CSC266 Introduction to Parallel Computing using GPUs
GPU Architecture II (Memory)

Sreepathi Pai

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URCS

Outline

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Memories

- Where data can be stored
- Two main, real spaces:
  - Off-chip: "Global" or "device" memory
  - On-chip: "Shared" memory
- Lots of "memory spaces" built on top of these two:
  - where data is stored (i.e., global or shared)
  - how data is accessed (i.e., which cache)
  - to whom data is visible (e.g., all threads or only thread block)

Outline

Global Memory

- GPU RAM, usually tens of gigabytes
- High-bandwidth access from GPU
  - 300 GB/s to 1TB/s (depending on the GPU)
- Memory allocated using `cudaMalloc` (and equivalents)
- Contains following memory spaces:
  - Global memory space
  - Local memory space
  - Texture memory space

Memory spaces in Global Memory

- Global Memory Space
  - Used for all GPU data accessed through pointers
  - Or for variables marked `__device__`
  - Data is accessed through L2 cache
  - Data is visible to all threads
- Local Memory space
  - Automatically used for *thread-local* data
  - E.g., register spills by compiler
  - Data is visible only to single thread
  - Data is accessed through L1/L2 cache
- Texture Memory Space
  - Used for *read-only texture* data
  - Data visible to all threads
  - Data accessed through texture unit (or separate cache)
  - More later today ...

Data Layout for GPU programs (AoS)

```
struct pt {
  int x;
  int y;
};

__global__
void aos_kernel(int n_pts, struct pt *p) {
  int tid = blockIdx.x * blockDim.x + threadIdx.x;
  int nthreads = blockDim.x * gridDim.x;

  for(int i = tid; i < n_pts; i += nthreads) {
    p[i].x = i;
    p[i].y = i * 10;
  }
}
```

```
In main():

struct pt *p;
cudaMalloc(&p, ...)
```

Data Layout for GPU programs (SoA)

```
struct pt {
  int *x;
  int *y;
};

__global__
void soa_kernel(int n_pts, struct pt p) {
  int tid = blockIdx.x * blockDim.x + threadIdx.x;
  int nthreads = blockDim.x * gridDim.x;

  for(int i = tid; i < n_pts; i += nthreads) {
    p.x[i] = i;
    p.y[i] = i * 10;
  }
}
```

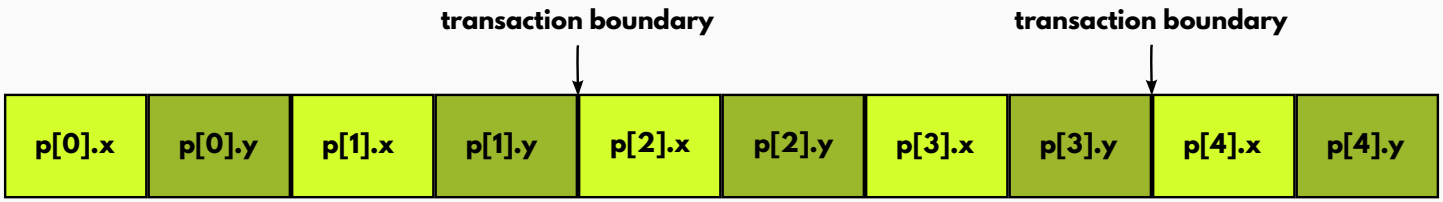
In main():

```
struct pt p;
cudaMalloc(&p.x, ...)
cudaMalloc(&p.y, ...)
```

