

# Analysis Report

**void computeROIwarpReadOnly<float, int=64, int=7, int=15>(float const \*, float\*, float const \*, float, unsigned int, unsigned int)**

Duration	102.114 µs
Grid Size	[ 104,1,1 ]
Block Size	[ 256,1,1 ]
Registers/Thread	32
Shared Memory/Block	0 B
Shared Memory Requested	96 KiB
Shared Memory Executed	96 KiB
Shared Memory Bank Size	4 B

## [0] GeForce GTX 960

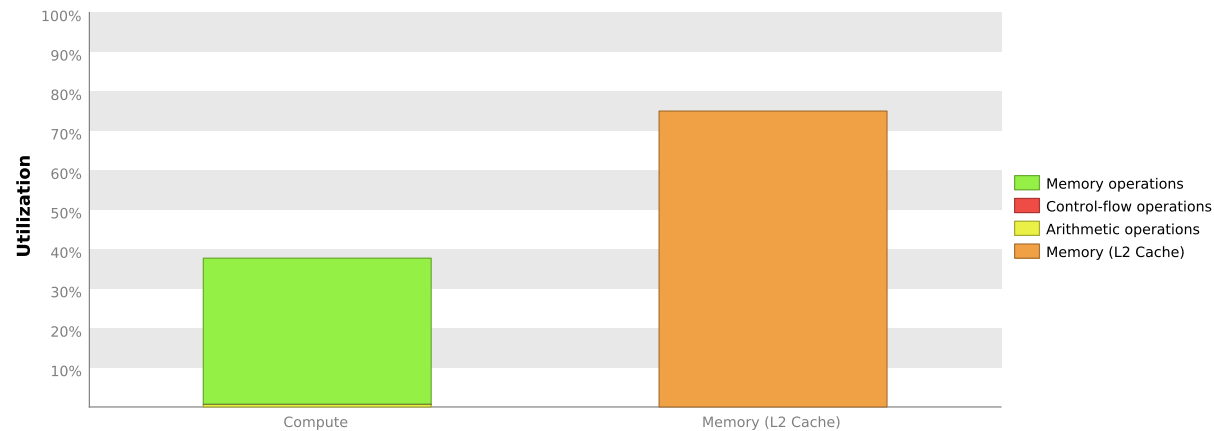
GPU UUID	GPU-0db32734-f94e-48a7-8b5d-4604317dc554
Compute Capability	5.2
Max. Threads per Block	1024
Max. Shared Memory per Block	48 KiB
Max. Registers per Block	65536
Max. Grid Dimensions	[ 2147483647, 65535, 65535 ]
Max. Block Dimensions	[ 1024, 1024, 64 ]
Max. Warps per Multiprocessor	64
Max. Blocks per Multiprocessor	32
Single Precision FLOP/s	2.644 TeraFLOP/s
Double Precision FLOP/s	82.624 GigaFLOP/s
Number of Multiprocessors	8
Multiprocessor Clock Rate	1.291 GHz
Concurrent Kernel	true
Max IPC	6
Threads per Warp	32
Global Memory Bandwidth	112.16 GB/s
Global Memory Size	4 GiB
Constant Memory Size	64 KiB
L2 Cache Size	1 MiB
Memcpy Engines	2
PCIe Generation	2
PCIe Link Rate	5 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 "void computeROIwarpReadOnly..." is most likely limited by memory bandwidth. You should first examine the information in the "Memory Bandwidth" section to determine how it is limiting performance.

## 1.1. Kernel Performance Is Bound By Memory Bandwidth

For device "GeForce GTX 960" the kernel's compute utilization is significantly lower than its memory utilization. These utilization levels indicate that the performance of the kernel is most likely being limited by the memory system. For this kernel the limiting factor in the memory system is the bandwidth of the L2 Cache memory.



## 2. 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. The results below indicate that the kernel is limited by the bandwidth available to the L2 cache.

### 2.1. GPU Utilization Is Limited By Memory Bandwidth

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. The results show that the kernel's performance is potentially limited by the bandwidth available from one or more of the memories on the device.

