

# Analysis Report

## two\_shareMemKernel(float\*, int)

Duration	84.19458 ms (84,194,582 ns)
Grid Size	[ 2097152,1,1 ]
Block Size	[ 256,1,1 ]
Registers/Thread	13
Shared Memory/Block	1 KiB
Shared Memory Executed	8 KiB
Shared Memory Bank Size	4 B

### [0] Quadro P4000

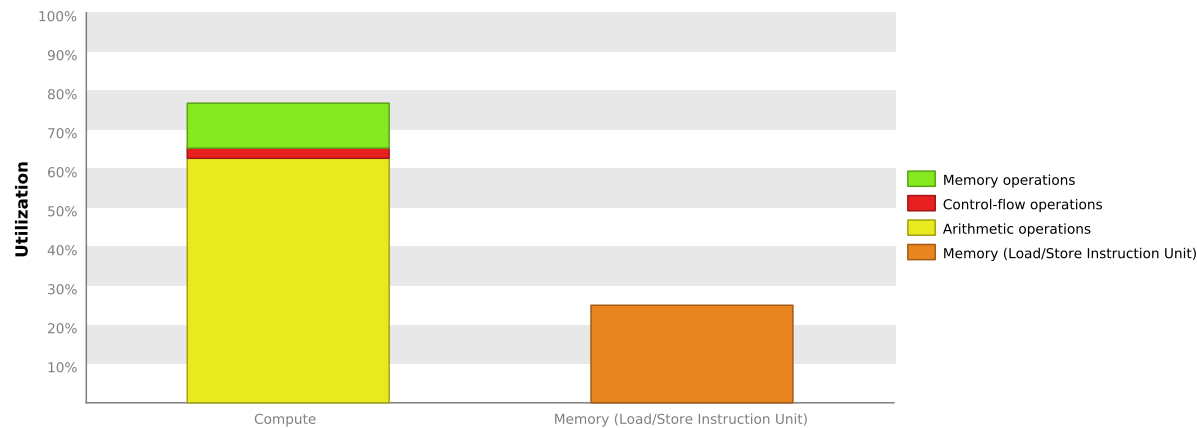
GPU UUID	GPU-55bcc7c2-f527-bf35-99ec-b54f8392185d
Compute Capability	6.1
Max. Threads per Block	1024
Max. Threads per Multiprocessor	2048
Max. Shared Memory per Block	48 KiB
Max. Shared Memory per Multiprocessor	96 KiB
Max. Registers per Block	65536
Max. Registers per Multiprocessor	65536
Max. Grid Dimensions	[ 2147483647, 65535, 65535 ]
Max. Block Dimensions	[ 1024, 1024, 64 ]
Max. Warps per Multiprocessor	64
Max. Blocks per Multiprocessor	32
Half Precision FLOP/s	41.44 GigaFLOP/s
Single Precision FLOP/s	5.304 TeraFLOP/s
Double Precision FLOP/s	165.76 GigaFLOP/s
Number of Multiprocessors	14
Multiprocessor Clock Rate	1.48 GHz
Concurrent Kernel	true
Max IPC	6
Threads per Warp	32
Global Memory Bandwidth	243.328 GB/s
Global Memory Size	7.929 GiB
Constant Memory Size	64 KiB
L2 Cache Size	2 MiB
Memcpy Engines	2
PCIe Generation	3
PCIe Link Rate	8 Gbit/s
PCIe Link Width	16

# 1. Compute, Bandwidth, or Latency Bound

The first step in analyzing an individual kernel is to determine if the performance of the kernel is bounded by computation, memory bandwidth, or instruction/memory latency. The results below indicate that the performance of kernel "two\_shareMemKernel" is most likely limited by compute. You should first examine the information in the "Compute Resources" section to determine how it is limiting performance.

## 1.1. Kernel Performance Is Bound By Compute

For device "Quadro P4000" the kernel's memory utilization is significantly lower than its compute utilization. These utilization levels indicate that the performance of the kernel is most likely being limited by computation on the SMs.



## 2. Compute Resources

GPU compute resources limit the performance of a kernel when those resources are insufficient or poorly utilized. Compute resources are used most efficiently when all threads in a warp have the same branching and predication behavior. The results below indicate that a significant fraction of the available compute performance is being wasted because branch and predication behavior is differing for threads within a warp.

