

# CS 193G

## Lecture 5: Performance Considerations

# But First!

- **Always measure where your time is going!**
  - Even if you think you know where it is going
  - Start coarse, go fine-grained as need be
- **Keep in mind Amdahl's Law when optimizing any part of your code**
  - Don't continue to optimize once a part is only a small fraction of overall execution time

# Performance Considerations

- **Memory Coalescing**
- **Shared Memory Bank Conflicts**
- **Control-Flow Divergence**
- **Occupancy**
- **Kernel Launch Overheads**

# MEMORY COALESCING

# Memory Coalescing

- **Off-chip memory is accessed in chunks**
  - Even if you read only a single word
  - If you don't use whole chunk, bandwidth is wasted
- **Chunks are aligned to multiples of 32/64/128 bytes**
  - Unaligned accesses will cost more

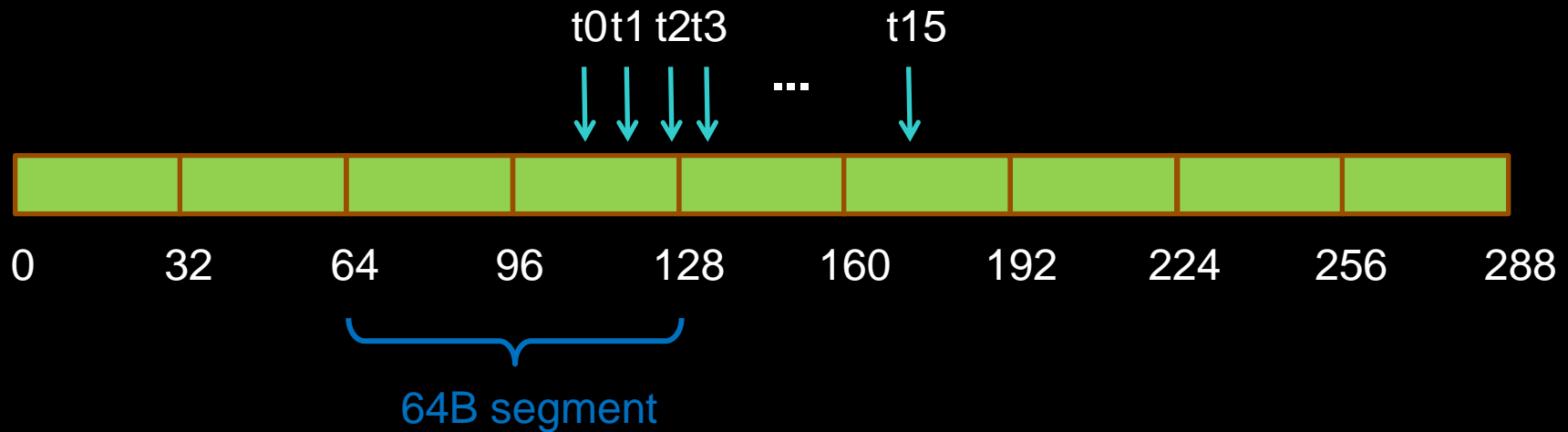
## Threads 0-15 access 4-byte words at addresses 116-176

- Thread 0 is lowest active, accesses address 116
- 128-byte segment: 0-127



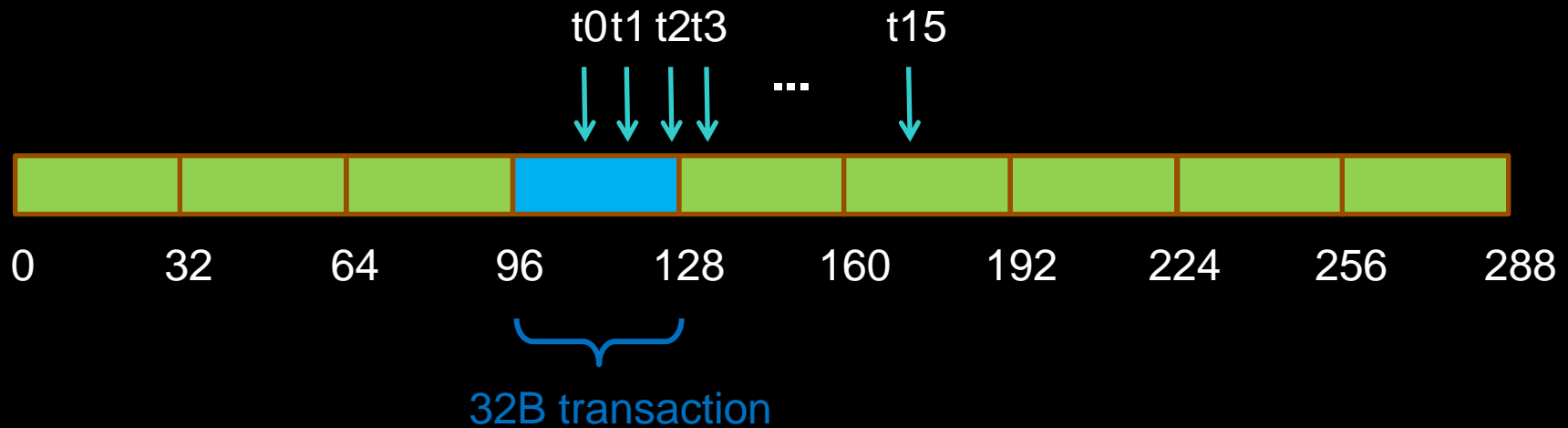
## Threads 0-15 access 4-byte words at addresses 116-176

- Thread 0 is lowest active, accesses address 116
- 128-byte segment: 0-127 (reduce to 64B)



