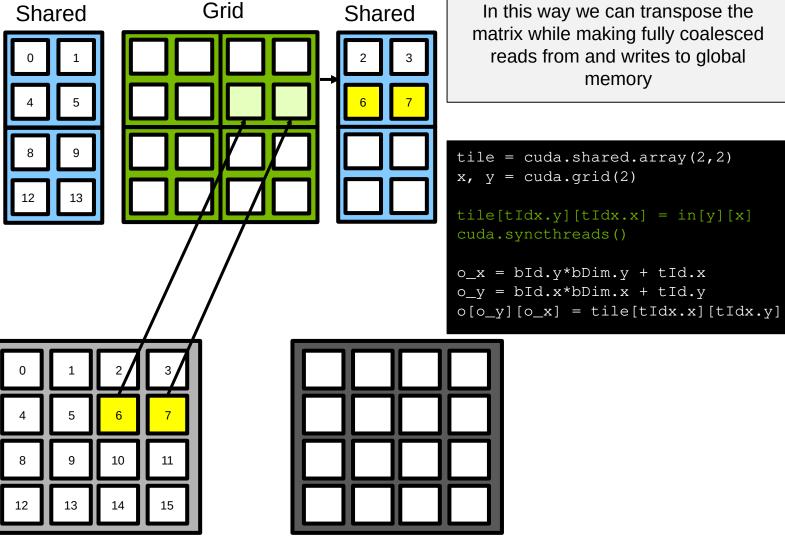




In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

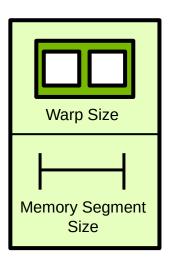


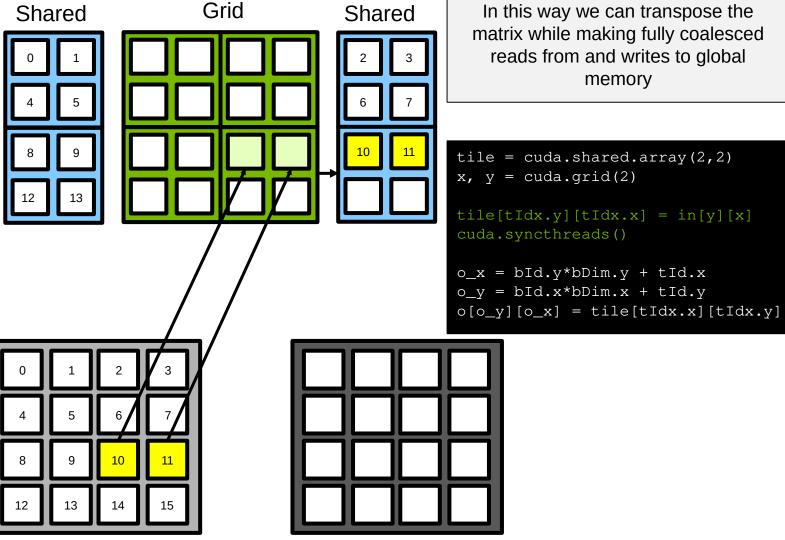




In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

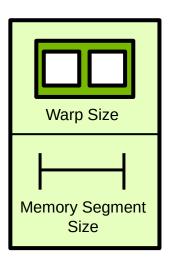


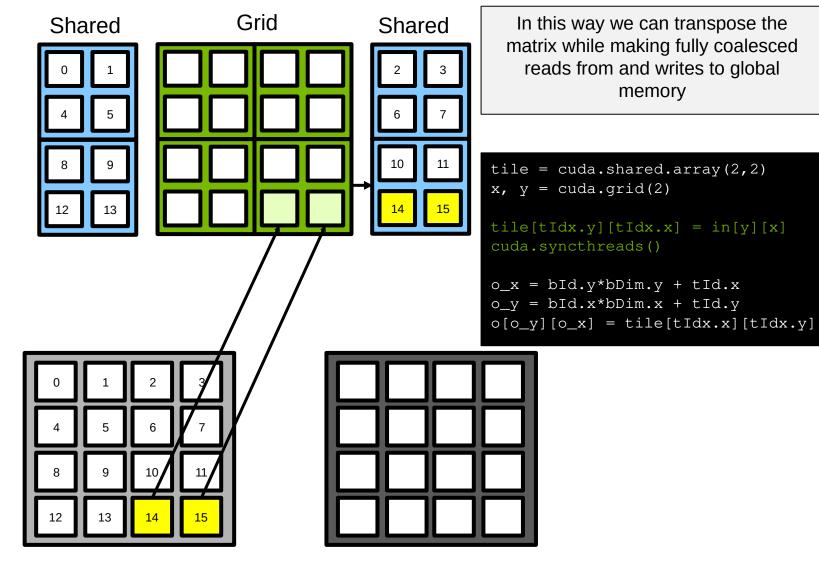




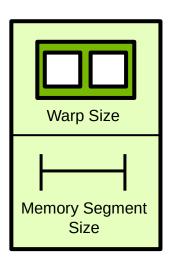
In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

