

# Parallel Computing with GPUs

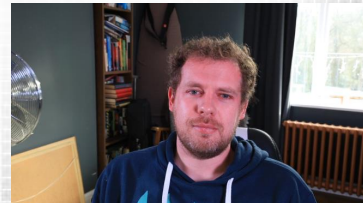
## Performance

### Part 1 – Memory Coalescing



Dr Paul Richmond

<http://paulrichmond.shef.ac.uk/teaching/COM4521/>



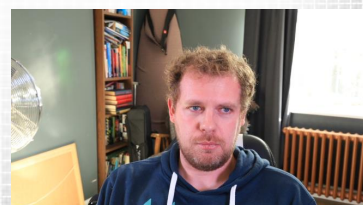
#### This Lecture (learning objectives)

- ❑ Memory Coalescing
  - ❑ Explain the process of memory moving via cache lines
  - ❑ Analyse the performance implications of strided access patterns
  - ❑ Classify use cases of memory access with respect to performance

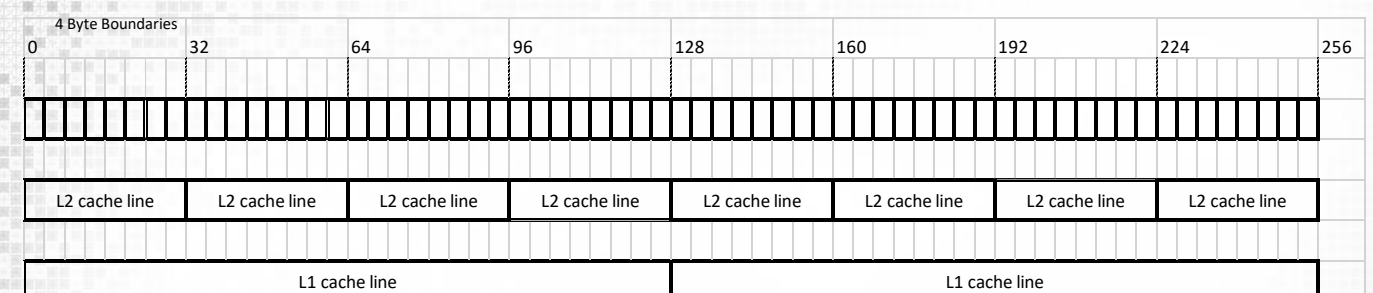


#### Coalesced Global Memory Access

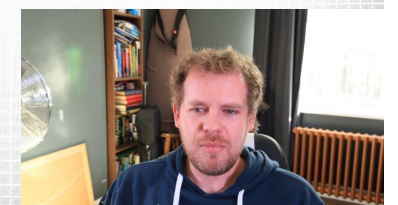
- ❑ When memory is loaded/stored from global memory to L2 (and L1) it is moved in cache lines
  - ❑ If threads within a warp access global memory in irregular patterns this can cause increased movement (transactions) of data
- ❑ Coalesced access is where sequential threads in a warp access sequentially adjacent 4 byte words (e.g. float or int values).
  - ❑ Having coalesced access will reduce the number of cache lines moved and increase memory performance
  - ❑ This is one of the most important performance considerations of GPU memory usage!



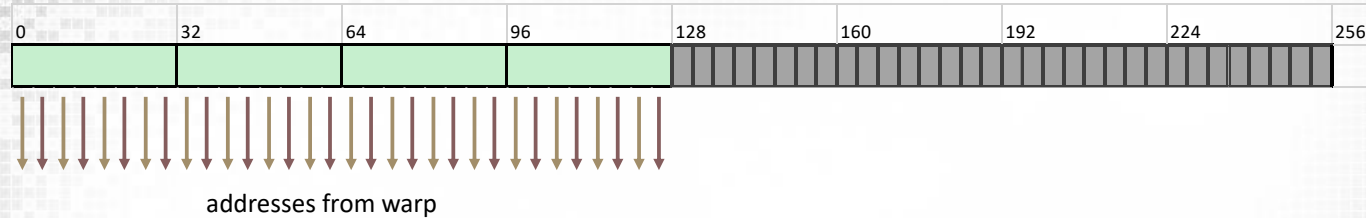
#### Use of Memory Cache Levels



- ❑ L1 Cache
  - ❑ 128B wide cache line transactions
  - ❑ Normally used for thread local variables
  - ❑ Can also be used for global loads (via read-only cache method from previous lecture)
  - ❑ Some hardware has L1 cache for all memory reads
    - ❑ Always via L2 cache first
    - ❑ Compute 3.5, 3.7 or 5.2 have opt in global L1 caching
    - ❑ Early Maxwell (Compute 5.0 cant opt in for L1 global loads)
- ❑ L2 Cache
  - ❑ 32B wide cache line transactions
  - ❑ All global and local memory pass through