AoS vs SoA for GPU programs

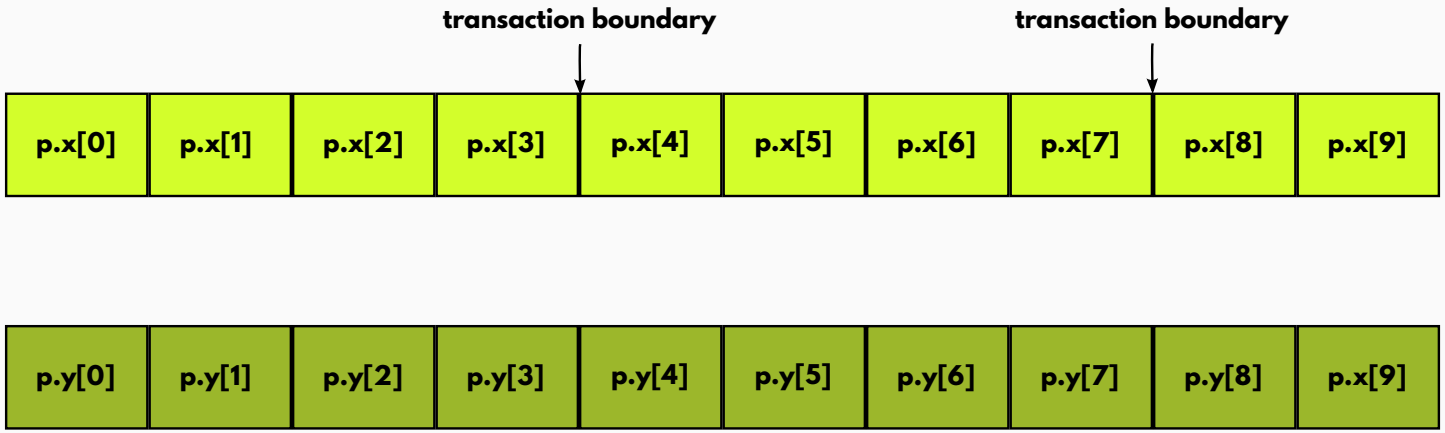
- Array of Structures
- Structure of Arrays
- Which is better for CPU?
- Which is better for GPU?

AoS memory layout



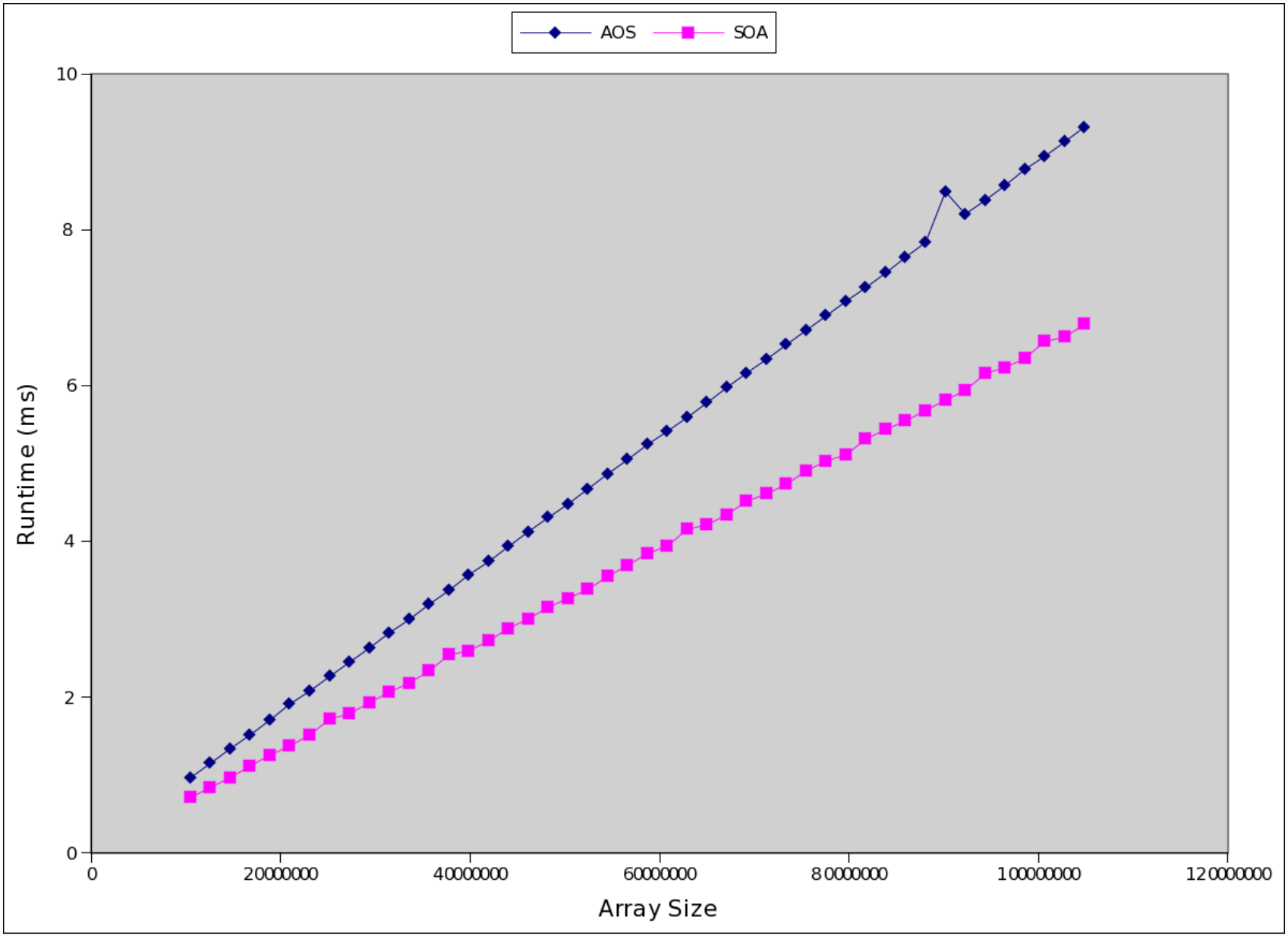
- `p[i].x` memory bandwidth utilization?