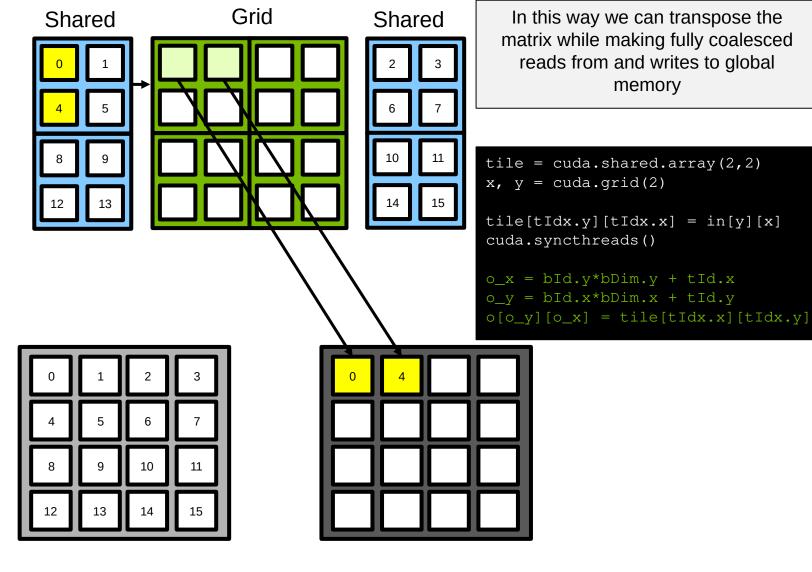




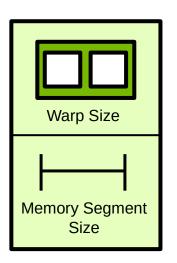


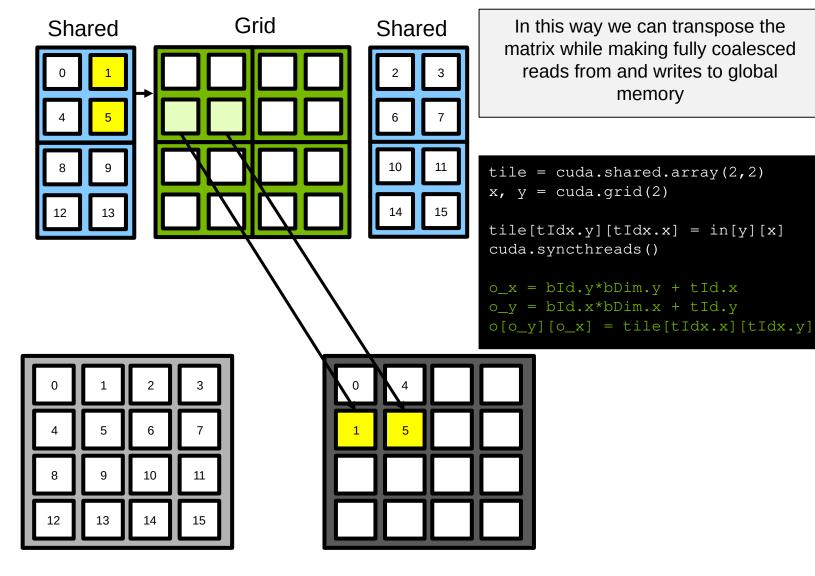




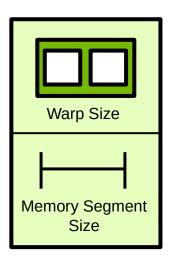


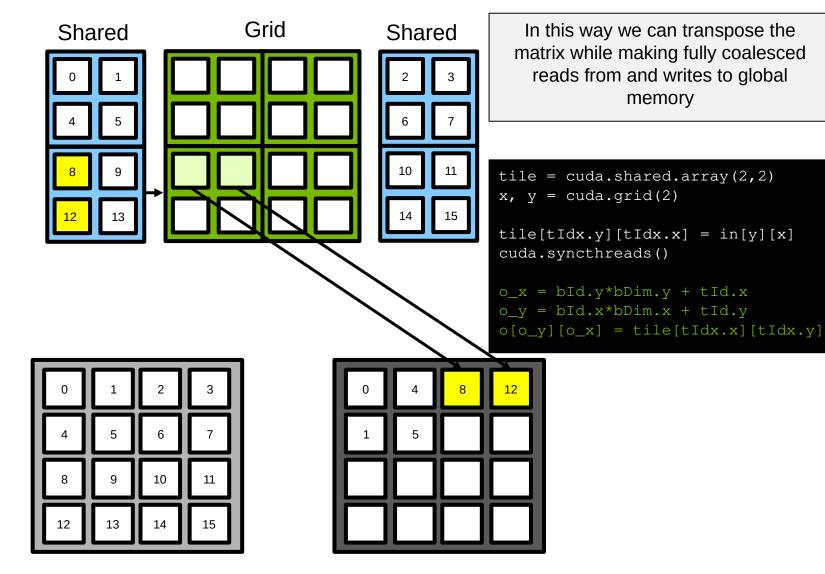




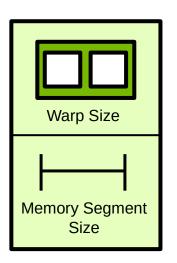


