

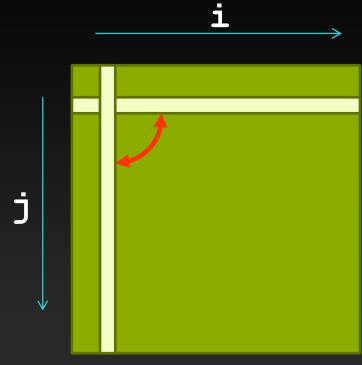
Exercise

- Today we have a progressive exercise
- The exercise is broken into 5 steps
- If you get lost you can always catch up by grabbing the corresponding directory
- If you need to peak at the solution for each step it is found in the directory named "solution"
- To start make a copy of the step1 directory
- We will now review the code

Case Study: Matrix Transpose

```
void transpose(float in[][], float out[][], int N)
{
   for(int j=0; j < N; j++)
      for(int i=0; i < N; i++)
      out[j][i] = in[i][j];
}</pre>
```

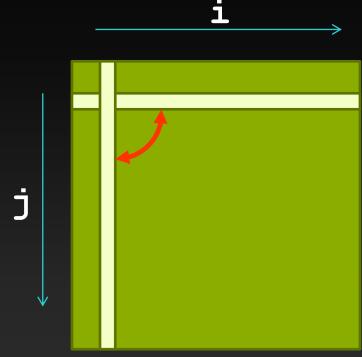
- Commonly used in applications
 - BLAS and FFT
- Stresses memory systems
 - Strided reads or writes



2D to 1D indexing

```
void transpose(float in[], float out[], int N)
{
   for(int j=0; j < N; j++)
      for(int i=0; i < N; i++)
      out[i*N+j] = in[j*N+i];
}</pre>
```

- This indexing is often used in numerical codes
- We will use this indexing during this presentation



Parallelization for CPU

%> aprun -n 1 -d 16 ./transpose

Kernel	Throughput
CPU+OMP	4.9 GB/s

Exercise: Compile with NVCC

- Modify make file to build with nvcc
 - For CUDA filenames must end in .cu
 - Specify architecture
 - -arch=sm_35
 - Pass an argument to the host compiler using –Xcompiler
 - -Xcompiler –fopenmp
- Recompile and run

```
%> module load cudatoolkit
%> make clean
%> make
%> aprun -n 1 -d 16 ./transpose
```

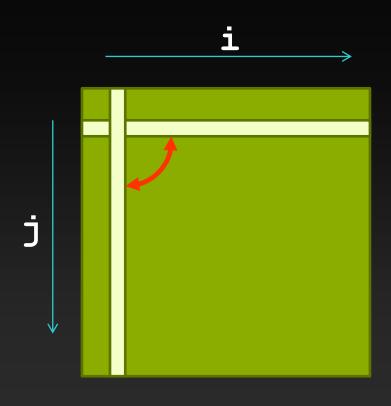
- Notice nvcc can build CPU only applications
- It actually passes host code through to the host compiler

Exercise: Add CUDA APIs

- Search for "TODO" and fill in cuda code
- Start with the host code
 - Create separate pointers for CUDA memory
 - Allocate & free memory device memory
 - cudaMalloc(**ptr, size_t size)
 - cudaFree(*ptr)
 - Copy data between CPU and GPU
 - cudaMemcpy(*dst, *src, size_t size, cudaMemcpyKind)
 - cudaMemcpyKind: cudaMemcpyHostToDevice, cudaMemcpyDeviceToHost
 - Synchronize the device to ensure timing is correct
 - cudaDeviceSynchronize()
 - Pass device pointers into transpose function

Exercise: Write Our First Kernel

- Create transpose kernel
 - global says this is a kernel
 - Parallelize over rows
 - 1 thread per row
 - Replace outer loop with index calculation
 - 1D indexing
 - blockDim.x*blockIdx.x+threadIdx.x
- Launch kernel
 - <<<gridDim,blockDim>>>
 - blockDim = 256 threads



Results

- Initial implementation 1.5x faster
- K20X theoretical bandwidth is 250 GB/s
 - Low percent of peak
 - Why?

