Agenda for Today

- **GPU as an accelerator**
  - Program structure
    - Bulk synchronous programming model
  - Memory hierarchy and memory management

- **Performance considerations**
  - Memory access
  - SIMD utilization
  - Atomic operations
  - Data transfers

- **Collaborative computing**
Recommended Readings

- CUDA Programming Guide

An Example GPU
Recall: NVIDIA GeForce GTX 285

- **NVIDIA-speak:**
  - 240 stream processors
  - “SIMT execution”

- **Generic speak:**
  - 30 cores
  - 8 SIMD functional units per core
NVIDIA GeForce GTX 285 “core”

- SIMD functional unit, control shared across 8 units
- multiply-add
- multiply
- instruction stream decode
- execution context storage

64 KB of storage for thread contexts (registers)

Slide credit: Kayvon Fatahalian
NVIDIA GeForce GTX 285 “core”

- Groups of 32 threads share instruction stream (each group is a Warp)
- Up to 32 warps are simultaneously interleaved
- Up to 1024 thread contexts can be stored

64 KB of storage for thread contexts (registers)

Slide credit: Kayvon Fatahalian
30 cores on the GTX 285: 30,720 threads
Recall: Evolution of NVIDIA GPUs
Recall: NVIDIA V100

- **NVIDIA-speak:**
  - 5120 stream processors
  - “SIMT execution”

- **Generic speak:**
  - 80 cores
  - 64 SIMD functional units per core

- Specialized Functional Units for Machine Learning (tensor "cores" in NVIDIA-speak)
Recall: NVIDIA V100 Block Diagram

80 cores on the V100

https://devblogs.nvidia.com/inside-volta/
Recall: NVIDIA V100 Core

15.7 TFLOPS Single Precision
7.8 TFLOPS Double Precision
125 TFLOPS for Deep Learning (Tensor “cores”)

https://devblogs.nvidia.com/inside-volta/
Food for Thought

What is the main bottleneck in GPU programs?

“Tensor cores”:
- Can you think about other operations than matrix multiplication?
- What other applications could benefit from specialized cores?

Compare and contrast GPUs vs other accelerators (e.g., systolic arrays)
- Which one is better for machine learning?
- Which one is better for image/vision processing?
- What types of parallelism each one exploits?
- What are the tradeoffs?
Recall: Latency Hiding via Warp-Level FGMT

- **Warp**: A set of threads that execute the same instruction (on different data elements)

- **Fine-grained multithreading**
  - One instruction per thread in pipeline at a time (No interlocking)
  - Interleave warp execution to hide latencies

- Register values of all threads stay in register file

- FGMT enables long latency tolerance
  - Millions of pixels

Slide credit: Tor Aamodt
Recall: Warp Execution

32-thread warp executing $ADD \ A[tid],B[tid] \rightarrow C[tid]$
Recall: SIMD Execution Unit Structure

- Registers for each Thread
  - Registers for thread IDs 0, 4, 8, ...
  - Registers for thread IDs 1, 5, 9, ...
  - Registers for thread IDs 2, 6, 10, ...
  - Registers for thread IDs 3, 7, 11, ...
- Lane
- Functional Unit
- Memory Subsystem

Slide credit: Krste Asanovic
Recall: Warp Instruction Level Parallelism

Can overlap execution of multiple instructions

- Example machine has 32 threads per warp and 8 lanes
- Completes 24 operations/cycle while issuing 1 warp/cycle

Slide credit: Krste Asanovic
# Clarification of some GPU Terms

<table>
<thead>
<tr>
<th>Generic Term</th>
<th>NVIDIA Term</th>
<th>AMD Term</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vector length</td>
<td>Warp size</td>
<td>Wavefront size</td>
<td>Number of threads that run in parallel (lock-step) on a SIMD functional unit</td>
</tr>
<tr>
<td>Pipelined functional unit / Scalar pipeline</td>
<td>Streaming processor / CUDA core</td>
<td>-</td>
<td>Functional unit that executes instructions for one GPU thread</td>
</tr>
<tr>
<td>SIMD functional unit / SIMD pipeline</td>
<td>Group of N streaming processors (e.g., N=8 in GTX 285, N=16 in Fermi)</td>
<td>Vector ALU</td>
<td>SIMD functional unit that executes instructions for an entire warp</td>
</tr>
<tr>
<td>GPU core</td>
<td>Streaming multiprocessor</td>
<td>Compute unit</td>
<td>It contains one or more warp schedulers and one or several SIMD pipelines</td>
</tr>
</tbody>
</table>
GPU Programming
Recall: Vector Processor Disadvantages

-- Works (only) if parallelism is regular (data/SIMD parallelism)
++ Vector operations
-- Very inefficient if parallelism is irregular
-- How about searching for a key in a linked list?