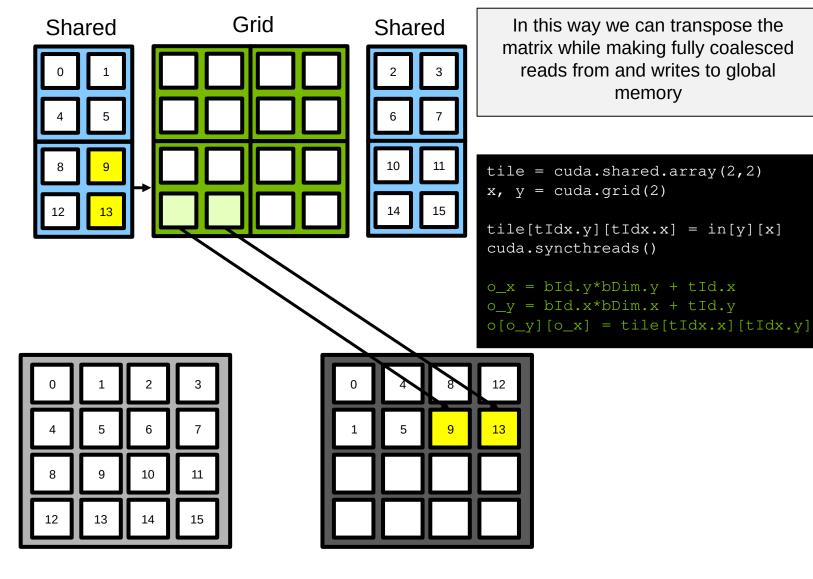




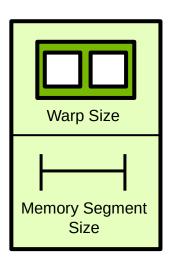


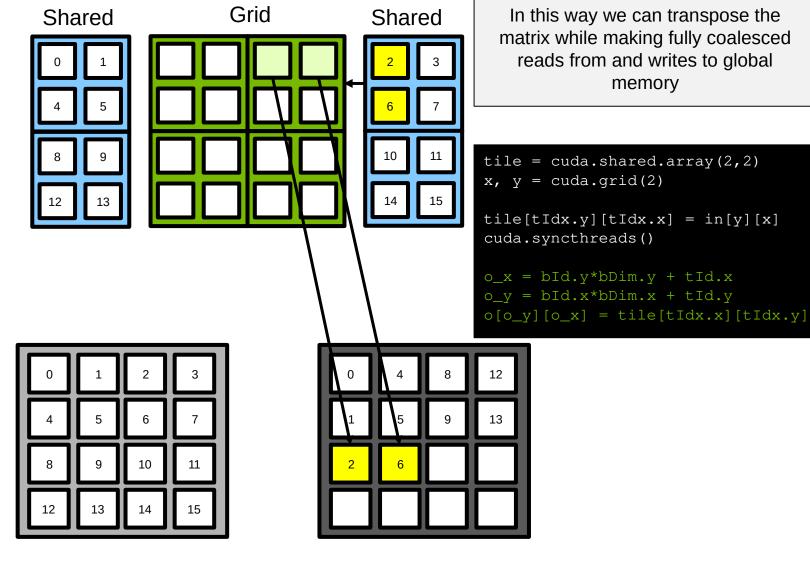




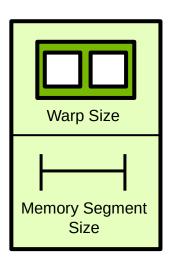


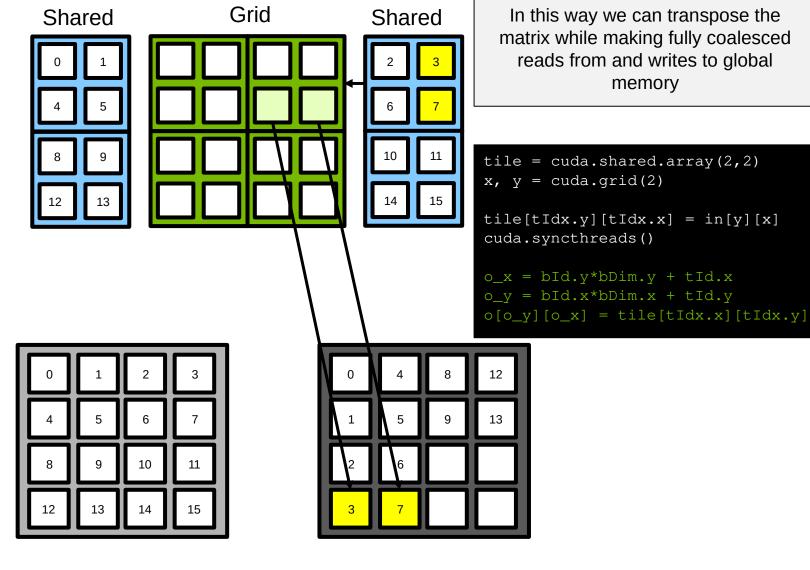




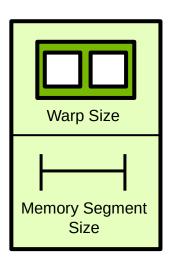


