Languages and Abstractions for High-Performance Scientific Computing
CS598 APK

Andreas Klobeckner

Fall 2018
Outline

Introduction

Notes
About This Class
Why Bother with Parallel Computers?
Lowest Accessible Abstraction: Assembly
Architecture of an Execution Pipeline
Architecture of a Memory System
Shared-Memory Multiprocessors

Machine Abstractions

Performance: Expectation, Experiment, Observation

Performance-Oriented Languages and Abstractions

Program Representation and Transformation
Outline

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Why this class?

Setting: Performance-Constrained Code
When is a code performance-constrained?

A desirable quality (fidelity/capability) is limited by computational cost on a given computer.

If your code is performance-constrained, what is the best approach?

Use a more efficient method/algorithm.

If your code is performance-constrained, what is the second-best approach?

Ensure the current algorithm uses your computer efficiently. Observe that this is a desperate measure.
Examples of Performance-Constrained Codes

- Simulation codes
  - Weather/climate models
  - Oil/gas exploration
  - Electronic structure
  - Electromagnetic design
  - Aerodynamic design
  - Molecular dynamics / biological systems
  - Cryptanalysis
- Machine Learning
- Data Mining

Discussion:
- In what way are these codes constrained?
- How do these scale in terms of the problem size?
What Problem are we Trying To Solve?

$$(C_{ij})_{i,j=1}^{m,n} = \sum_{k=1}^{\ell} A_{ik} B_{kj}$$

Reference BLAS DGEMM code:

OpenBLAS DGEMM code:
https://github.com/xianyi/OpenBLAS/blob/develop/kernel/x86_64/dgemm_kernel_4x8_sandy.S

Demo: intro/DGEMM Performance

Demo Instructions: Compare OpenBLAS against Fortran BLAS on large square matrix
Goals: What are we Allowed to Ask For?

- Goal: “make efficient use of the machine”
- In general: not an easy question to answer
- In theory: limited by some peak machine throughput
  - Memory Access
  - Compute
- In practice: many other limits (Instruction cache, TLB, memory hierarchy, NUMA, registers)
Class web page


contains:

- Class outline
- Slides/demos/materials
- Assignments
- Virtual Machine Image
- Piazza
- Grading Policies
- Video
- HW1 (soon)
Welcome Survey

Please go to:


and click on 'Start Activity'.

If you are seeing this later, you can find the activity at Activity: welcome-survey.
Grading / Workload

Four components:

- Homework: 25%
- Paper Presentation: 25%
  - 30 minutes (two per class)
  - Presentation sessions scheduled throughout the semester
  - Paper list on web page
  - Sign-up survey: soon
- Paper Reactions: 10%
- Computational Project: 40%
Approaches to High Performance

- Libraries (seen)
- Black-box Optimizing Compilers
- Compilers with Directives
- Code Transform Systems
- “Active Libraries”

Q: Give examples of the latter two.

- Code Transform System: CHiLL
- Active Library: PyTorch
Libraries: A Case Study

\[(C_{ij})^{m,n}_{i,j=1} = \sum_{k=1}^{\ell} A_{ik} B_{kj}\]

Demo: intro/DGEMM Performance

Demo Instructions: Compare OpenBLAS on large square and small odd-shape matrices
Do Libraries Stand a Chance? (in general)

▶ Tremendously successful approach — Name some examples

(e.g.) LAPACK, Eigen, UMFPACK, FFTW, Numpy, Deal.ii

▶ Saw: Three simple integer parameters suffice to lose ’good’ performance
  ▶ Recent effort: “Batch BLAS” e.g.

▶ Separation of Concerns

Example: Finite differences — e.g. implement $\partial_x$, $\partial_y$, $\partial_z$ as separate (library) subroutines — What is the problem?

Data locality $\rightarrow$ data should be traversed once, $\partial_x$, $\partial_y$, $\partial_z$ computed together
Separation of concerns $\rightarrow$ each operator traverses the data separately.

▶ Flexibility and composition
Why is black-box optimizing compilation so difficult?

- Application developer knowledge lost
  - Simple example: “Rough” matrix sizes
  - Data-dependent control flow
  - Data-dependent access patterns
  - Activities of other, possibly concurrent parts of the program
  - Profile-guided optimization can recover some knowledge

- Obtain proofs of required properties

- Size of the search space

Consider

Directive-Based Compiler: Challenges

What is a directive-based compiler?

Demo Instructions: Show `12dformta_qbx` from `pyfmmlib/vec_wrappers.f90`.

- Generally same as optimizing compiler
- Make use of extra promises made by the user
- What should the user promise?
  - Ideally: feedback cycle between compiler and user
    - Often broken in both directions
    - User may not know what the compiler did
    - Compiler may not be able to express what it needs
- Directives: generally not mandatory
Lies, Lies Everywhere

- Semantics form a contract between programmer and language/environment
- Within those bounds, the implementation is free to do as it chooses
- True at every level:
  - Assembly
  - “High-level” language (C)

Give examples of lies at these levels:

- Assembly: Concurrent execution
- “High-level” language (C): (e.g.) strength reduction, eliminated ops

One approach: *Lie to yourself*

- “Domain-specific languages” ← A fresh language, I can do what I want!
- Consistent semantics are notoriously hard to develop
  - Especially as soon as you start allowing subsets of even (e.g.)
Class Outline

High-level Sections:

- Intro, Armchair-level Computer Architecture
- Machine Abstractions
- Performance: Expectation, Experiment, Observation
- Programming Languages for Performance
- Program Representation and Optimization Strategies
- Code Generation/JIT
Survey: Class Makeup

- Compiler class: 11 no, 3 yes
- HPC class: 10 yes, 4 no
- C: very proficient on average
- Python: proficient on average
- Assembly: some have experience
- GPU: Half the class has experience, some substantial
- CPU perf: Very proficient
- 10 PhD, 4 Masters, mostly CS (plus physics, CEE, MechSE)
Survey: Learning Goals