To program a vector machine, the compiler or hand coder must make the data structures in the code fit nearly exactly the regular structure built into the hardware. That’s hard to do in first place, and just as hard to change. One tweak, and the low-level code has to be rewritten by a very smart and dedicated programmer who knows the hardware and often the subtleties of the application area. Often the rewriting is

General Purpose Processing on GPU

- **Easier programming of SIMD processors with SPMD**
  - GPUs have democratized High Performance Computing (HPC)
  - Great FLOPS/$, massively parallel chip on a commodity PC

- **Many workloads exhibit inherent parallelism**
  - Matrices
  - Image processing
  - Deep neural networks

- **However, this is not for free**
  - New programming model
  - Algorithms need to be re-implemented and rethought

- **Still some bottlenecks**
  - CPU-GPU data transfers (PCIe, NVLINK)
  - DRAM memory bandwidth (GDDR5, GDDR6, HBM2)
    - Data layout
**CPU vs. GPU**

- **Different design philosophies**
  - CPU: A few out-of-order cores
  - GPU: Many in-order FGMT cores

---

Slide credit: Hwu & Kirk
GPU Computing

- Computation is offloaded to the GPU
- Three steps
  - CPU-GPU data transfer (1)
  - GPU kernel execution (2)
  - GPU-CPU data transfer (3)
Traditional Program Structure

- CPU threads and GPU kernels
  - Sequential or modestly parallel sections on CPU
  - Massively parallel sections on GPU

Serial Code (host)

Parallel Kernel (device)
KernelA<<< nBlk, nThr >>>(args);

Serial Code (host)

Parallel Kernel (device)
KernelB<<< nBlk, nThr >>>(args);

Slide credit: Hwu & Kirk
Recall: SPMD

- Single procedure/program, multiple data
  - This is a programming model rather than computer organization

- Each processing element executes the same procedure, except on different data elements
  - Procedures can synchronize at certain points in program, e.g. barriers

- Essentially, multiple instruction streams execute the same program
  - Each program/procedure 1) works on different data, 2) can execute a different control-flow path, at run-time
  - Many scientific applications are programmed this way and run on MIMD hardware (multiprocessors)
  - Modern GPUs programmed in a similar way on a SIMD hardware
CUDA/OpenCL Programming Model

- SIMT or SPMD

- Bulk synchronous programming
  - Global (coarse-grain) synchronization between kernels

- The host (typically CPU) allocates memory, copies data, and launches kernels

- The device (typically GPU) executes kernels
  - Grid (NDRange)
  - Block (work-group)
    - Within a block, shared memory, and synchronization
  - Thread (work-item)
Hardware is **free to schedule** thread blocks.

Each block can execute in any order relative to other blocks.
Memory Hierarchy
Traditional Program Structure in CUDA

- **Function prototypes**
  
  ```
  float serialFunction(...);
  __global__ void kernel(...);
  ```

- **main()**
  
  1) **Allocate memory** space on the device – cudaMalloc(&d_in, bytes);
  2) Transfer data from **host to device** – cudaMemcpy(d_in, h_in, ...);
  3) Execution configuration setup: #blocks and #threads
  4) **Kernel call** – kernel<<<execution configuration>>>(args...);
  5) Transfer results from **device to host** – cudaMemcpy(h_out, d_out, ...);

- **Kernel** – __global__ void kernel(type args,...)
  
  - Automatic variables transparently assigned to **registers**
  - **Shared memory**: __shared__
  - Intra-block **synchronization**: __syncthreads();
CUDA Programming Language

- Memory allocation
  
  ```
  cudaMalloc((void**)&d_in, #bytes);
  ```

- Memory copy
  
  ```
  cudaMemcpy(d_in, h_in, #bytes, cudaMemcpyHostToDevice);
  ```

- Kernel launch
  
  ```
  kernel<<< #blocks, #threads >>>(args);
  ```

- Memory deallocation
  
  ```
  cudaFree(d_in);
  ```

- Explicit synchronization
  
  ```
  cudaDeviceSynchronize();
  ```
**Indexing and Memory Access**

- **Images are 2D data structures**
  - height x width
  - `Image[j][i]`, where `0 ≤ j < height`, and `0 ≤ i < width`

![Image Diagram]

- `Image[0][1]`
- `Image[1][2]`
Image Layout in Memory

- Row-major layout
- Image[j][i] = Image[j x width + i]

Stride = width

Image[0][1] = Image[0 x 8 + 1]
Image[1][2] = Image[1 x 8 + 2]
Indexing and Memory Access: 1D Grid

- One GPU thread per pixel
- Grid of Blocks of Threads
  - gridDim.x, blockIdx.x
  - blockDim.x, threadIdx.x

\[ \text{blockIdx.x} \]
\[ \text{threadIdx.x} \]

\[ 6 \times 4 + 1 = 25 \]
\[ \text{blockIdx.x} \times \text{blockDim.x} + \text{threadIdx.x} \]
Indexing and Memory Access: 2D Grid

