CS267
Applications of Parallel Computers

www.cs.berkeley.edu/~demmel/cs267_Spr16/

Lecture 1: Introduction

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Outline

- Why ~~powerful~~ all computers must be parallel processors
  - Including your laptops and handhelds
- Large Computational Science and Engineering (CSE) problems require powerful computers
  - Commercial problems too
- Why writing (fast) parallel programs is hard
  - But things are improving
- Structure of the course

Units of Measure

- **High Performance Computing (HPC) units are:**
  - **Flop: floating point operation, usually double precision unless noted**
  - **Flop/s: floating point operations per second**
  - **Bytes: size of data (a double precision floating point number is 8 bytes)**
- **Typical sizes are millions, billions, trillions…**

Mega	**Mflop/s = 10^6 flop/sec**	**Mbyte = 2^{20} = 1048576 ~ 10^6 bytes**
Giga	**Gflop/s = 10^9 flop/sec**	**Gbyte = 2^{30} ~ 10^9 bytes**
Tera	**Tflop/s = 10^{12} flop/sec**	**Tbyte = 2^{40} ~ 10^{12} bytes**
Peta	**Pflop/s = 10^{15} flop/sec**	**Pbyte = 2^{50} ~ 10^{15} bytes**
Exa	**Eflop/s = 10^{18} flop/sec**	**Ebyte = 2^{60} ~ 10^{18} bytes**
Zetta	**Zflop/s = 10^{21} flop/sec**	**Zbyte = 2^{70} ~ 10^{21} bytes**
Yotta	**Yflop/s = 10^{24} flop/sec**	**Ybyte = 2^{80} ~ 10^{24} bytes**

- **Current fastest (public) machine ~ 55 Pflop/s, 3.1M cores**
  - **Up-to-date list at www.top500.org**

Why ~~powerful~~ all computers are parallel

(2007)

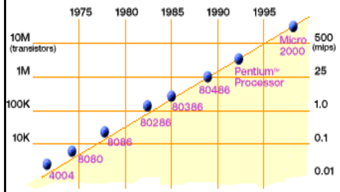
circa 1991-2006

Tunnel Vision by Experts

- “I think there is a world market for maybe five computers.”
  - Thomas Watson, chairman of IBM, 1943.
- “There is no reason for any individual to have a computer in their home”
  - Ken Olson, president and founder of Digital Equipment Corporation, 1977.
- “640K [of memory] ought to be enough for anybody.”
  - Bill Gates, chairman of Microsoft,1981.
- “On several recent occasions, I have been asked whether parallel computing will soon be relegated to the trash heap reserved for promising technologies that never quite make it.”
  - Ken Kennedy, CRPC Directory, 1994

Slide source: Warfield et al.

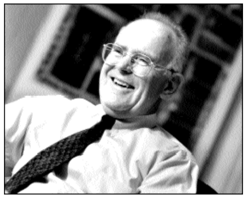
Technology Trends: Microprocessor Capacity



2X transistors/Chip Every 1.5 years

Called “Moore’s Law”

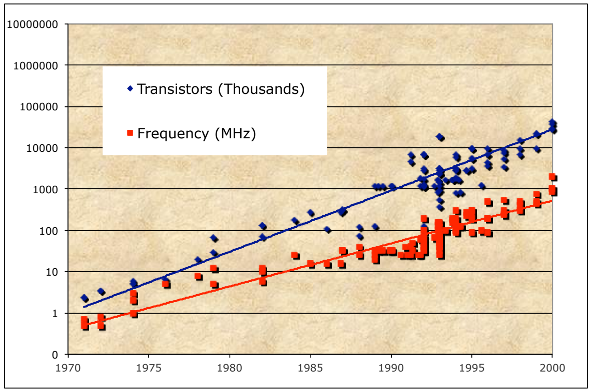
Microprocessors have become smaller, denser, and more powerful.



Gordon Moore (co-founder of Intel) predicted in 1965 that the transistor density of semiconductor chips would double roughly every 18 months.

Slide source: Jack Dongarra

Microprocessor Transistors / Clock (1970-2000)



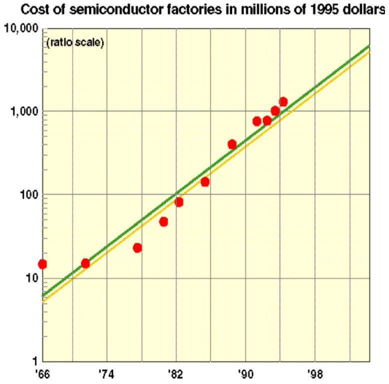
Impact of Device Shrinkage

- What happens when the feature size (transistor size) shrinks by a factor of x ?
- Clock rate goes up by x because wires are shorter
  - actually less than x, because of power consumption
- Transistors per unit area goes up by x^2
- Die size also tends to increase
  - typically another factor of ~x
- Raw computing power of the chip goes up by ~ x^4 !
  - typically x^3 is devoted to either on-chip
    - parallelism: hidden parallelism such as ILP
    - locality: caches
- So most programs x^3 times faster, without changing them

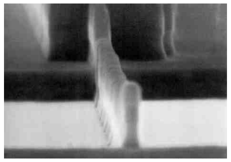
1/18/16

Manufacturing Issues Limit Performance

Manufacturing costs and yield problems limit use of density



- **Moore's 2nd law (Rock's law): costs go up**



Demo of 0.06 micron CMOS

Source: Forbes Magazine

- **Yield**
  - -What percentage of the chips are usable?
  - -E.g., Cell processor (PS3) was sold with 7 out of 8 "on" to improve yield