- How to use hardware efficiently to write fast code (1 response)
- I want to learn about commonly encountered problems in HPC and efficient ways to approach and solve them. (1 response)
- About writing high performance code for large scale problems. (1 response)
- More (and more) about high-performance computing beyond parallel programming. (1 response)
- This summer (while interning at Sandia national labs), I got familiar with GPU programming using Kokkos as the back end. I enjoyed this work immensely, and hope to continue learning about it, especially so that I can become better at writing GPU code myself. I am also interested in the relationship between a higher level abstraction (Kokkos), the compiler, and the actual compute device (GPU/CPU) relate together, and what tricks we have to help fix issues regarding this. For example, Kokkos uses a small amount of template metaprogramming to convert the source code into actual code. (1 response)
- Some GPU stuff, course description sounded interesting for my research in HPC/Parallel Computing. Would be interesting to look at different programming models or abstractions for HPC. (1 response)
- Getting better at doing high performance computing. (1 response)
- Become more familiar with abstractions (1 response)
- I want to be able to auto generate performance portable C++ code, specifically for small batched tensor contractions. (1 response)
- Languages and abstractions for high-performance scientific computing (1 response)
- Investigating problems in high performance computing and looking for solutions, especially large-scale and using GPUs. (1 response)
- Better ways to efficiently (in terms of human time) write high-performance code that may be useful to/readable by others (1 response)
- About high-level languages and frameworks for high performance computing, the different interfaces they expose, compilation and runtime techniques they use, and the tradeoffs of these for an application developer. (1 response)
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Program Representation and Transformation
Moore’s Law

**Issue:** More transistors = faster?

\[
\frac{\text{Work}}{s} = \text{Clock Frequency} \times \frac{\text{Work}}{\text{Clock}}
\]
Dennard Scaling of MOSFETs

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Factor</th>
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<tr>
<td>Dimension</td>
<td>$1/\kappa$</td>
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<td>Voltage</td>
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<td>Current</td>
<td>$1/\kappa$</td>
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<tr>
<td>Capacitance</td>
<td>$1/\kappa$</td>
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<tr>
<td>Delay Time</td>
<td>$1/\kappa$</td>
</tr>
<tr>
<td>Power dissipation/circuit</td>
<td>$1/\kappa^2$</td>
</tr>
<tr>
<td>Power density</td>
<td>1</td>
</tr>
</tbody>
</table>

[Dennard et al. ’74, via Bohr ’07]

- Frequency = Delay time$^{-1}$
MOSFETs ("CMOS" – "complementary" MOS): Schematic

[Dennard et al. ’74]
MOSFETs: Scaling

'New' problem at small scale:
Sub-threshold leakage (due to low voltage, small structure)
Dennard scaling is over – and has been for a while.
Peak Architectural Instructions per Clock: Intel

<table>
<thead>
<tr>
<th>CPU</th>
<th>IPC</th>
<th>Year</th>
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<tr>
<td>Pentium 1</td>
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<td>1993</td>
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<td>Pentium MMX</td>
<td>1.2</td>
<td>1996</td>
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<tr>
<td>Pentium 3</td>
<td>1.9</td>
<td>1999</td>
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<tr>
<td>Pentium 4 (Willamette)</td>
<td>1.5</td>
<td>2003</td>
</tr>
<tr>
<td>Pentium 4 (Northwood)</td>
<td>1.6</td>
<td>2003</td>
</tr>
<tr>
<td>Pentium 4 (Prescott)</td>
<td>1.8</td>
<td>2003</td>
</tr>
<tr>
<td>Pentium 4 (Gallatin)</td>
<td>1.9</td>
<td>20</td>
</tr>
<tr>
<td>Pentium D</td>
<td>2</td>
<td>2005</td>
</tr>
<tr>
<td>Pentium M</td>
<td>2.5</td>
<td>2003</td>
</tr>
<tr>
<td>Core 2</td>
<td>3</td>
<td>2006</td>
</tr>
<tr>
<td>Sandy Bridge...</td>
<td>4ish</td>
<td>2011</td>
</tr>
</tbody>
</table>

[Charlie Brej http://brej.org/blog/?p=15]
Discuss: How do we get out of this dilemma?
The Performance Dilemma

- IPC: Brick Wall
- Clock Frequency: Brick Wall

Ideas:

- Make one instruction do more copies of the same thing ("SIMD")
- Use copies of the same processor ("SPMD"/"MPMD")

Question: What is the conceptual difference between those ideas?

- SIMD executes multiple program instances in lockstep.
- SPMD has no synchronization assumptions.
The Performance Dilemma: Another Look

- **Really**: A crisis of the ’starts-at-the-top-ends-at-the-bottom’ programming model
- **Tough luck**: Most of our codes are written that way
- **Even tougher luck**: Everybody on the planet is trained to write codes this way

So:

- **Need**: Different tools/abstractions to write those codes
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Performance-Oriented Languages and Abstractions

Program Representation and Transformation
A Basic Processor: Closer to the Truth

- Address ALU
- Register File
- Flags
- Data ALU
- Address ALU
- Memory Interface
- Address Bus
- Data Bus
- Internal Bus
- Control Unit
- PC
- Data ALU
- Insn. fetch

- loosely based on Intel 8086
- What’s a bus?
A Very Simple Program

```c
int a = 5;
int b = 17;
int z = a * b;
```

Things to know:

- **Question:** Which is it?
  - `<opcode> <src>, <dest>`
  - `<opcode> <dest>, <src>`

- **Addressing modes** (Immediate, Register, Base plus Offset)

- **0xHexadecimal**
A Very Simple Program: Another Look

```
4: c7 45 f4 05 00 00 00 00 movl $0x5,-0xc(%rbp)
b: c7 45 f8 11 00 00 00 00 movl $0x11,-0x8(%rbp)
12: 8b 45 f4 mov -0xc(%rbp),%eax
15: 0f af 45 f8 imul -0x8(%rbp),%eax
19: 89 45 fc mov %eax,-0x4(%rbp)
1c: 8b 45 fc mov -0x4(%rbp),%eax
```
A Very Simple Program: Intel Form

4: c7 45 f4 05 00 00 00 mov DWORD PTR [rbp-0xc], 0x5
b: c7 45 f8 11 00 00 00 mov DWORD PTR [rbp-0x8], 0x11
12: 8b 45 f4 mov eax, DWORD PTR [rbp-0xc]
15: 0f af 45 f8 imul eax, DWORD PTR [rbp-0x8]
19: 89 45 fc mov DWORD PTR [rbp-0x4], eax
1c: 8b 45 fc mov eax, DWORD PTR [rbp-0x4]

▶ “Intel Form”: (you might see this on the net)
<opcode> <sized dest>, <sized source>

▶ Previous: “AT&T Form”: (we’ll use this)

▶ Goal: Reading comprehension.