## L2 Coalesced Memory Access

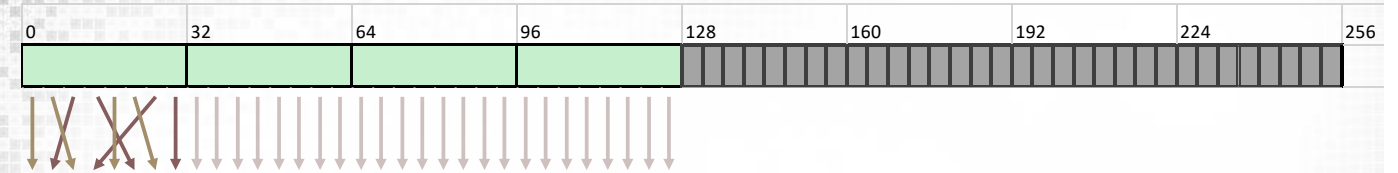


```
__global__ void copy(float *odata, float* idata)
{
    int xid = blockIdx.x * blockDim.x + threadIdx.x;
    odata[xid] = idata[xid];
}
```

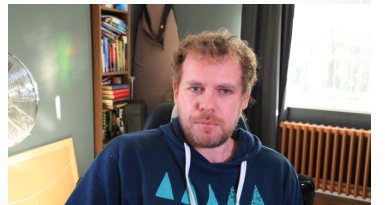
- ☐ Global memory always moves through L2
  - ☐ But not always through L1 depending on architecture
- ☐ In L2 cache line size is 32B
  - ☐ For a coalesced read/write within a warp, 4 transactions required
  - ☐ 100% memory bus speed



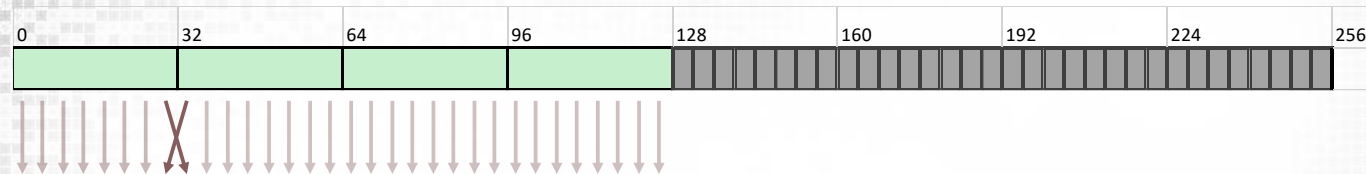
## L2 Permuted Memory Access



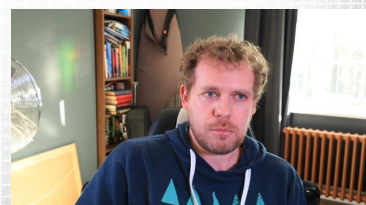
- ☐ Permuted Access
  - ☐ Within the cache line accesses can be permuted between threads
  - ☐ No performance penalty



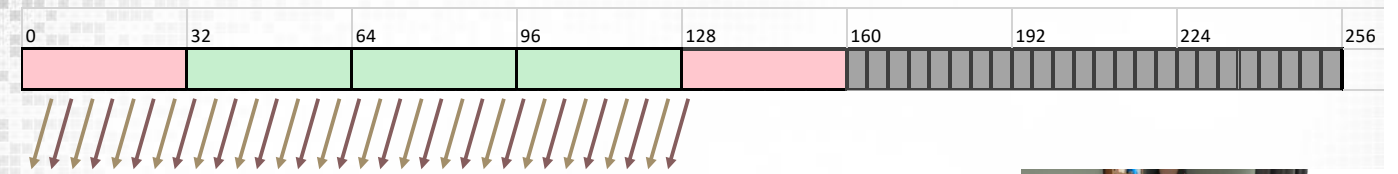
## L2 Permuted Memory Access



- ☐ Permuted Access
  - ☐ Permuted access within 128 byte segments is permitted
    - ☐ Will NOT cause multiple loads
    - ☐ Must not be permuted over the 128 byte boundary

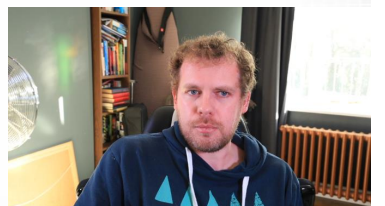


## L2 Offset Memory Access



```
__global__ void copy(float *odata, float* idata)
{
    int xid = blockIdx.x * blockDim.x + threadIdx.x + OFFSET;
    odata[xid] = idata[xid];
}
```

- ☐ If memory accesses are offset then parts of the cache line will be unused (shown in red) e.g.
  - ☐ 5 transactions of 160B of which 128B is required: 80% utilisation
- ☐ Use thread blocks sizes of multiples of 32!