- **2D blocks**
  - `gridDim.x`, `gridDim.y`

Row = \( \text{blockIdx.y} \times \text{blockDim.y} + \text{threadIdx.y} \)

Col = \( \text{blockIdx.x} \times \text{blockDim.x} + \text{threadIdx.x} \)

Row = 1 \times 2 + 1 = 3

Col = 0 \times 2 + 1 = 1

Image[3][1] = Image[3 \times 8 + 1]
Brief Review of GPU Architecture (I)

- Streaming Processor Array
  - Tesla architecture (G80/GT200)
Brief Review of GPU Architecture (II)

- Streaming Multiprocessors (SM)
  - Streaming Processors (SP)

- Blocks are divided into **warps**
  - SIMD unit (32 threads)

![NVIDIA Fermi architecture diagram]

**NVIDIA Fermi architecture**
Brief Review of GPU Architecture (III)

- **Streaming Multiprocessors (SM) or Compute Units (CU)**
  - SIMD pipelines

- **Streaming Processors (SP) or CUDA "cores"**
  - Vector lanes

- **Number of SMs x SPs across generations**
  - Tesla (2007): 30 x 8
  - Fermi (2010): 16 x 32
  - Kepler (2012): 15 x 192
  - Maxwell (2014): 24 x 128
  - Pascal (2016): 56 x 64
  - Volta (2017): 80 x 64
Performance Considerations
Performance Considerations

- Main bottlenecks
  - Global memory access
  - CPU-GPU data transfers

- Memory access
  - Latency hiding
    - Occupancy
  - Memory coalescing
  - Data reuse
    - Shared memory usage

- SIMD (Warp) Utilization: Divergence

- Atomic operations: Serialization

- Data transfers between CPU and GPU
  - Overlap of communication and computation
Memory Access
Latency Hiding

- **FGMT** can hide long latency operations (e.g., memory accesses)
- **Occupancy**: ratio of active warps

---

4 active warps

- Warp 0: Instruction 3
- Warp 1: Instruction 2
- Warp 2: Instruction 1
- Warp 3: Instruction 1

---

2 active warps

- Warp 0: Instruction 3
- Warp 1: Instruction 2

---

Warp 0: Instruction 4 (Long latency)
Occupancy

- SM resources (typical values)
  - Maximum number of warps per SM (64)
  - Maximum number of blocks per SM (32)
  - Register usage (256KB)
  - Shared memory usage (64KB)

- Occupancy calculation
  - Number of threads per block (defined by the programmer)
  - Registers per thread (known at compile time)
  - Shared memory per block (defined by the programmer)
Memory Coalescing

- When accessing global memory, we want to make sure that concurrent threads access nearby memory locations.
- Peak bandwidth utilization occurs when all threads in a warp access one cache line.

![Memory Coalescing Diagram](slide.png)

Slide credit: Hwu & Kirk
Uncoalesced Memory Accesses

Access direction in Kernel code

Time Period 1

Time Period 2

Slide credit: Hwu & Kirk
Coalesced Memory Accesses

Access direction in Kernel code

Time Period 1
T₁ T₂ T₃ T₄

Time Period 2
T₁ T₂ T₃ T₄

...
Array of Structures vs. Structure of Arrays

Tenemos 2 data layouts principales (AoS y SoA) y uno nuevo propuesto (ASTA).

ASTA permite transformar uno en otro más rápido y facilita hacerlo in-place, para ahorrar memoria.

En la siguiente figura se ven los tres:

La granularidad en ASTA, es decir, el ancho del tile, estará relacionado con la granularidad de acceso a la memoria (warp_size = 32, por ejemplo).

Convertir entre los distintos layouts, en realidad es transponer. Por ejemplo, AoS a ASTA:

Y transponer es permutar (los números representan posiciones en la memoria y los colores, tipo de dato):

data_layout_conversion_and_transposition.png

`Converting AoS to ASTA is not too different from transposing a bunch of small tiles`

La primera intención, barrier-sync, más probablemente se haría igual que un arreglo bidimensional, pero para poder aprovechar el paralelismo, se haría como si fuera un único arreglo, y cada tarea se encargaría de un bloque de los tiles que compondría uno de sus respectivos arreglos unidimensionales.

La familiarización con los conceptos de la programación paralela puede ser un buen punto de partida para comprender el funcionamiento de estos arreglos unidimensionales:

La transposición es un ejemplo prototipo de un problema de permutación, que a menudo se puede decomposed a ciclos independientes de desplazamientos.

La notación de una permutación se representa como una secuencia de números, donde el número i se mueve a la posición del número en la posición i de la secuencia original.