▶ Don’t understand an opcode?
Assembly Loops

```c
#include <stdio.h>

int main()
{
    int y = 0, i;
    for (i = 0; y < 10; ++i)
        y += i;
    return y;
}
```

```assembly
0: 55    push %rbp
1: 48 89 e5 mov %rsp,%rbp
4: c7 45 f8 00 00 00 00 movl $0x0,-0x8(%rbp)
b: c7 45 fc 00 00 00 00 movl $0x0,-0x4(%rbp)
12: eb 0a jmp 1e <main+0x1e>
14: 8b 45 fc mov -0x4(%rbp),%eax
17: 01 45 f8 add %eax,-0x8(%rbp)
1a: 83 45 fc 01 addl $0x1,-0x4(%rbp)
1e: 83 7d f8 09 cmpl $0x9,-0x8(%rbp)
22: 7e f0 jle 14 <main+0x14>
24: 8b 45 f8 mov -0x8(%rbp),%eax
27: c9 leaveq
28: c3 retq
```

Things to know:

- **Condition Codes (Flags)**: Zero, Sign, Carry, etc.
- **Call Stack**: Stack frame, stack pointer, base pointer
- **ABI**: Calling conventions

Demo Instructions: C → Assembly mapping from [https://github.com/ynh/cpp-to-assembly](https://github.com/ynh/cpp-to-assembly)
Demo: intro/Assembly Reading Comprehension

Demo: Source-to-assembly mapping
Code to try:

```c
int main()
{
    int y = 0, i;
    for (i = 0; y < 10; ++i)
        y += i;
    return y;
}
```
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Program Representation and Transformation
Modern Processors?

All of this can be built in about 4000 transistors.
(e.g. MOS 6502 in Apple II, Commodore 64, Atari 2600)

So what exactly are Intel/ARM/AMD/Nvidia doing with the other billions of transistors?
Execution in a Simple Processor

- **[IF]** Instruction fetch
- **[ID]** Instruction Decode
- **[EX]** Execution
- **[MEM]** Memory Read/Write
- **[WB]** Result Writeback

[Wikipedia ℗]
Solution: Pipelining
MIPS Pipeline: 110,000 transistors
Q: Types of Pipeline Hazards? (aka: what can go wrong?)

- Data
- Structural
- Control
Demo: intro/Pipeline Performance Mystery

- a, a: elapsed time 3.83603 s
- a, b: elapsed time 2.58667 s
- a, a unrolled: elapsed time 3.83673 s
- aa, bb unrolled: elapsed time 1.92509 s
- a, b unrolled: elapsed time 1.92084 s
A Glimpse of a More Modern Processor: Frontend

[Sandy Bridge Diagram]

144 Entry L1 ITLB (4 way) → 32KB L1 I-Cache (8 way) → 16B Predecode, Fetch Buffer → 6 instructions → 18+ Entry Instruction Queue → μcode Engine, Complex Decode, Simple Decode, Simple Decode, Simple Decode → 1.5K μop Cache (8 way) → 28 μop Decoder Queue

[David Kanter / Realworldtech.com]
A Glimpse of a More Modern Processor: Backend

- New concept: Instruction-level parallelism ("ILP", "superscalar")
- Where does the IPC number from earlier come from?

[David Kanter / Realworldtech.com]
Demo

Demo: intro/More Pipeline Mysteries
Q: Potential issues?

- $n \times$ the cache demand!
- Power?
- Some people just turn it off and manage their own ILP.
SMT/“Hyperthreading”

Q: Potential issues?

- $n \times$ the cache demand!
- Power?
- Some people just turn it off and manage their own ILP.
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More bad news from Dennard

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<tbody>
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<td>Dimension</td>
<td>$1/\kappa$</td>
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<tr>
<td>Line Resistance</td>
<td>$\kappa$</td>
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<td>Voltage drop</td>
<td>$\kappa$</td>
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<tr>
<td>Response time</td>
<td>1</td>
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<td>Current density</td>
<td>$\kappa$</td>
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[Dennard et al. ‘74, via Bohr ‘07]

- The above scaling law is for on-chip interconnects.
- Current $\sim$ Power vs. response time

Getting information from

- processor to memory
- one computer to the next

is

- slow (in latency)
- power-hungry
Performance characteristics of memory:

- Bandwidth
- Latency

Flops are cheap
Bandwidth is money
Latency is physics

- M. Hoemmen

Minor addition (but important for us)?

- Bandwidth is money and code structure
Latency is Physics: Distance
Latency is Physics: Electrical Model
Latency is Physics: DRAM

[Wikipedia]
What is the performance impact of high memory latency?

Processor stalled, waiting for data.

Idea:

- Put a look-up table of recently-used data onto the chip.
- Cache
Memory Hierarchy

- **Registers**: 1 kB, 1 cycle
- **L1 Cache**: 10 kB, 10 cycles
- **L2 Cache**: 100 kB, 10 cycles
- **L3 Cache**: 10 MB, 100 cycles
- **DRAM**: 1 GB, 1000 cycles
- **Virtual Memory (hard drive)**: 1 TB, 1 M cycles
A Basic Cache

Demands on cache implementation:

- Fast, small, cheap, low power
- Fine-grained
- High "hit"-rate (few "misses")

Design Goals: at odds with each other. Why?

Address matching logic expensive

[Wikipedia ©]
Engineering Decisions:

- More data per unit of access matching logic
  → Larger “Cache Lines”

- Simpler/less access matching logic
  → Less than full “Associativity”

- Eviction strategy

- Size
Associativity

Direct Mapped:

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<th>Cache</th>
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<tr>
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2-way set associative:

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<th>Memory</th>
<th>Cache</th>
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...
Miss rate versus cache size on the Integer portion of SPEC CPU2000 [Cantin, Hill 2003]
Demo: Learning about Caches

Demo: intro/Cache Organization on Your Machine
Experiments: 1. Strides: Setup

```c
int go(unsigned count, unsigned stride)
{
    const unsigned array_size = 64 * 1024 * 1024;
    int *ary = (int *) malloc(sizeof(int) * array_size);

    for (unsigned it = 0; it < count; ++it)
    {
        for (unsigned i = 0; i < array_size; i += stride)
            ary[i] *= 17;
    }

    int result = 0;
    for (unsigned i = 0; i < array_size; ++i)
        result += ary[i];

    free(ary);
    return result;
}
```