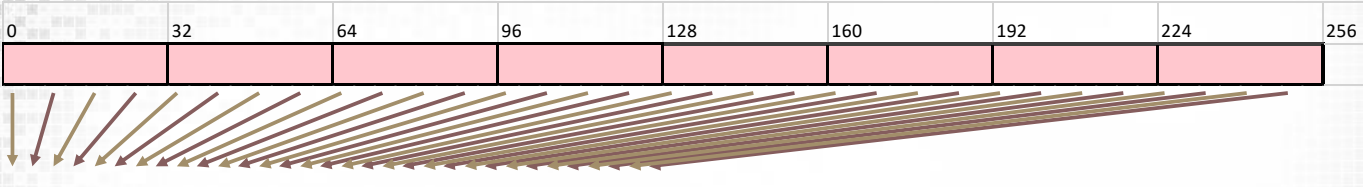
## L2 Strided Memory Access

```
__global__ void copy(float *odata, float* idata)
{
    int xid = (blockIdx.x * blockDim.x + threadIdx.x) * STRIDE;
    odata[xid] = idata[xid];
}
```

❑ How many cache lines transactions for warp if STRIDE = 2?



## L2 Strided Memory Access

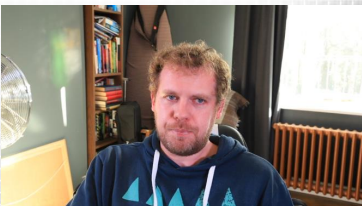
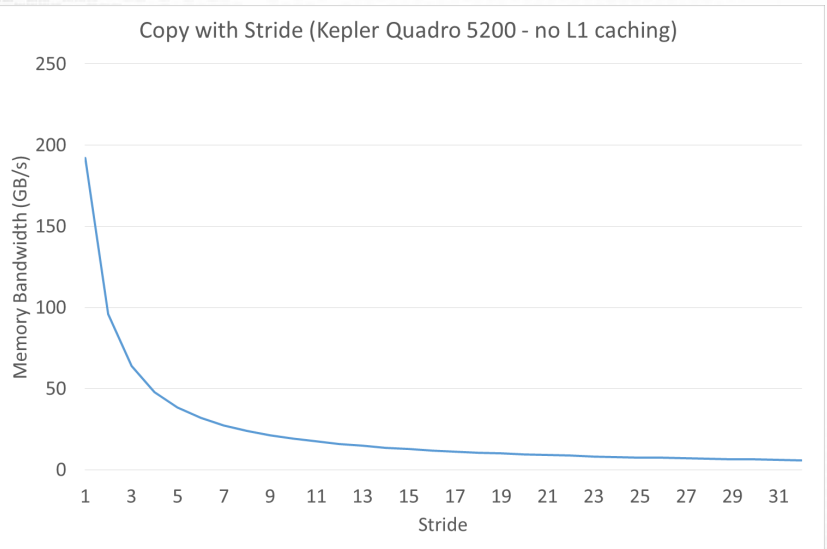


```
__global__ void copy(float *odata, float* idata)
{
    int xid = (blockIdx.x * blockDim.x + threadIdx.x) * STRIDE;
    odata[xid] = idata[xid];
}
```

- ❑ Strided memory access can result in bad performance e.g.
  - ❑ A stride of 2 causes **8 transactions**: 50% useful memory bandwidth
  - ❑ As stride of >32 causes 32 transactions: **ONLY 3.125% bus utilisation!**
    - ❑ This is as bad as random access
    - ❑ Transpose data if it is stride-N



## Degradation in Strided Access Performance



## Array of Structures vs Structures of Arrays

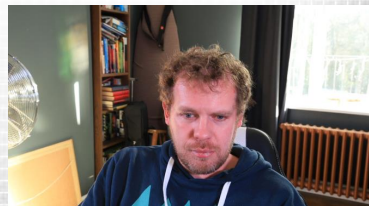
- ❑ Array of Structures (AoS)
  - ❑ Common method to store groups of data (e.g. points)

```
struct point {
    float x, y, z;
};
__device__ struct point d_points[N];

__global__ void manipulate_points()
{
    float x = d_points[blockIdx.x*blockDim.x + threadIdx.x].x;
    float y = d_points[blockIdx.x*blockDim.x + threadIdx.x].y;
    float z = d_points[blockIdx.x*blockDim.x + threadIdx.x].z;

    func(x, y, z);
}
```

Is this a good kernel?



## Array of Structures vs Structures of Arrays

### ❑ Array of Structures (AoS)

#### ❑ Common method to store groups of data (e.g. points)

```
struct point {  
    float x, y, z;  
};  
__device__ struct point d_points[N];  
  
__global__ void manipulate_points()  
{  
    float x = d_points[blockIdx.x*blockDim.x + threadIdx.x].x;  
    float y = d_points[blockIdx.x*blockDim.x + threadIdx.x].y;  
    float z = d_points[blockIdx.x*blockDim.x + threadIdx.x].z;  
  
    func(x, y, z);  
}
```