### 2.1. Divergent Branches

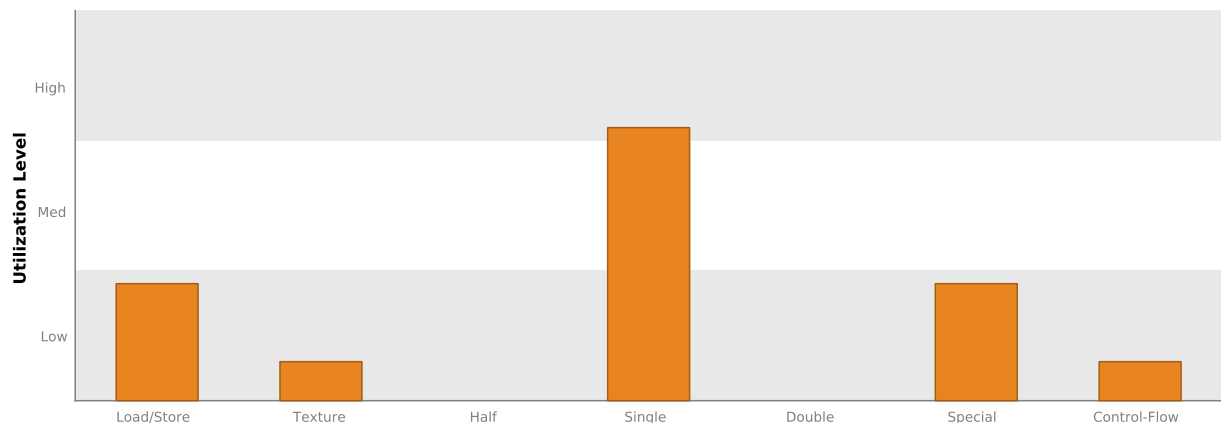
Compute resource are used most efficiently when all threads in a warp have the same branching behavior. When this does not occur the branch is said to be divergent. Divergent branches lower warp execution efficiency which leads to inefficient use of the GPU's compute resources.

*Optimization: Each entry below points to a divergent branch within the kernel. For each branch reduce the amount of intra-warp divergence.*

### 2.2. Function Unit Utilization

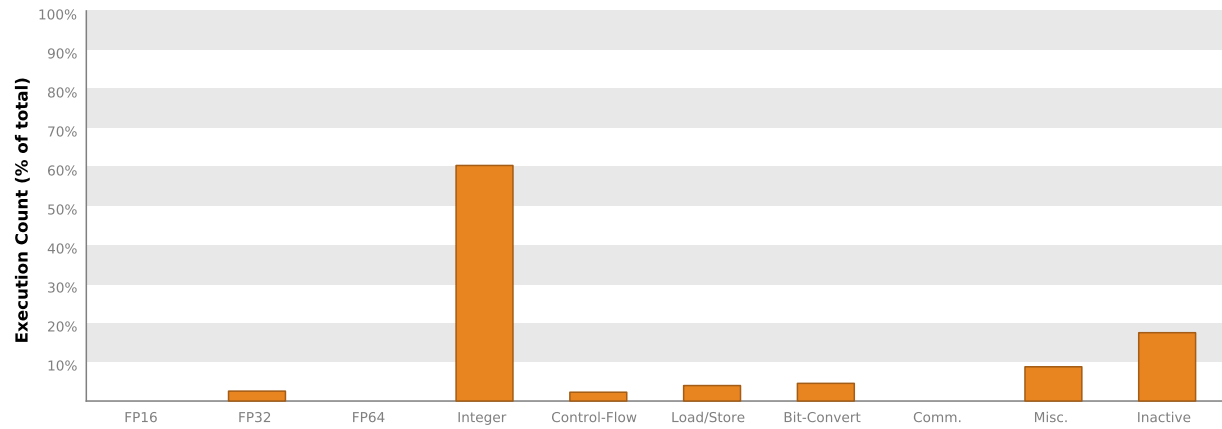
Different types of instructions are executed on different function units within each SM. Performance can be limited if a function unit is over-used by the instructions executed by the kernel. The following results show that the kernel's performance is not limited by overuse of any function unit.

- Load/Store - Load and store instructions for shared and constant memory.
- Texture - Load and store instructions for local, global, and texture memory.
- Half - Half-precision floating-point arithmetic instructions.
- Single - Single-precision integer and floating-point arithmetic instructions.
- Double - Double-precision floating-point arithmetic instructions.
- Special - Special arithmetic instructions such as sin, cos, popc, etc.
- Control-Flow - Direct and indirect branches, jumps, and calls.



