Performance Optimization

- Host-device data transfers
 - Page-locked transfers
 - Asynchronous transfers
- Device memory
 - Coalescing
 - Shared memory
 - Textures
- Execution Configuration
 - Thread-level parallelism
 - Instruction-level parallelism7

Coalescing

- Device data accessed by a group of 16 or 32 sequential threads can result in as little as a single transaction if certain requirements are met
 - Alignment
 - Stride
 - Generation of GPU architecture

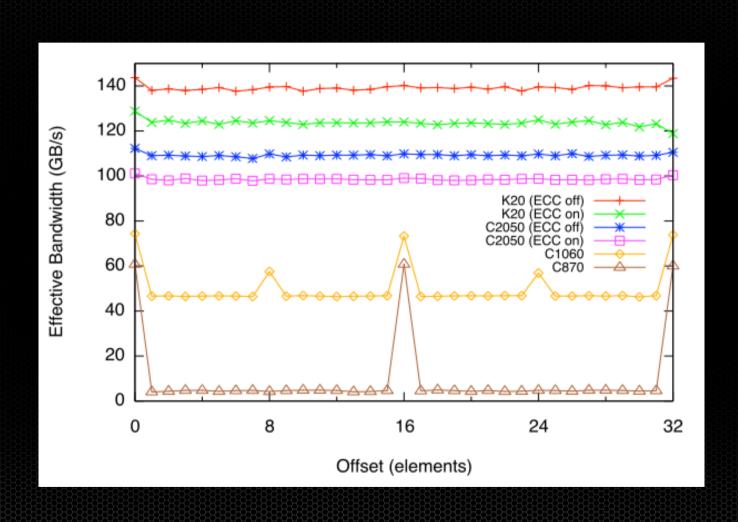
Misaligned Data Access

• Use array increment kernel with variable misalignment

```
attributes(global) subroutine offset(a, s)
  real :: a(*)
  integer, value :: s
  integer :: i
  i = blockDim%x*(blockIdx%x-1)+threadIdx%x + s
  a(i) = a(i)+1
end subroutine offset
```

Array a() allocated with padding to avoid out-of-bounds accesses

Misaligned Data Access



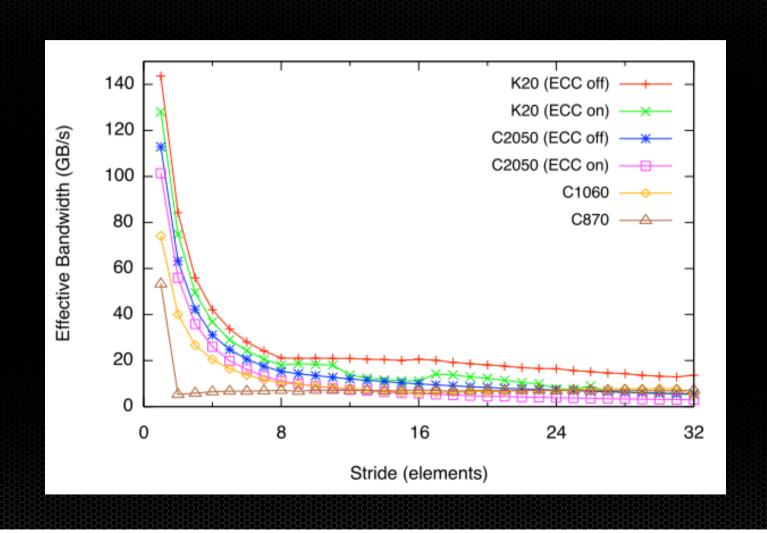
Strided Data Access

• Use array increment kernel with variable stride

```
attributes(global) subroutine stride(a, s)
  real :: a(*)
  integer, value :: s
  integer :: i
  i = (blockDim%x*(blockIdx%x-1)+threadIdx%x) * s
  a(i) = a(i)+1
end subroutine stride
```

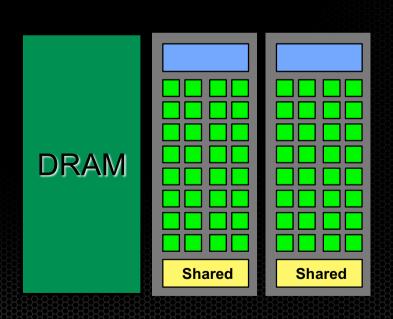
Array a() allocated with padding to avoid out-of-bounds accesses

Strided Data Access



Shared Memory

- On-chip
- All threads in a block have access to same shared memory
- Used to reduce multiple loads of device data
- Used to accommodate coalescing



Matrix Transpose (transpose.cuf)

```
attributes(global) subroutine transposeNaive(odata, idata)
  real, intent(out) :: odata(ny,nx)
  real, intent(in) :: idata(nx,ny)
  integer :: x, y
  x = (blockIdx%x-1) * blockDim%x + threadIdx%x
  y = (blockIdx%y-1) * blockDim%y + threadIdx%y
   odata(y,x) = idata(x,y)
end subroutine transposeNaive
                                         idata
                                                                  odata
```