## Threads 0-15 access 4-byte words at addresses 116-176

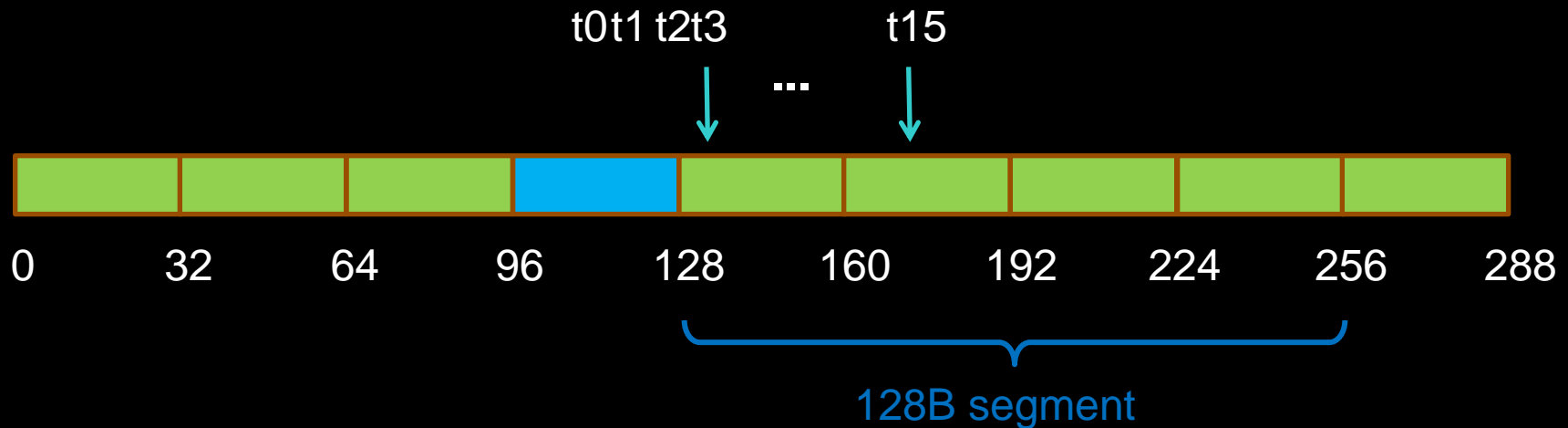
- Thread 0 is lowest active, accesses address 116
- 128-byte segment: 0-127 (reduce to 32B)





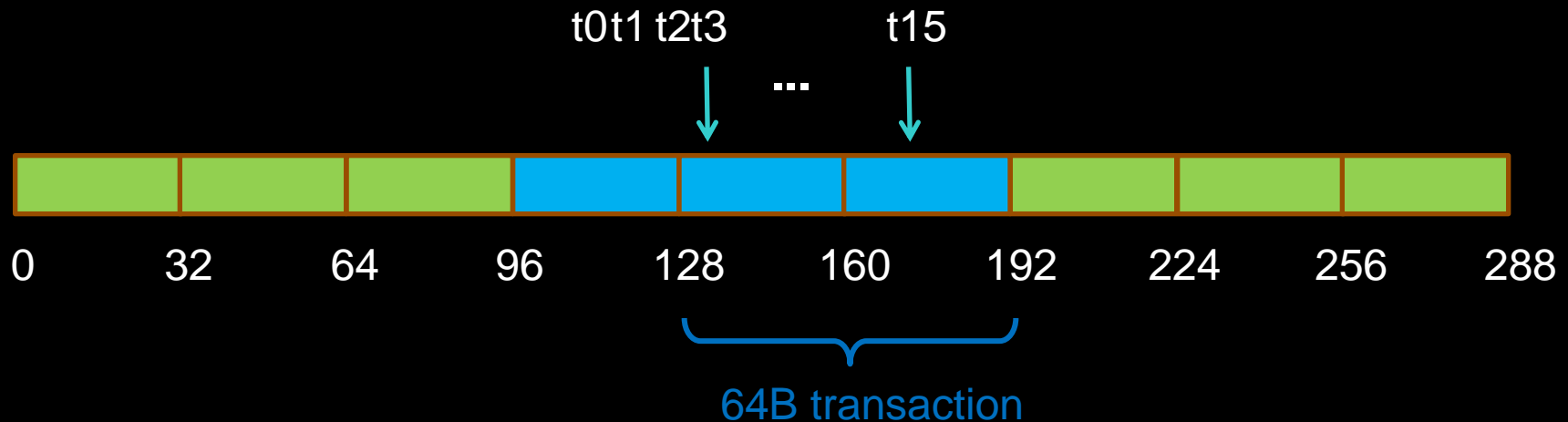
## Threads 0-15 access 4-byte words at addresses 116-176

- Thread 3 is lowest active, accesses address 128
- 128-byte segment: 128-255



## Threads 0-15 access 4-byte words at addresses 116-176

- Thread 3 is lowest active, accesses address 128
- 128-byte segment: 128-255 (reduce to 64B)



# Consider the stride of your accesses

```
__global__ void foo(int* input,
                    float3* input2)
{
    int i = blockDim.x * blockIdx.x
          + threadIdx.x;
    // Stride 1
    int a = input[i];
    // Stride 2, half the bandwidth is wasted
    int b = input[2*i];
    // Stride 3, 2/3 of the bandwidth wasted
    float c = input2[i].x;
}
```

## Example: Array of Structures (AoS)

```
struct record
```

```
{
```

```
    int key;
```

```
    int value;
```

```
    int flag;
```

```
};
```

```
record    *d_records;
```

```
cudaMalloc((void**) &d_records, ...);
```