What do you expect? [Ostrovsky '10]
Experiments: 1. Strides: Results

![Graph showing the relationship between stride and time](image-url)
Experiments: 2. Bandwidth: Setup

```c
int go(unsigned array_size, unsigned steps)
{
    int *ary = (int *) malloc(sizeof(int) * array_size);
    unsigned asm1 = array_size - 1;

    for (unsigned i = 0; i < 100*steps;)
    {
        #define ONE ary[(i++*16) & asm1] ++;
        #define FIVE ONE ONE ONE ONE ONE
        #define TEN FIVE FIVE
        #define FIFTY TEN TEN TEN TEN TEN
        #define HUNDRED TEN TEN TEN TEN TEN
        HUNDRED
    }

    int result = 0;
    for (unsigned i = 0; i < array_size; ++i)
        result += ary[i];

    free(ary);
    return result;
}
```

What do you expect? [Ostrovsky ‘10]
Experiments: 2. Bandwidth: Results

![Graph showing efficiency bandwidth vs. array size]
Experiments: 3. A Mystery: Setup

```c
int go(unsigned array_size, unsigned stride, unsigned steps)
{
    char *ary = (char *) malloc(sizeof(int) * array_size);

    unsigned p = 0;
    for (unsigned i = 0; i < steps; ++i)
    {
        ary[p] ++;
        p += stride;
        if (p >= array_size)
            p = 0;
    }

    int result = 0;
    for (unsigned i = 0; i < array_size; ++i)
        result += ary[i];

    free(ary);
    return result;
}
```

What do you expect? [Ostrovsky '10]
Experiments: 3. A Mystery: Results

Color represents achieved bandwith:
- Red: high
- Blue: low
Thinking about the Memory Hierarchy

- What is a working set?
- What is data locality of an algorithm?
- What does this have to with caches?
Q: Estimate expected throughput for saxpy on an architecture with caches. What are the right units?

\[ z_i = \alpha x_i + y_i \quad (i = 1, \ldots, n) \]

- Units: GBytes/s
- Net memory accessed: \( n \times 4 \times 3 \) bytes
- Actual memory accessed: \( n \times 4 \times 4 \) bytes
  (To read \( z \) read into the cache before modification)

Demo: [https://github.com/lcw/stream_ispc](https://github.com/lcw/stream_ispc)
Special Store Instructions

At least two aspects to keep apart:

- **Temporal Locality**: Are we likely to refer to this data again soon? (*non-temporal* store)
- **Spatial Locality**: Will (e.g.) the entire cache line be overwritten? (*streaming* store)

What hardware behavior might result from these aspects?

- **Non-temporal**: Write past cache entirely (/invalidate), or evict soon
- **Spatial**: Do not fetch cache line before overwriting

- Comment on what a compiler can promise on these aspects.
- Might these ‘flags’ apply to loads/prefetches?

(see also: [McCalpin ‘18])
Case study: Matrix-Matrix Mult. ('MMM'): Code Structure

- How would you structure a high-performance MMM?
- What are sources of concurrency?
- What should you consider your working set?

Sources of concurrency:
- row, column loop, summation loop (?)
- Working set: artificially created blocks
- Provide enough concurrency: SIMD, ILP, Core
Case study: Matrix-Matrix Mult. ('MMM') via Latency

Come up with a simple cost model for MMM in a two-level hierarchy based on latency:

\[
\text{Avg latency per access} = (1 - \text{Miss ratio}) \cdot \text{Cache Latency} + \text{Miss ratio} \cdot \text{Mem Latency}
\]

Assume: Working set fits in cache, No conflict misses

Calculation:
1. Total accesses: \(4N_B^3\) (\(N_B\): block size)
2. Misses: \(3N_B^2\)
3. Miss rate: \(\frac{3}{4N_B \cdot \text{cache line size}}\)

[Yotov et al. '07]
Case study: Matrix-Matrix Mult. ('MMM') via Bandwidth

Come up with a cost model for MMM in a two-level hierarchy based on bandwidth:

- **FMA throughput**: $16 \times 2$ SP FMAs per clock (e.g.)
- **Cycle count**: $2N^3/(2 \times 32) = N^3/32$
- **Required cache bandwidth**: 
  \[
  \frac{\text{words accessed}}{\text{cycles}} = 4N^3/(N^3/32) = 128 \text{ floats/cycle (GB/s?)}
  \]
- **Total mem. data motion**: 
  \[
  \# \text{blocks} \times 4 \times \text{(block size)} = (N/N_B)^3 \times 4N_B^2 = 4N^3/N_B
  \]
- **Required mem. bandwidth**: 
  \[
  \frac{\text{Mem.motion}}{\text{cycles}} = 4N^3/N_B/(N^3/32) = 128/N_B \text{ floats/cycle (GB/s?)}
  \]
- **What size cache do we need to get to feasible memory bandwidth?**

[Yotov et al. ’07]
Case study: Matrix-Matrix Mult. (’MMM’): Discussion

Discussion: What are the main simplifications in each model?

Bandwidth:
- Miss assumptions
- Multiple cache levels
- Latency effects

Latency:
- Miss assumptions
- Concurrency/parallelism of memory accesses
- (HW) prefetching
- Machine Limits

[Yotov et al. ’07]

General Q: How can we analyze cache cost of algorithms in general?
Hong/Kung: Red/Blue Pebble Game

Simple means of I/O cost analysis: “Red/blue pebble game”

► A way to quantify I/O cost on a DAG (why a DAG?)
► “Red Hot” pebbles: data that can be computed on
► “Blue Cool” pebbles: data that is stored, but not available for computation without I/O

Note: Can allow “Red/Purple/Blue/Black”: more levels

Q: What are the cost metrics in this model?

► I/O Cost: Turn a red into a blue pebble and vice versa
► Number of red pebbles (corresponding to size of ’near’ storage)

[Hong/Kung ‘81]
Cache-Oblivious Algorithms

Annoying chore: Have to pick multiple machine-adapted block sizes in cache-adapted algorithms, one for each level in the memory hierarchy, starting with registers.

Idea:

- Step 1: Express algorithm recursively in divide & conquer manner
- Step 2: Pick a strategy to decrease block size

Give examples of block size strategies, e.g. for MMM:

- All dimensions
- Largest dimension

Result:
- Asymptotically optimal on Hong/Kung metric
Cache-Oblivious Algorithms: Issues

What are potential issues on actual hardware?

- In pure form:
  - Function call overhead
  - Register allocation
- With good base case:
  - I-cache overflow
  - Instruction scheduling

[Yotov et al. ’07]
Recall: Big-O Notation

Classical Analysis of Algorithms (e.g.):

\[ \text{Cost}(n) = O(n^3). \]

Precise meaning? Anything missing from that statement?