Matrix Transpose - Shared Memory

```
attributes(global) subroutine transposeCoalesced(odata, idata)
real, intent(out) :: odata(ny,nx)
real, intent(in) :: idata(nx,ny)
real, shared :: tile(TILE_DIM, TILE_DIM)
integer :: x, y

x = (blockIdx%x-1)*blockDim%x + threadIdx%x
y = (blockIdx%y-1)*blockDim%y + threadIdx%y
tile(threadIdx%x, threadIdx%y) = idata(x,y)

call syncthreads()

x = (blockIdx%y-1)*blockDim%y + threadIdx%x
y = (blockIdx%x-1)*blockDim%x + threadIdx%y
odata(x,y) = tile(threadIdx%y, threadIdx%x)
end subroutine transposeCoalesced
idata
```

odata

Shared Memory Bank Conflicts

- Shared memory is divided into banks that can be accessed simultaneously
- Successive 32-bit words are assigned to successive banks
- Requests for different data in the same bank by threads in a warp (SIMD unit of 32 successive threads) are serialized
- Common workaround is to pad shared memory arrays

```
real, shared :: tile(TILE_DIM +1, TILE_DIM)
```

Constant Memory

- Small (64KB), read-only in a kernel, written by the host
 - assignment or API
 - used for small coefficient tables, common pointers
- Hardware cached
 - separate 16KB constant cache

Textures

- Different pathway for accessing data in device DRAM
- Read-only by device code
- Cached on chip in texture cache
- Uses F90 pointer notation

 - Bind and unbind texture in host code using pointer notation
- Equivalent to tex1Dfetch() in CUDA C
 - No filtering or wrapping modes

Texture Memory as a Read-only Cache

CUDA Fortran module

real, texture, pointer :: q(:)

CUDA Fortran host code

```
real, device, target :: p(:)
...
allocate(p(n))
q => p
```

CUDA Fortran device code

```
i = threadldx%x
j = (blockldx%x-1)*blockDim%x + i
s(j) = s(j) + q(i)
```

CUDA C/C++ global

texture<float, 1,
 cudaReadModeElementType> tq;

CUDA C/C++ host code

CUDA C/C++ device code

```
i = threadIdx.x;
j = blockIdx.x*blockDim.x + i;
s[j] = s[j] + tex1Dfetch(tq, i);
```

Texture Memory Performance (Measured Gbytes/sec)

		blockDim = 32		blockDim = 128	
module memtests	stride	stridem	stridet	stridem	stridet
integer, texture, pointer :: t(:)	1	53.45	50.94	141.93	135.43
contains	2	49.77	49.93	100.37	99.61
attributes(global) subroutine stridem(m,b,s)	3	46.96	48.07	75.25	74.91
integer, device :: m(*), b(*)	4	44.25	45.90	60.19	60.00
integer, value :: s	5	39.06	39.89	50.09	49.96
i = blockDim%x*(blockIdx%x-1) + threadIdx%x	6	37.14	39.33	42.95	42.93
j = i * s	7	32.88	35.94	37.56	37.50
b(i) = m(j) + 1	8	32.48	32.98	33.38	33.42
return	9	29.90	32.94	30.01	33.38
end subroutine	10	27.43	32.86	27.28	33.07
Cha sabioachic	11	25.17	32.77	24.98	32.91
attributes(global) subroutine stridet(b,s)	12	23.23	33.19	23.07	33.01
integer, device :: b(*)	13	21.57	33.13	21.40	32.26
	14	20.15	32.98	19.97	31.76
integer, value :: s	15	18.87	32.80	18.72	30.80
i = blockDim%x*(blockIdx%x-1) + threadIdx%x	16	17.78	32.66	17.60	31.83
j = i * s	20	14.38	33.37	14.23	26.84
b(i) = t(j) + 1	24	12.08	33.71	11.94	24.30
return	28	10.41	33.38	10.27	19.97
end subroutine	32	9.15	33.42	9.02	20.19
end module memtests					

Texture Example

• strideTex.cuf

Alternative to texture fetches

Use INTENT(IN) as attribute for dummy arguments

```
attributes(global) subroutine test( a, b )
integer, device :: a(*)
integer, device, intent(in) :: b(*)
```

- Compile with -Mcuda=keeptx,cc35
 - Verify with search for ld.global.nc operations in ptx file
- Compile with -Mcuda=keepbin,cc35
 - Verify with "cuobjdump -dump-sass" on the .bin file

Performance Optimization

- Host-device data transfers
 - Page-locked transfers
 - Asynchronous transfers
- Device memory
 - Coalescing
 - Shared memory
 - Textures
- Execution Configuration
 - Thread-level parallelism
 - Instruction-level parallelism

Execution Configuration

- GPUs are high latency, 100s of cycles per device memory request
- For good performance, you need to ensure there is enough parallelism to hide this latency
- Such parallelism can come from:
 - Thread-level parallelism
 - Instruction-level parallelism