Kernel	Throughput
CPU+OMP	4.9 GB/s
CUDA-1D	7.2 GB/s

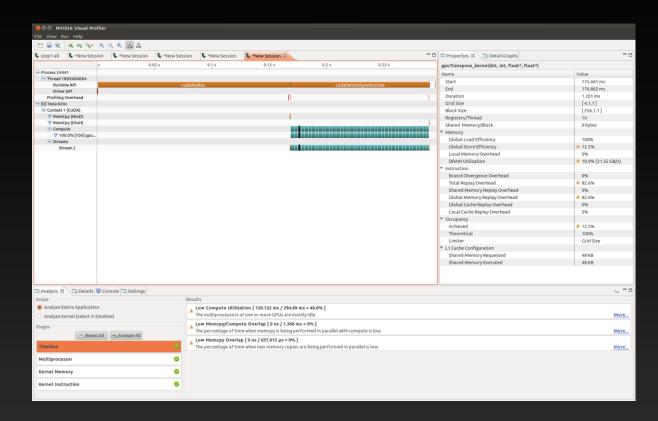
Tools for Profiling

Profile-driven optimization

- Tools:
 - nsight: Visual Studio Edition or Eclipse Edition
 - nvvp: NVIDIA Visual Profiler
 - nvprof: Command-line profiling

Introducing NVVP

- Cuda profiling tool
 - Analyzes performance
 - Identifies hotspots
 - Suggests improvements
- Let's open NVVP
 - Import profiles
 - Interpret results



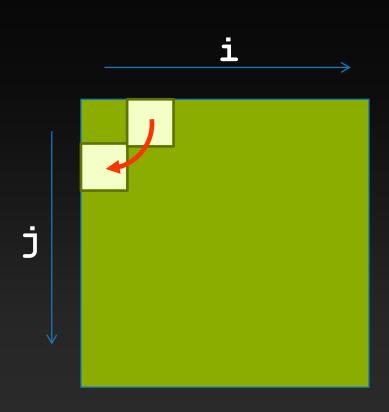
NVVP: Step1

- Always look at occupancy first!
- Each block is scheduled on an SM
 - There are 14 SMs on K20X
 - Only 4 blocks!
- Bottleneck
 - Grid size
 - Most of the GPU is idle
- Solution
 - Express more parallelism

Duration		1.201 ms
Grid Size		[4,1,1]
Block Size		[256,1,1]
Registers/Thread		16
Shared Memory/Block		0 bytes
Memory		
Global Load Efficiency		100%
Global Store Efficiency	۵	12.5%
Local Memory Overhead		0%
DRAM Utilization	۵	10.9% (21.55 GB/s)
Instruction		
Branch Divergence Overhead		0%
Total Replay Overhead	▲	82.6%
Shared Memory Replay Overhead		0%
Global Memory Replay Overhead	۵	82.6%
Global Cache Replay Overhead		0%
Local Cache Replay Overhead		0%
Осси рансу		
Achieved	▲	12.5%
Theoretical		100%
Limi ter		Grid Size

Exercise: Express More Parallelism

- The CPU version parallelizes over rows and columns
- Lets do the same on the GPU
 - Replace columns loop with an index calculation
 - Change launch configuration to 2D
 - blockSize = 32x32
 - <<<gridDim,blockDim>>>
 - dim3(xdim,ydim)
 - Don't forget to update both gridDim and blockDim



Results

- We are now at a 12x speedup over the parallel CPU version
- But how are we doing overall?
 - Peak for K20X is 250 GB/s
 - ~24% of peak
- Why is bandwidth utilization low?