SoA memory layout

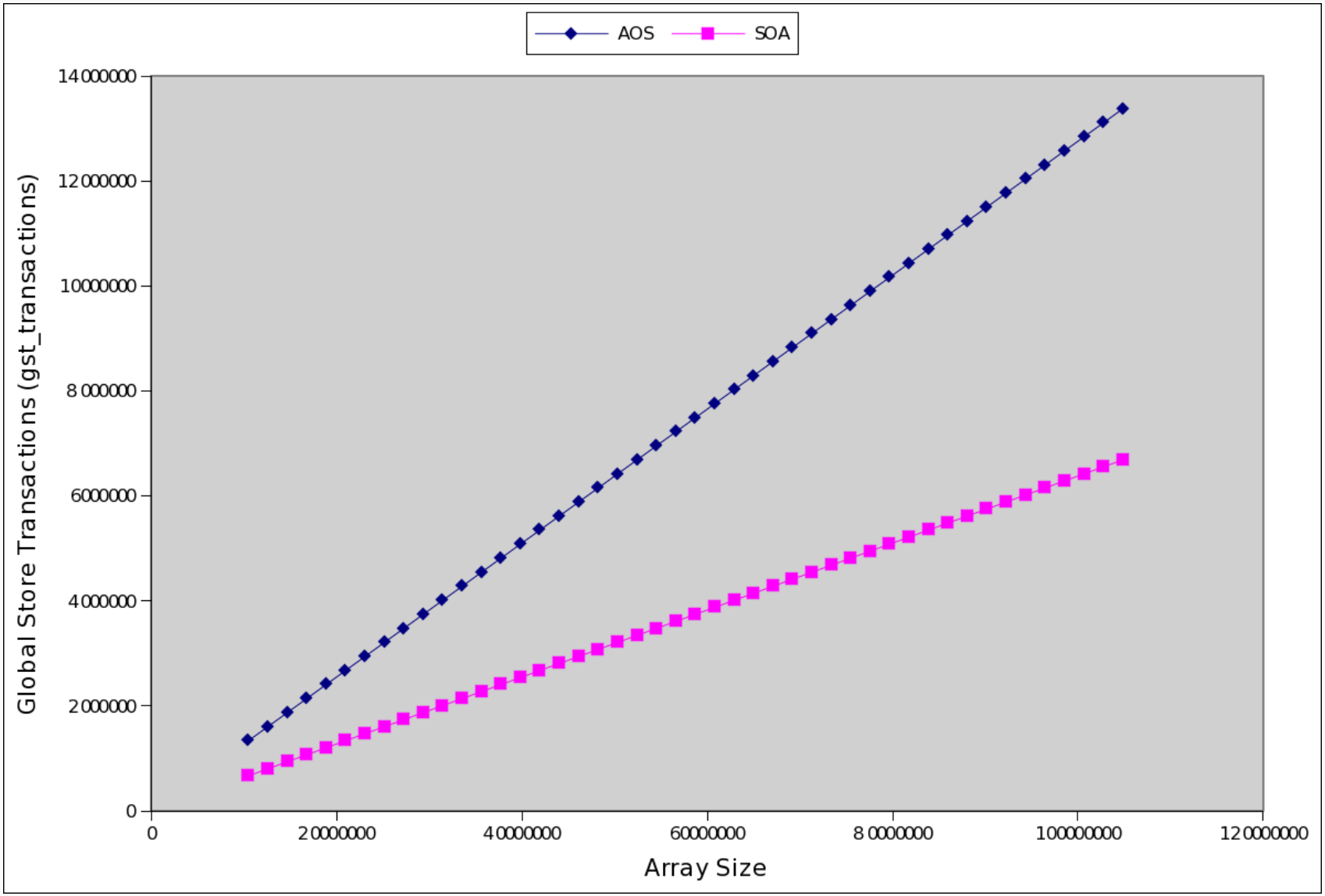


- `p.x[i]` memory bandwidth utilization?

AoS vs SoA Performance



AoS vs SoA: Number of Memory Transactions



Assigning Work to Threads

Blocked:

```
start = tid * blksize;