*Optimization: Try the following optimizations for the memory with high bandwidth utilization.*

*Shared Memory - If possible use 64-bit accesses to shared memory and 8-byte bank mode to achieved 2x throughput.*

*L2 Cache - Align and block kernel data to maximize L2 cache efficiency.*

*Unified Cache - Reallocate texture data to shared or global memory. Resolve alignment and access pattern issues for global loads and stores.*

*Device Memory - Resolve alignment and access pattern issues for global loads and stores.*

*System Memory (via PCIe) - Make sure performance critical data is placed in device or shared memory.*

Transactions	Bandwidth	Utilization	
Shared Memory			
Shared Loads	0	0 B/s	
Shared Stores	0	0 B/s	
Shared Total	0	0 B/s	
L2 Cache			
Reads	738267	228.093 GB/s	
Writes	836	258.289 MB/s	
Total	739103	228.352 GB/s	
Unified Cache			
Local Loads	0	0 B/s	
Local Stores	0	0 B/s	
Global Loads	2788800	646.216 GB/s	
Global Stores	830	256.435 MB/s	
Texture Reads	1394400	430.811 GB/s	
Unified Total	4184030	1,077.283 GB/s	
Device Memory			
Reads	13179	4.072 GB/s	
Writes	6288	1.943 GB/s	
Total	19467	6.014 GB/s	
System Memory			
[ PCIe configuration: Gen2 x16, 5 Gbit/s ]			
Reads	0	0 B/s	
Writes	5	1.545 MB/s	

### 3. 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 results below indicate that the GPU does not have enough work because instruction execution is stalling excessively.

#### 3.1. Kernel Profile - PC Sampling

The Kernel Profile - PC Sampling gives the number of samples for each source and assembly line with various stall reasons. Using this information you can pinpoint portions of your kernel that are introducing latencies and the reason for the latency. Samples are taken in round robin order for all active warps at a fixed number of cycles regardless of whether the warp is issuing an instruction or not.

Instruction Issued - Warp was issued

Instruction Fetch - The next assembly instruction has not yet been fetched.

Execution Dependency - An input required by the instruction is not yet available. Execution dependency stalls can potentially be reduced by increasing instruction-level parallelism.

Memory Dependency - A load/store cannot be made because the required resources are not available or are fully utilized, or too many requests of a given type are outstanding. Data request stalls can potentially be reduced by optimizing memory alignment and access patterns.

Texture - The texture sub-system is fully utilized or has too many outstanding requests.

Synchronization - The warp is blocked at a `__syncthreads()` call.

Constant - A constant load is blocked due to a miss in the constants cache.

Pipe Busy - The compute resource(s) required by the instruction is not yet available.

Memory Throttle - Large number of pending memory operations prevent further forward progress. These can be reduced by combining several memory transactions into one.

Not Selected - Warp was ready to issue, but some other warp issued instead. You may be able to sacrifice occupancy without impacting latency hiding and doing so may help improve cache hit rates.