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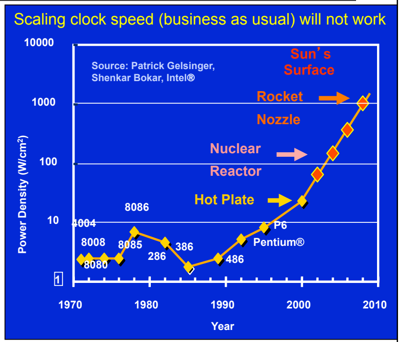
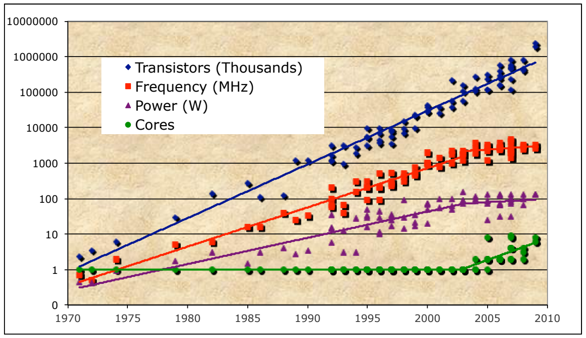
Power Density Limits Serial Performance

- Concurrent systems are more power efficient
  - Dynamic power is proportional to V^2fC
  - Increasing frequency (f) also increases supply voltage (V) → cubic effect
  - Increasing cores increases capacitance (C) but only linearly
  - Save power by lowering clock speed



- High performance serial processors waste power
  - Speculation, dynamic dependence checking, etc. burn power
  - Implicit parallelism discovery
- More transistors, but not faster serial processors

Revolution in Processors



- Chip density is continuing increase ~2x every 2 years
- Clock speed is not
- Number of processor cores may double instead
- Power is under control, no longer growing

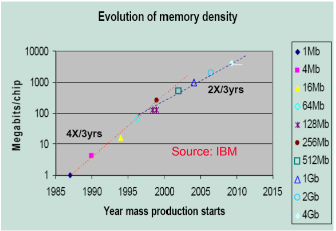
Parallelism in 2016?

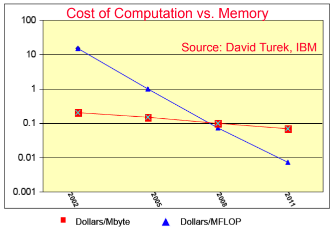
- These arguments are no longer theoretical
- All major processor vendors are producing *multicore* chips
  - Every machine will soon be a parallel machine
  - To keep doubling performance, parallelism must double
- Which (commercial) applications can use this parallelism?
  - Do they have to be rewritten from scratch?
- Will all programmers have to be parallel programmers?
  - New software model needed
  - Try to hide complexity from most programmers – eventually
  - In the meantime, need to understand it
- Computer industry betting on this big change, but does not have all the answers
  - Berkeley ParLab, then ASPIRE, established to work on this

Memory is Not Keeping Pace

Technology trends against a constant or increasing memory per core

- Memory density is doubling every three years; processor logic is every two
- Storage costs (dollars/Mbyte) are dropping gradually compared to logic costs





The cost to sense, collect, generate and calculate data is declining much faster than the cost to access, manage and store it

Question: Can you double concurrency without doubling memory?

- **Strong scaling:** fixed problem size, increase number of processors
- **Weak scaling:** grow problem size proportionally to number of processors

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The TOP500 Project

- Listing the 500 most powerful computers in the world
- Yardstick: Rmax of Linpack
  - Solve Ax=b, dense problem, matrix is random
  - Dominated by dense matrix-matrix multiply
- Updated twice a year:
  - ISC'xy in June in Germany
  - SCxy in November in the U.S.
- All information available from the TOP500 web site at: www.top500.org

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The TOP10 in November 2015

#	Site	Manufacturer	Computer	Country	Cores	Rmax [Pflops]	Power [MW]
1	National University of Defense Technology	NUDT	Tianhe-2, NUDT TH-IVB-FEP, Xeon 12C 2.2GHz, IntelXeon Phi	China	3,120,000	33.9	17.8
2	Oak Ridge National Laboratory	Cray	Titan, Cray XK7, Opteron 16C 2.2GHz, Gemini, NVIDIA K20x	USA	560,640	17.6	8.21
3	Lawrence Livermore National Laboratory	IBM	Sequoia, BlueGene/Q, Power BQC 16C 1.6GHz, Custom	USA	1,572,864	17.2	7.89
4	RIKEN Advanced Institute for Computational Science	Fujitsu	K Computer, SPARC64 VIIIfx 2.0GHz, Tofu Interconnect	Japan	795,024	10.5	12.7
5	Argonne National Laboratory	IBM	Mira, BlueGene/Q, Power BQC 16C 1.6GHz, Custom	USA	786,432	8.59	3.95
6	Los Alamos NL / Sandia NL	Cray	Trinity, Cray XC40, Xeon E5 16C 2.3GHz, Aries	USA	301,0564	8.10	?
7	Swiss National Supercomputing Centre	Cray	Piz Daint, Cray XC30, Xeon E5 8C 2.6GHz, Aries, NVIDIA K20x	Switzerland	115,984	6.27	2.33
8	HLRS – Stuttgart	Cray	Hazel Hen, Cray XC40, Xeon E5 12C 2.5GHz, Aries	Germany	185,088	5.64	?
9	King Abdullah University of Science and Technology	Cray	Shaheen II, Cray XC40, Xeon E5 16C 2.3GHz, Aries	Saudi Arabia	196,608	5.54	2.83
10	Texas Advanced Computing Center/UT	Dell	Stampede, PowerEdge C8220, Xeon E5 8C 2.7GHz, Intel Xeon Phi	USA	462,462	5.17	4.51

