Parallel Programming

Introduction to Parallel Programming

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曙光高性能计算机

曙光1号

全对称共享存储
多处理机系统

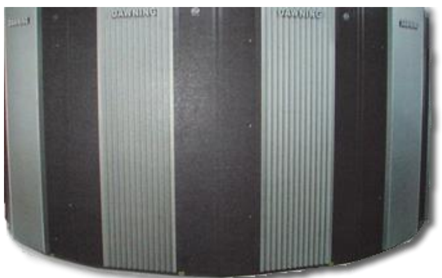
曙光1000

当时中国最快的计算机
峰值25.6亿次/秒

曙光2000

中国首个机群系统
峰值1117亿次/秒

曙光3000



工业标准机群
峰值4032亿次/秒

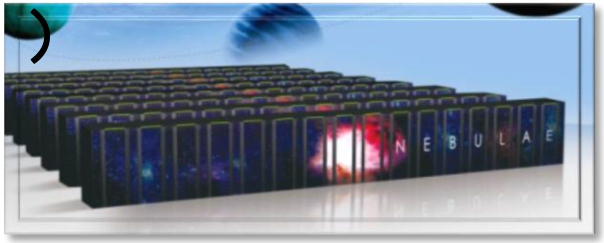
曙光4000

中国首个进入TOP500
前十名的高性能计算机、
峰值11万亿次/秒

曙 5000

当时中国最快的计算机、
中国首个刀片式机群、
峰值230万亿次/秒

曙光6000（星云）



中国首个实测性能超过千万亿
次的高性能计算机、
世界TOP500第二名、
峰值3千万亿次/秒

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

Unites 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

all (2007)

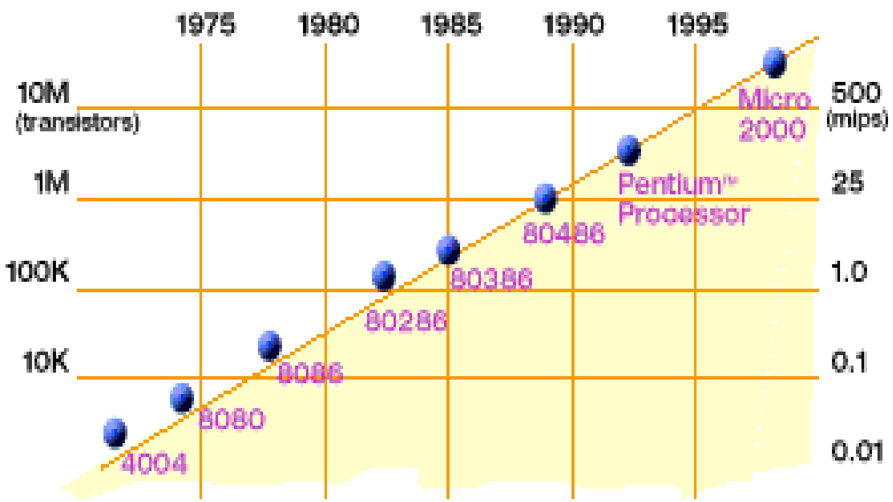
Why ~~powerful~~ computers are parallel

circa 1991-2006

Tunnel Vision by Experts

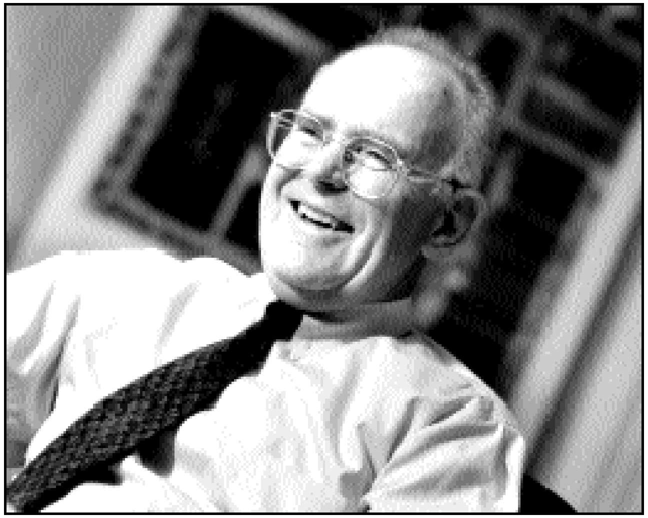
- **"I think there is a world market for maybe five computers."**
  - Thomas Watson, chairman of IBM, 1943.
- **"There is no reason for any individual to have a computer in their home"**
  - Ken Olson, president and founder of Digital Equipment Corporation, 1977.
- **"640K [of memory] ought to be enough 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