- Execution configuration dictates number of threads per block
 - Limit on number of threads per block for each architecture
- Number of concurrent blocks on a multiprocessor limited by
 - Register use per thread
 - Shared memory use per thread block
 - Limit on number of threads per multiprocessor

Occupancy

- Ratio of actual to maximum number of concurrent threads per multiprocessor

```
attributes(global) subroutine copy(odata, idata)
  real :: odata(*), idata(*), tmp
  integer :: i
  i = (blockIdx%x-1)*blockDim%x + threadIdx%x
  tmp = idata(i)
  odata(i) = tmp
end subroutine copy
```

• Run on K20

- Maximum of 2048 concurrent threads per multiprocessor
- Maximum of 16 concurrent blocks per multiprocessor
- Maximum of 1024 threads per block

Thread Block Size	Occupancy	Bandwidth (GB/s)
32	0.25	96
64	0.5	125
128	1	136
256	1	137
512	1	137
1024	1	133
		&P&P&P&P&P&P&P&P&P&P&P&P&P&P&P&P&P&P&P

- Mimic high resource use
 - Specify enough shared memory so only one thread block can reside on a multiprocessor at a time

call copy<<<grid, threadBlock, 0.9*smBytes>>>(b_d, a_d)

	No Shared Mo	emory	Shared Memory			
Thread Block	Occupancy	Bandwidth	Occupancy	Bandwidth		
32	0.25	96	0.016	8		
64	0.5	125	0.031	15		
128	1	136	0.063	29		
256	1	137	0.125	53		
512	1	137	0.25	91		
1024	1	133	0.5	123		

Instruction-Level Parallelism

• Have each thread process multiple elements

```
attributes(global) subroutine copy_ILP(odata, idata)
  real :: odata(*), idata(*), tmp(ILP)
  integer :: i,j

i = (blockIdx%x-1)*blockDim%x*ILP + threadIdx%x
  do j = 1, ILP
    tmp(j) = idata(i+(j-1)*blockDim%x)
  enddo
  do j = 1, ILP
    odata(i+(j-1)*blockDim%x) = tmp(j)
  enddo
end subroutine copy ILP
```

Instruction-Level Parallelism

	No Shared I	Memory	Shared Memory				
Thread Block Size	Occupancy	Bandwidth	Occupancy	Bandwidth No ILP	Bandwidth ILP = 4		
32	0.25	96	0.016	8	26		
64	0.5	125	0.031	15	50		
128	1	136	0.063	29	90		
256	1	137	0.125	53	125		
512	1	137	0.25	91	140		
1024	1	133	0.5	123	139		

Calling CUBLAS from CUDA Fortran

- Module which defines interfaces to CUBLAS from CUDA Fortran
 - use cublas
- Interfaces in three forms
 - Overloaded BLAS interfaces that take device array arguments
 - call saxpy(n, a_d, x_d, incx, y_d, incy)
 - Legacy CUBLAS interfaces
 - call cublasSaxpy(n, a_d, x_d, incx, y_d, incy)
 - Multi-GPU version (CUDA 4.0) that utilizes a handle h
 - istat = cublasSaxpy_v2(h, n, a_d, x_d, incx, y_d, incy)
- Mixing the three forms is allowed

Calling CUBLAS from CUDA Fortran

```
program cublasTest
  use cublas
  implicit none
  real, allocatable :: a(:,:),b(:,:),c(:,:)
  real, device, allocatable :: a d(:,:),b d(:,:),c d(:,:)
  integer :: k=4, m=4, n=4
  real :: alpha=1.0, beta=2.0, maxError
  allocate (a(m,k), b(k,n), c(m,n), a d(m,k), b d(k,n), c d(m,n))
  a = 1; a d = a
  b = 2; b d = b
  c = 3; c d = c
  call cublasSgemm('N','N',m,n,k,alpha,a d,m,b d,k,beta,c d,m) ! or sgemm(..)
  c=c d
  write(*,*) 'Maximum error: ', maxval(abs(c-14.0))
  deallocate (a,b,c,a d,b d,c d)
end program cublasTest
```

CUDA Fortran Profiling and Debugging

 Some examples of profiling CUDA Fortran and the current status of CUDA Fortran debugging.

Performance Measurement

- CUDA Event management
- pgcollect / pgprof
- nvvp visual profiler; nvprof text profiler
- others (TAU, Vampir, ...)