end = start + blksize;

for(i = start; i < N && i < end; i++)
    a[i] = b[i] + c[i]
```

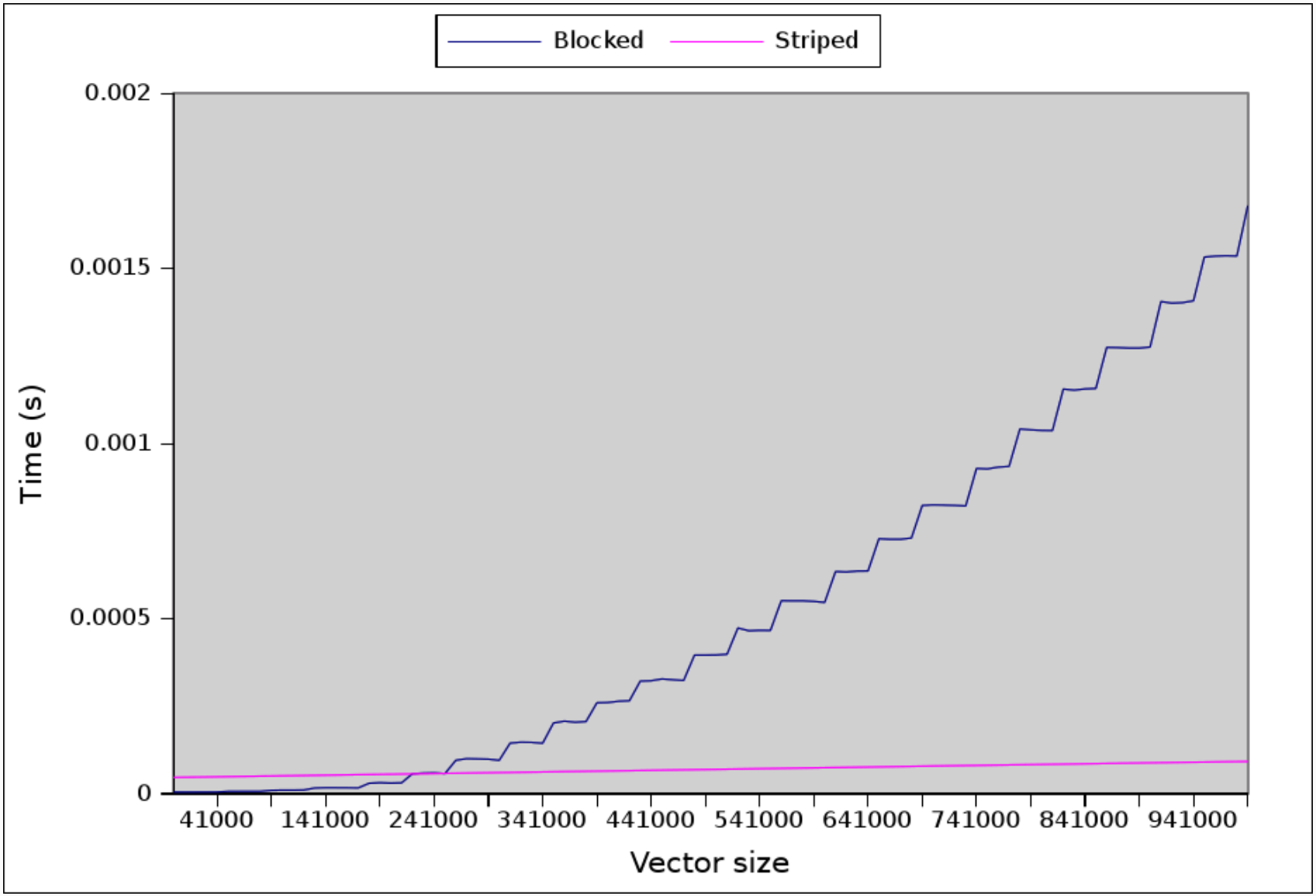
Interleaved:

```
start = tid;

for(i = start; i < N; i+=nthreads)
    a[i] = b[i] + c[i]
```