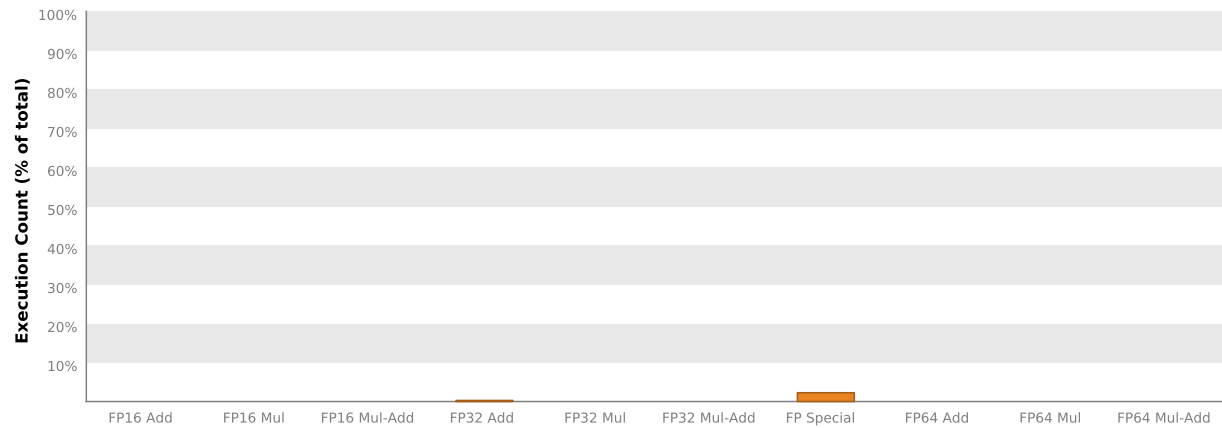
### 2.3. Instruction Execution Counts

The following chart shows the mix of instructions executed by the kernel. The instructions are grouped into classes and for each class the chart shows the percentage of thread execution cycles that were devoted to executing instructions in that class. The "Inactive" result shows the thread executions that did not execute any instruction because the thread was predicated or inactive due to divergence.



## 2.4. Floating-Point Operation Counts

The following chart shows the mix of floating-point operations executed by the kernel. The operations are grouped into classes and for each class the chart shows the percentage of thread execution cycles that were devoted to executing operations in that class. The results do not sum to 100% because non-floating-point operations executed by the kernel are not shown in this chart.



### 3. Memory Bandwidth

Memory bandwidth limits the performance of a kernel when one or more memories in the GPU cannot provide data at the rate requested by the kernel.

#### 3.1. Memory Bandwidth And Utilization

The following table shows the memory bandwidth used by this kernel for the various types of memory on the device. The table also shows the utilization of each memory type relative to the maximum throughput supported by the memory.

Transactions	Bandwidth	Utilization	
Shared Memory			
Shared Loads	199229440	335.164 GB/s	<div><div></div></div> <div>IdleLowMediumHighMax</div>
Shared Stores	115343360	194.042 GB/s	
Shared Total	314572800	529.206 GB/s	
L2 Cache			
Reads	67113555	28.226 GB/s	<div><div></div></div> <div>IdleLowMediumHighMax</div>
Writes	2097293	882.07 MB/s	
Total	69210848	29.108 GB/s	
Unified Cache			
Local Loads	0	0 B/s	<div><div></div></div> <div>IdleLowMediumHighMax</div>
Local Stores	0	0 B/s	
Global Loads	268435458	28.224 GB/s	
Global Stores	2097152	882.01 MB/s	
Texture Reads	67108864	28.224 GB/s	
Unified Total	337641474	57.331 GB/s	
Device Memory			
Reads	67111389	28.225 GB/s	<div><div></div></div> <div>IdleLowMediumHighMax</div>
Writes	289363	121.699 MB/s	
Total	67400752	28.347 GB/s	
System Memory			
[ PCIe configuration: Gen3 x16, 8 Gbit/s ]			
Reads	0	0 B/s	<div><div></div></div> <div>IdleLowMediumHighMax</div>
Writes	5	2.102 kB/s	<div><div></div></div> <div>IdleLowMediumHighMax</div>

#### 3.2. Memory Statistics

The following chart shows a summary view of the memory hierarchy of the CUDA programming model. The green nodes in the diagram depict logical memory space whereas blue nodes depicts actual hardware unit on the chip. For the various caches the reported percentage number states the cache hit rate; that is the ratio of requests that could be served with data locally available to the cache over all requests made.