**Missing:** ‘as \( n \to \infty \)’

There exists a \( C \) and an \( N_0 \) independent of \( n \) so that for all \( n \geq N_0 \),

\[ \text{Cost}(n) \leq C \cdot n^3. \]
Comment: “Asymptotically Optimal”

Comments on asymptotic statements about cost in relation to high performance?

- No statement about finite $n$
- No statement about the constant

Net effect: Having an understanding of asymptotic cost is necessary, but not sufficient for high performance.

HPC is in the business of minimizing $C$ in:

$$\text{Cost}(n) \leq C \cdot n^3 \quad (\text{for all } n)$$
Alignment describes the process of matching the base address of:

- Single word: double, float
- SIMD vector
- Larger structure

To machine granularities:

- Natural word size
- Vector size
- Cache line

Q: What is the performance impact of misalignment?
Performance Impact of Misalignment

Matched structure

Matched structure
SIMD: Basic Idea

What’s the basic idea behind SIMD?

What architectural need does it satisfy?

- Insufficient instruction decode/dispatch bandwidth
- Tack more operations onto one decoded instruction

Typically characterized by width of data path:

- SSE: 128 bit (4 floats, 2 doubles)
- AVX-2: 256 bit (8 floats, 4 doubles)
- AVX-512: 512 bit (16 floats, 8 doubles)
SIMD: Architectural Issues

Realization of inter-lane comm. in SIMD? Find instructions.

- Misaligned stores/loads? (no)
- Broadcast, Unpack+Interleave, Shuffle, Permute
- Reductions ("horizontal")

Name tricky/slow aspects in terms of expressing SIMD:

- Divergent control flow
  - Masking
  - Reconvergence
- Indirect addressing: gather/scatter

x86 SIMD suffixes: What does the "ps" suffix mean? "sd"?

- ps: Packed single precision
- sd: Scalar double precision
Why are transposes important? Where do they occur?

- Whenever SIMD encounters a mismatched data layout
- For example: MMM of two row-major matrices

Example implementation aspects:

- HPTT: [Springer et al. '17](#)
- github: springer13/hptt 8x8 transpose microkernel
- Q: Why 8x8?
Outline

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About This Class
Why Bother with Parallel Computers?
Lowest Accessible Abstraction: Assembly
Architecture of an Execution Pipeline
Architecture of a Memory System
Shared-Memory Multiprocessors

Machine Abstractions

Performance: Expectation, Experiment, Observation

Performance-Oriented Languages and Abstractions

Program Representation and Transformation
Multiple Cores vs Bandwidth

Assume (roughly right for Intel):

- memory latency of 100 ns
- peak DRAM bandwidth of 50 GB/s (per socket)

How many cache lines should be/are in flight at one time?

- $100\text{ns} \times 50\text{GB/s} = 5000\text{bytes}$
- About 80 cache lines

Oops: Intel hardware can only handle about 10 pending requests per core at one time

- $10 \times 64/100\text{ns} \approx 6.4\text{GB/s}$

[McCalpin ‘18]
Notes:
• See Chapter 2 for detailed information on jumpers, I/O ports and JF1 front panel connections.
• " indicates the location of "Pin 1".
• Jumpers/LED Indicators not indicated are for testing only.
• LAN1/LAN2 ports support Gigabit LAN (GLAN) connections on the X10DRi, and 10G (T) LAN connections on the X10DRi-T.
• Use only the correct type of onboard CMOS battery as specified by the manufacturer. Do not install the onboard battery upside down to avoid possible explosion.

Demo: Show lstopo on porter, from hwloc.
Placement and Pinning

Who decides on what core my code runs? How?

- The OS scheduler: “Oh, hey, look! A free core!”
- You, explicitly, by pinning:
  - OMP_PLACES=cores
  - pthread_setaffinity_np()

Who decides on what NUMA node memory is allocated?

- malloc uses 'first touch'
- You can decide explicitly (through libnuma)

Demo: intro/NUMA and Bandwidths

What is the main expense in NUMA?

Latency (but it impacts bandwidth by way of queuing)
Cache Coherence

What is cache coherence?

- As soon as you make a copy of (cache) something, you risk inconsistency with the original
- A set of guarantees on how (and in what order) changes to memory become visible to other cores

How is cache coherence implemented?

- Snooping
- Protocols, operating on cache line states (e.g. “MESI”)

What are the performance impacts?

- Demo: intro/Threads vs Cache
- Demo: intro/Lock Contention
'Conventional' vs Atomic Memory Update

![Diagram showing the process of Read, Increment, and Write with Interruptible and Protected states.]

- Conventional: Read → Increment → Write, both Interruptible!
- Atomic: Read → Increment → Write, both Protected
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  C
  OpenCL/CUDA
  Convergence, Differences in Machine Mapping
  Lower-Level Abstractions: SPIR-V, PTX

Performance: Expectation, Experiment, Observation

Performance-Oriented Languages and Abstractions

Program Representation and Transformation

Polyhedral Representation and Transformation
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Polyhedral Representation and Transformation
Atomic Operations: Compare-and-Swap

```c
#include <stdatomic.h>
_Bool atomic_compare_exchange_strong(
    volatile A* obj,
    C* expected, C desired);
```

What does `volatile` mean?

Memory may change at any time, do not keep in register.

What does this do?

- Store (*obj == *expected) ? desired : *obj into *obj.
- Return true iff memory contents was as expected.

How might you use this to implement atomic FP multiplication?

Read previous, perform operation, try CAS, maybe retry
Memory Ordering

Why is Memory Ordering a Problem?

- Out-of-order CPUs reorder memory operations
- Compilers reorder memory operations

What are the different memory orders and what do they mean?

- Atomicity itself is unaffected
- Makes sure that 'and then' is meaningful

Types:
- Sequentially consistent: no reordering
- Acquire: later loads may not reorder across
- Release: earlier writes may not reorder across
- Relaxed: reordering OK
Example: A Semaphore With Atomics

```c
#include <stdatomic.h> // mo->memory_order, a->atomic
typedef struct { atomic_int v; } naive_sem_t;
void sem_down(naive_sem_t *s) {
    while (1) {
        while (a_load_explicit(&s->v), mo_acquire) < 1)
            spinloop_body();
        int tmp=a_fetch_add_explicit(&s->v), -1, mo_acq_rel;
        if (tmp >= 1)
            break; // we got the lock
        else /* undo our attempt */
            a_fetch_add_explicit(&s->v), 1, mo_relaxed);
    }
}
void sem_up(naive_s_t *s) {
    a_fetch_add_explicit(&s->v), 1, mo_release);
}

[Cordes '16] — Hardware implementation: how?
```
C: What is ’order’?