# Example: Structure of Arrays (SoA)

```
struct SoA
```

```
{
```

```
    int * keys;
```

```
    int * values;
```

```
    int * flags;
```

```
};
```

```
SoA d_SoA_data;
```

```
cudaMalloc((void**) &d_SoA_data.keys, ...);
```

```
cudaMalloc((void**) &d_SoA_data.values, ...);
```

```
cudaMalloc((void**) &d_SoA_data.flags, ...);
```

## Example: SoA vs. AoS

```
__global__ void bar(record *AoS_data,  
                    SoA SoA_data)  
{  
    int i = blockDim.x * blockIdx.x  
        + threadIdx.x;  
    // AoS wastes bandwidth  
    int key = AoS_data[i].key;  
    // SoA efficient use of bandwidth  
    int key_better = SoA_data.keys[i];  
}
```

# Memory Coalescing

- **AoS is often better than SoA**
  - **Very clear win on regular, stride 1 access patterns**
  - **Unpredictable or irregular access patterns are case-by-case**

# SHARED MEMORY BANK CONFLICTS

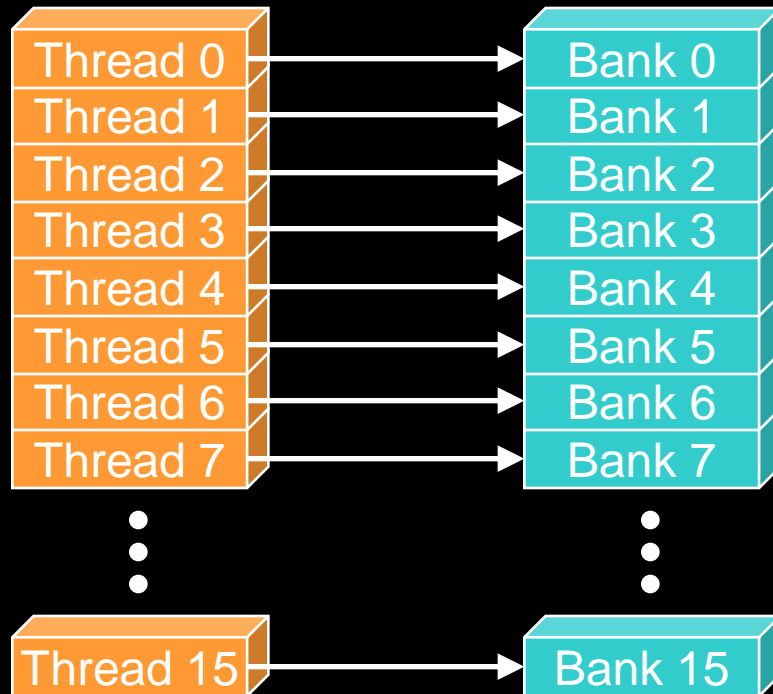


# Shared Memory

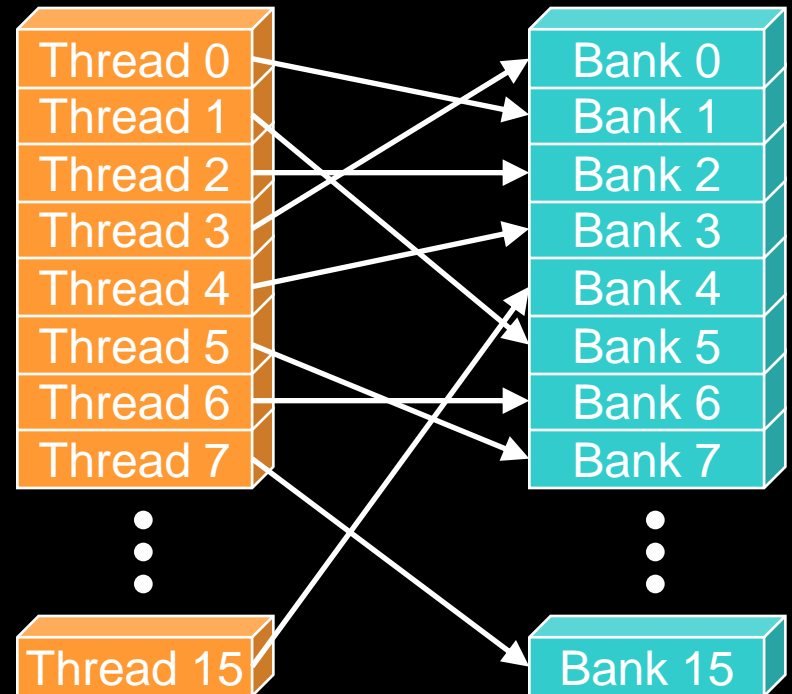
- **Shared memory is banked**
  - Only matters for threads within a warp
  - Full performance with some restrictions
  - Threads can each access different banks
  - Or can all access the same value
- **Consecutive words are in different banks**
- **If two or more threads access the same bank but different value, get bank conflicts**