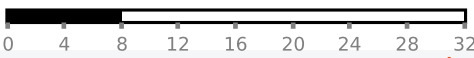


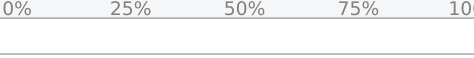






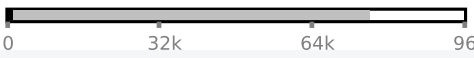

The links between the nodes in the diagram depict the data paths between the SMs to the memory spaces into the memory system. Different metrics are shown per data path. The data paths from the SMs to the memory spaces report the total number of memory instructions executed, it includes both read and write operations. The data path between memory spaces and "Unified Cache" or "Shared Memory" reports the total amount of memory requests made (read or write). All other data paths report the total amount of transferred memory in bytes.

## 4. Instruction and Memory Latency

Instruction and memory latency limit the performance of a kernel when the GPU does not have enough work to keep busy. The performance of latency-limited kernels can often be improved by increasing occupancy. Occupancy is a measure of how many warps the kernel has active on the GPU, relative to the maximum number of warps supported by the GPU. Theoretical occupancy provides an upper bound while achieved occupancy indicates the kernel's actual occupancy.

### 4.1. Occupancy Is Not Limiting Kernel Performance

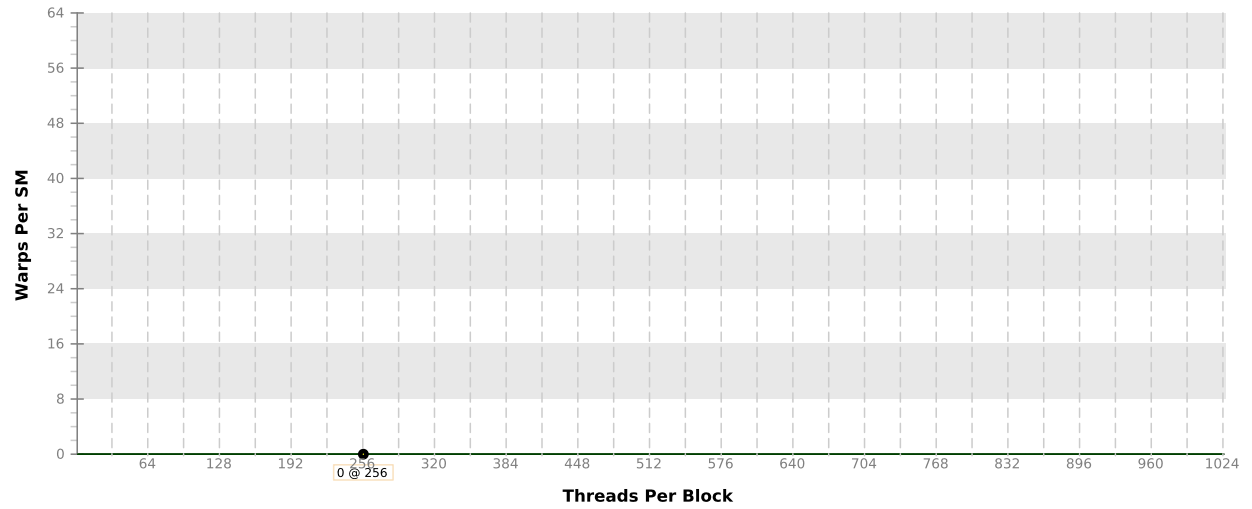
The kernel's block size, register usage, and shared memory usage allow it to fully utilize all warps on the GPU.

Variable	Achieved	Theoretical	Device Limit	Grid Size: [ 2097152,1,1 ] (2097152 blocks) Block Size:
Occupancy Per SM				
Active Blocks		8	32	
Active Warps	61.57	64	64	
Active Threads		2048	2048	
Occupancy	96.2%	100%	100%	
Warps				
Threads/Block		256	1024	
Warps/Block		8	32	
Block Limit		8	32	
Registers				
Registers/Thread		13	255	
Registers/Block		4096	65536	
Block Limit		16	32	
Shared Memory				
Shared Memory/Block		1024	98304	
Block Limit		76	32	