Event Management

```
integer cudaEventCreate( event )
  type(cudaEvent), intent(out) :: event
integer cudaEventRecord( event, stream )
  type(cudaEvent), intent(in) :: event
  integer, intent(in) :: stream

integer cudaEventSynchronize( event )
  type(cudaEvent), intent(in) :: event

integer cudaEventElapsedTime( time,e1,e2 )
  real, intent(out) :: time
  type(cudaEvent), intent(in) :: e1, e2

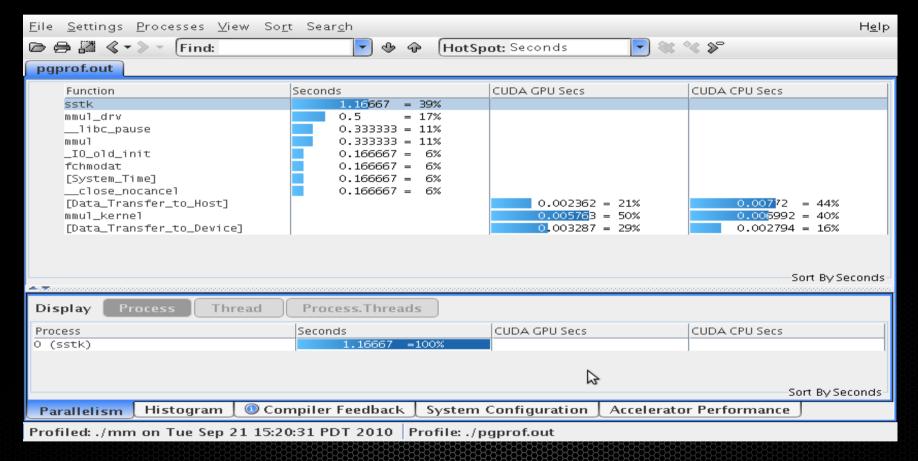
integer cudaEventDestroy( event )
  type(cudaEvent), intent(in) :: event
```

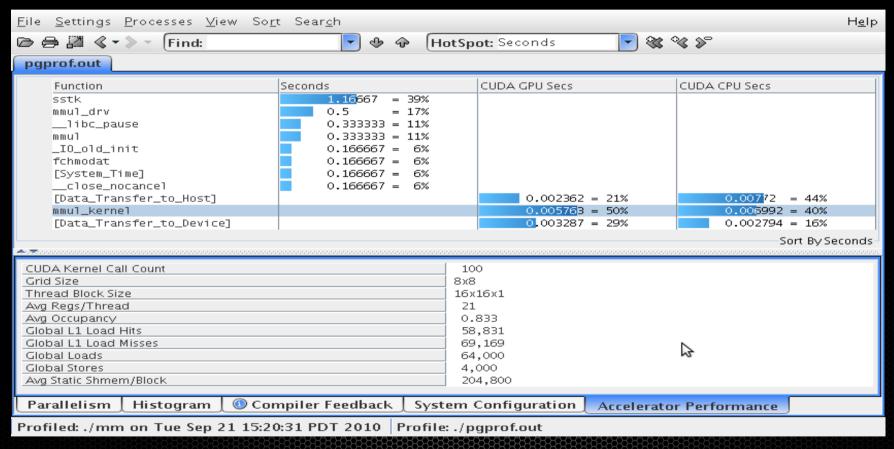
Events Example

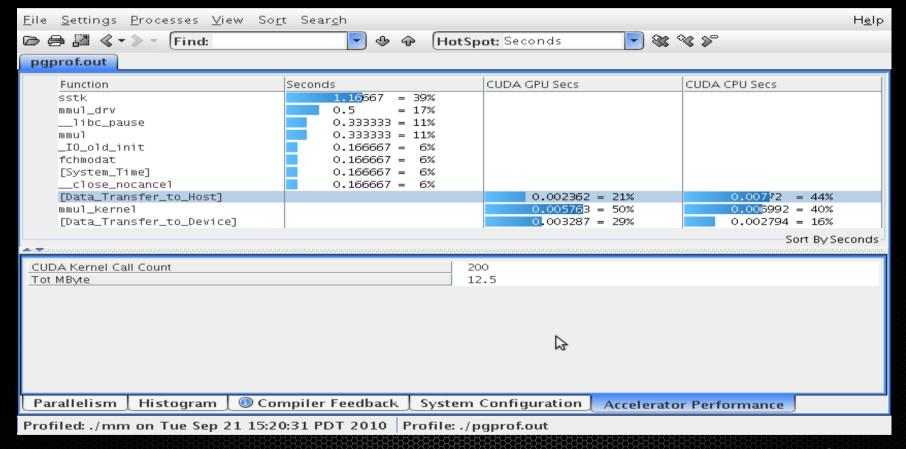
```
! timing experiment
time = 0.0
istat = cudaEventRecord(start, 0)
do j = 1, NREPS
    call sgemmNN_16x16<<<blooks, threads>>>(dA, dB, dC, m, N, k, alpha, beta)
end do
istat = cudaEventRecord(stop, 0)
istat = cudaDeviceSynchronize()
istat = cudaEventElapsedTime(time, start, stop)
time = time / (NREPS*1.0e3)
```

pgcollect / pgprof

- pgcollect [-cuda] a.out
 - Use -cuda to collect compute profile data
- pgprof [-exe a.out] [pgprof.out]