Technology Trends: Microprocessor Capacity



2X transistors/Chip Every 1.5 years

Called "Moore's Law"



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

- Microprocessors have become smaller, denser, and more powerful.

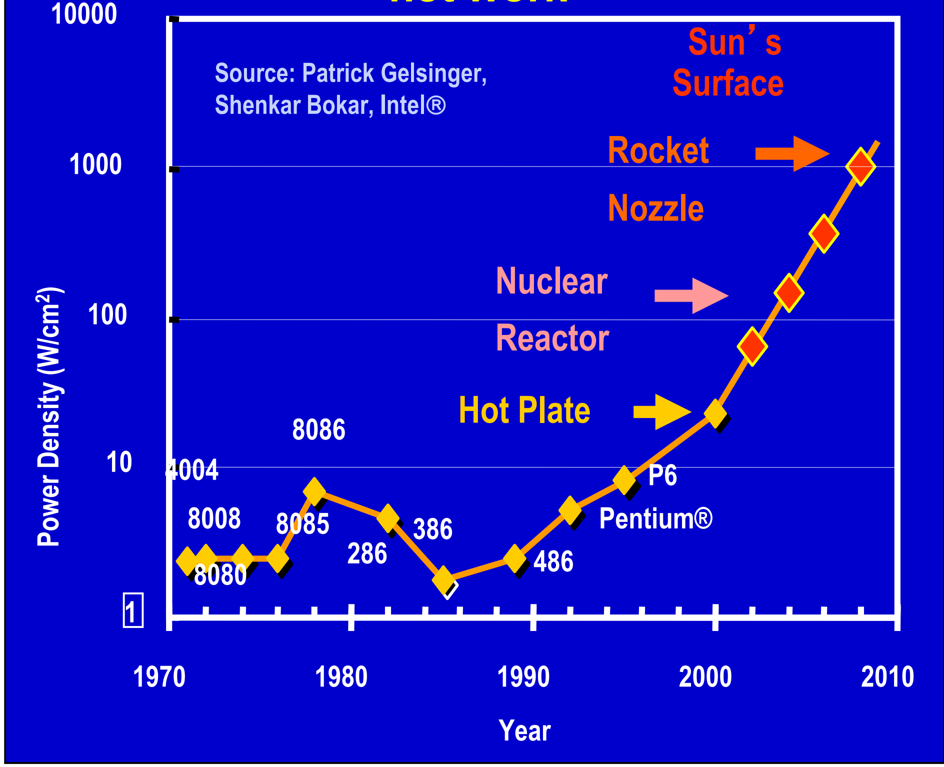
Impact of Device Shrinkage

- 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

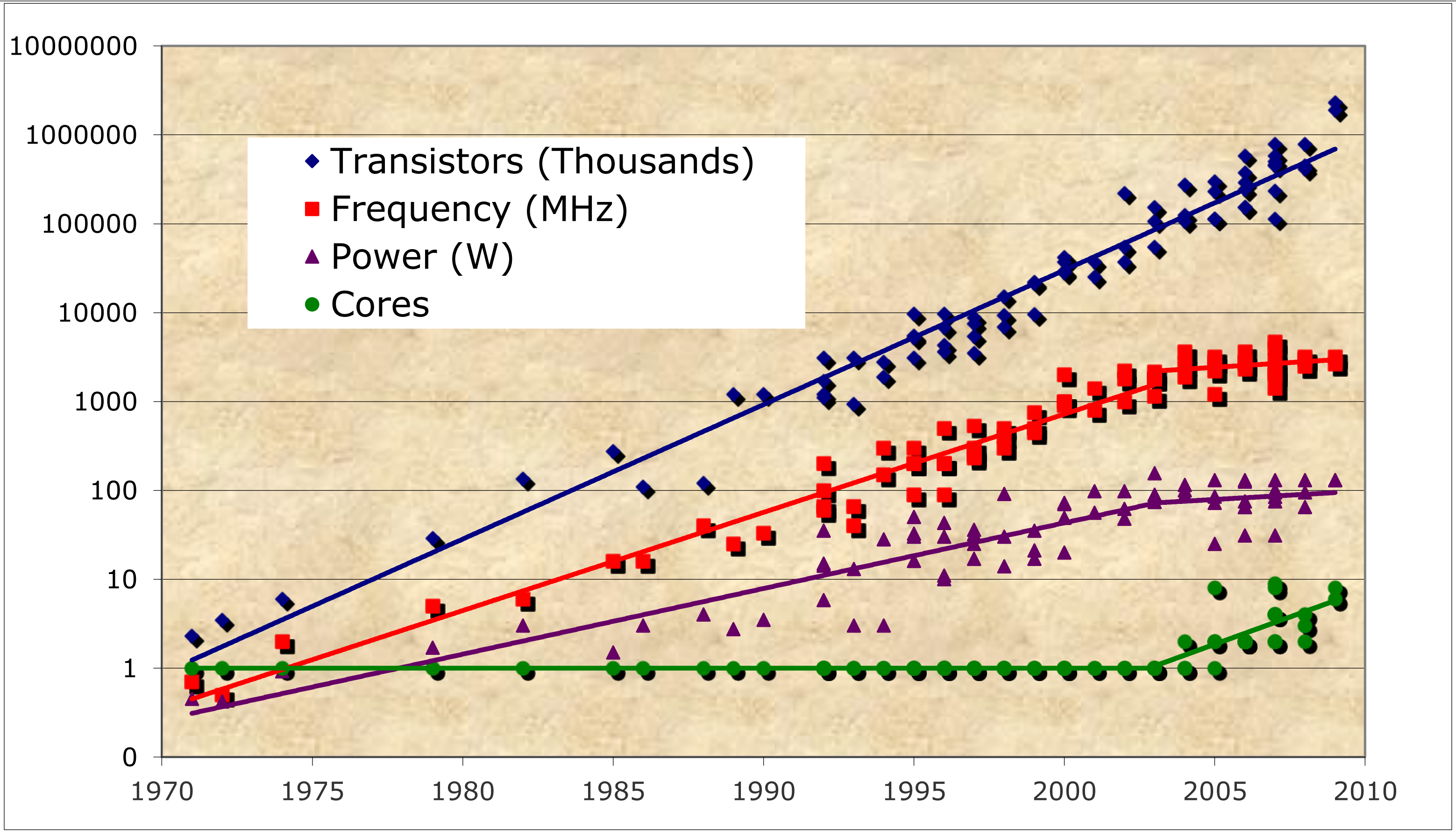
Power Density Limits Serial Performance

- 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

Scaling clock speed (business as usual) will not work



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