Back to NVVP

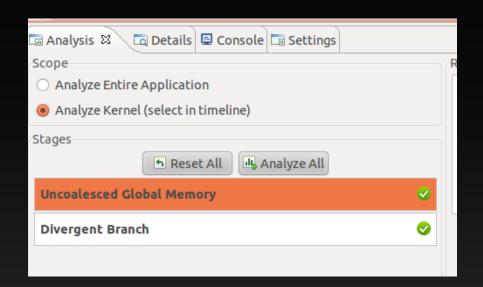
Kernel	Throughput
CPU+OMP	4.9 GB/s
GPU-1D	7.2 GB/s
GPU-2D	59 GB/s

NVVP Profile: Step2

- Occupancy is now much better
- All SMs have work
- DRAM utilization is low
- Global store efficiency is low
- Global memory replay overhead is high
- Bottleneck
 - Uncoalesced stores

157.508 µs
[32,32,1]
[32,32,1]
-8
0 bytes
100%
12.5%
0%
35.3% (70.06 GB/s)
0%
64.5%
0%
6 4.5%
0%
0%
75%
7370

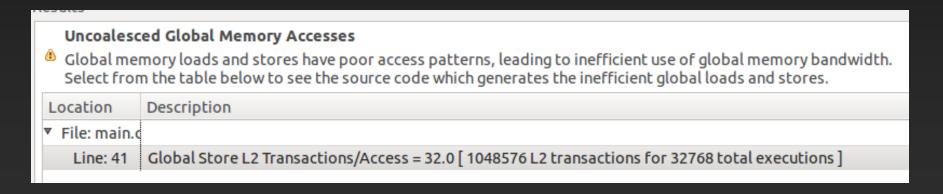
Use NVVP to Find Coalescing Problems



Compile with -lineinfo

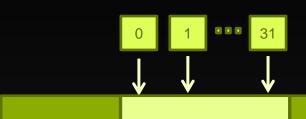
```
__global__ void gpuTranspose_kernel(int rows, int co
{
   int i; int j;

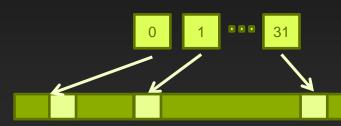
   i = blockIdx.x * blockDim.x + threadIdx.x;
   j = blockIdx.y * blockDim.y + threadIdx.y;
   out[i*cols + j] = in[j*cols + i];
}
```



What is an Uncoalesced Global Store?

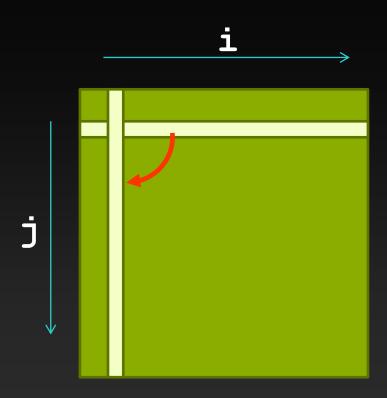
- Global memory access happens in transactions of 32 or 128 bytes
- Coalesced access:
 - A group of 32 contiguous threads ("warp") accessing adjacent words
 - Few transactions and high utilization
- Uncoalesced access:
 - A warp of 32 threads accessing scattered words
 - Many transactions and low utilization



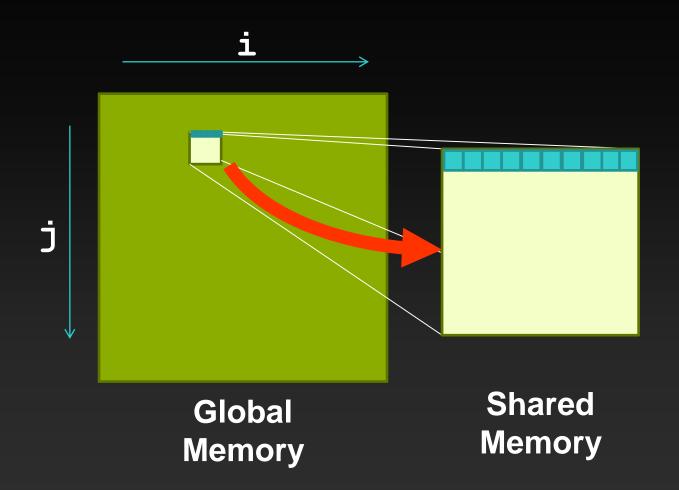


Memory Coalescing

- When we write column j memory access pattern is strided
- Solution
 - Read coalesced into shared memory
 - Transpose in shared memory
 - Write coalesced from shared memory