nvprof a.out

```
==30736== NVPROF is profiling process 30736, command: a.out
==30736== Profiling application: a.out
==30736== Profiling result:
Time (%)
                     Calls
            Time
                                 Avg
                                           Min
                                                     Max
                                                          Name
                                                          [CUDA memcpy HtoD]
 38.89% 393.41us
                            98.352us
                                      98.176us
                                                98.496us
 38.88% 393.25us
                            98.312us
                                      97.760us
                                                98.688us
                                                          [CUDA memcpy DtoH]
  6.05% 61.184us
                            61.184us
                                      61.184us
                                               61.184us
                                                         testasync 31 gpu
  5.92% 59.872us
                            59.872us
                                      59.872us
                                                59.872us testasync 41 gpu
  5.88% 59.520us
                            59.520us
                                      59.520us
                                                59.520us
                                                         testasync 51 gpu
                                               44.320us testasync 21 gpu
  4.38% 44.320us
                         1 44.320us 44.320us
```

nvprof -print-gpu-trace -csv a.out

Start	Duration Grid X	Gr		id Z B	lock X F	Block Y B		Registers Per Thread	Static SMem	Dynamic SMem	Size	Throughput Device	Context	Stream Name
ms	us				1001171	JIOCK I B	IOUN L	rinead	В	В		GB/s	оотпеле	
	43										IVID	GD/3		
												Tesla		
249.4308	98.304										1	10.17253 K40c (0)	1	8[CUDA memcpy HtoD]
												Tesla		
250.1725	44.064 977		1	1	256	1	1	19	0	0		K40c (0)	1	8testasync_21_gpu [22]
230.1723	44.004 377			1	230	1		19	U	U		K40C (U)	1	o testasync_z1_gpu [22]
												Tesla		
250.22	98.272										1	10.17584 K40c (0)	1	8 [CUDA memcpy DtoH]
												Tesla		
269.0212	98.528										1	10.1494 K40c (0)	1	9 [CUDA memcpy HtoD]
												Tesla		
269.6442	60.032 977		1	1	256	1	1	19	0	0		K40c (0)	1	9testasync_31_gpu [36]
209.0442	00.032 377			878	230			19	U	U		K40C (0)	•	otestasync_o1_gpu [50]
												Tesla		
269.7065	98.272										1	10.17584 K40c (0)	1	9 [CUDA memcpy DtoH]
												Tesla		
288.3552	98.304										1	10.17253 K40c (0)	1	10[CUDA memcpy HtoD]
														36

Performance Optimization

- Profile the CPU application
 - ensure you are accelerating the right part of your code
- Look at data movement
 - look for hidden data transfers
- Look at expensive kernels

Analyzing Kernels

- Launch configuration
 - block size > 1
 - grid size > 1
- Occupancy
 - registers per thread
- Memory operations
 - too many memory loads/stores (no caching)
 - stride-1 in vector index

Performance Tuning

- Performance Measurement
- Choose an appropriately parallel algorithm
- Optimize data movement between host and GPU
 - frequency, volume, regularity
- Optimize device memory accesses
 - strides, alignment
 - use shared memory, avoid bank conflicts
 - use constant memory
- Optimize kernel code
 - redundant code elimination
 - loop unrolling
 - Optimize compute intensity
 - unroll the parallel loop

Host-GPU Data Movement

- Avoid movement altogether
- Move outside of loops
- Better to move a whole array than subarray
- Update halo regions rather than whole array
 - use GPU to move halo region to contiguous area?
- Use streams, overlap data / compute
 - requires pinned host memory

Occupancy

- How many simultaneously active warps / maximum
 (maximum is 24, 32 (Tesla-10), 48 (Fermi), 64 (Kepler))
- Limits
 - threads per multiprocessor
 - threads per thread block 512 (Tesla) or 1024 (Fermi/Kepler)
 - thread blocks per multiprocessor 8 (Tesla/Fermi) or 16 (Kepler)
 - register usage 8K / 16K / 32K / 64K registers per multiprocessor
 - each warp uses 32n, so 16Kreg = 512wreg
 - shared memory usage 16KB (Tesla) or 48KB (Fermi, Kepler)
- Low occupancy often leads to low performance
- High occupancy does not guarantee high performance

Execution Configuration

- Execution configuration affects occupancy
- Want many threads per thread block
 - multiple of 32
 - 64, 128, 192, 256
- Want many many thread blocks

Divergence

Scalar threads executing in SIMD mode

```
if( threadidx%x <= 10 ) then
  foo = foo * 2
else
  foo = 0
endif</pre>
```

Each path taken

```
do i = 1, threadidx%x
  a(threadidx%x,i) = 0
enddo
```

Only matters within a warp

Divergence

Pad arrays to multiples of block size

```
i = (blockidx%x-1)*64 + threadidx%x
if( i \le N ) A(i) = ...
```

Global Memory

- Stride-1 accesses
 - address is aligned to mod(threadidx%x,16)
 - threadidx%x and threadidx%x+1 access consecutive addresses
- Using shared memory as data cache
 - Redundant data access within a thread
 - Redundant data access across threads
 - Stride-1 data access within a thread