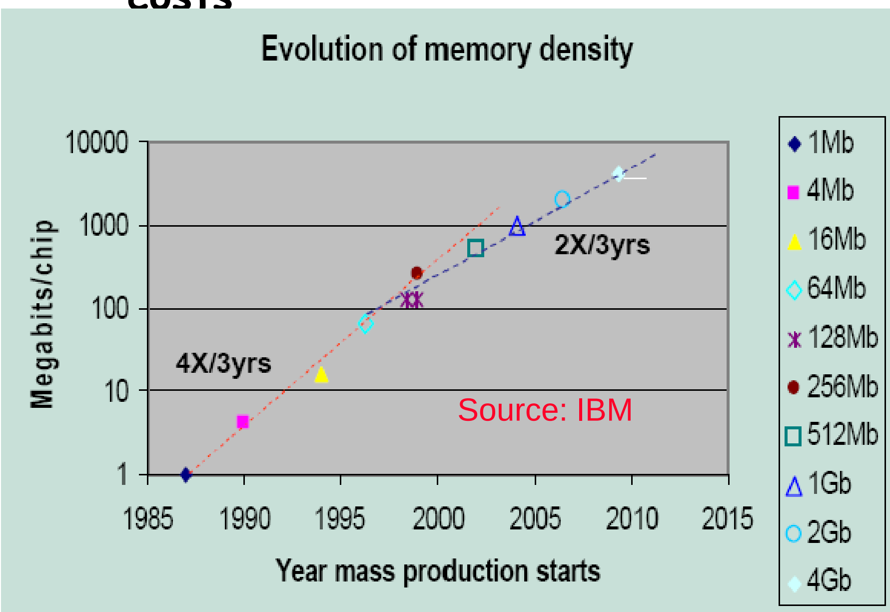
Parallelism in 2015?

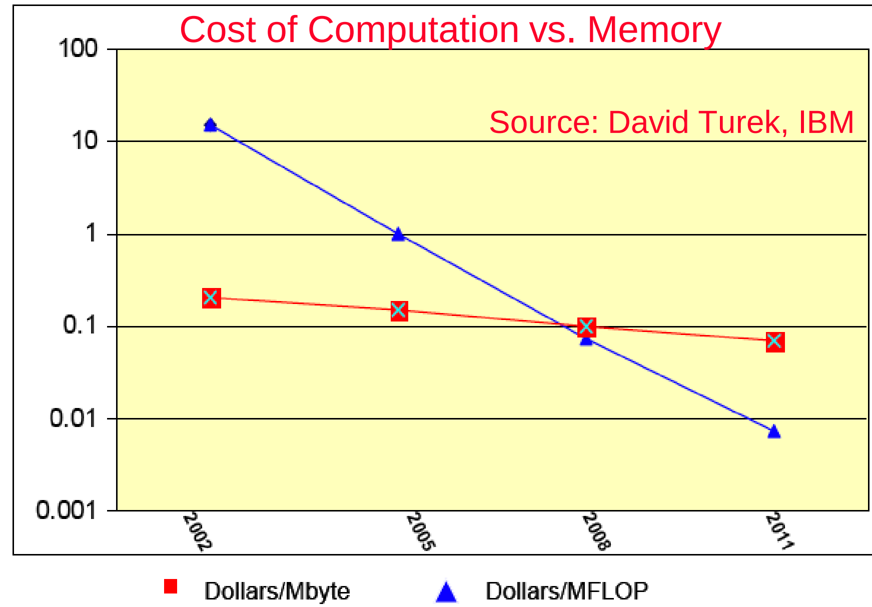
- **These arguments are no longer theoretical**
- **All major processor vendors are producing *multicore* chips**
  - Every machine will soon be a parallel machine
  - To keep doubling performance, parallelism must double
- **Which (commercial) applications can use this parallelism?**
  - Do they have 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**
  - YOU!

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

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

The TOP10 in November 2014

#	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	Swiss National Supercomputing Centre (CSCS)	Cray	Piz Daint Cray XC30, Xeon E5 8C 2.6GHz, Aries, NVIDIA K20x	Switzer-land	115,984	6.27	2.33
7	Texas Advanced Computing Center/UT	Dell	Stampede PowerEdge C8220, Xeon E5 8C 2.7GHz, Intel Xeon Phi	USA	462,462	5.17	4.51
8	Forschungszentrum Juelich (FZJ)	IBM	JuQUEEN BlueGene/Q, Power BQC 16C 1.6GHz, Custom	Germany	458,752	5.01	2.30
9	Lawrence Livermore National Laboratory	IBM	Vulcan BlueGene/Q, Power BQC 16C 1.6GHz, Custom	USA	393,216	4.29	1.97
10	Government	Cray	Cray CS-Storm, Xeon E5 10C 2.2GHz, I-FDR, NVIDIDA K40	USA	72,800	3.58	1.50