Una permutación puede ser descomposto en ciclos independientes de desplazamientos:
CPUs Prefer AoS, GPUs Prefer SoA

- Linear and strided accesses

**Diagram:**
- **GPU**
  - Throughput (GB/s) vs. Stride (Structure size)
  - Shows a decrease in throughput with increasing stride size.

- **CPU**
  - Throughput (GB/s) vs. Stride (Structure size)
  - Shows an increase in throughput with increasing stride size.

**AMD Kaveri A10-7850K**

Sung+, “DL: A data layout transformation system for heterogeneous computing,” INPAR 2012
Data Reuse

- Same memory locations accessed by neighboring threads

```c
for (int i = 0; i < 3; i++){
    for (int j = 0; j < 3; j++){
        sum += gauss[i][j] * Image[(i+row-1)*width + (j+col-1)];
    }
}
```
Data Reuse: Tiling

- To take advantage of data reuse, we divide the input into tiles that can be loaded into shared memory

```c
__shared__ int l_data[(L_SIZE+2)*(L_SIZE+2)];
...
Load tile into shared memory
__syncthreads();
for (int i = 0; i < 3; i++){
    for (int j = 0; j < 3; j++){
        sum += gauss[i][j] * l_data[(i+l_row-1)*(L_SIZE+2)+j+l_col-1];
    }
}
```
Shared Memory

- Shared memory is an *interleaved (banked) memory*
  - Each bank can service one address per cycle

- Typically, 32 banks in NVIDIA GPUs
  - Successive 32-bit words are assigned to successive banks
    - Bank = Address % 32

- Bank conflicts are *only possible within a warp*
  - No bank conflicts between different warps
Shared Memory Bank Conflicts (I)

- Bank conflict free

Linear addressing: stride = 1

Random addressing 1:1

Slide credit: Hwu & Kirk
Shared Memory Bank Conflicts (II)

- **N-way bank conflicts**

2-way bank conflict: stride = 2

8-way bank conflict: stride = 8

Slide credit: Hwu & Kirk
Reducing Shared Memory Bank Conflicts

- Bank conflicts are only possible within a warp
  - No bank conflicts between different warps

- If strided accesses are needed, some optimization techniques can help
  - Padding
  - Randomized mapping
  - Hash functions
SIMD Utilization
Control Flow Problem in GPUs/SIMT

- A GPU uses a SIMD pipeline to save area on control logic
  - Groups scalar threads into warps

- Branch divergence occurs when threads inside warps branch to different execution paths

This is the same as conditional/predicated/masked execution. Recall the Vector Mask and Masked Vector Operations?
Intra-warp divergence

Compute(threadIdx.x);
if (threadIdx.x % 2 == 0){
    Do_this(threadIdx.x);
}
else{
    Do_that(threadIdx.x);
}
Increasing SIMD Utilization

- **Divergence-free execution**

```c
Compute(threadIdx.x);
if (threadIdx.x < 32){
    Do_this(threadIdx.x * 2);
}
else{
    Do_that((threadIdx.x%32)*2+1);
}
```
Vector Reduction: Naïve Mapping (I)

Slide credit: Hwu & Kirk
Program with **low SIMD utilization**

```c
__shared__ float partialSum[]

unsigned int t = threadIdx.x;

for (int stride = 1; stride < blockDim.x; stride *= 2) {

    __syncthreads();

    if (t % (2*stride) == 0)
        partialSum[t] += partialSum[t + stride];
}
```
Divergence-Free Mapping (I)

- All active threads belong to the same warp

Slide credit: Hwu & Kirk
Program with **high SIMD utilization**

```c
__shared__ float partialSum[]

unsigned int t = threadIdx.x;

for (int stride = blockDim.x; stride > 1; stride >>= 1){
    __syncthreads();
    if (t < stride)
        partialSum[t] += partialSum[t + stride];
}
```
Atomic Operations
Atomic Operations are needed when threads might update the same memory locations at the same time.

- **CUDA**: `int atomicAdd(int*, int);`

- **PTX**: `atom.shared.add.u32 %r25, [%rd14], %r24;`

- **SASS**:

```
/*00a0*/ LDSLK P0, R9, [R8];
/*00a8*/ @P0 IADD R10, R9, R7;
/*00b0*/ @P0 STSCUL P1, [R8], R10;
/*00b8*/ @!P1 BRA 0xa0;
```

Tesla, Fermi, Kepler

Maxwell, Pascal, Volta

```
/*01f8*/ ATOMS.ADD RZ, [R7], R11;
```

Native atomic operations for 32-bit integer, and 32-bit and 64-bit atomicCAS
We define the intra-warp conflict degree as the number of threads in a warp that update the same memory position. The conflict degree can be between 1 and 32.