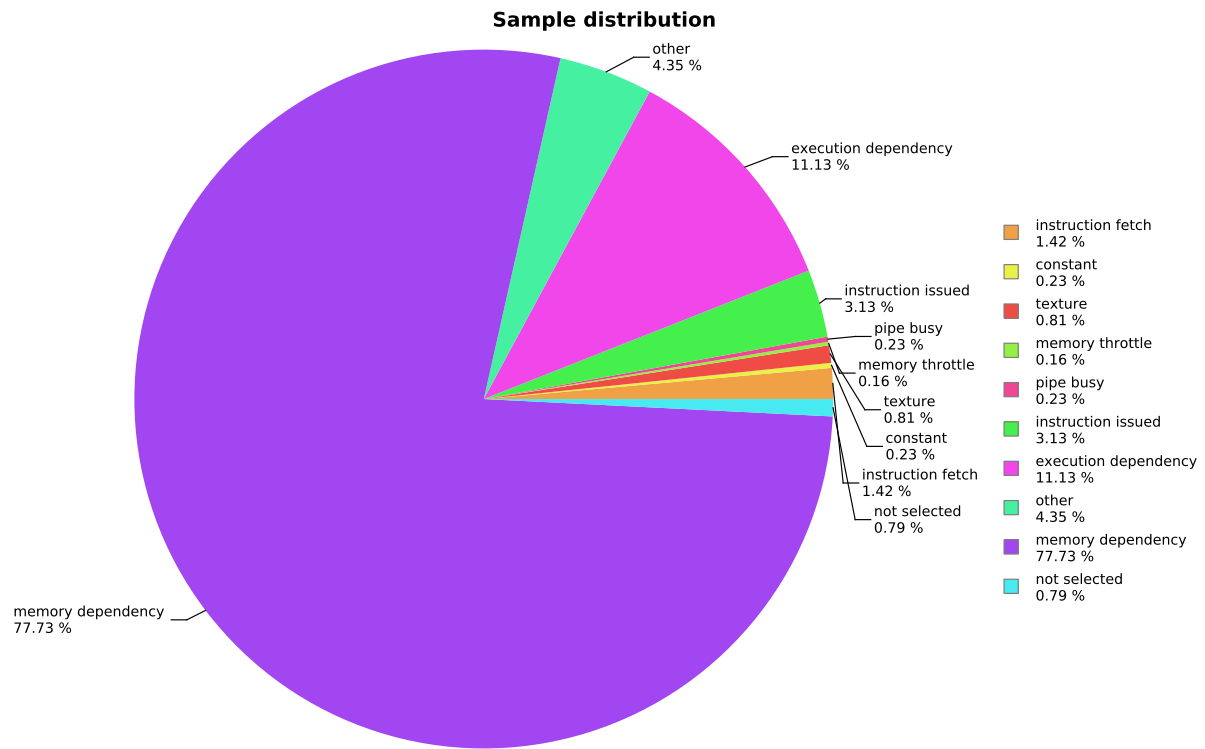
Other - The warp is blocked for a uncommon reason.

*Examine portions of the kernel that have high number of samples to know where the maximum time was spent and observe the latency reasons for those samples to identify optimization opportunities.*

Cuda Functions	Sample Count	% of Kernel Samples
void computeROIwarpReadOnly<float, int=64, int=7, int=15>(float const *, float*, float const *, float, unsigned int, unsigned int)	7311	100.0

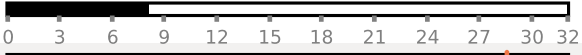


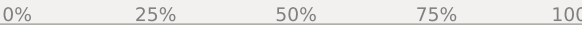


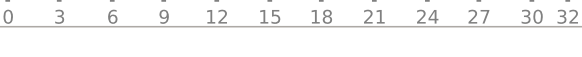


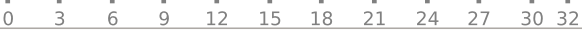

#### Source Files :

/home/adas/cuda-workspace/CudaVisionSysDeploy/Release/./src/init/./device/SVM/SVMclassification.h
/usr/local/cuda-7.5/bin/./targets/x86_64-linux/include/sm_32_intrinsics.hpp
/usr/local/cuda-7.5/bin/./targets/x86_64-linux/include/sm_30_intrinsics.hpp
/home/adas/cuda-workspace/CudaVisionSysDeploy/Release/./src/init/./device/ImageProcessing/resize.cuh



