CS 5220: Introduction

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CS 5220: Applications of Parallel Computers

`http://www.cs.cornell.edu/courses/cs5220/2017fa/`

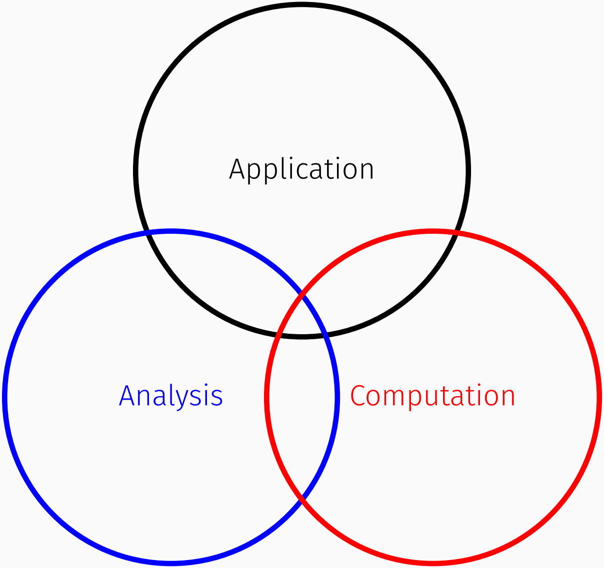
Time:	TR 8:40–9:55
Location:	Gates G01
Instructor:	David Bindel (`bindel@cs`)
TA:	Eric Hans Lee (`erichanslee@cs`)

Enrollment

http://www.cs.cornell.edu/courseinfo/enrollment

- Many CS classes (including 5220) limit pre-enrollment to ensure majors and MEng students can get in.
- We almost surely will have enough space for all comers.
- Enroll if you want access to class resources.
- Enrolling as an auditor is OK.
- If you will not take the class, please formally drop!

The Computational Science & Engineering Picture



Applications Everywhere!

These tools are used in more places than you might think:

- Climate modeling
- CAD tools (computers, buildings, airplanes, ...)
- Control systems
- Computational biology
- Computational finance
- Machine learning and statistical models
- Game physics and movie special effects
- Medical imaging
- Information retrieval
- ...

Parallel computing shows up in all of these.

Why Parallel Computing?

- Scientific computing went parallel long ago
    - Want an answer that is right enough, fast enough
    - Either of those might imply a lot of work!
    - … and we like to ask for more as machines get bigger
    - … and we have a lot of data, too
- Today: Hard to get a non-parallel computer!
    - Totient nodes (2015): 12-core compute nodes
    - Totient accelerators (2015): 60-core Xeon Phi 5110P
    - My laptop (late 2013): Dual core i5 + built in graphics
- Cluster access $\approx$ internet connection + credit card

Lecture Plan

Roughly three parts:

1. **Basics:** architecture, parallel concepts, locality and parallelism in scientific codes
2. **Technology:** OpenMP, MPI, CUDA/OpenCL, cloud systems, compilers and tools
3. **Patterns:** Monte Carlo, dense and sparse linear algebra and PDEs, graph partitioning and load balancing, fast multipole, fast transforms

Objectives

- Reason about code performance
  - Many factors: HW, SW, algorithms
  - Want simple “good enough” models
- Learn about high-performance computing (HPC)
  - Learn parallel concepts and vocabulary
  - Experience parallel platforms (HW and SW)
  - Read/judge HPC literature
  - Apply model numerical HPC patterns
  - Tune existing codes for modern HW
- Apply good software practices

Prerequisites

Basic logistical constraints:

- Default class codes will be in C
- Our focus is numerical codes

Fine if you're not a numerical C hacker!

- I want a diverse class
- Most students have *some* holes
- Come see us if you have concerns

Coursework: Lecture (10%)

- Lecture = theory + practical demos
    - 60 minutes lecture
    - 15 minutes mini-practicum
    - Bring questions for both!
- Notes posted in advance
- May be prep work for mini-practicum
- Course evaluations are also required!

Coursework: Homework (15%)

- Five individual assignments plus “HW0”
- Intent: Get everyone up to speed
- Assigned Tues, due one week later

Coursework: Small group assignments (45%)

- Three projects done with partners (1–3)
- Analyze, tune, and parallelize a baseline code
- Scope is 2-3 weeks

Coursework: Final project (30%)

- Groups are encouraged!
- Bring your own topic or we will suggest
- Flexible, but *must* involve performance
- Main part of work in November–December

Homework 0

- Posted on the class web page.
- Complete and submit by CMS by 8/29.

Questions?

How Fast Can We Go?

Speed records for the Linpack benchmark:

`http://www.top500.org`

Speed measured in flop/s (floating point ops / second):

- Giga (10^9) – a single core
- Tera (10^{12}) – a big machine
- Peta (10^{15}) – current top 10 machines (5 in US)
- Exa (10^{18}) – favorite of funding agencies

Current Record: China's Sunway TaihuLight

- 93 petaflop/s (125 petaflop/s peak)
- 15 MW (LAPACK) – relatively energy efficient
    - Does not include custom chilled-water cooling unit
- Based on SW26010 manycore RISC processors
    - Management processing element (CPE) = 64-bit RISC core
    - Computer processing element (CPE) = 8×8 core mesh
    - Custom interconnect
    - Sunway Raise OS (Linux)
    - Custom compilers (Sunway OpenACC)

Performance on TaihuLight (Dongarra, June 2016)

- Theoretical peak: 125.4 petaflop/s
- Linpack: 93 petaflop/s (74% peak)
- Three SC16 Gordon Bell finalists
    - Explicit PDE solves: 30–40 petaflop/s (25–30%)
    - Implicit solver: 1.5 petaflop/s (1%)
    - Numbers taken from June 2016, may have improved
    - Even with improvements: peak is not indicative!