No atomic conflict = concurrent updates

Atomic conflict = serialized updates
Histogram Calculation

- Histograms count the number of data instances in disjoint categories (bins)

```plaintext
for (each pixel i in image I) {
    Pixel = I[i]       // Read pixel
    Pixel’ = Computation(Pixel)   // Optional computation
    Histogram[Pixel’]++       // Vote in histogram bin
}
```

Input data

```
<table>
<thead>
<tr>
<th>data[0]</th>
<th>data[1]</th>
<th>data[2]</th>
<th>...</th>
<th>data[n-1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>data[n]</td>
<td>data[n+1]</td>
<td>data[n+2]</td>
<td>...</td>
<td>data[2n-1]</td>
</tr>
</tbody>
</table>
```

Atomic additions
Histogram Calculation of Natural Images

- **Frequent conflicts** in natural images
Optimizing Histogram Calculation

- **Privatization**: Per-block sub-histograms in shared memory

Data Transfers between CPU and GPU
Data Transfers

- Synchronous and asynchronous transfers
- Streams (Command queues)
  - Sequence of operations that are performed in order
    - CPU-GPU data transfer
    - Kernel execution
      - D input data instances, B blocks
    - GPU-CPU data transfer
  - Default stream
Asynchronous Transfers

- **Computation** divided into nStreams
  - D input data instances, B blocks
  - nStreams
    - D/nStreams data instances
    - B/nStreams blocks

- **Estimates**
  - \( t_E + \frac{t_T}{nStreams} \)
  - \( t_T + \frac{t_E}{nStreams} \)

\( t_E \geq t_T \) (dominant kernel)
\( t_T > t_E \) (dominant transfers)
Applications with independent computation on different data instances can benefit from asynchronous transfers.

For instance, *video processing*

---

**Non-streamed execution**

A sequence of 6 frames is transferred to device

6 \( \times \) 6 blocks compute on the sequence of frames

**Streamed execution**

A chunk of 2 frames is transferred to device

2 \( \times \) 6 blocks compute on the chunk, while the second chunk is being transferred

Execution time saved thanks to streams

---

Summary

- GPU as an accelerator
  - Program structure
    - Bulk synchronous programming model
  - Memory hierarchy and memory management

- Performance considerations
  - Memory access
    - Latency hiding: occupancy (TLP)
    - Memory coalescing
    - Data reuse: shared memory
  - SIMD utilization
  - Atomic operations
  - Data transfers
Collaborative Computing
Review

- Device allocation, CPU-GPU transfer, and GPU-CPU transfer
  - `cudaMalloc();`
  - `cudaMemcpy();`

```c
// Allocate input
malloc(input, ...);
cudaMalloc(d_input, ...);
cudaMemcpy(d_input, input, ..., HostToDevice);  // Copy to device memory

// Allocate output
malloc(output, ...);
cudaMalloc(d_output, ...);

// Launch GPU kernel
gpu_kernel<<<blocks, threads>>>(d_output, d_input, ...);

// Synchronize
cudaDeviceSynchronize();

// Copy output to host memory
cudaMemcpy(output, d_output, ..., DeviceToHost);
```
Unified Memory (I)

- Unified Virtual Address
- Since CUDA 6.0: **Unified memory**
- Since CUDA 8.0 + Pascal: **GPU page faults**

CUDA 6 Unified Memory

- Kepler GPU
- CPU
- Unified Memory
  (Limited to GPU Memory Size)

Pascal Unified Memory

- Pascal GPU
- CPU
- Unified Memory
  (Limited to System Memory Size)
Unified Memory (II)

- Easier programming with Unified Memory
  - `cudaMallocManaged();`

```c
// Allocate input
malloc(input, ...);
cudaMallocManaged(d_input, ...);
memcpy(d_input, input, ...); // Copy to managed memory

// Allocate output
cudaMallocManaged(d_output, ...);

// Launch GPU kernel
gpu_kernel<<<blocks, threads>>> (d_output, d_input, ...);

// Synchronize
cudaDeviceSynchronize();
```
Case studies using CPU and GPU

- Kernel launches are asynchronous
  - CPU can work while waits for GPU to finish
  - Traditionally, this is the most efficient way to exploit heterogeneity

```c
// Allocate input
malloc(input, ...);
cudaMalloc(d_input, ...);
cudAmemcpy(d_input, input, ..., HostToDevice); // Copy to device memory

// Allocate output
malloc(output, ...);
cudaMalloc(d_output, ...);

// Launch GPU kernel
gpu_kernel<<<blocks, threads>>>(d_output, d_input, ...);

// CPU can do things here

// Synchronize
cudaDeviceSynchronize();

// Copy output to host memory
cudAmemcpy(output, d_output, ..., DeviceToHost);
```
Fine-Grained Heterogeneity