# Bank Addressing Examples

## No Bank Conflicts

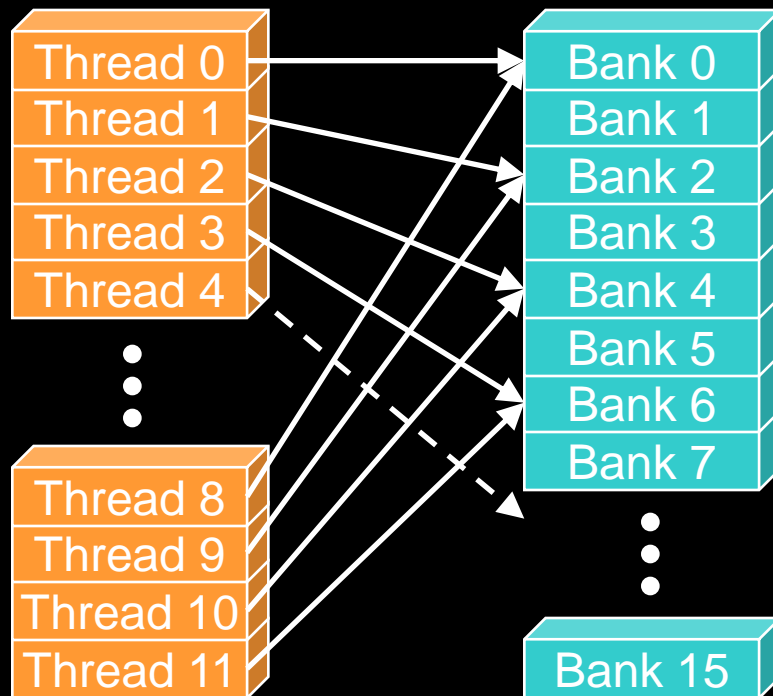


## No Bank Conflicts

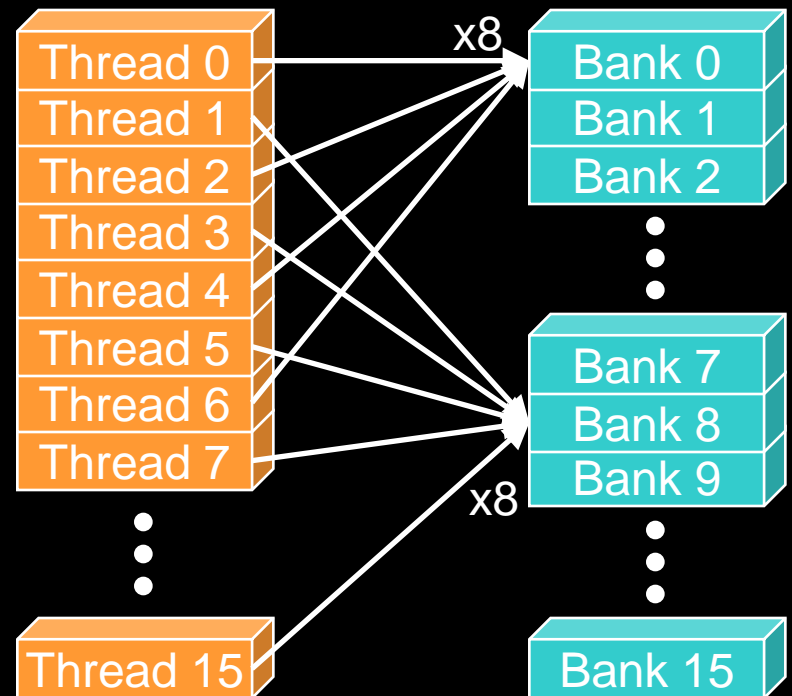


# Bank Addressing Examples

## 2-way Bank Conflicts



## 8-way Bank Conflicts



# Trick to Assess Impact On Performance

- **Change all SMEM reads to the same value**
  - All broadcasts = no conflicts
  - Will show how much performance could be improved by eliminating bank conflicts
- **The same doesn't work for SMEM writes**
  - So, replace SMEM array indices with `threadIdx.x`
  - Can also be done to the reads

# Additional “memories”

- **texture** and **\_\_constant\_\_**
- Read-only
- Data resides in global memory
- Different read path:
  - includes specialized caches

# Constant Memory

- Data stored in global memory, read through a constant-cache path
  - \_\_constant\_\_ qualifier in declarations
  - Can only be read by GPU kernels
  - Limited to **64KB**
- To be used when all threads in a warp read the same address
  - Serializes otherwise
- Throughput:
  - **32 bits** per warp per clock per multiprocessor

**CONTROL FLOW  
DIVERGENCE**

# Control Flow

- Instructions are issued per 32 threads (warp)
- Divergent branches:
  - Threads within a single warp take different paths
    - `if-else`, ...
  - Different execution paths within a warp are serialized
- Different warps can execute different code with no impact on performance



# Control Flow

- Avoid diverging within a warp

- Example with divergence:

```
if (threadIdx.x > 2) { ... }  
else { ... }
```

Branch granularity < warp size

- Example without divergence:

```
if (threadIdx.x / WARP_SIZE > 2)  
{ ... }  
else { ... }
```

Branch granularity is a whole multiple of warp size

# Example: Divergent Iteration

```
__global__ void per_thread_sum(int *indices,
                                float *data,
                                float *sums)
{
    ...
    // number of loop iterations is data
    // dependent
    for(int j=indices[i]; j<indices[i+1]; j++)
    {
        sum += data[j];
    }
    sums[i] = sum;
}
```