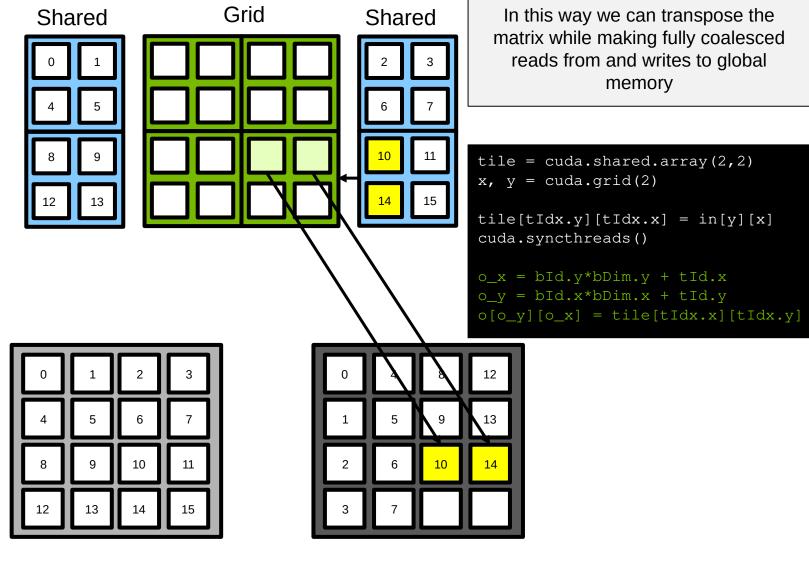




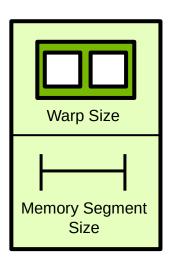


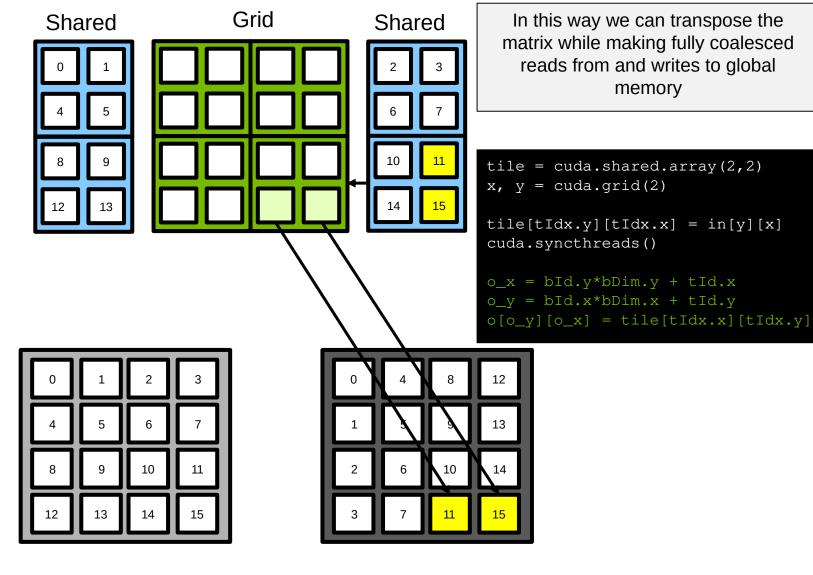




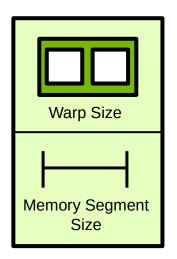


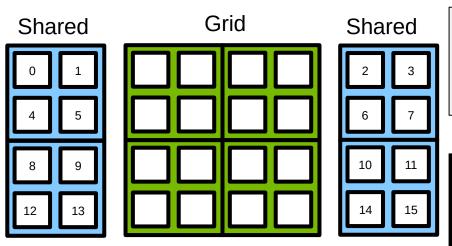












In this way we can transpose the matrix while making fully coalesced reads from and writes to global memory

```
tile = cuda.shared.array(2,2)
x, y = cuda.grid(2)

tile[tIdx.y][tIdx.x] = in[y][x]
cuda.syncthreads()

o_x = bId.y*bDim.y + tId.x
o_y = bId.x*bDim.x + tId.y
o[o_y][o_x] = tile[tIdx.x][tIdx.y]
```