- **Fine-grain heterogeneity** becomes possible with Pascal/Volta architecture
- Pascal/Volta Unified Memory
  - CPU-GPU memory coherence
  - System-wide atomic operations

```c
// Allocate input
cudaMallocManaged(input, ...);

// Allocate output
cudaMallocManaged(output, ...);

// Launch GPU kernel
gpu_kernel<<<blocks, threads>>> (output, input, ...);

// CPU can do things here
output[x] = input[y];
output[x+1].fetch_add(1);
```
Since CUDA 8.0

- Unified memory
  
  \[
  \text{cudaMallocManaged}(& \text{h\_in}, \text{in\_size});
  \]

- System-wide atomics
  
  \[
  \text{old} = \text{atomicAdd\_system}(\& \text{h\_out}[x], \text{inc});
  \]
Since OpenCL 2.0

- **Shared virtual memory**
  
  ```c
  XYZ * h_in = (XYZ *)clSVMAlloc(
      ocl.clContext, CL_MEM_SVM_FINE_GRAIN_BUFFER, in_size, 0);
  ```

- **More flags:**
  
  ```c
  CL_MEM_READ_WRITE
  CL_MEM_SVM_ATOMICS
  ```

- **C++11 atomic operations**
  
  ```c
  (memory_scope_all_svm_devices)
  old = atomic_fetch_add(&h_out[x], inc);
  ```
C++ AMP (HCC)

- Unified memory space (HSA)

  \[
  \text{XYZ } *h\_in = (\text{XYZ } *)\text{malloc(in\_size)};
  \]

- C++11 atomic operations

  (memory\_scope\_all\_svm\_devices)

  - Platform atomics (HSA)

    \[
    \text{old} = \text{atomic\_fetch\_fetch\_add}(&h\_out[x], \text{inc});
    \]
Collaborative Patterns (I)

Program Structure

- Data-parallel tasks
- Sequential sub-tasks
- Coarse-grained synchronization

Data Partitioning

Device 1

Device 2
Collaborative Patterns (II)

Program Structure

Coarse-grained Task Partitioning

data-parallel tasks

sequential sub-tasks

coarse-grained synchronization
Collaborative Patterns (III)

Program Structure

data-parallel tasks

sequential sub-tasks

coarse-grained synchronization

Fine-grained Task Partitioning

Device 1

Device 2
Histogram (I)

- Previous generations: separate CPU and GPU histograms are merged at the end

```c
malloc(CPU image);
cudaMalloc(GPU image);
cudaMemcpy(GPU image, CPU image, ...,
    Host to Device);
malloc(CPU histogram);
memset(CPU histogram, 0);
cudaMalloc(GPU histogram);
cudaMemset(GPU histogram, 0);

// Launch CPU threads
// Launch GPU kernel

cudaMemcpy(GPU histogram, DeviceToHost);

// Launch CPU threads for merging
```
Histogram (II)

- System-wide atomic operations: one single histogram

```c
cudaMallocManaged(Histogram);
cudaMemset(Histogram, 0);

// Launch CPU threads
// Launch GPU kernel (atomicAdd_system)
```
Bézier Surfaces (I)

- Bézier surface: 4x4 net of control points
Bézier Surfaces (II)

- Parametric non-rational formulation
  - Bernstein polynomials
  - Bi-cubic surface \( m = n = 3 \)

\[
S(u, v) = \sum_{i=0}^{m} \sum_{j=0}^{n} P_{i,j} B_{i,m}(u) B_{j,n}(v), \quad (1)
\]

\[
B_{i,m}(u) = \binom{m}{i} (1 - u)^{(m-i)} u^i, \quad (2)
\]
Bézier Surfaces (III)

- Collaborative implementation
  - Tiles calculated by GPU blocks or CPU threads
  - Static distribution

![Diagram of Bézier Surfaces (III)]
Bézier Surfaces (IV)

- **Without Unified Memory**

```c
// Allocate control points
malloc(control_points, ...);
generate_cp(control_points);
cudaMalloc(d_control_points, ...);
cudaMemcpy(d_control_points, control_points, ..., HostToDevice); // Copy to device memory

// Allocate surface
malloc(surface, ...);
cudaMalloc(d_surface, ...);

// Launch CPU threads
std::thread main_thread (run_cpu_threads, control_points, surface, ...);

// Launch GPU kernel
gpu_kernel<<<blocks, threads>>>(d_surface, d_control_points, ...);

// Synchronize
main_thread.join();
cudaDeviceSynchronize();

// Copy gpu part of surface to host memory
cudaMemcpy(&surface[end_of_cpu_part], d_surface, ..., DeviceToHost);
```
Bézier Surfaces (V)

- Execution results
  - Bezier surface: 300x300, 4x4 control points
  - %Tiles to CPU
  - NVIDIA Jetson TX1 (4 ARMv8 + 2 SMX): 17% speedup wrt GPU only
Bézier Surfaces (VI)