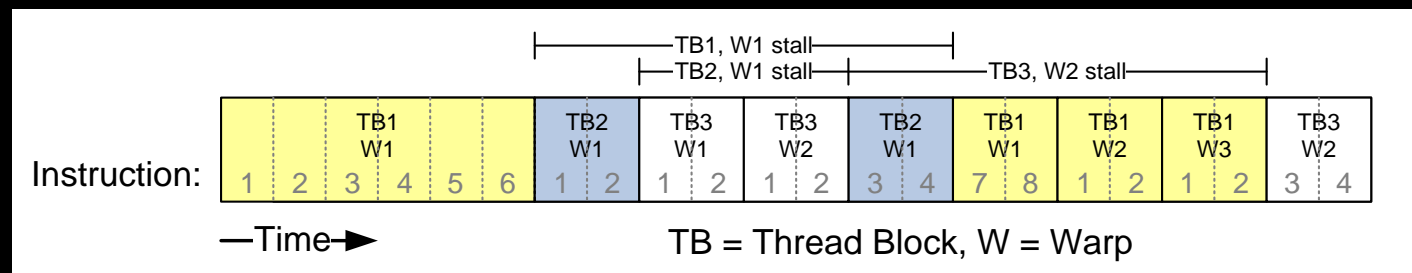
# Iteration Divergence

- A single thread can drag a whole warp with it for a long time
- Know your data patterns
- If data is unpredictable, try to flatten peaks by letting threads work on multiple data items

**OCCUPANCY**

# Reminder: Thread Scheduling

- SM implements zero-overhead warp scheduling
  - At any time, only one of the warps is executed by SM \*
  - Warps whose next instruction has its inputs ready for consumption are eligible for execution
  - Eligible Warps are selected for execution on a prioritized scheduling policy
  - All threads in a warp execute the same instruction when selected



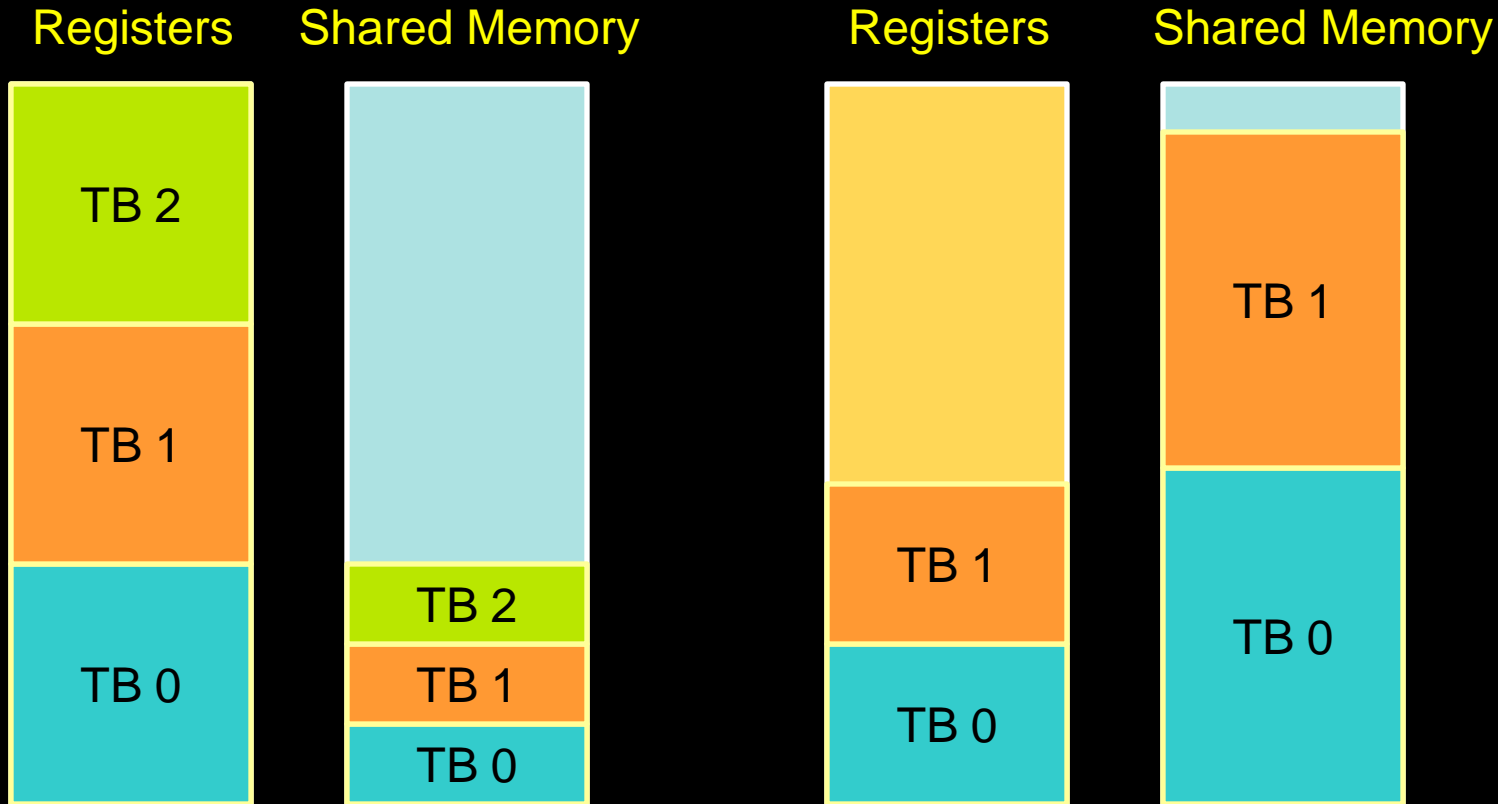
# Thread Scheduling

- **What happens if all warps are stalled?**
  - **No instruction issued → performance lost**
- **Most common reason for stalling?**
  - **Waiting on global memory**
- **If your code reads global memory every couple of instructions**
  - **You should try to maximize occupancy**