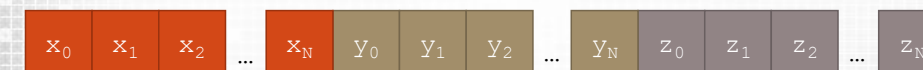
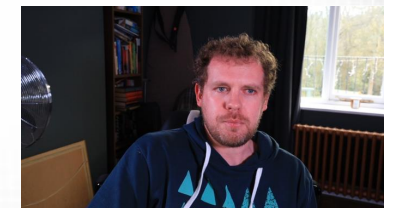
Is this a good kernel? No: Stride of 3 has only 33% memory bandwidth



## Array of Structures vs Structures of Arrays

### ❑ An Alternative: Structure of Arrays (SoA)

```
struct points {  
    float x[N], y[N], z[N];  
};  
  
__device__ struct points d_points;  
  
__global__ void manipulate_points()  
{  
    float x = d_points.x[blockIdx.x*blockDim.x + threadIdx.x];  
    float y = d_points.y[blockIdx.x*blockDim.x + threadIdx.x];  
    float z = d_points.z[blockIdx.x*blockDim.x + threadIdx.x];  
  
    func(x, y, z);  
}
```



100% effective memory bandwidth

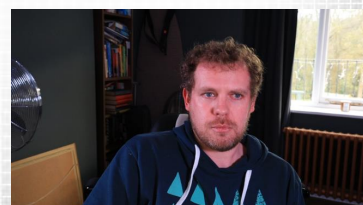


## Summary

### ❑ Memory Coalescing

- ❑ Explain the process of memory moving via cache lines
- ❑ Analyse the performance implications of strided access patterns
- ❑ Classify use cases of memory access with respect to performance

### ❑ Next Lecture: The L1 Cache (and more on Coalescing)

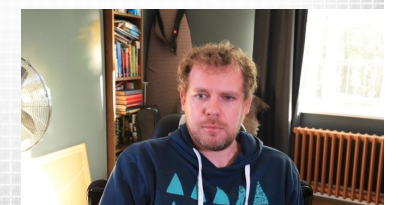


# Parallel Computing with GPUs

## Performance Part 2 – L1 Cache



Dr Paul Richmond  
<http://paulrichmond.shef.ac.uk/teaching/COM4521/>





# This Lecture (learning objectives)

- ❑The L1 Cache
  - ❑Describe how to enable global L1 caching
  - ❑Analyse the performance implications of example access patterns

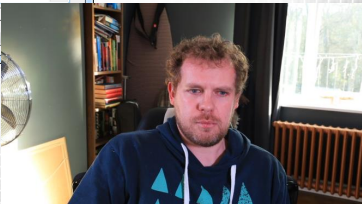
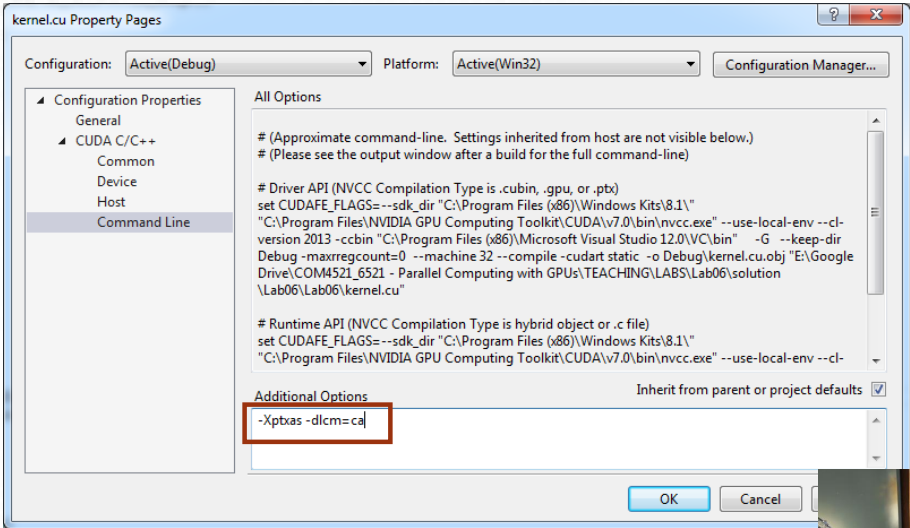