- **With Unified Memory (Pascal/Volta)**

```c
// Allocate control points
malloc(control_points, ...);
generate_cp(control_points);
cudaMalloc(d_control_points, ...);
cudaMemcpy(d_control_points, control_points, ..., HostToDevice); // Copy to device memory

// Allocate surface
cudaMallocManaged(surface, ...);

// Launch CPU threads
std::thread main_thread (run_cpu_threads, control_points, surface, ...);

// Launch GPU kernel
gpu_kernel<<<blocks, threads>>>(surface, d_control_points, ...);

// Synchronize
main_thread.join();
cudaDeviceSynchronize();
```
Bézier Surfaces (VII)

- Static vs. dynamic implementation

(a) Static Distribution

(b) Dynamic Distribution

- Pascal/Volta Unified Memory: system-wide atomic operations

```cpp
while(true){
    if(threadIdx.x == 0)
        my_tile = atomicAdd_system(tile_num, 1);  // my_tile in shared memory; tile_num in UM

    __syncthreads();  // Synchronization

    if(my_tile >= number_of_tiles) break;  // Break when all tiles processed

    ...
}
```
Benefits of Collaboration

- Data partitioning improves performance
  - AMD Kaveri (4 CPU cores + 8 GPU CUs)

![Graph showing execution time for different configurations. The graph indicates that data partitioning improves performance, with up to a 47% improvement over GPU only for Bézier Surfaces.](image-url)
Matrix padding

- Memory alignment
- Transposition of near-square matrices

Traditionally, it can only be performed out-of-place
Padding (II)

- Execution results
  - Matrix size: 4000x4000, padding = 1
  - NVIDIA Jetson TX1 (4 ARMv8 + 2 SMX): 29% speedup wrt GPU only
In-Place Padding

- Pascal/Volta Unified Memory

<table>
<thead>
<tr>
<th>Coherent memory</th>
<th>Flags</th>
<th>GPU temporary location</th>
<th>CPU temporary location</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 1 2 3 4</td>
<td>1</td>
<td>15 16 17 18 19</td>
<td>30 31 32 33 34</td>
</tr>
<tr>
<td>5 6 7 8 9</td>
<td>1</td>
<td>20 21 22 23 24</td>
<td></td>
</tr>
<tr>
<td>10 11 12 13 14</td>
<td>1</td>
<td>25 26 27 28 29</td>
<td></td>
</tr>
<tr>
<td>15 16 17 18 19</td>
<td>1</td>
<td></td>
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</tr>
<tr>
<td>20 21 22 23 24</td>
<td>1</td>
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<td>25 26 27 28 29</td>
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<td></td>
</tr>
<tr>
<td>30 31 32 33 34</td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adjacent synchronization: CPU and GPU
In-place implementation will be possible.
Benefits of Collaboration

- Optimal number of devices is not always max
  - AMD Kaveri (4 CPU cores + 8 GPU CUs)
Stream Compaction (I)

- Stream compaction
  - Saving memory storage in sparse data
  - Similar to padding, but local reduction result (non-zero element count) is propagated

```
Input: 2 1 3 0 0 1 3 4 0 0 2 1
Predicate: Element > 0
Output: 2 1 3 1 3 4 2 1
```
Stream Compaction (II)

- Execution results
  - Array size: 2 MB, Filtered items = 50%
  - NVIDIA Jetson TX1 (4 ARMv8 + 2 SMX): 25% speedup wrt GPU only

![Graph showing execution time vs. %CPU workload]
Benefits of Collaboration

- Data partitioning improves performance
  - AMD Kaveri (4 CPU cores + 8 GPU CUs)

Stream Compaction
(up to 82% improvement over GPU only)
Breadth-First Search

- Small-sized and big-sized frontiers
  - Top-down approach
  - Kernel 1 and Kernel 2

- Atomic-based block synchronization
  - Avoids kernel re-launch

- Very small frontiers
  - Underutilize GPU resources

- Collaborative implementation
Atomic-Based Block Synchronization (I)

- Combine Kernel 1 and Kernel 2
- We can **avoid** kernel re-launch
- We need to use persistent thread blocks
  - Kernel 2 launches \((\text{frontier\_size} / \text{block\_size})\) blocks
  - Persistent blocks: up to \((\text{number\_SMs} \times \text{max\_blocks\_SM})\)
Atomic-Based Block Synchronization (II)

- Code (simplified)

```c
// GPU kernel
const int gtid = blockIdx.x * blockDim.x + threadIdx.x;

while(frontier_size != 0){
    for(node = gtid; node < frontier_size; node += blockDim.x*gridDim.x){
        // Visit neighbors
        // Enqueue in output queue if needed (global or local queue)
    }
    // Update frontier_size
    // Global synchronization
}
```
Global synchronization (simplified)