Which, if any, is faster?

Blocking vs Interleaved



Summary of Global Memory Performance

- Global memory accessed in 32-byte chunks on current GPUs
- Ideally, each warp accesses four 32-byte chunks
  - Bandwidth underutilized otherwise
  - L2 cache is unable to exploit temporal locality
- Hence, for GPUs, prefer:
  - SoA over AoS
  - Assign work in interleaved vs blocked (if this affects memory access pattern)

Outline

Exploiting Locality: Shared Memory

- "Shared Memory" is on-chip software-managed cache, also known as a scratchpad
- 48K maximum size/thread block
  - GPU can have upto 128K
- Partitioned among thread blocks
- `__shared__` qualifier places variables in shared memory
- Can be used for communicating between threads of the same thread block

```
__shared__ int x;

if(threadIdx.x == 0)
     x = 1;

__syncthreads(); //required!

printf("%d\n", x);
```

Using shared memory for communication

- (Contrived) Find maximum number in each 256 element chunk of large array

```
__global__ void chunkmax(int *a, int N, int *out) {
int tid = threadIdx.x + blockIdx.x * blockDim.x
  ...
}
main() {

    cudaMallocManaged(&a, N*sizeof(int));

    // fillup a

    blocks = (N + 255) / 256;
    cudaMallocManaged(&out, blocks*sizeof(int))
    chunkmax<<<blocks, 256>>>(a, N, out);
    cudaDeviceSynchronize();

    // print out
}
```

Serial Code

```
for(int block = 0; block < blocks; block++) {

   blockmax = a[block*256];

   for(int elem = block * 256;
       elem < (block + 1) * 256 && elem < N;
       elem++)
   {
      if(a[elem] > blockmax)
        blockmax = a[elem];
   }

   out[block] = blockmax;
}
```

Try 1

- (Contrived) Find maximum number in each 256 element chunk of large array

```
__global__ void chunkmax(int *a, int N, int *out) {
int tid = threadIdx.x + blockIdx.x * blockDim.x

__shared__ int tbmax;

if (tid < N)
    return;

if(threadIdx.x == 0)
   tbmax = a[tid]

__syncthreads()

if(a[tid] > tbmax)
  tbmax = a[tid]

__syncthreads()

if(threadIdx.x == 0)
  out[blockIdx.x] = tbmax
}
```

Try 2

```
__global__ void chunkmax(int *a, int N, int *out) {

__shared__ int tbmax;

 ...

if(threadIdx.x == 0)
   tbmax = a[tid]

__syncthreads()
int mycopy;

do {
  mycopy = tbmax;
  __syncthreads();

  if (a[tid] > mycopy)
     tbmax = a[tid];
  __syncthreads();

} while(a[tid] > tbmax);

if(threadIdx.x == 0)
  out[blockIdx.x] = tbmax
}
```