# L1 Cache

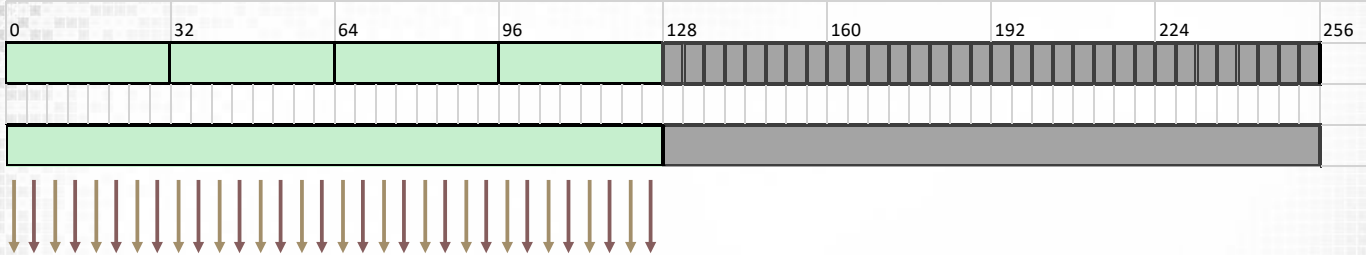
- ❑Can utilise L1 via unified L1/Texture/Read-only memory
- ❑Can also be enabled globally
  - ❑What affect does this have on performance of memory movement?
    - ❑Can be good in certain circumstances
      - ❑Coalesced access with adjacent warps reading same data
    - ❑Can also be bad
      - ❑Un-coalesced access performance is worse
      - ❑Increases over-fetch
  - ❑Does my card support global L1 Caching?
    - ❑Check globalL1CacheSupported and localL1CacheSupported CUDA device properties
      - ❑Maxwell 5.2 reports globalL1CacheSupported false when in fact true!
  - ❑Enabling L1 caching of global loads
    - ❑Pass the `-Xptxas -dlcm=ca` flag to nvcc at compile time
    - ❑`-dlcm=cg` can be used to disable L1 on devices which use it by default



# Enabling L1 Cache in Visual Studio

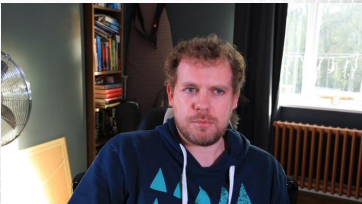


# L1 Coalesced Memory Access

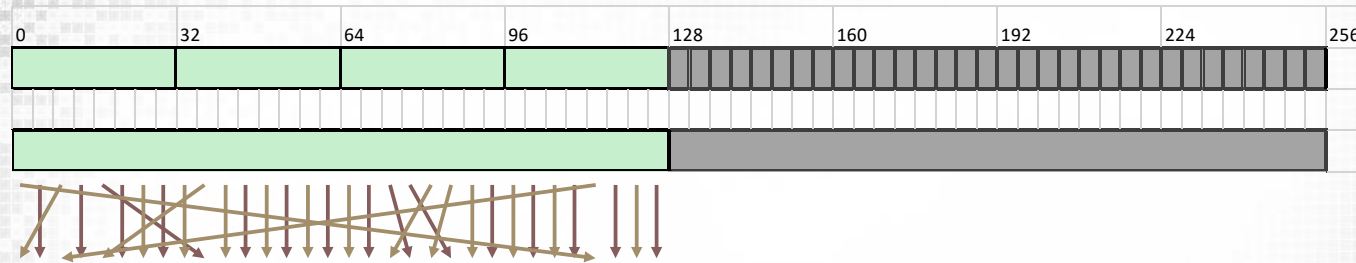


```
__global__ void copy(float *odata, float* idata)
{
    int xid = blockIdx.x * blockDim.x + threadIdx.x;
    odata[xid] = idata[xid];
}
```

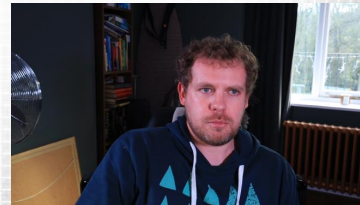
- ❑All addresses fall in one 128B cache line
  - ❑Single transaction
- ❑100% bus utilisation



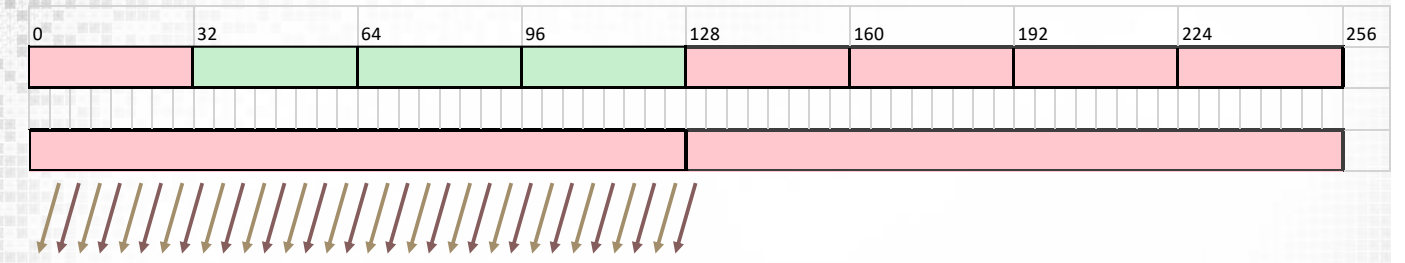
## L1 Permuted Memory Access



- ❑ Any thread within the warp can permute access
- ❑ Same as L2



## L1 Offset Memory Access



```
__global__ void copy(float *odata, float* idata)
{
    int xid = blockIdx.x * blockDim.x + threadIdx.x + OFFSET;
    odata[xid] = idata[xid];
}
```