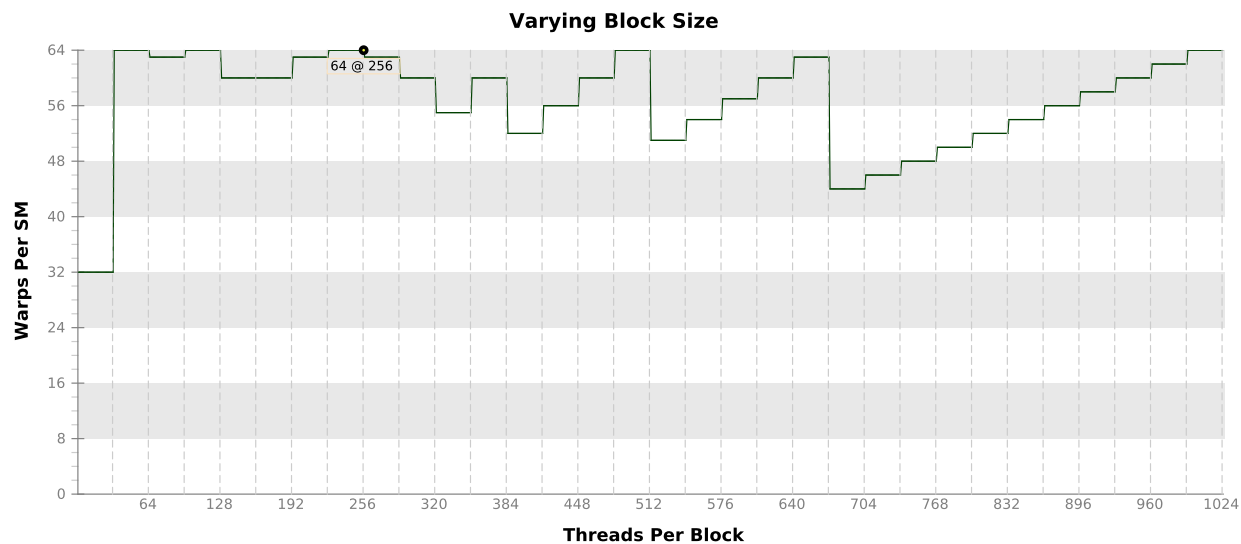
### 3.2. Occupancy Is Not Limiting Kernel Performance

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

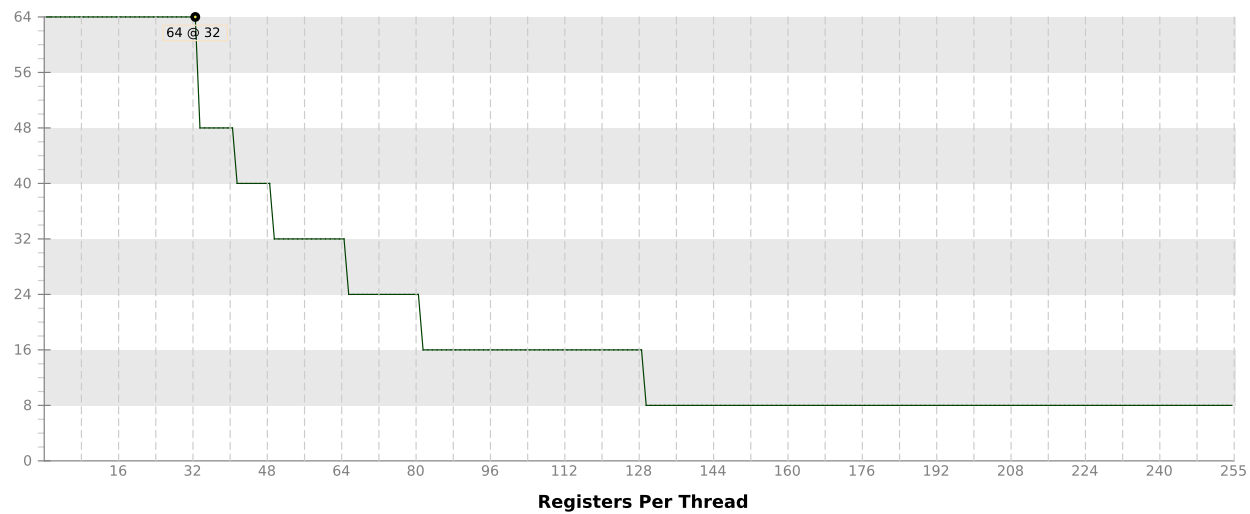
Variable	Achieved	Theoretical	Device Limit	Grid Size: [ 104,1,1 ] (104 blocks) Block Size: [ 256,1,1 ] (256 threads)
Occupancy Per SM				
Active Blocks		8	32	
Active Warps	56.82	64	64	
Active Threads		2048	2048	
Occupancy	88.8%	100%	100%	
Warps				
Threads/Block		256	1024	
Warps/Block		8	32	
Block Limit		8	32	
Registers				
Registers/Thread		32	255	
Registers/Block		8192	65536	
Block Limit		8	32	
Shared Memory				
Shared Memory/Block		0	98304	
Block Limit			32	