Redundant Access Within a GPU Thread

```
! threadidx%x from 1:64
! this thread block does 256 'i' iterations
ilo = (blockidx%x-1)*256
ihi = blockidx*256 - 1
...
do j = jlo, jhi
  do i = ilo+threadidx%x, ihi, 64
    A(i,j) = A(i,j) * B(i)
  enddo
enddo
```

Redundant Access Within a GPU Thread

```
real, shared :: BB(256)
...
do ii = 0, 255, 64
   BB(threadidx%x+ii) = B(ilo+ii)
enddo
call syncthreads()
do j = jlo, jhi
   do i = ilo+threadidx%x, ihi, 64
    A(i,j) = A(i,j) * BB(i-ilo)
   enddo
enddo
```

Redundant Access Across GPU Threads

```
! threadidx%x from 1:64
i = (blockidx%x-1)*64 + threadidx%x
...
do j = jlo, jhi
   A(i,j) = A(i,j) * B(j)
enddo
```

Redundant Access Across GPU Threads

```
real, shared :: BB(64)

i = (blockidx%x-1)*64 + threadidx%x

do jb = jlo, jhi, 64

BB(threadidx%x) = B(jb+threadidx%x)
call syncthreads()
do j = jb, min(jhi,jb+63)
    A(i,j) = A(i,j) * BB(j-jb+1)
enddo
call syncthreads()
enddo
```

stride-1 access!

Shared Memory

- 16 memory banks
- Use threadidx%x in leading (stride-1) dimension
- Avoid stride of 16

Unroll the Parallel Loop

- If thread 'j' and 'j+1' share data, where
 - j is a parallel index
 - j is not the stride-1 index
- Unroll two or more iterations of 'j' into the kernel

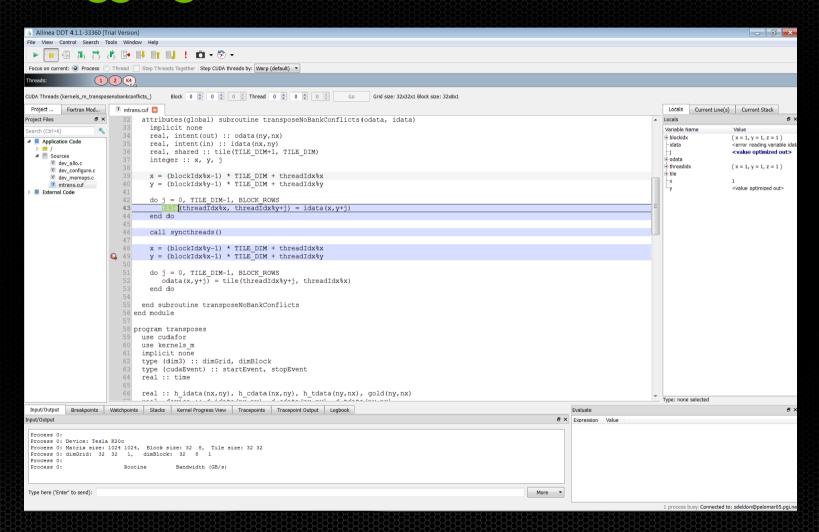
CUDA Fortran 2012/2013 Features

- PGI 2012 (CUDA 4.1 and 4.2)
 - Texture memory support
 - Support for double precision atomic add
- PGI 2013 (CUDA 5.0 and 5.5)
 - Support for dynamic parallelism
 - Relocatable device code, linking, device libraries
 - Full atomic datatype support
 - Kepler shuffle support

Latest Features in CUDA Fortran

- PGI 2014 (CUDA 6.0 and beyond)
 - DWARF generation, GPU-side debugging
 - Full shuffle datatype support
 - Overloaded reduction intrinsics
 - Support for Unified Memory
 - Improved interoperability with OpenACC

Debugging CUDA Fortran with Allinea DDT



Dwarf Generation Enables Tools

```
% pgf90 -g -O0 -Mcuda=cc35 saxpy.cuf
% cuda-memcheck ./a.out
====== CUDA-MEMCHECK
0: copyout Memcpy (host=0x68e9e0, dev=0x500200200, size=124)
FAILED: 4(unspecified launch failure)
====== Invalid __global__ read of size 4
            at 0x00000530 in /home/brentl/saxpy.cuf:10:m_saxpy_
            by thread (31,0,0) in block (0,0,0)
       9 ! if (i \le n) y(i) = alpha * x(i) + y(i)
      10 y(i) = alpha * x(i) + y(i)
```

Extending F90 Intrinsics to Device Data

Evaluate sum() of device array and return result to host

```
! host code
sum h = sum(a d)
```

- Typical reduction uses two kernels
 - Calculate partial sum for threads within a block
 - Launch a one-block kernel to perform a final sum