Where you will do your homework and projects

#	Site	Manufacturer	Computer	Country	Cores	Rmax [Pflops]	Power [MW]
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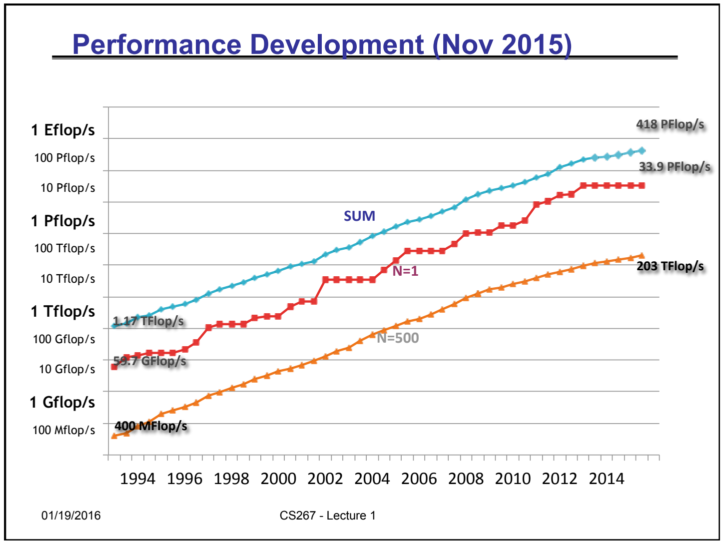
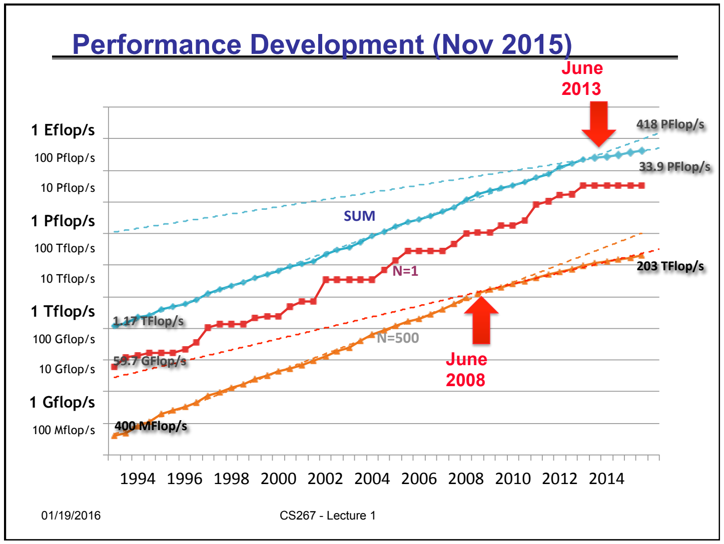
40	Lawrence Berkeley National Laboratory	Cray	Edison, Cray XC30, Intel Xeon E5-2695v2, 2.4GHz	USA	133,824	1.65	?



Performance Development (Nov 2015)

01/19/2016 CS267 - Lecture 1



Performance Development (Nov 2015)

June 2013

June 2008

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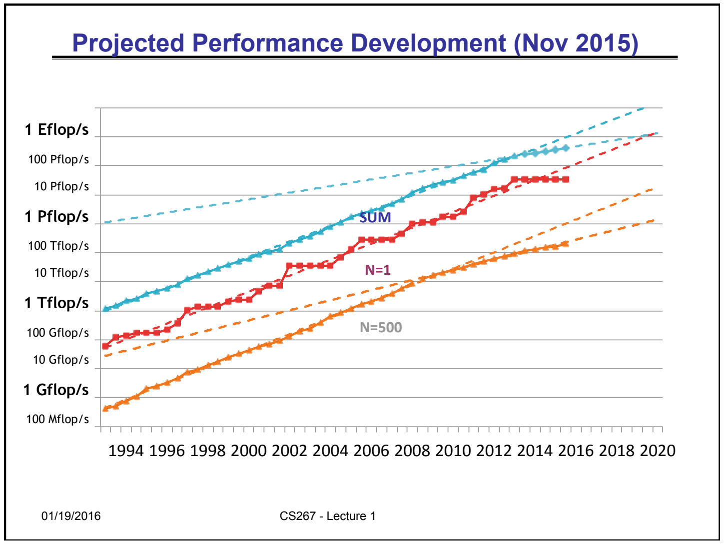

Projected Performance Development (Nov 2015)