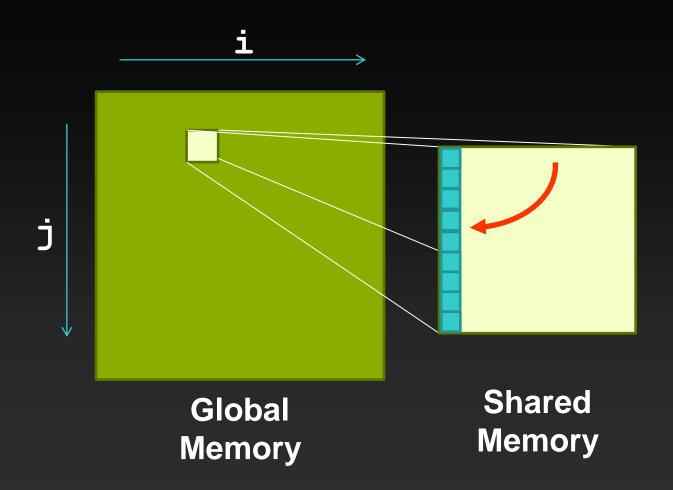


Transposing with Shared Memory



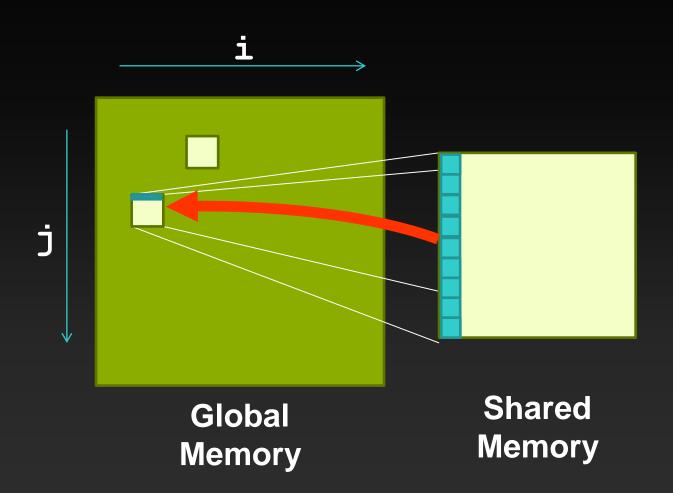
Read block coalesced into shared memory

Transposing with Shared Memory



- Read block coalesced into shared memory
- Transpose shared memory indices

Transposing with Shared Memory



- Read block_ij coalesced into shared memory
- Transpose shared memory indices
- Write transposed block to global memory

Exercise: Stage Through Shared Memory

- Allocate a static 2D array using __shared__ keyword
- Read from global to shared memory
 - Global read indices are unchanged
 - Shared write indices use threadldx.{x,y}
- Write from shared to global memory
 - Global write indices: transpose block
 - Shared read indices: transpose threads
- Sync between read and write: __syncthreads()

Results

 We got a small improvement but we are still low compared to peak

Back to NVVP

Kernel	Throughput
CPU+OMP	4.9 GB/s
GPU-1D	7.2 GB/s
GPU-2D	59 GB/s
GPU-Shared	73 GB/s