- At the end of each iteration

```c
const int tid = threadIdx.x;
const int gtid = blockIdx.x * blockDim.x + threadIdx.x;
atomicExch(ptr_threads_run, 0);
atomicExch(ptr_threads_end, 0);
int frontier = 0;
...
frontier++;
if(tid == 0){
    atomicAdd(ptr_threads_end, 1);  // Thread block finishes iteration
}
if(gtid == 0){
    while(atomicAdd(ptr_threads_end, 0) != blockDim.x){}  // Wait until all blocks finish
    atomicExch(ptr_threads_end, 0);  // Reset
    atomicAdd(ptr_threads_run, 1);  // Count iteration
}
if(tid == 0 && gtid != 0){
    while(atomicAdd(ptr_threads_run, 0) < frontier){}  // Wait until ptr_threads_run is updated
}
__syncthreads();  // Rest of threads wait here
...
Collaborative Implementation (I)

**Motivation**
- Small-sized frontiers underutilize GPU resources
  - NVIDIA Jetson TX1 (4 ARMv8 CPUs + 2 SMXs)
  - New York City roads
Collaborative Implementation (II)

- Choose the most appropriate device

small frontiers processed on CPU

large frontiers processed on GPU
Choose **CPU or GPU depending on frontier size**

```c
// Host code
while(frontier_size != 0){
    if(frontier_size < LIMIT){
        // Launch CPU threads
    }
    else{
        // Launch GPU kernel
    }
}
```

**CPU threads or GPU kernel keep running while the condition is satisfied**
Collaborative Implementation (IV)

- Execution results

![Collaborative Implementation (IV) Graph](image-url)
Collaborative Implementation (V)

- **Without** Unified Memory
  - Explicit memory copies

```c
// Host code
while(frontier_size != 0){
    if(frontier_size < LIMIT){
        // Launch CPU threads
    }
    else{
        // Copy from host to device (queues and synchronization variables)
        // Launch GPU kernel
        // Copy from device to host (queues and synchronization variables)
    }
}
```
Collaborative Implementation (VI)

- **Unified Memory**
  - `cudaMallocManaged();`
  - Easier programming
  - No explicit memory copies

```c
// Host code
while(frontier_size != 0){
    if(frontier_size < LIMIT){
        // Launch CPU threads
    } else{
        // Launch GPU kernel
            cudaDeviceSynchronize();
    }
}
```
Collaborative Implementation (VII)

- **Pascal/Volta Unified Memory**
  - CPU/GPU coherence
  - System-wide atomic operations
  - No need to re-launch kernel or CPU threads
  - Possibility of CPU and GPU working on the same frontier
Benefits of Collaboration

- **SSSP** performs more computation than BFS

![Graph showing execution time for different configurations](image)

**Single Source Shortest Path**
(up to 22% improvement over GPU only)
Egomotion Compensation and Moving Objects Detection (I)

- **Hexapod robot OSCAR**
  - Rescue scenarios
  - Strong egomotion on uneven terrains

- **Algorithm**
  - Random Sample Consensus (RANSAC): F-o-F model
Egomotion Compensation and Moving Objects Detection (II)

Fast moving object in strong egomotion scenario detected by vector clustering
**SISD and SIMD phases**

- **RANSAC** (Fischler *et al.* 1981)

```plaintext
While (iteration < MAX_ITER){
  Fitting stage (Compute F-o-F model)   // SISD phase
  Evaluation stage (Count outliers)    // SIMD phase
  Comparison to best model             // SISD phase
  Check if best model is good enough and iteration >= MIN_ITER   // SISD phase
}
```

- Fitting stage picks two flow vectors randomly
- Evaluation generates motion vectors from F-o-F model, and compares them to real flow vectors
Collaborative Implementation

- Randomly picked vectors: **Iterations are independent**
  - We assign one iteration to one CPU thread and one GPU block
Chai Benchmark Suite (I)

- Collaboration patterns
  - 8 data partitioning benchmarks
  - 3 coarse-grain task partitioning benchmarks
  - 3 fine-grain task partitioning benchmarks

https://chai-benchmarks.github.io
# Chai Benchmark Suite (II)

<table>
<thead>
<tr>
<th>Collaboration Pattern</th>
<th>Short Name</th>
<th>Benchmark</th>
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<tbody>
<tr>
<td>Data Partitioning</td>
<td>BS</td>
<td>Bézier Surface</td>
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<td>CEDD</td>
<td>Canny Edge Detection</td>
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<td>Image Histogram (Input Partitioning)</td>
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<td>HSTO</td>
<td>Image Histogram (Output Partitioning)</td>
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<td>Padding</td>
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<tr>
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<td>SSSP</td>
<td>Single-Source Shortest Path</td>
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