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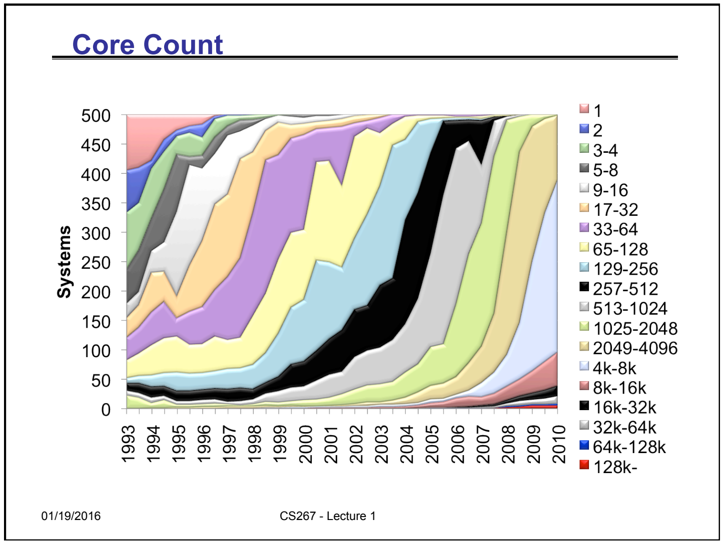

Core Count

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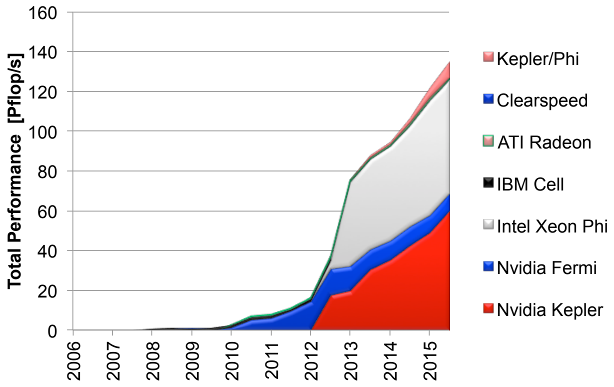
Performance of Accelerators



Moore's Law reinterpreted

- Number of cores per chip can double every two years
- Clock speed will not increase (possibly decrease)
- Need to deal with systems with millions of concurrent threads
- Need to deal with inter-chip parallelism as well as intra-chip parallelism

Outline

- Why all ~~powerful~~ computers must be parallel processors
  - Including your laptops and handhelds
- Large CSE problems require powerful computers
  - Commercial problems too
- Why writing (fast) parallel programs is hard
  - But things are improving
- Structure of the course

Computational Science - News

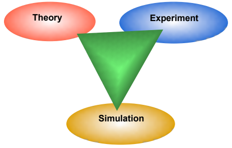
"An important development in sciences is occurring at the intersection of computer science and the sciences that has the potential to have a profound impact on science. It is a leap from the application of computing … to the *integration of computer science concepts, tools, and theorems* into the very fabric of science." -*Science* 2020 Report, March 2006

Nature, March 23, 2006

Drivers for Change

- **Continued exponential increase in computational power**
  - **Can simulate what theory and experiment can't do**
- **Continued exponential increase in experimental data**
  - **Moore's Law applies to sensors too**
  - **Need to analyze all that big data**

Simulation: The Third Pillar of Science



- **Traditional scientific and engineering method:**
  - **(1) Do theory or paper design**
  - **(2) Perform experiments or build system**
- **Limitations:**
  - **–Too difficult—build large wind tunnels**
  - **–Too expensive—build a throw-away passenger jet**
  - **–Too slow—wait for climate or galactic evolution**
  - **–Too dangerous—weapons, drug design, climate experimentation**
- **Computational science and engineering paradigm:**
  - **(3) Use computers to simulate and analyze the phenomenon**
  - **- Based on known physical laws and efficient numerical methods**
  - **- Analyze simulation results with computational tools and methods beyond what is possible manually**

Data Driven Science

- Scientific data sets are growing exponentially
  - Ability to generate data is exceeding our ability to store and analyze
  - Simulation systems and some observational devices grow in capability with Moore's Law
- Petabyte (PB) data sets will soon be common:
  - *Climate modeling:* estimates of the next IPCC data is in 10s of petabytes
  - *Genome:* JGI alone will have .5 petabyte of data this year and double each year
  - *Particle physics*: LHC is projected to produce 16 petabytes of data per year
  - *Astrophysics*: LSST and others will produce 5 petabytes/year (via 3.2 Gigapixel camera)
- Create scientific communities with "Science Gateways" to data

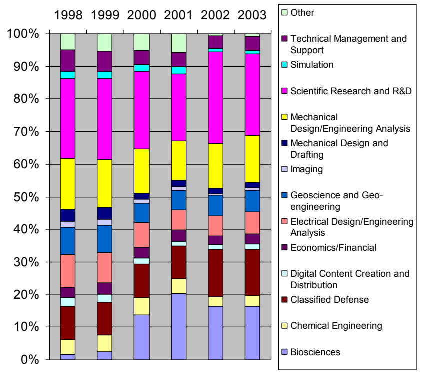
Some Particularly Challenging Computations

- **Science**
  - **Global climate modeling**
  - **Biology: genomics; protein folding; drug design**
  - **Astrophysical modeling**
  - **Computational Chemistry**
  - **Computational Material Sciences and Nanosciences**
- **Engineering**
  - **Semiconductor design**
  - **Earthquake and structural modeling**
  - **Computation fluid dynamics (airplane design)**
  - **Combustion (engine design)**
  - **Crash simulation**
- **Business**
  - **Financial and economic modeling**
  - **Transaction processing, web services and search engines**
- **Defense**
  - **Nuclear weapons -- test by simulations**
  - **Cryptography**