Extending F90 Intrinsics to Device Data

- Small arrays transfer data to host and sum there
 - Limited parallelism for small array
 - Device to host transfer is mostly overhead
- Large arrays perform partial sum on device, final sum on host
- Cutoff for optimal performance depends on host system
 - Configurable via initialization routine

Stages of Partial Sum

- Reduce to grid of threads using grid-stride loop
- Reduce within warp using SHFL (shuffle) functions
- One thread in each warp writes the value to shared memory, all call syncthreads(), then warp 1 reads the values into registers and uses a set of SHFL operations again
- This results in gridDim%x partial sums which are moved to the host

First Stage of Partial Sum

Reduce to grid of threads using grid-stride loop

```
nGrid = gridDim%x*blockDim%x
s = 0.0
ig = (blockIdx%x-1)*blockDim%x + threadIdx%x
do i = ig, n, nGrid
    s = s + a(i)
end do
```

SHFL (shuffle) functions

- Intra-warp data exchange
- Threads can read other threads' registers
- No shared memory required, no synchronization barriers
- Requires compute capability >= 3.0

s = threadIdx%x

$$t = _shfl_xor(s, 1)$$

$$t = _shfl_xor(s, 2)$$

$$s = s + t$$

Reduce within warp using SHFL functions

```
! reduce within warp
t = __shfl_xor(s, 1)
    s = s + t

t = __shfl_xor(s, 2)
    s = s + t

t = __shfl_xor(s, 4)
    s = s + t

t = __shfl_xor(s, 8)
    s = s + t

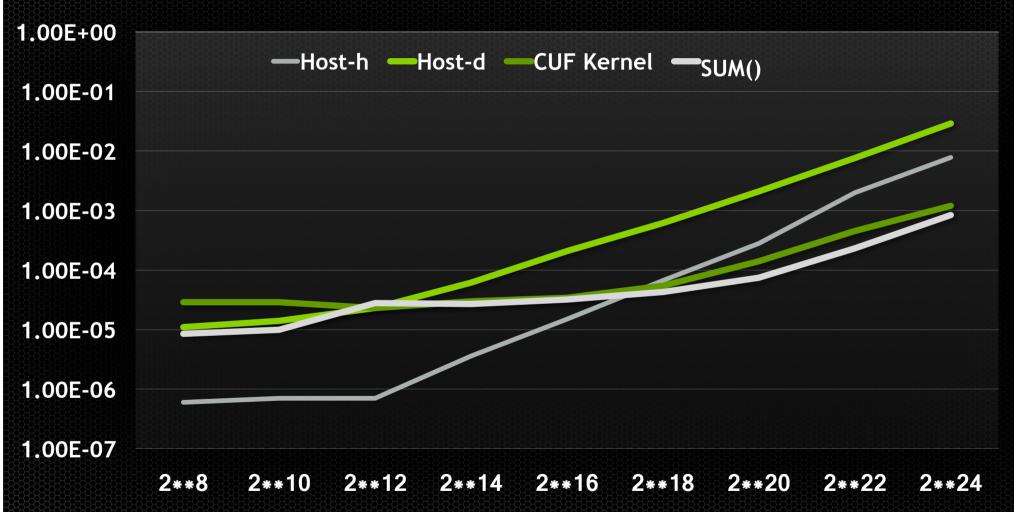
t = __shfl_xor(s, 16)
    s = s + t
```

Last Stage of Partial Sum

Reduce to gridDim%x partial sums, one from each thread block

```
if (BlockDim%x == 32) then
   if (threadIdx%x == 1) p(blockIdx%x) = s
else
  warpID = (threadIdx%x-1)/32+1
   laneID = iand(threadIdx%x,31)
   if (laneID == 1) p s(warpID) = s
   call syncthreads()
   if (warpID == 1) then ! Reduce in warp 1
      width = blockDim%x/32
      s = p s(threadIdx%x)
      i = 1
      do while (i < width)
         t = shfl xor(s, i, width)
         s = s + t
         i = i*2
      end do
      if (threadIdx%x == 1) p(blockIdx%x) = s
   end if
end if
```





CUDA Runtime API Routines

- Device management
- Thread management
- Memory management
- Event management
- Fortran: use cudafor

```
integer cudaGetDeviceCount( icount )
  integer, intent(out) :: icount
```

```
integer cudaSetDevice( inum )
   integer, intent(in) :: inum
```

integer cudaGetDevice(inum)
 integer, intent(out) inum

```
integer cudaGetDeviceProperties(prop,inum)
    type(cudaDeviceProp),intent(out) :: prop
    integer, intent(in) :: inum
```

```
integer cudaChooseDevice( inum, prop )
    type(cudaDeviceProp),intent(in) :: prop
    integer, intent(out) :: inum
```

- prop%name [character]
- prop%major
- o prop%minor
- prop%totalGlobalMem
- prop%regsPerBlock
- prop%maxThreadsPerBlock
- prop%maxThreadDim(3)
- prop%maxGridSize(3)
- prop%clockRate
- prop%totalConstMem