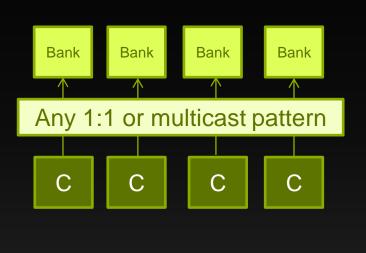
NVVP Profile: Step3

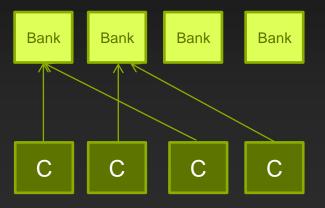
- Global Store Efficiency is now 100%
- Global memory replay are much lower
- Shared memory replays are much higher
- Bottleneck
 - Shared memory bank conflicts

Duration	128.163 µs
Grid Size	[32,32,1]
Block Size	[32,32,1]
Registers/Thread	10
Shared Memory/Block	4 KB
Memory	
Global Load Efficiency	100%
Global Store Efficiency	100%
Local Memory Overhead	9%
DRAM Utilization	6 37.9% (75.18 GB/s)
Instruction	
Branch Divergence Overhead	0%
Total Replay Overhead	6 36.5%
Shared Memory Replay Overhead	30.7%
Global Memory Replay Overhead	5.8%
Global Cache Replay Overhead	0%
Local Cache Replay Overhead	0%
Occupancy	
Achieved	86.2%
Theoretical	100%

Shared Memory Organization

- Organized in 32 independent banks
- Optimal access: all words from different banks
 - Separate banks per thread
 - Banks can multicast
- Multiple words from same bank serialize



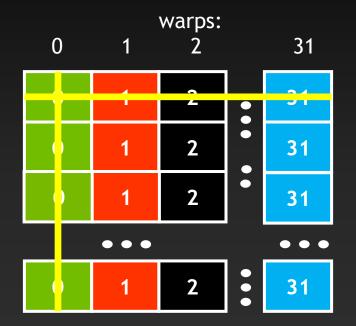


Shared Memory: Avoiding Bank Conflicts

- Example: 32x32 SMEM array
- Warp accesses a column:
 - 32-way bank conflicts (threads in a warp access the same bank)

Bank 0 Bank 1

... Bank 31



Accesses along row produces 0 bank conflicts

Accesses along column produces 32 bank conflicts

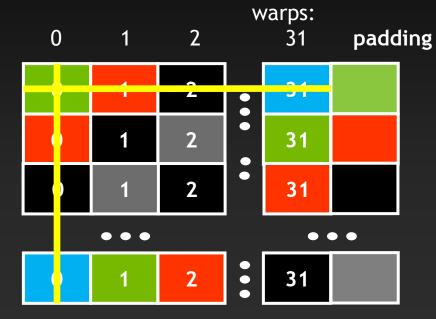
Shared Memory: Avoiding Bank Conflicts

- Add a column for padding:
 - 32x33 SMEM array
- Warp accesses a column:
 - 32 different banks, no bank conflicts

Bank 0 Bank 1

•••

Bank 31



Accesses along row produces 0 bank conflicts

Accesses along column produces 0 bank conflicts

Exercise: Fix bank conflicts

Add padding

Results

Getting much better

Back to NVVP

Kernel	Throughput
CPU+OMP	4.9 GB/s
GPU-1D	7.2 GB/s
GPU-2D	59 GB/s
GPU-Shared	73 GB/s
GPU-no-conflicts	114 GB/s

NVVP Profile: Step4

- Bank conflicts are fixed
- DRAM utilization is >50%

Can we do better?