Economic Impact of HPC

- **Airlines:**
  - **System-wide logistics optimization systems on parallel systems.**
  - **Savings: approx. $100 million per airline per year.**
- **Automotive design:**
  - **Major automotive companies use large systems (500+ CPUs) for:**
    - **CAD-CAM, crash testing, structural integrity and aerodynamics.**
    - **One company has 500+ CPU parallel system.**
  - **Savings: approx. $1 billion per company per year.**
- **Semiconductor industry:**
  - **Semiconductor firms use large systems (500+ CPUs) for**
    - **device electronics simulation and logic validation**
  - **Savings: approx. $1 billion per company per year.**
- **Energy**
  - **Computational modeling improved performance of current nuclear power plants, equivalent to building two new power plants.**

$5B World Market in Technical Computing in 2004



Source: IDC 2004, from NRC Future of Supercomputing Report

What Supercomputers Do – Two Examples

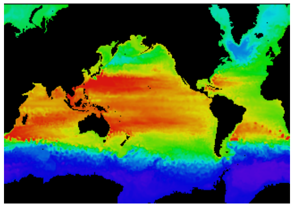
- **Climate modeling**
  - **simulation replacing experiment that is too slow**
- **Cosmic microwave background radition**
  - **analyzing massive amounts of data with new tools**

Global Climate Modeling Problem

- Problem is to compute:

  f(latitude, longitude, elevation, time) → "weather" =

  (temperature, pressure, humidity, wind velocity)
- Approach:
  - *Discretize* the domain, e.g., a measurement point every 10 km
  - Devise an algorithm to predict weather at time t+δt given t
- Uses:
  - Predict major events, e.g., El Nino
  - Use in setting air emissions standards
  - Evaluate global warming scenarios



Source: http://www.epm.ornl.gov/chammp/chammp.html

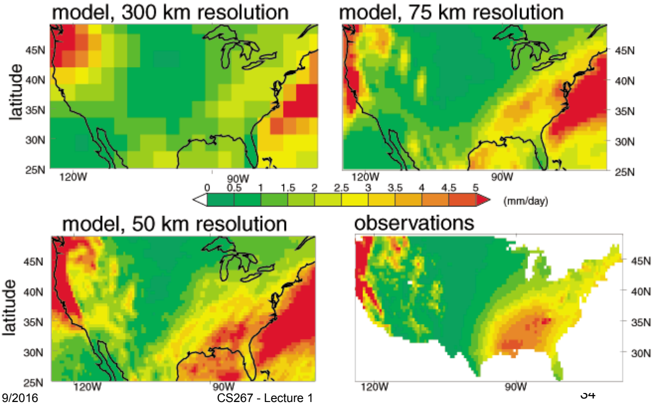
Global Climate Modeling Computation

- One piece is modeling the fluid flow in the atmosphere
  - Solve Navier-Stokes equations
    - Roughly 100 Flops per grid point with 1 minute timestep
    - One grid point every 10 Km in every direction
- Computational requirements:
  - To match real-time, need 5 x 10^{11} flops in 60 seconds = 8 Gflop/s
  - Weather prediction (7 days in 24 hours) → 56 Gflop/s
  - Climate prediction (50 years in 30 days) → 4.8 Tflop/s
  - To use in policy negotiations (50 years in 12 hours) → 288 Tflop/s
- To double the grid resolution, computation is 8x to 16x
- State of the art models require integration of atmosphere, clouds, ocean, sea-ice, land models, plus possibly carbon cycle, geochemistry and more
- Current models are coarser than this

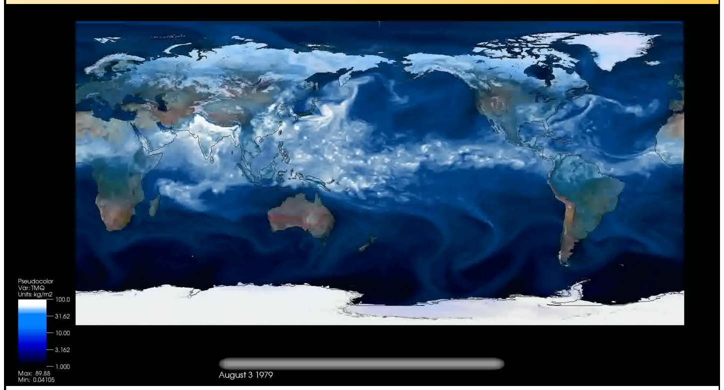
High Resolution Climate Modeling on NERSC-3 – P. Duffy, et al., LLNL

Wintertime Precipitation (millimeters/day)

As model resolution becomes finer, results converge towards observations

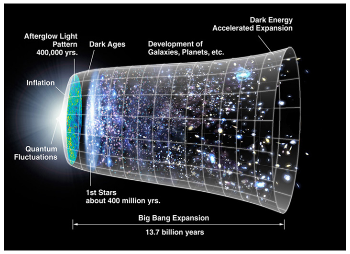


U.S.A. Hurricane



Source: Data from M.Wehner, visualization by Prabhat, LBNL

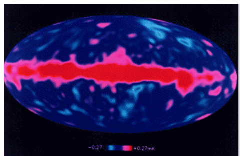
NERSC User George Smoot wins 2006 Nobel Prize in Physics