C11 Committee Draft, December ‘10, Sec. 5.1.2.3, “Program execution”:

- (3) Sequenced before is an asymmetric, transitive, pair-wise relation between evaluations executed by a single thread, which induces a partial order among those evaluations. Given any two evaluations A and B, if A is sequenced before B, then the execution of A shall precede the execution of B. (Conversely, if A is sequenced before B, then B is sequenced after A.) If A is not sequenced before or after B, then A and B are unsequenced. Evaluations A and B are indeterminately sequenced when A is sequenced either before or after B, but it is unspecified which. The presence of a sequence point between the evaluation of expressions A and B implies that every value computation and side effect associated with A is sequenced before every value computation and side effect associated with B. (A summary of the sequence points is given in annex C.)

Q: Where is this definition used (in the standard document)?

In defining the semantics of atomic operations.
C: What is ‘order’? (Encore)

C11 Draft, 5.1.2.4 “Multi-threaded executions and data races”:

- All modifications to a particular atomic object M occur in some particular total order, called the *modification order* of M.
- An evaluation A *carries a dependency* to an evaluation B if . . .
- An evaluation A is *dependency-ordered* before an evaluation B if . . .
- An evaluation A *inter-thread happens before* an evaluation B if . . .
- An evaluation A *happens before* an evaluation B if . . .

Why is this so subtle?

- Many common optimizations depend on the ability to reorder operations.
- Two options:
  1. Lose the ability to do those optimizations
  2. Specify precisely how much of the order should be externally observable
C: How Much Lying is OK?

C11 Committee Draft, December ‘10, Sec. 5.1.2.3, “Program execution”:

▶ (1) The semantic descriptions in this International Standard describe the behavior of an abstract machine in which issues of optimization are irrelevant.

▶ (2) Accessing a volatile object, modifying an object, modifying a file, or calling a function that does any of those operations are all side effects, which are changes in the state of the execution environment. […]
C: How Much Lying is OK?

(4) In the abstract machine, all expressions are evaluated as specified by the semantics. An actual implementation need not evaluate part of an expression if it can deduce that its value is not used and that no needed side effects are produced (including any caused by calling a function or accessing a volatile object).

(6) The least requirements on a conforming implementation are:

- Accesses to volatile objects are evaluated strictly according to the rules of the abstract machine.
- At program termination, all data written into files shall be identical to the result that execution of the program according to the abstract semantics would have produced.
- The input and output dynamics of interactive devices shall take place as specified in 7.21.3. The intent of these requirements is that unbuffered or line-buffered output appear as soon as possible, to ensure that prompting messages actually appear prior to a program waiting for input. This is the observable behavior of the program.
Arrays

Why are arrays the dominant data structure in high-performance code?

- Performance is mostly achieved with regular, structured code (e.g. SIMD, rectangular loops)
- Arrays are a natural fit for that type of code
- Abstractions of linear algebra map directly onto arrays

Any comments on C’s arrays?

- 1D arrays: fine, no surprises
- nD arrays: basically useless: sizes baked into types
  - Interestingly: Fortran is (incrementally) smarter
Arrays vs Abstraction

Arrays-of-Structures or Structures-of-Arrays? What’s the difference? Give an example.

Example: Array of XYZ coordinates:
- XYZXYZXYZ...
- XXX....YYY...ZZZ...

Which of these will be suitable for SIMD? (e.g. computing a norm?)

Structures-of-Arrays if at all possible – to expose regularity

Language aspects of the distinction? Salient example?

C struct forces you into arrays-of-structures
- AoS: more “conceptually sound”
- SoA: better for performance

Complex numbers
C and Multi-Dimensional Arrays: A Saving Grace

// YES:
void f(int m, int n, double (*)[m][n]);

// NO:
struct ary {
    int m;
    int n;
    double (*array)[m][n];
};

// YES:
struct ary {
    int m;
    int n;
    double a[];
};
Name language mechanisms for SIMD:

- Inline Assembly
- Intrinsics
- Vector Types
  ```c
  typedef int v4si __attribute__((vector_size (16)));
  ```
- #pragma simd
- Merging of scalar program instances (in hw/sw)

Demo: machabstr/Ways to SIMD
Outer-Loop/inner-Loop Vectorization

Contrast *outer-loop vs inner-loop vectorization*.

- **Inner-loop**: Inner-most loop vectorized
- **Outer loop**: Vectorize a whole kernel. Requires:
  - Changed memory layout
  - Must be able to express *all* control flow

**Side q**: Would you consider GPUs outer- or inner-loop-vectorizing?
The old way:

```c
int __attribute__((aligned (8))) a_int;
```

Difference between these two?

```c
int __attribute__((aligned (8))) * ptr_t_1;
int *__attribute__((aligned (8))) ptr_t_2;
```

The 'new' way (C/C++11):

```c
struct alignas(64) somestruct_t { /* ... */ };
struct alignas(alignof(other_t))
    somestruct_t { /* ... */ };
struct
    alignas(
        std::hardware_destructive_interference_size)
    somestruct_t { /* ... */ };
```

What is constructive interference?
Alignment: Why?

What is the concrete impact of the constructs on the previous slide?

- Compiler needs to *know* whether data is aligned
  - Generate the correct instructions (which encode alignment promises)
  - Stack-allocate memory of the correct alignment
- Heap-allocated memory needs to actually satisfy the alignment promise!
  - `posix_memalign`
  - Hack it by overallocating
  - In `numpy`: overallocate in bytes, get base address, offset, obtain view
Pointers and Aliasing

Demo: machabstr/Pointer Aliasing
Register Pressure

What if the register working set gets larger than the registers can hold? What is the performance impact?

- “Register Spill”: save/reload code being generated
- CPU: L1 is relatively fast
- Other architectures: can be quite dramatic

Demo: machabstr/Register Pressure
Object-Oriented Programming

Object-oriented programming: The weapon of choice for encapsulation and separation of concerns!

Performance perspective on OOP?

- Fine-grain OOP leads to an AoS disaster
- Long expressions create many temporaries
  - Memory traffic
- Return values
- Run-time polymorphism (virtual methods) lead to fine-grain flow control

Summary: No good, very bad. *Must* have sufficient granularity to offset cost.