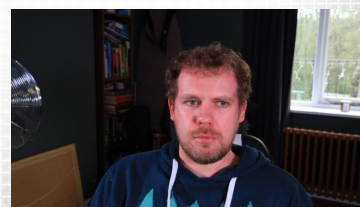
- ❑ If memory accesses are offset then parts of the cache line will be unused (shown in red)  
e.g.
  - ❑ 2 transactions of 256B of which 128B is required: 50% utilisation
- ❑ For strided and random access performance is much worse with L1



## Summary

- ❑ The L1 Cache
  - ❑ Describe how to enable global L1 caching
  - ❑ Analyse the performance implications of example access patterns

- ❑ Next Lecture: Occupancy

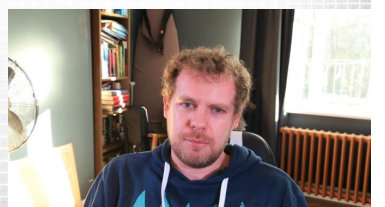


# Parallel Computing with GPUs

## Performance Part 3 – Occupancy



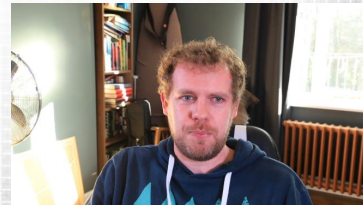
Dr Paul Richmond  
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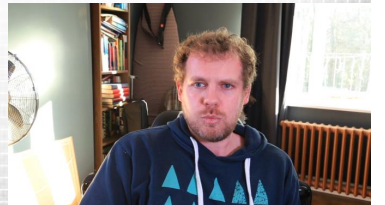
## This Lecture (learning objectives)

- ❑ Occupancy
  - ❑ Define occupancy as a metric of resource utilisation
  - ❑ Explain the implications of occupancy on performance
  - ❑ Demonstrate methods to maximise occupancy
  - ❑ Examine the impact of thread block size on occupancy and performance



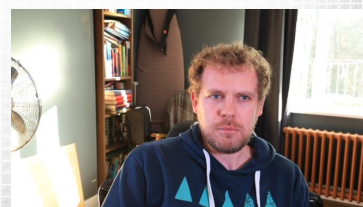
## Occupancy

- ❑ Occupancy is the ratio of active warps on an SMP to the maximum number of active warps supported by the SMP
  - ❑  $\text{Occupancy} = \text{Active Warps} / \text{Maximum Active Warps}$
- ❑ Why does it vary?
  - ❑ Resources are allocated at thread block level and resources are finite
  - ❑ Multiple thread blocks can be assigned to a single Streaming Multi Processor
  - ❑ Your occupancy might be limited by either
    1. Number of registers
    2. Shared memory usage
    3. Limitations on physical block size



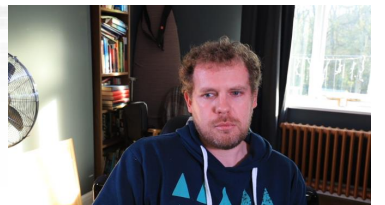
## Why is occupancy important

- ❑ Implications of Increasing Occupancy
  - ❑ Memory bound code
    - ❑ Higher occupancy will hide memory latency
    - ❑ If bandwidth is less than peak then increasing active warps might improve this
  - ❑ Compute bound code
    - ❑ Will not improve performance
  - ❑ 100% occupancy not required for maximum performance
    - ❑ Instruction throughput might be optimal
    - ❑ Memory bandwidth might be fully saturated