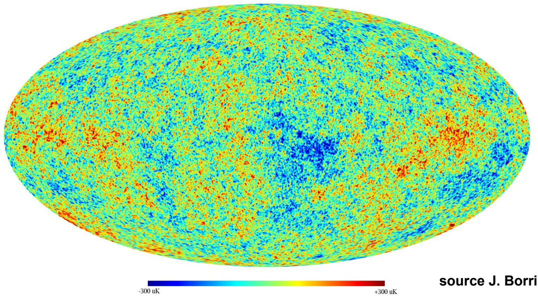
Cosmic Microwave Background Radiation (CMB): an image of the universe at 400,000 years

Smoot and Mather 1992

COBE Experiment showed anisotropy of CMB



The Current CMB Map



source J. Borrill, LBNL

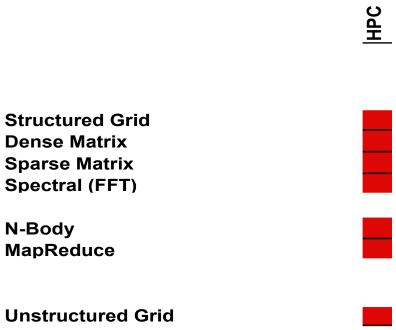
- Unique imprint of primordial physics through the tiny anisotropies in temperature and polarization.
- Extracting these μKelvin fluctuations from inherently noisy data is a serious computational challenge.

Evolution Of CMB Data Sets: Cost > O(Np^3)

Experiment	N_t	N_p	N_b	Limiting Data	Notes
COBE (1989)	$2x10^9$	$6x10^3$	$3x10^1$	Time	Satellite, Workstation
BOOMERanG (1998)	$3x10^8$	$5x10^5$	$3x10^1$	Pixel	Balloon, 1st HPC/NERSC
(4yr) WMAP (2001)	$7x10^{10}$	$4x10^7$	$1x10^3$	?	Satellite, Analysis-bound
Planck (2007)	$5x10^{11}$	$6x10^8$	$6x10^3$	Time/ Pixel	Satellite, Major HPC/DA effort
POLARBEAR (2007)	$8x10^{12}$	$6x10^6$	$1x10^3$	Time	Ground, NG-multiplexing
CMBPol (~2020)	10^{14}	10^9	10^4	Time/ Pixel	Satellite, Early planning/design

data compression →

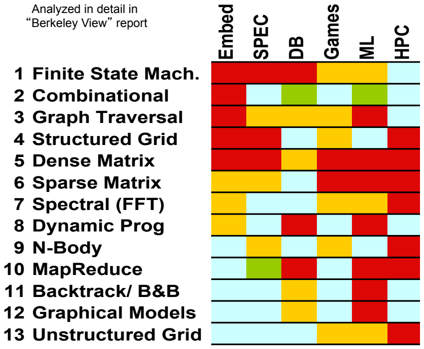
Which commercial applications *require* parallelism?



	HPC
Structured Grid	🟥
Dense Matrix	🟥
Sparse Matrix	🟥
Spectral (FFT)	🟥
N-Body	🟥
MapReduce	🟥
Unstructured Grid	🟥

Which commercial applications *require* parallelism?

Analyzed in detail in
"Berkeley View" report



	Embed	SPEC	DB	Games	ML	HPC
1 Finite State Mach.	🟥	🟥	🟥	🟨	🟨	🟦
2 Combinational	🟥	🟦	🟩	🟦	🟩	🟦
3 Graph Traversal	🟥	🟨	🟨	🟨	🟥	🟦
4 Structured Grid	🟥	🟥	🟦	🟨	🟦	🟥
5 Dense Matrix	🟥	🟥	🟨	🟥	🟥	🟥
6 Sparse Matrix	🟨	🟨	🟦	🟥	🟥	🟥
7 Spectral (FFT)	🟨	🟦	🟦	🟨	🟨	🟥
8 Dynamic Prog	🟨	🟦	🟥	🟦	🟥	🟦
9 N-Body	🟦	🟨	🟦	🟨	🟦	🟥
10 MapReduce	🟦	🟩	🟥	🟦	🟥	🟥
11 Backtrack/ B&B	🟦	🟦	🟨	🟦	🟥	🟦
12 Graphical Models	🟦	🟦	🟨	🟦	🟥	🟦
13 Unstructured Grid	🟦	🟦	🟦	🟨	🟨	🟥

Analyzed in detail in
"Berkeley View" report
www.eecs.berkeley.edu/Pubs/
TechRpts/2006/
EECS-2006-183.html

What do commercial and CSE applications have in common?