Second: Tianhe-2 (33.9 pflop/s Linpack)

Commodity nodes, custom interconnect:

- Nodes consist of Xeon E5-2692 + Xeon Phi accelerators
- Intel compilers + Intel math kernel libraries
- MPICH2 MPI with customized channel
- Kylin Linux
- TH Express-2

Alternate Benchmark: Graph 500

Graph processing benchmark (data-intensive)

- Metric: traversed edges per second (TEPS)
- K computer (Japan) tops the list (38.6 teraTEPS)
- Sunway TaihuLight is second (23.8 teraTEPS)
- Tianhe-2 is at 8 (2.1 teraTEPS)

Punchline

- Some high-end machines look like high-end clusters
  - Except custom networks.
- Achievable performance is
  - $\ll$ peak performance
  - Application-dependent
- Hard to achieve peak on more modest platforms, too!

Parallel Performance in Practice

So how fast can I make my computation?

- Peak > Linpack > Gordon Bell > Typical
- Measuring performance of real applications is hard
  - Even figure of merit may be unclear (flops, TEPS, ...?)
  - Typically a few bottlenecks slow things down
  - And figuring out why they slow down can be tricky!
- And we *really* care about time-to-solution
  - Sophisticated methods get answer in fewer flops
  - ... but may look bad in benchmarks (lower flop rates!)

See also David Bailey's comments:

- Twelve Ways to Fool the Masses When Giving Performance Results on Parallel Computers (1991)
- Twelve Ways to Fool the Masses: Fast Forward to 2011 (2011)

Quantifying Parallel Performance

- Starting point: good *serial* performance
- Strong scaling: compare parallel to serial time on the same problem instance as a function of number of processors (p)

$$\text{Speedup} = \frac{\text{Serial time}}{\text{Parallel time}}$$

$$\text{Efficiency} = \frac{\text{Speedup}}{p}$$

- Ideally, speedup = p. Usually, speedup $< p$.
- Barriers to perfect speedup
    - Serial work (Amdahl's law)
    - Parallel overheads (communication, synchronization)

Amdahl's Law

Parallel scaling study where some serial code remains:

$$
\begin{aligned}
p &= \text{number of processors} \\
s &= \text{fraction of work that is serial} \\
t_s &= \text{serial time} \\
t_p &= \text{parallel time} \geq s t_s + (1-s) t_s / p
\end{aligned}
$$

Amdahl's law:

$$\text{Speedup} = \frac{t_s}{t_p} = \frac{1}{s + (1-s)/p} > \frac{1}{s}$$

So 1% serial work $\implies$ max speedup < 100$\times$, regardless of p.

A Little Experiment

Let's try a simple parallel attendance count:

- **Parallel computation:** Rightmost person in each row counts number in row.
- **Synchronization:** Raise your hand when you have a count
- **Communication:** When all hands are raised, each row representative adds their count to a tally and says the sum (going front to back).

(Somebody please time this.)

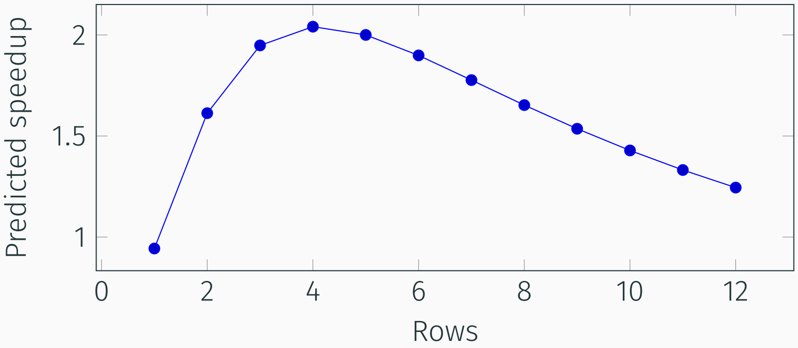
A Toy Analysis

Parameters:

$$\begin{aligned} n &= \text{number of students} \\ r &= \text{number of rows} \\ t_c &= \text{time to count one student} \\ t_t &= \text{time to say tally} \\ t_s &\approx n t_c \\ t_p &\approx n t_c / r + r t_t \end{aligned}$$

How much could I possibly speed up?

Modeling Speedup



(Parameters: $n = 80$, $t_c = 0.3$, $t_t = 1$.)

Modeling Speedup

The bound

$$\text{speedup} < \frac{1}{2}\sqrt{\frac{nt_c}{t_t}}$$

is usually tight.

Poor speed-up occurs because:

- The problem size n is small
- The communication cost is relatively large
- The serial computation cost is relatively large

Some of the usual suspects for parallel performance problems!

Things would look better if I allowed both n and r to grow — that would be a *weak* scaling study.

Summary: Thinking about Parallel Performance

Today:

- We're approaching machines with peak *exaflop* rates
- But codes rarely get peak performance
- Better comparison: tuned serial performance
- Common measures: *speedup* and *efficiency*
- Strong scaling: study speedup with increasing p
- Weak scaling: increase both p and n
- Serial overheads and communication costs kill speedup
- Simple analytical models help us understand scaling

And in case you arrived late

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… and please enroll and submit HW0!