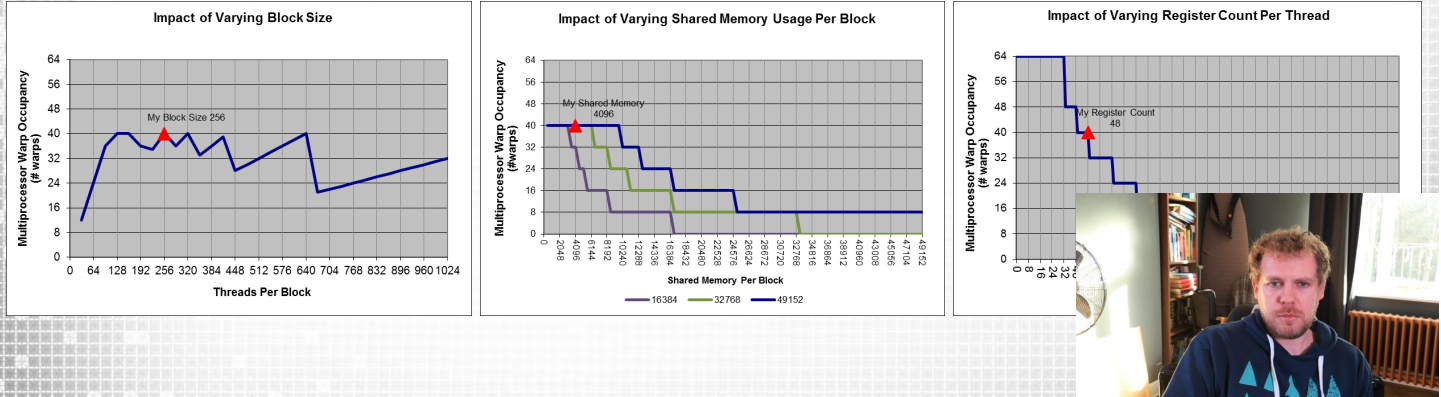
## Occupancy and Thread Block Size

- ❑ Thread Block Limitations
  - ❑ Always a factor of 32 (warp size)
- ❑ Changing the thread block size will change occupancy
  - ❑ If thread block size is too small
    - ❑ There is a fixed limit on the number of active thread blocks per SM (16 in Kepler, 32 in Maxwell)
  - ❑ If thread block is too big
    - ❑ Not enough resources for another block
    - ❑ Block is stalled until enough resource is available
- ❑ The relationship between thread block size and occupancy is non linear
  - ❑ Complex interplay between resources



# Occupancy Calculator

- ❑The CUDA Occupancy calculator is available for download
  - ❑[http://developer.download.nvidia.com/compute/cuda/CUDA\\_Occupancy\\_calculator.xls](http://developer.download.nvidia.com/compute/cuda/CUDA_Occupancy_calculator.xls)
  - ❑By giving a Compute Capability, Threads per block usage registers per thread and shared memory per block occupancy can be predicted.
  - ❑It will also inform you what factor is limiting occupancy (registers, SM, block size)



# Occupancy Calculator

- ❑How do I know what my SM usage per block is?
  - ❑You either statically declared it or dynamically requested it as a kernel argument
- ❑How do I know what my register usage is?
  - ❑CUDA build rule Device Properties-> Verbose PTX Output = Yes
    - ❑i.e. nvcc -ptxas-options=-v

```
1>----- Build started: Project: Lab06, Configuration: Debug Win32 -----
1> Compiling CUDA source file kernel.cu...
1>
1> E:\Lab06>"nvcc.exe" -gencode=arch=compute_35,code="sm_35,compute_35" --use-local-env --cl-
version 2013 -ccbin "C:\MSVS12.0\VC\bin" -I"C:\CUDA\v7.0\include" -I"C:\CUDA\v7.0\include" -G
-keep-dir Debug -maxrregcount=0 --ptxas-options=-v --machine 32 --compile -cudart static -Xptxas -
dlcm=ca -g -D_CUDACC__ -DWIN32 -D_DEBUG -D_CONSOLE -D_MBCS -Xcompiler "/EHsc /W3 /nologo /Od
/Zi /RTC1 /MDd " -o Debug\kernel.cu.obj "E:\Lab06\kernel.cu"
1> ptxas info : 0 bytes gmem
1> ptxas info : Function properties for cudaGetDevice
1> 8 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> ptxas info : Function properties for cudaFuncGetAttributes
1> 8 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> ptxas info : Function properties for cudaOccupancyMaxActiveBlocksPerMultiprocessorWithFlags
1> 24 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> ptxas info : Function properties for cudaDeviceGetAttribute
1> 16 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> ptxas info : Compiling entry function '_Z9addKernelPiS_S_' for 'sm_35'
1> ptxas info : Function properties for _Z9addKernelPiS_S_
1> 0 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> ptxas info : Used 6 registers, 332 bytes cmem[0]
1> ptxas info : Function properties for cudaMalloc
1> 8 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> ptxas info : Function properties for cudaOccupancyMaxActiveBlocksPerMultiprocessor
1> 16 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
1> kernel.cu
1> Lab06.vcxproj -> E:\Lab06.exe
1> copy "C:\CUDA\v7.0\bin\cudart*.dll" "E:\Lab06\Debug\"
1> C:\CUDA\v7.0\bin\cudart32_70.dll
1> C:\CUDA\v7.0\bin\cudart64_70.dll
1> 2 file(s) copied.
===== Build: 1 succeeded, 0 failed, 0 up-to-date, 0 s
```

# Intelligent Launching

- ❑Since CUDA 6.5 It is possible to launch block sizes to maximise occupancy (using the Occupancy API)
  - ❑This does not guarantee good performance!
  - ❑However: Usually a good compromise
- ❑cudaOccupancyMaxPotentialBlockSize: will find best block size and minimum grid size
  - ❑Actual grid size must be calculated

```
int blockSize;
int minGridSize;
int gridSize;

cudaOccupancyMaxPotentialBlockSize(&minGridSize, &blockSize, MyKernel, 0, 0);
gridSize = (arrayCount + blockSize - 1) / blockSize; //round up
MyKernel <<< gridSize, blockSize >>>(d_data, arrayCount);
```