Motif/Dwarf: Common Computational Patterns

(Red Hot → Blue Cool)

	Embed	SPEC	DB	Games	ML	HPC	Health	Image	Speech	Music	Browser
1 Finite State Mach.	🟥	🟥	🟥	🟨	🟨	🟦	🟦	🟦	🟦	🟦	🟥
2 Combinational	🟥	🟦	🟩	🟦	🟩	🟦	🟦	🟦	🟦	🟦	🟥
3 Graph Traversal	🟥	🟨	🟨	🟨	🟥	🟦	🟥	🟦	🟥	🟩	🟩
4 Structured Grid	🟥	🟥	🟦	🟨	🟦	🟥	🟦	🟥	🟦	🟦	🟦
5 Dense Matrix	🟥	🟥	🟨	🟥	🟥	🟥	🟦	🟥	🟥	🟥	🟦
6 Sparse Matrix	🟨	🟨	🟦	🟥	🟥	🟥	🟥	🟦	🟦	🟥	🟦
7 Spectral (FFT)	🟨	🟦	🟦	🟨	🟨	🟥	🟦	🟩	🟥	🟥	🟥
8 Dynamic Prog	🟨	🟦	🟥	🟦	🟥	🟦	🟦	🟦	🟨	🟦	🟥
9 N-Body	🟦	🟨	🟦	🟨	🟦	🟥	🟩	🟦	🟦	🟦	🟦
10 MapReduce	🟦	🟩	🟥	🟦	🟥	🟥	🟥	🟥	🟨	🟥	🟨
11 Backtrack/ B&B	🟦	🟦	🟨	🟦	🟥	🟦	🟦	🟦	🟦	🟨	🟦
12 Graphical Models	🟦	🟦	🟨	🟦	🟥	🟦	🟦	🟦	🟦	🟥	🟦
13 Unstructured Grid	🟦	🟦	🟦	🟨	🟨	🟥	🟥	🟦	🟦	🟥	🟦

Outline

- Why ~~powerful~~ all computers must be parallel processors
  - Including your laptops and handhelds
- Large CSE problems require powerful computers
  - Commercial problems too
- Why writing (fast) parallel programs is hard
  - But things are improving
- Structure of the course

Principles of Parallel Computing

- Finding enough parallelism (Amdahl’s Law)
- Granularity – how big should each parallel task be
- Locality – moving data costs more than arithmetic
- Load balance – don’t want 1K processors to wait for one slow one
- Coordination and synchronization – sharing data safely
- Performance modeling/debugging/tuning

➡ All of these things makes parallel programming even harder than sequential programming.

“Automatic” Parallelism in Modern Machines

- Bit level parallelism
  - within floating point operations, etc.
- Instruction level parallelism (ILP)
  - multiple instructions execute per clock cycle
- Memory system parallelism
  - overlap of memory operations with computation
- OS parallelism
  - multiple jobs run in parallel on commodity SMPs

Limits to all of these -- for very high performance, need user to identify, schedule and coordinate parallel tasks

Finding Enough Parallelism

- Suppose only part of an application seems parallel
- Amdahl's law
  - let s be the fraction of work done sequentially, so (1-s) is fraction parallelizable
  - P = number of processors

Speedup(P) = Time(1)/Time(P)

<= 1/(s + (1-s)/P)

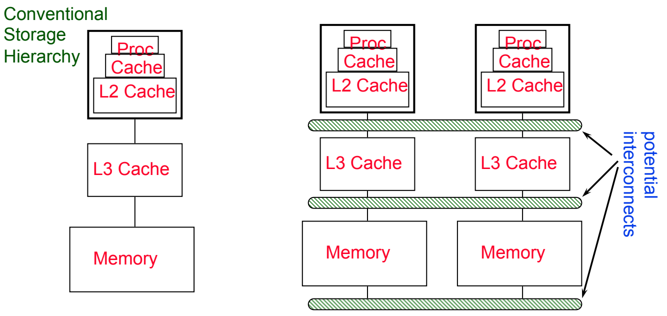
<= 1/s

- Even if the parallel part speeds up perfectly performance is limited by the sequential part
- Top500 list: currently fastest machine has P~3.1M; 2^{nd} fastest has ~560K

Overhead of Parallelism

- Given enough parallel work, this is the biggest barrier to getting desired speedup
- Parallelism overheads include:
  - cost of starting a thread or process
  - cost of communicating shared data
  - cost of synchronizing
  - extra (redundant) computation
- Each of these can be in the range of milliseconds (=millions of flops) on some systems
- Tradeoff: Algorithm needs sufficiently large units of work to run fast in parallel (i.e. large granularity), but not so large that there is not enough parallel work

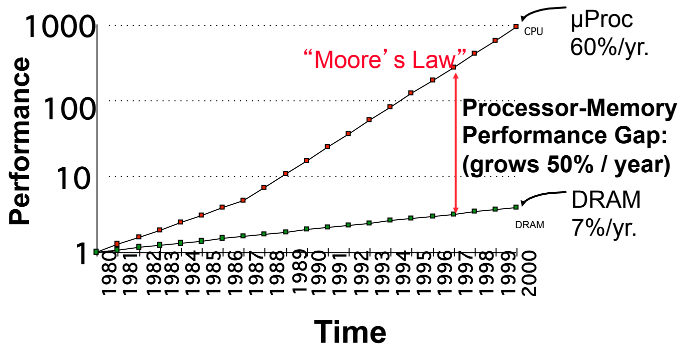
Locality and Parallelism



- Large memories are slow, fast memories are small
- Storage hierarchies are large and fast on average
- Parallel processors, collectively, have large, fast cache
  - the slow accesses to "remote" data we call "communication"
- Algorithm should do most work on local data

Processor-DRAM Gap (latency)

Goal: find algorithms that minimize communication, not necessarily arithmetic



Load Imbalance

- Load imbalance is the time that some processors in the system are idle due to
  - insufficient parallelism (during that phase)
  - unequal size tasks
- Examples of the latter
  - adapting to "interesting parts of a domain"
  - tree-structured computations
  - fundamentally unstructured problems
- Algorithm needs to balance load
  - Sometimes can determine work load, divide up evenly, before starting
    - "Static Load Balancing"
  - Sometimes work load changes dynamically, need to rebalance dynamically
    - "Dynamic Load Balancing," eg work-stealing