# What determines occupancy?

- **Register usage per thread & shared memory per thread block**

# Resource Limits (1)



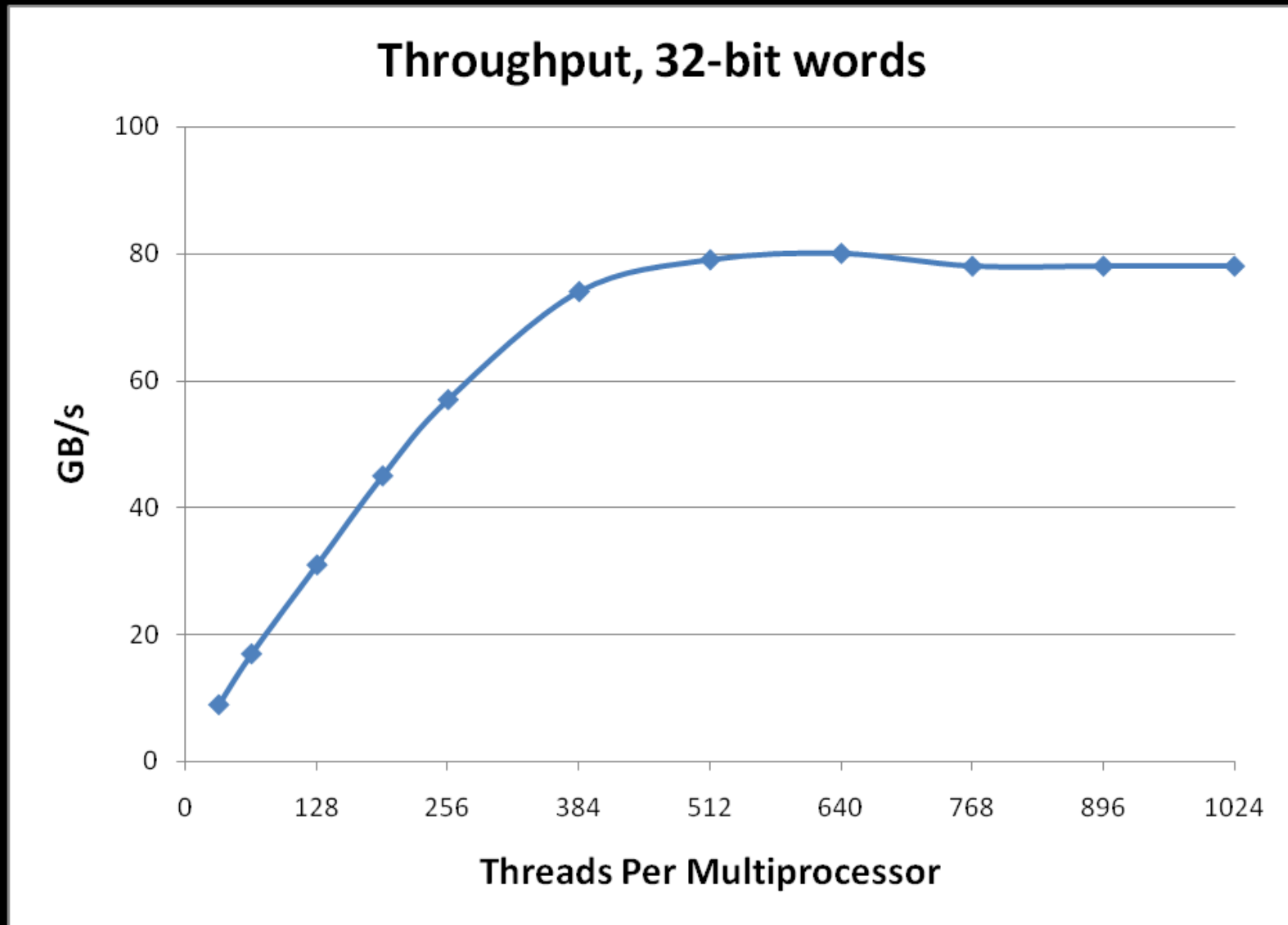
- **Pool of registers and shared memory per SM**
  - Each thread block grabs registers & shared memory
  - If one or the other is fully utilized -> no more thread blocks



## Resource Limits (2)

- **Can only have 8 thread blocks per SM**
  - If they're too small, can't fill up the SM
  - Need 128 threads / TB (gt200), 192 thread/ TB (gf100)
- **Higher occupancy has diminishing returns for hiding latency**

# Hiding Latency with more threads



# How do you know what you're using?

- Use `nvcc -Xptxas -v` to get register and shared memory usage
- Plug those numbers into CUDA Occupancy Calculator

The other data points represent the range of possible block sizes, register counts, and shared memory allocation.

1.) Select Compute Capability (click): 1.3 (Help)

2.) Enter your resource usage:

Threads Per Block 128 (Help)

Registers Per Thread 25

Shared Memory Per Block (bytes) 640

(Don't edit anything below this line)

3.) GPU Occupancy Data is displayed here and in the graphs: (Help)