Demo: machabstr/Object Orientation vs Performance
Some rules of thumb:

- Use indices rather than pointers
- Extract common subexpressions
- Make functions static
- Use const
- Avoid store-to-load dependencies

What are the concrete impacts of doing these things?
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Chip Real Estate

65 nm, 4 SP ops at a time, 1 MiB L2.
“CPU-style” Cores

[Fatahalian ‘08]
Idea #1:
Remove components that help a single instruction stream run fast

[Fatahalian '08]
More Space: Double the Number of Cores

[Fatahalian ‘08]
Even more

[16 cores = 16 simultaneous instruction streams]

[Fatahalian ‘08]
Idea #2: SIMD

Amortize cost/complexity of managing an instruction stream across many ALUs

[Fatahalian '08]
Idea #2: SIMD

Amortize cost/complexity of managing an instruction stream across many ALUs

[Fatahalian ‘08]
Idea #2: SIMD

Amortize cost/complexity of managing an instruction stream across many ALUs

[Fatahalian '08]
Idea #2: SIMD

Amortize cost/complexity of managing an instruction stream across many ALUs

[Fatahalian `08]
Latency Hiding

- Latency (mem, pipe) hurts non-OOO cores
- Do something while waiting

What is the unit in which work gets scheduled on a GPU?

A SIMD vector ('warp' (Nvidia), 'Wavefront' (AMD))

How can we keep busy?

- More vectors (bigger group)
- ILP

Change in architectural picture?

Before:
- Fetch/Decode
- Scratchpad/L1
- Register File

After:
- Fetch/Decode
- Scratchpad/L1
- Register File
- More state space!
GPUs: Core Architecture Ideas

Three core ideas:

- Remove things that help with latency in single-thread
- Massive core and SIMD parallelism
- Cover latency with concurrency
  - SMT
  - ILP
'SIMT'
Wrangling the Grid

get_local_id(axis)/size(axis)?
get_group_id(axis)/num_groups(axis)?
get_global_id(axis)/size(axis)?
axis=0,1,2,...
Demo CL code

Demo: machabstr/Hello GPU
‘SIMT’ and Branches

But what about branches?

Time (clocks)

ALU 1  ALU 2  ...  ...  ALU 8

T T F T F F F F

if (x > 0) {
    y = pow(x, exp);
    y *= Ks;
    refl = y + Ka;
} else {
    x = 0;
    refl = Ka;
}

Fatahalian ‘08
GPU Abstraction: Core Model Ideas

How do these aspects show up in the model?

- View concrete counts as an implementation detail
  - SIMD lane
  - Core
  - Scheduling slot
- Program as if there are infinitely many of them
- Hardware division is expensive
  Make $n$D grids part of the model to avoid it
- Design the model to expose *extremely* fine-grain concurrency
  (e.g. between loop iterations!)
- Draw from the same pool of concurrency to hide latency
## GPU Program 'Scopes'

<table>
<thead>
<tr>
<th>Hardware</th>
<th>CL adjective</th>
<th>OpenCL</th>
<th>CUDA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIMD lane</td>
<td>private</td>
<td>Work Item</td>
<td>Thread</td>
</tr>
<tr>
<td>SIMD Vector</td>
<td>—</td>
<td>Subgroup</td>
<td>Warp</td>
</tr>
<tr>
<td>Core</td>
<td>local</td>
<td>Workgroup</td>
<td>Thread Block</td>
</tr>
<tr>
<td>Processor</td>
<td>global</td>
<td>NDRange</td>
<td>Grid</td>
</tr>
</tbody>
</table>
What forms of communication exist at each scope?

- **Subgroup**: Shuffles (!)
- **Workgroup**: Scratchpad + barrier, local atomics + mem fence
- **Grid**: Global atomics

Can we just do locking like we might do on a CPU?

- Independent forward progress of all threads is not guaranteed: no.
  (true until recently)
- But: Device partitioning can help!
GPU Programming Model: Commentary

▶ “Vector” / “Warp” / “Wavefront”
  ▶ Important hardware granularity
  ▶ Poorly/very implicitly represented

▶ What is the impact of reconvergence?
What limits the amount of concurrency exposed to GPU hardware?

- Amount of register space
  - Important: Size of (per-lane) register file is variable
- Amount of scratchpad space
  - Size of (per-group) scratchpad space is variable
- Block size
- Available ILP
- Number of scheduler (warp/group) slots (not really)
- Synchronization
Parallel Memories

**Problem:** Memory chips have only one data bus. So how can multiple threads read multiple data items from memory simultaneously?

**Broadly:**
- Split a really wide data bus, but have only one address bus
- Have many 'small memories' ('banks') with separate data and address busses, select by address LSB.

**Where does banking show up?**
- Scratchpad
- GPU register file
- Global memory
Memory Banking

Fill in the access pattern:

3  7  11  15  19  23  ⋯

Bank:

2  6  10  14  18  22  ⋯

1  5  9  13  17  21  ⋯

0  4  8  12  16  20  ⋯

Address

Thread:

3

2

1

0
Memory Banking

Fill in the access pattern:

Bank

Address

Thread

local_variable[lid(0)]
Memory Banking

Fill in the access pattern:

```
3 7 11 15 19 23 ⋯
```

Bank:

```
2 6 10 14 18 22 ⋯
```

```
1 5 9 13 17 21 ⋯
```

```
0 4 8 12 16 20 ⋯
```

local_variable[BANK_COUNT*lid(0)]
Memory Banking

Fill in the access pattern:

Bank

Thread

Address

local_variable[(BANK_COUNT+1)*lid(0)]
Memory Banking

Fill in the access pattern:

Bank

0 4 8 12 16 20 24 ... 1 5 9 13 17 21 ... 2 6 10 14 18 22 ... 3 7 11 15 19 23 ...

Thread

0 1 2 3

Address

local_variable[ODD_NUMBER*lid(0)]
Memory Banking

Fill in the access pattern:

```
3  7 11 15 19 23 ⋮
```

Bank

```
0  4  8 12 16 20 ⋮
```

```
1  5  9 13 17 21 ⋮
```

```
2  6 10 14 18 22 ⋮
```

```
3  7 11 15 19 23 ⋮
```

```
local_variable[lid(0)]
local_variable[BANK_COUNT*lid(0)]
local_variable[(BANK_COUNT+1)*lid(0)]
local_variable[ODD_NUMBER*lid(0)]
local_variable[2*lid(0)]
local_variable[f(gid(0))]
```

local_variable[2*lid(0)]
Memory Banking

Fill in the access pattern:

Bank

Address

Thread

local_variable[f(gid(0))]
Memory Banking: Observations

- Factors of two in the stride: generally bad
- In a conflict-heavy access pattern, padding can help
  - Usually not a problem since scratchpad is transient by definition
- Word size (bank offset) may be adjustable (Nvidia)

Given that unit strides are beneficial on global memory access, how do you realize a transpose?