Parallel Software Eventually – ParLab view

- 2 types of programmers ➔ 2 layers of software
- **Efficiency Layer** (10% of programmers)
  - Expert programmers build Libraries implementing kernels, "Frameworks", OS, ….
  - Highest fraction of peak performance possible
- **Productivity Layer** (90% of programmers)
  - Domain experts / Non-expert programmers productively build parallel applications by composing frameworks & libraries
  - Hide as many details of machine, parallelism as possible
  - Willing to sacrifice some performance for productive programming
- Expect students may want to work at either level
  - In the meantime, we all need to understand enough of the efficiency layer to use parallelism effectively

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Course Mechanics

- Web page:

  http://www.cs.berkeley.edu/~demmel/cs267_Spr16/
- Normally a mix of CS, EE, and other engineering and science students
- **Please fill out survey on web page (posted)**
- Grading:
  - Warmup assignment (homework 0 on the web)
    - **Build a web page on an interest of yours in CSE**
  - Three programming assignments in first half of semester
    - We will team up CS/nonCS students for HW1
  - Final projects
    - Could be parallelizing an application, building or evaluating a tool, etc.
    - We encourage interdisciplinary teams, since this is the way parallel scientific software is generally built
- Class computer accounts on Edison at NERSC, Stampede at TACC
  - Fill out forms next time

Instructors

- Jim Demmel, EECS & Mathematics
- GSIs:
  - Orianna DeMasi, EECS
  - Marquita Ellis, EECS
- Contact information on web page

Students

- 116 registered or on the waitlist (100 grad, 16 undergrad)
- 64 CS or EECS students, rest from

Applied Science &Technology
Astrophysics
Bioengineering
Biostatistics
Chemical Engineering
Civil & Environmental Engineering
Energy & Resources
Earth & Planetary Systems

Industrial Engineering and Operations Research
Information Management and Systems
Mechanical Engineering
Nuclear Engineering
Physics
Political Science
Statistics

Remote instruction

- Lectures will be webcast, archived, as in past semesters
  - See class webpage for details
- XSEDE is nationwide project supporting users of NSF supercomputer facilities
  - XSEDE offering CS267 to students nationwide, starting 2013
  - Based on Videos from Spring 2012 offering
  - Free accounts on NSF supercomputer
  - This year: local instructors at 11 universities to give real grades
  - Challenges to "scaling up" education
    - Q&A – piazza for CS267, moodle for XSEDE
    - Autograding
      - For correctness – run test cases (not as easy as it sounds)
      - For performance – timing on suitable platform

Rough List of Topics

- Basics of computer architecture, memory hierarchies, performance
- Parallel Programming Models and Machines
  - Shared Memory and Multithreading
  - Distributed Memory and Message Passing
  - Data parallelism, GPUs
  - Cloud computing
- Parallel languages and libraries
  - Shared memory threads and OpenMP
  - MPI
  - Other Languages , frameworks (UPC, CUDA, Spark, PETSC, "Pattern Language", …)
- "Seven Dwarfs" of Scientific Computing
  - Dense & Sparse Linear Algebra
  - Structured and Unstructured Grids
  - Spectral methods (FFTs) and Particle Methods
- 6 additional motifs
  - Graph algorithms, Graphical models, Dynamic Programming, Branch & Bound, FSM, Logic
- General techniques
  - Autotuning, Load balancing, performance tools
- Applications: climate modeling, materials science, astrophysics … (guest lecturers)

Reading Materials

- Pointers on class web page
- Must read:
  - "The Landscape of Parallel Processing Research: The View from Berkeley"
    - http://www.eecs.berkeley.edu/Pubs/TechRpts/2006/EECS-2006-183.pdf
- Some on-line texts:
  - Demmel's notes from CS267 Spring 1999, which are similar to 2000 and 2001. However, they contain links to html notes from 1996.
    - http://www.cs.berkeley.edu/~demmel/cs267_Spr99/
  - Ian Foster's book, "Designing and Building Parallel Programming".
    - http://www-unix.mcs.anl.gov/dbpp/
- Potentially useful texts:
  - "Sourcebook for Parallel Computing", by Dongarra, Foster, Fox, ..
    - A general overview of parallel computing methods
  - "Performance Optimization of Numerically Intensive Codes" by Stefan Goedecker and Adolfy Hoisie
    - This is a practical guide to optimization, mostly for those of you who have never done any optimization

Reading Materials (cont.)

- Recent books with papers about the current state of the art
  - David Bader (ed.), "Petascale Computing, Algorithms and Applications", Chapman & Hall/CRC, 2007
  - Michael Heroux, Padma Ragahvan, Horst Simon (ed.),"Parallel Processing for Scientific Computing", SIAM, 2006.
  - M. Sottile, T. Mattson, C. Rasmussen, Introduction to Concurrency in Programming Languages, Chapman & Hall/CRC, 2009.
- More pointers on the web page

What you should get out of the course

In depth understanding of:

- When is parallel computing useful?
- Understanding of parallel computing hardware options
- Overview of programming models (software) and tools, and experience using some of them
- Some important parallel applications and the algorithms
- Performance analysis and tuning
- Exposure to various open research questions