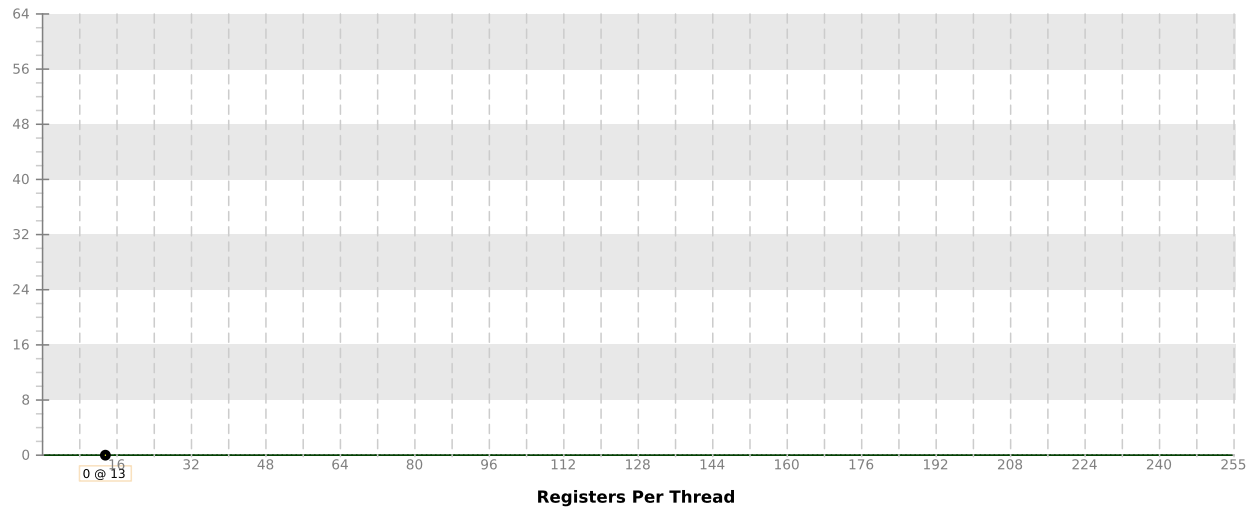
### 4.2. Occupancy Charts

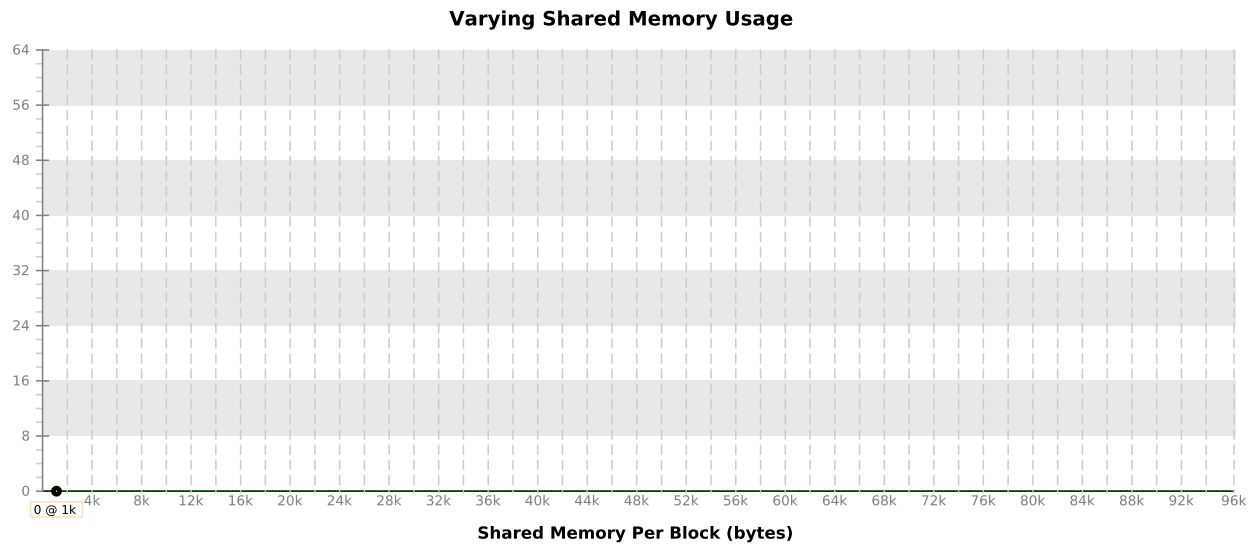
The following charts show how varying different components of the kernel will impact theoretical occupancy.

**Varying Block Size**



**Varying Register Count**





### 4.3. Multiprocessor Utilization

The kernel's blocks are distributed across the GPU's multiprocessors for execution. Depending on the number of blocks and the execution duration of each block some multiprocessors may be more highly utilized than others during execution of the kernel. The following chart shows the utilization of each multiprocessor during execution of the kernel.