Try 3?

```
__global__ void chunkmax(int *a, int N, int *out) {

 ...

if(threadIdx.x == 0)
   tbmax = a[tid]

__syncthreads()
int mycopy;

do {
  mycopy = tbmax;
  __syncthreads();

  if (a[tid] > mycopy)
     tbmax = a[tid];
  __syncthreads();

} while(mycopy != tbmax);

if(threadIdx.x == 0)
  out[blockIdx.x] = tbmax
}
```

Using Shared Memory as a cache (SGEMM)

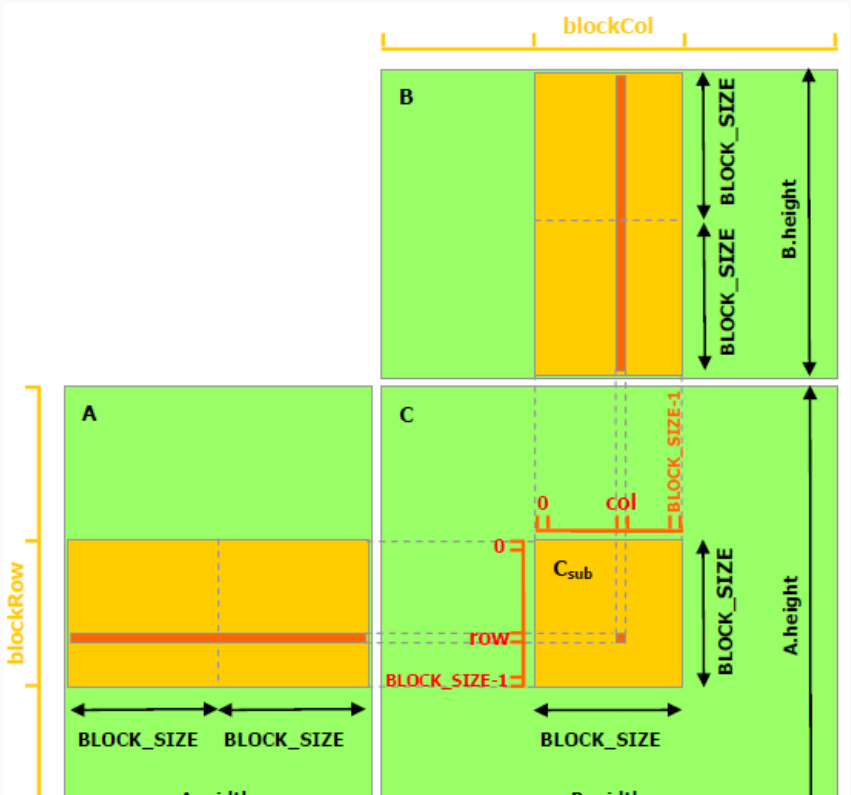
```
__shared__ float c_sub[BLOCKSIZE][BLOCKSIZE];

// calculate c_sub

__syncthreads();

// write out c_sub to memory
```

- Read Section 3.2.3 in CUDA C Programming Guide



Outline

Exploiting Spatial Locality: Texture Caches

- Textures are 2-D images that are "wrapped" around 3-D models
- Exhibit 2-D locality, so textures have a separate cache
- GPU contains a texture fetch unit that non-graphics programs can also use
  - Step 1: map arrays to textures
  - Step 2: replace array reads by `tex1Dfetch()`, `tex2Dfetch()`
- Catch: Only read-only data can be cached
  - you can write to the array, but it may not become visible through the texture in the same kernel call
  - i.e. texture caches are not coherent with GPU memory
- Easiest way to use textures:
  - `const __restrict__ *`
  - Compiler will automatically use texture cache for marked arrays

Constant Data Cache

- 64KB of "constant" data
  - not written by kernel
- Suitable for read-only, "broadcast" data
- All threads in a warp read the same constant data item at the same time
  - what type of locality is this?
- Uses: Filter coefficients
  - `2dconv`: convolution matrix entries
- Lab 7 uses `__constant__` for image properties

Summary of Memory Performance

- Layout data structures in memory to maximize bandwidth utilization
- Assign work to threads to maximize bandwidth utilization
- Rethink caching strategies
  - identify readonly data
  - identify blocks that you can load into shared memory
  - identify tables of constants