- prop%warpSize
- prop%textureAlignment
- prop%deviceOverlap
- prop%multiProcessorCount
- prop%kernelExecTimeoutEnabled
- prop%memPitch
- prop%integrated
- prop%canMapHostMemory
- prop%computeMode

Stream Management

- integer cudaStreamCreate(stream)
 integer,intent(out) :: stream
- integer cudaStreamQuery(stream)
 integer,intent(in) :: stream
- integer cudaStreamSynchronize(stream)
 integer,intent(in) :: stream
- integer cudaStreamDestroy(stream)
 integer,intent(in) :: stream

Memory Management

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```
integer cudaMallocHost( ptr, size )
  type(c ptr),intent(out) :: ptr
  integer, intent(in) :: size
integer cudaFreeHost( ptr )
  type(c ptr),intent(in) :: ptr
 integer cudaMalloc( ptr, count )
  <type>, device, allocatable, dimension(:)::&
     ptr
  integer, intent(in) :: count
integer cudaFree( ptr )
  <type>, device, dimension(*) :: ptr
```

Memory Management

dir values:

cudaMemcpyHostToHost
cudaMemcpyHostToDevice
cudaMemcpyDeviceToHost
cudaMemcpyDeviceToDevice

Memory Management

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```
integer cudaMallocPitch(ptr, pitch, w, h)
  <type>, device, allocatable, dimension(:,:) &
     :: ptr
  integer, intent(out) :: pitch
  integer, intent(in) :: w, h
integer cudaMemset( ptr, value, count )
  <type>, device<, dimension(*)> :: ptr
  <type> :: value
  integer :: count
integer cudaMemset2D(ptr,pitch,value,w,h)
  <type>, device<, dimension> :: ptr
```

CUDA Fortran with Managed Data

```
program pgil4x
    use cudafor
    integer, parameter :: n = 100000
    integer, managed :: a(n), b(n), c(n)
    a = [(i,i=1,n)]
    b = 1
!$cuf kernel do <<< *, * >>>
    do i = 1, n
        c(i) = a(i) + b(i)
    end do
    if (sum(c).ne.n*(n+1)/2+n) then
        print *,c(1),c(n)
    end if
end
```

What is CUDA Managed Data?

Host Code

```
attributes(global) subroutine mm kernel
            ( A, B, C, N, M, L )
real :: A(N,M), B(M,L), C(N,L), Cij
integer, value :: N, M, L
integer :: i, j, kb, k, tx, ty
real, shared :: Asub(16,16), Bsub(16,16)
tx = threadidx%x
ty = threadidx%y
i = blockidx%x * 16 + tx
j = blockidx y * 16 + ty
Cij = 0.0
do kb = 1, M, 16
   Asub(tx,ty) = A(i,kb+tx-1)
   Bsub(tx,ty) = B(kb+ty-1,j)
   call syncthreads()
   do k = 1,16
      Cij = Cij + Asub(tx,k) * Bsub(k,ty)
   enddo
   call syncthreads()
enddo
C(i,j) = Cij
end subroutine mmul kernel
```

Device Code

Managed Data enables Derived Type Usage

```
type tCM
  integer, allocatable, device :: fine(:)
  real, allocatable, device :: mat_matrix(:,:,:)
  real, allocatable, device :: src_matrix(:,:,:)
end type
type(tCM), allocatable, managed :: cm_list(:)
```

Array of derived type can be allocated on the host and used on the device

CUDA Fortran/OpenACC Interoperability

- Calling CUDA Fortran kernels from accelerator data regions
- Using CUDA Fortran device data in compute regions

```
!$acc data create(x) copy(y)
a = 3.0
!$acc kernels loop
do i = 1, n
    x(i) = x_dev(i) + 1.0
    y(i) = y(i) + real(i)
end do
call mysaxpy <<<block, thread>>> (n, a, x, y)
!$acc end data
```

Support of arguments with the device attribute in our OpenACC
 2.0 Runtime Library Routines

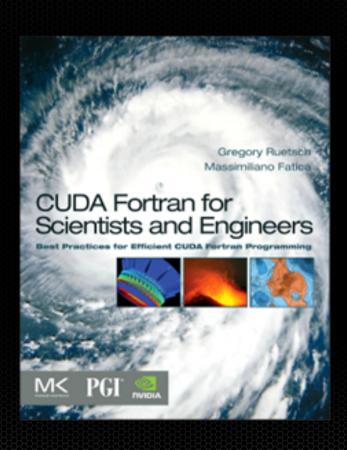
Calling CUDA Fortran Subroutines From OpenACC Programs

```
!$acc data region copyin(x)
! some compute regions . . .

k = isamax(N,x,1)
! maybe some other compute regions . . .
!$acc end data region
```

 You can call CUDA routines by creating explicit interfaces to hostresident data and device-resident data specific functions for a generic call

CUDA Fortran Literature



- Book Released in 2013
- PGInsider articles at http://www.pgroup.com
- CUDA Fortran Reference Manual