Workgroup size (e.g.): 16x16

```c
__local float tmp[16 * 17];
tmp[lid(0)*17 + lid(1)] = a[lid(1) * 16 + lid(0)];
barrier(CLK_LOCAL_MEM_FENCE);
```
GPU Global Memory Channel Map: Example

Byte address decomposition:

<table>
<thead>
<tr>
<th>Address</th>
<th>Bank</th>
<th>Chnl</th>
<th>Address</th>
</tr>
</thead>
<tbody>
<tr>
<td>31</td>
<td>?</td>
<td>11</td>
<td>108</td>
</tr>
</tbody>
</table>

Implications:

- Transfers between compute unit and channel have granularity
  - Reasonable guess: warp/wavefront size × 32 bits
  - Should strive for good utilization ('Coalescing')
- Channel count often *not* a power of two -> complex mapping
  - *Channel conflicts* possible
- Also *banked*
  - *Bank conflicts* also possible
GPU Global Memory: Performance Observations

Key quantities to observe for GPU global memory access:

- Stride
- Utilization

Are there any guaranteed-good memory access patterns?

Unit stride, just like on the CPU

- Need to consider access pattern *across entire device*
- *GPU caches*: Use for *spatial*, not for temporal locality
- Switch available: L1/Scratchpad partitioning
  - Settable on a per-kernel basis
- Since GPUs have meaningful caches at this point: Be aware of cache annotations (see later)
Host-Device Concurrency

- Host and Device run asynchronously
- Host submits to queue:
  - Computations
  - Memory Transfers
  - Sync primitives
- Host can wait for:
  - *drained* queue
  - Individual “events”
- Profiling
Host-Device Data Exchange

- Sad fact: Must get data onto device to compute
  - Transfers can be a bottleneck
  - If possible, overlap with computation
  - Pageable memory incurs difficulty in GPU-host transfers, often entails (another!) CPU side copy
  - "Pinned memory": unpageable, avoids copy
    - Various system-defined ways of allocating pinned memory
- "Unified memory":
  - GPU directly accesses host memory
  - "Fine grain": Byte-for-byte coherent
  - "Coarse grain": Per-buffer fences
Performance: Ballpark Numbers?

Bandwidth host/device:

PCIe v2: 8 GB/s — PCIe v3: 16 GB/s — NVLink: 200 GB/s

Bandwidth on device:

Registers: 10 TB/s — Scratch: 1 TB/s — Global: 500 GB/s

Flop throughput?

10 TFLOPS single precision – 3 TFLOPS double precision

Good source of details: Wikipedia: List of Nidia GPUs
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Die Shot Gallery

Nv GT200 (2008)

Nv Fermi (2010)

Intel IVB (2012)

AMD Tahiti (2012)

Nv GK110 (2012?)
Trends in Processor Architecture

What can we expect from future processor architectures?

- Commodity chips
- “Ininitely” many cores
- “Infinite” vector width
- Must hide memory latency (→ ILP, SMT)
- Compute bandwidth $\gg$ Memory bandwidth
- Bandwidth only achievable by homogeneity
- Can’t keep the whole thing powered all the time anyway. Consequence?
  Lots of weird stuff springs up. Examples: “Raytracing Cores”, “Tensor Cores”
Common Challenges

What are the common challenges encountered by both CPUs and GPUs?

- Dealing with Latency (ILP/SMT/Caches)
- Exposing concurrency
- Expose a coherent model for talking to SIMD
- Making memory system complexity manageable

Goal: Try to see CPUs and GPUs as points in a design space ‘continuum’ rather than entirely different things.
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- C
- OpenCL/CUDA
- Convergence, Differences in Machine Mapping
- Lower-Level Abstractions: SPIR-V, PTX

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Demo: machabstr/PTX and SASS
Nvidia PTX manual
PTX: Cache Annotations

Loads:

- .ca  Cache at all levels—likely to be accessed again
- .cg  Cache at global level (cache in L2 and below and not L1)
- .cs  Cache streaming—likely to be accessed once
- .lu  Last use
- .cv  Consider cached system memory lines stale—fetch again

Stores:

- .wb  Cache write-back all coherent levels
- .cg  Cache at global level (cache in L2 and below and not L1)
- .cs  Cache streaming—likely to be accessed once
- .wt  Cache write-through (to system memory)

Lost/hidden at the C level!
SPIR-V

Currently: C (OpenCL C, GLSL, HLSL) used as intermediate representations to feed GPUs.

Downsides:

- Compiler heuristics may be focused on human-written code
- Parsing overhead (preprocessor!)
- C semantics may not match (too high-level)

SPIR-V:

- Goal: Common intermediate representation (“IR”) for all GPU-facing code (Vulkan, OpenCL)
- “Extended Instruction Sets”:
  - General compute (OpenCL/CUDA) needs: pointers, special functions
- Different from “SPIR” (tweaked LLVM IR)
SPIR-V Example

%2 = OpTypeVoid
%3 = OpTypeFunction %2 ; void ()
%6 = OpTypeFloat 32 ; 32-bit float
%7 = OpTypeVector %6 4 ; vec4
%8 = OpTypePointer Function %7 ; function-local vec4*
%10 = OpConstant %6 1
%11 = OpConstant %6 2
%12 = OpConstantComposite %7 %10 %10 %11 %10 ; vec4(1.0, 1.0, 2.0, 1.0)
%13 = OpTypeInt 32 0 ; 32-bit int, sign-less
%14 = OpConstant %13 5
%15 = OpTypeArray %7 %14 ; vec4 array

%34 = OpLoad %7 %33
%38 = OpAccessChain %37 %20 %35 %21 %36 ; s.v[2]
%39 = OpLoad %7 %38
%40 = OpFAdd %7 %34 %39
OpStore %31 %40
OpBranch %29

%41 = OpLabel ; else
%43 = OpLoad %7 %42
%44 = OpExtInst %7 %1 Sqrt %43 ; extended instruction sqrt
%45 = OpLoad %7 %9
%46 = OpFMul %7 %44 %45
OpStore %31 %46
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Q: What is the cost of `array.T` in numpy?

$O(1)$ in data volume: Only need to return a view with changed strides.
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