	Duration	90.146 µs
	Grid Size	[32,32,1]
	Block Size	[32,32,1]
	Registers/Thread	10
	Shared Memory/Block	4.125 KB
₩	Memory	
	Global Load Efficiency	100%
	Global Store Efficiency	100%
	Local Memory Overhead	0%
<	DRAM Utilization	57.1% (113.34 GB/s)
₩	Instruction	·
₩	Instruction Branch Divergence Overhead	0%
₩		0% 9.1%
▼	Branch Divergence Overhead	
▼	Branch Divergence Overhead Total Replay Overhead	9.1%
~	Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead	9.1%
~	Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead	9.1% 0% 9.1%
	Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead Global Cache Replay Overhead	9.1% 0% 9.1% 0%
	Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead Global Cache Replay Overhead Local Cache Replay Overhead	9.1% 0% 9.1% 0%

profiles/step4.nvvp

NVVP Profile: Step4

- DRAM Utilization is still a little low.
 - Aim for 70%-80% of peak
- Problem:
 - Kepler requires 100+ lines in flight per SM to saturate DRAM
 - 1 line-in-flight per warp @ 100%occupancy = 64 lines in flight
- Solution:
 - Process multiple elements per thread
 - Instruction-level parallelism
 - More lines-in-flight
 - Less __syncthreads overhead
 - Amortize cost of indexing and thread launch

Duration	00 146 us
	90.146 µs
Grid Size	[32,32,1]
Block Size	[32,32,1]
Registers/Thread	10
Shared Memory/Block	4.125 KB
▼ Memory	
Global Load Efficiency	100%
Global Store Efficiency	100%
Local Memory Overhead	0%
DRAM Utilization	57.1% (113.34 GB/s)
	` ' '
▼ Instruction	, , , , ,
	0%
▼ Instruction	
▼ Instruction Branch Divergence Overhead	0%
▼ Instruction Branch Divergence Overhead Total Replay Overhead	0% 9.1%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead	0% 9.1% 0%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead	0% 9.1% 0% 9.1%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead Global Cache Replay Overhead	0% 9.1% 0% 9.1% 0%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead Global Cache Replay Overhead Local Cache Replay Overhead	0% 9.1% 0% 9.1% 0%

profiles/step4.nvvp

Exercise: Multiple Elements Per Thread

- Change block size to 32 x 4
 - BLOCKY = 4
 - NUM_ELEMS_PER_THREAD = 8
 - Should the grid size also change?
- Loop over 8 elements on input
 - Update indexing whenever you see threadIdx.y and threadDim.y
- Loop over 8 elements on output
 - Update indexing whenever you see threadldx.y and threadDim.y
- Unroll all loops using #pragma unroll

NVVP Profile: Step5

- 80% of peak bandwidth
- Occupancy dropped
 - This is not a problem
 - ILP makes up for loss in occupancy
 - In general ILP is as good as high occupancy

Duration	56.13 µs
Grid Size	[32,32,1]
Block Size	[32,4,1]
Registers/Thread	24
Shared Memory/Block	4.125 KB
▼ Memory	
Global Load Efficiency	100%
Global Store Efficiency	100%
Local Memory Overhead	0%
DRAM Utilization	79.9% (158.5 GB/s)
	,
▼ Instruction	
	0%
▼ Instruction	
▼ Instruction Branch Divergence Overhead	0%
▼ Instruction Branch Divergence Overhead Total Replay Overhead	0% 9.9%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead	0% 9.9% 0%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead	0% 9.9% 0% 9.9%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead Global Cache Replay Overhead	0% 9.9% 0% 9.9% 0%
▼ Instruction Branch Divergence Overhead Total Replay Overhead Shared Memory Replay Overhead Global Memory Replay Overhead Global Cache Replay Overhead Local Cache Replay Overhead	0% 9.9% 0% 9.9% 0%

Final Results

- Use NVVP to identify bottlenecks
- Use optimization techniques to eliminate bottlenecks
- Refer to GTC archives for complete optimization techniques

Kernel	Throughput
CPU+OMP	4.9 GB/s
GPU-1D	7.2 GB/s
GPU-2D	59 GB/s
GPU-Shared	73 GB/s
GPU-no-conflicts	114 GB/s
GPU-multi-element	173 GB/s

- www.gputechconf.com/gtcnew/on-demand-gtc.php
- Search "GPU Performance Analysis and Optimization"