Active Threads per Multiprocessor 512

Active Warps per Multiprocessor 16

Active Thread Blocks per Multiprocessor 4

Occupancy of each Multiprocessor 50%

Physical Limits for GPU Compute Capability: 1.3

Threads per Warp 32

Warps per Multiprocessor 32

Threads per Multiprocessor 1024

Thread Blocks per Multiprocessor 8

Total # of 32-bit registers per Multiprocessor 16384

Register allocation unit size 512

Register allocation granularity block

Shared Memory per Multiprocessor (bytes) 16384

Shared Memory Allocation unit size 512

Warp allocation granularity (for register allocation) 2

Allocation Per Thread Block

Warps 4

Registers 3584

Shared Memory 1024

These data are used in computing the occupancy data in blue

Maximum Thread Blocks Per Multiprocessor Blocks

Limited by Max Warps / Blocks per Multiprocessor 8

Limited by Registers per Multiprocessor 4

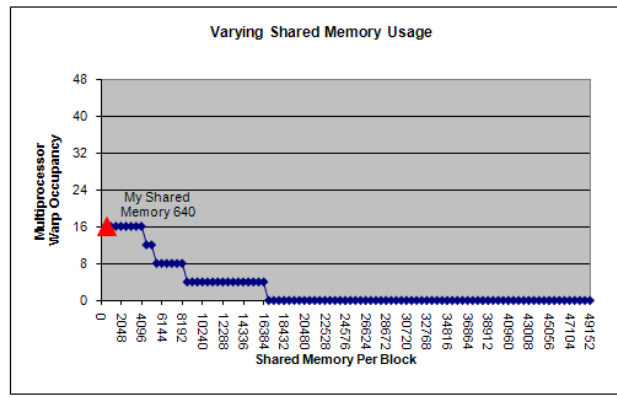
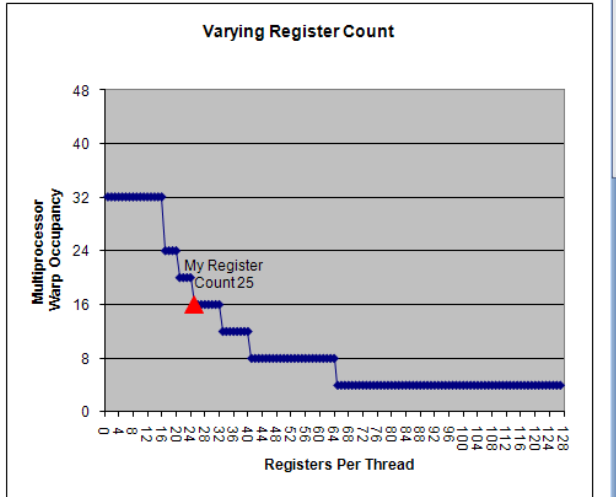
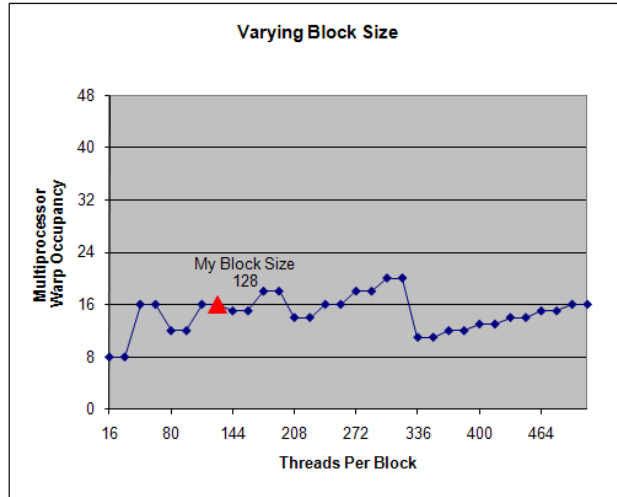
Limited by Shared Memory per Multiprocessor 16

Thread Block Limit Per Multiprocessor highlighted RED

CUDA Occupancy Calculator

Version: 2.0

Copyright and License



MySharedMemory

$f_x$

=5\*MyThreadCount

A

B

# CUDA GPU Occupancy Calculator

Just follow steps 1, 2, and 3 below! (or click here for help)

1.) Select Compute Capability (click):

1.3

2.) Enter your resource usage:

Threads Per Block

128

Registers Per Thread

25

Shared Memory Per Block (bytes)

640

(Don't edit anything below this line)

3.) GPU Occupancy Data is displayed here and in the graphs:

Calculator

Help

GPU Data

Copyright

Ready



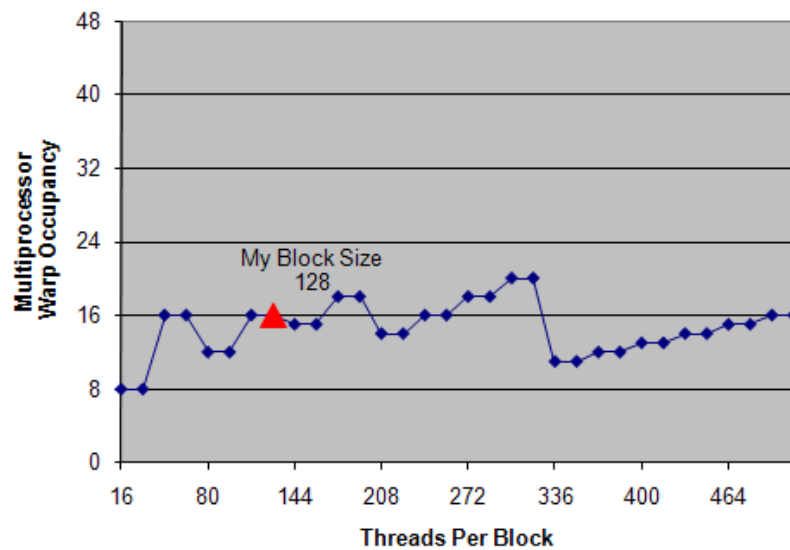
100%



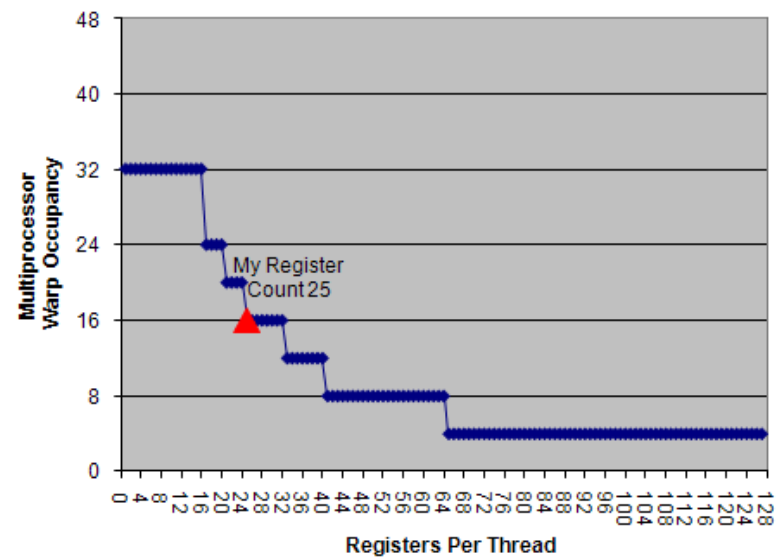
	A	B
14		
15	3.) GPU Occupancy Data is displayed here and in the graphs:	
16	Active Threads per Multiprocessor	512
17	Active Warps per Multiprocessor	16
18	Active Thread Blocks per Multiprocessor	4
19	Occupancy of each Multiprocessor	50%
20		
21		
22	Physical Limits for GPU Compute Capability:	1.3
23	Threads per Warp	32
24	Warps per Multiprocessor	32
25	Threads per Multiprocessor	1024
26	Thread Blocks per Multiprocessor	8
27	Total # of 32-bit registers per Multiprocessor	16384
28	Register allocation unit size	512
29	Register allocation granularity	block
30	Shared Memory per Multiprocessor (bytes)	16384
31	Shared Memory Allocation unit size	512
32	Warp allocation granularity (for register allocation)	2
33		
34	Allocation Per Thread Block	
35	Warps	4
36	Registers	3584
37	Shared Memory	1024
38	These data are used in computing the occupancy data in blue	
39		
40	Maximum Thread Blocks Per Multiprocessor	Blocks
41	Limited by Max Warps / Blocks per Multiprocessor	8
42	Limited by Registers per Multiprocessor	4
43	Limited by Shared Memory per Multiprocessor	16
44	Thread Block Limit Per Multiprocessor highlighted	RED

The other data points represent the range of possible block sizes, register counts, and shared memory allocation.

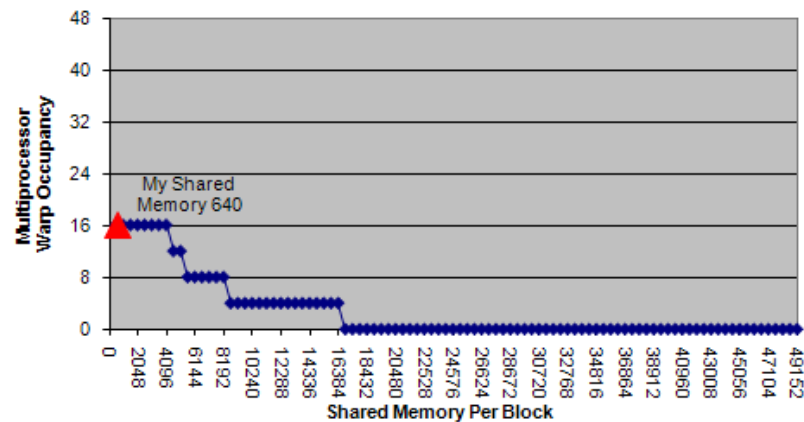
### Varying Block Size



### Varying Register Count



### Varying Shared Memory Usage



# How to influence how many registers you use

- Pass option `-maxrregcount=X` to nvcc
- This isn't magic, won't get occupancy for free
- Use this very carefully when you are right on the edge



# KERNEL LAUNCH OVERHEAD

# Kernel Launch Overhead

- **Kernel launches aren't free**
  - A null kernel launch will take non-trivial time
  - Actual number changes with HW generations and driver software, so I can't give you one number
- **Independent kernel launches are cheaper than dependent kernel launches**
  - Dependent launch: Some readback to the cpu
- **If you are launching lots of small grids you will lose substantial performance due to this effect**

# Kernel Launch Overheads

- If you are reading back data to the cpu for control decisions, consider doing it on the GPU
- Even though the GPU is slow at serial tasks, can do surprising amounts of work before you used up kernel launch overhead

# Performance Considerations

- **Measure, measure, then measure some more!**
- **Once you identify bottlenecks, apply judicious tuning**
  - **What is most important depends on your program**
  - **You'll often have a series of bottlenecks, where each optimization gives a smaller boost than expected**

**Questions?**

# Backup

# Shared Memory

- **Uses:**
  - Inter-thread communication within a block
  - Cache data to reduce global memory accesses
  - Use it to avoid non-coalesced access
- **Organization:**
  - 16 banks, 32-bit wide banks (Tesla)
  - 32 banks, 32-bit wide banks (Fermi)
  - Successive 32-bit words belong to different banks
- **Performance:**
  - 32 bits per bank per 2 clocks per multiprocessor
  - smem accesses are per 16-threads (half-warp)
  - **serialization:** if  $n$  threads (out of 16) access the same bank,  $n$  accesses are executed serially
  - **broadcast:**  $n$  threads access the same word in one fetch

# Example: Averaging Peaks

```
__global__ void per_thread_sum(...)
{
    while(!done)
    {
        for(int j=indices[i];
            j<min(indices[i+1],indices[i]+MAX_ITER);
            j++)
        { ... }
    }
}
```