Static SM size



# Occupancy SDK for Shared Memory

- ❑What if SM use varies depending on block size?

```
int SMFunc(int blockSize){
    return blockSize*sizeof(int);
}

void launchMyKernel(int *d_data, int arrayCount)
{
    int blockSize;
    int minGridSize;
    int gridSize;

    cudaOccupancyMaxPotentialBlockSizeVariableSMem(&minGridSize, &blockSize, MyKernel, SMFunc, 0);
    gridSize = (N + blockSize - 1) / blockSize;
    MyKernel <<< gridSize, blockSize, SMFunc(gridSize) >>>(d_data, arrayCount);
}
```





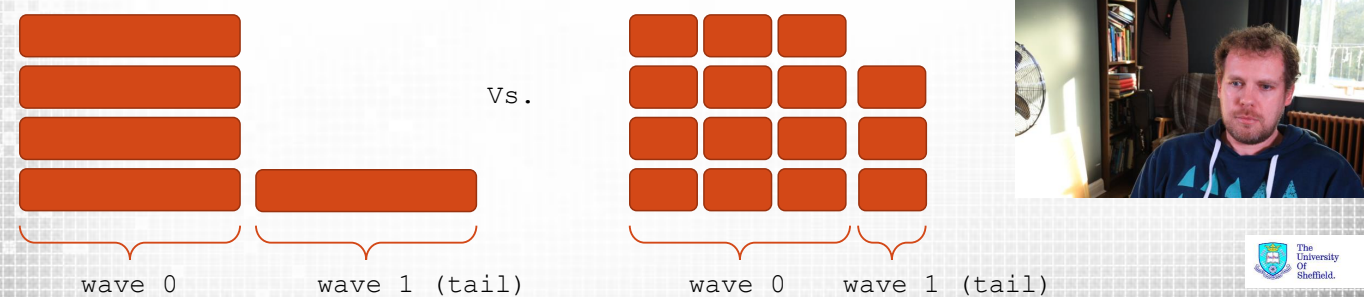
## Other considerations for block sizes

### ❑ Waves and Tails

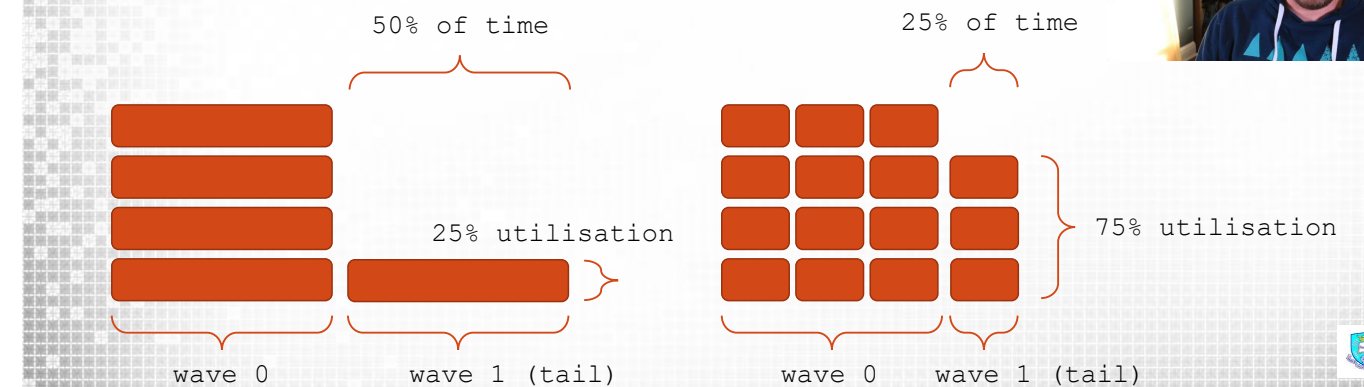
- ❑ A Wave is a set of thread blocks that run concurrently on the device
  - ❑ Grid launch may have multiple waves
- ❑ A Tail is the partial thread block left as a result of dividing problem size by thread block dimensions

### ❑ Performance Implications

- ❑ Larger thread block sizes may result in inefficient execution



## Other considerations for block sizes



## Summary

### ❑ Occupancy

- ❑ Define occupancy as a metric of resource utilisation
- ❑ Explain the implications of occupancy on performance
- ❑ Demonstrate methods to maximise occupancy
- ❑ Examine the impact of thread block size on occupancy and performance

## Acknowledgements and Further Reading

### ❑ Cache line sizes

### ❑ GPU Performance Analysis

- ❑ <http://on-demand.gputechconf.com/gtc/2012/presentations/S0514-GTC2012-GPU-Performance-Analysis.pdf>

### ❑ Waves and Tails (<http://on-demand.gputechconf.com/gtc/2012/presentations/S0514-GTC2012-GPU-Performance-Analysis.pdf>)

### ❑ How to enable use of L1 cache

- ❑ <http://acceleware.com/blog/opt-in-L1-caching-global-loads>

### ❑ Better Performance at Lower Occupancy

- ❑ <http://nvidia.fullviewmedia.com/gtc2010/0922-a5-2238.html>