### 3.3. Occupancy Charts

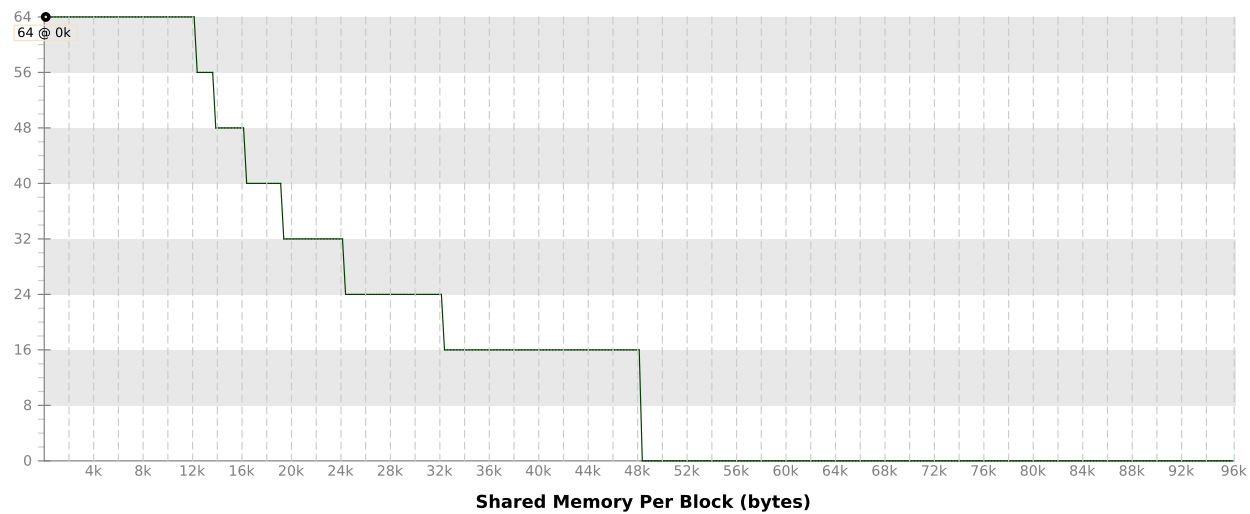
The following charts show how varying different components of the kernel will impact theoretical occupancy.



Varying Register Count



Varying Shared Memory Usage



## 4. 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.

### 4.1. Kernel Profile - Instruction Execution

The Kernel Profile - Instruction Execution shows the execution count, inactive threads, and predicated threads for each source and assembly line of the kernel. Using this information you can pinpoint portions of your kernel that are making inefficient use of compute resource due to divergence and predication.

*Examine portions of the kernel that have high execution counts and inactive or predicated threads to identify optimization opportunities.*

Cuda Functions :

```
void computeROIwarpReadOnly<float, int=64, int=7, int=15>(float const *, float*, float const *, float, unsigned int, unsigned int)
```

Maximum instruction execution count in assembly: 832

Average instruction execution count in assembly: 828

Instructions executed for the kernel: 1729788

Thread instructions executed for the kernel: 55121646

Non-predicated thread instructions executed for the kernel: 54962862

Warp non-predicated execution efficiency of the kernel: 99.3%

Warp execution efficiency of the kernel: 99.6%

Source files :

```
/home/adas/cuda-workspace/CudaVisionSysDeploy/Release/./src/init/./device/SVM/SVMclassification.h
/usr/local/cuda-7.5/bin/./targets/x86_64-linux/include/sm_32_intrinsics.hpp
/usr/local/cuda-7.5/bin/./targets/x86_64-linux/include/sm_30_intrinsics.hpp
/home/adas/cuda-workspace/CudaVisionSysDeploy/Release/./src/init/./device/ImageProcessing/resize.cuh
```

### 4.2. 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.*

**/home/adas/cuda-workspace/CudaVisionSysDeploy/Release/./src/init/./device/SVM/SVMclassification.h**

Line 42	Divergence = 100% [ 830 divergent executions out of 830 total executions ]
---------	--

### 4.3. 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.

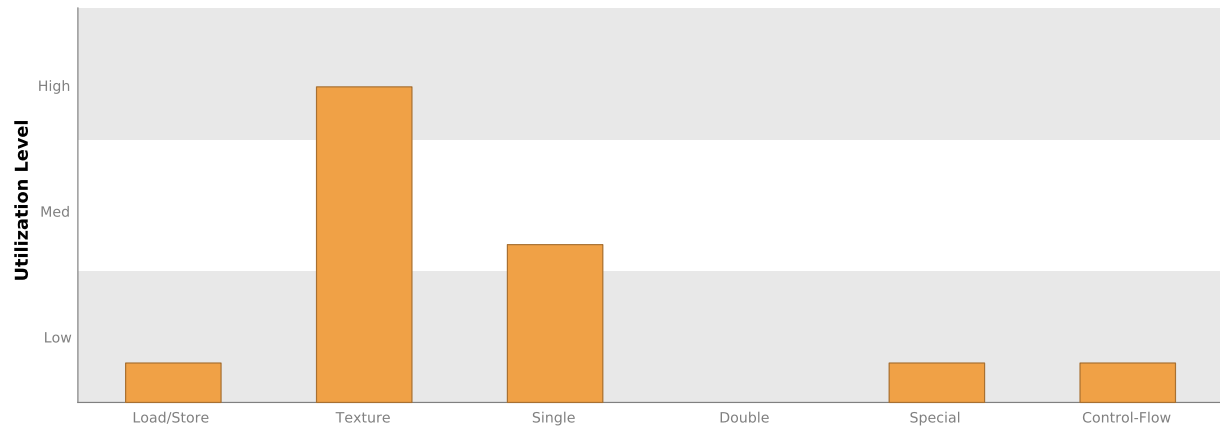
Single - Single-precision integer and floating-point arithmetic instructions.

Double - Double-precision floating-point arithmetic instructions.

Special - Special arithmetic instructions such as sin, cos, popc, etc.

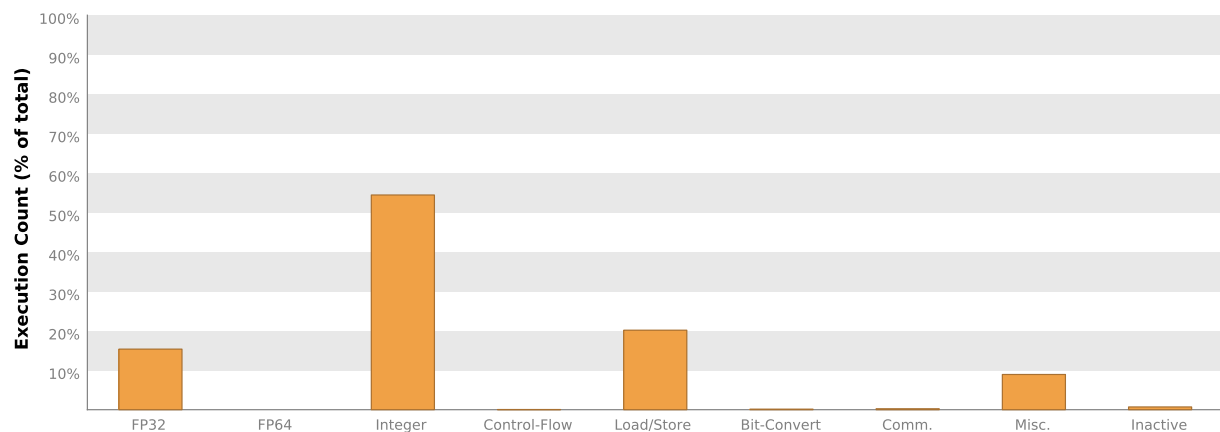
Control-Flow - Direct and indirect branches, jumps, and calls.





#### 4.4. 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.



#### 4.5. 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.