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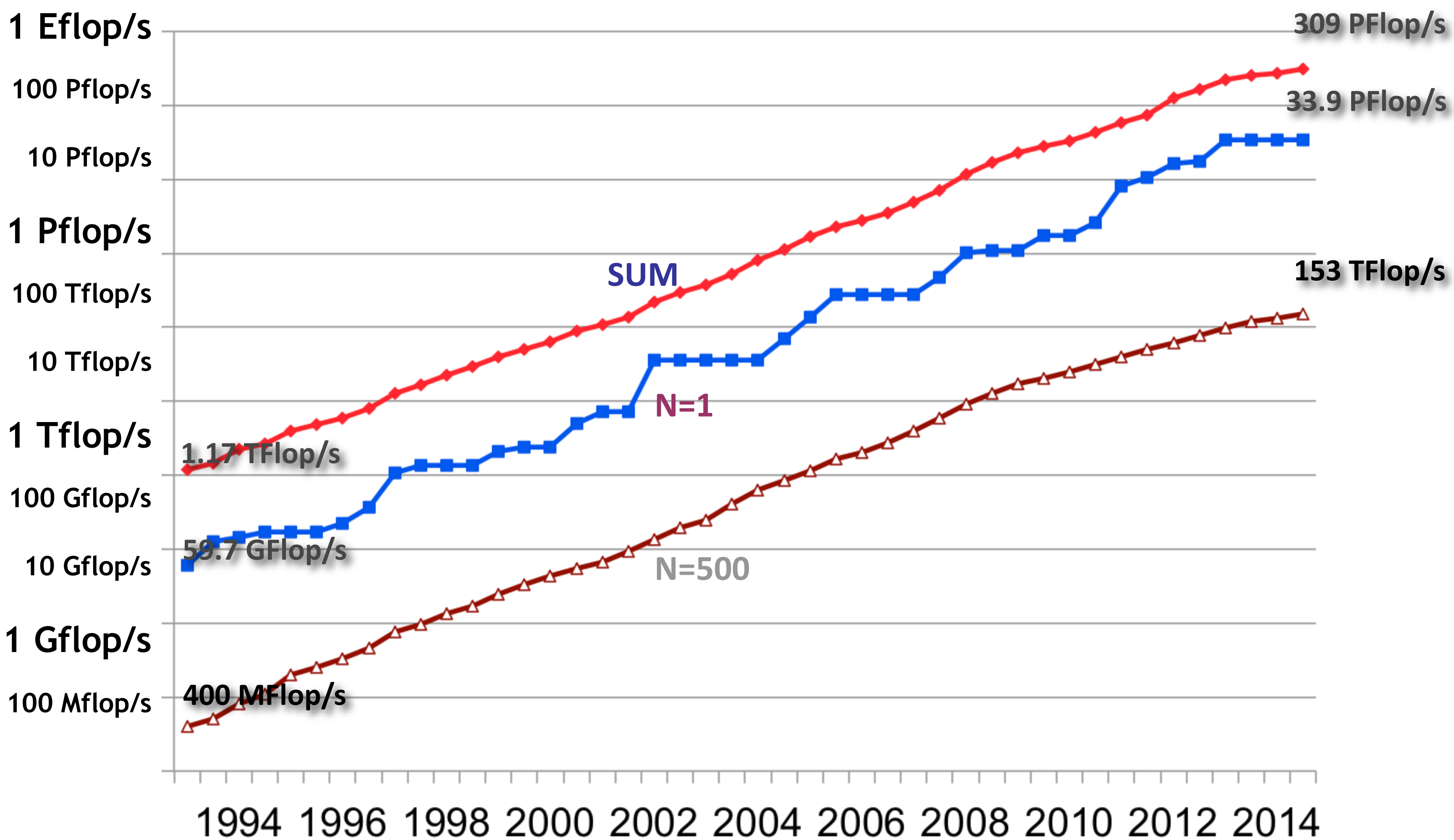
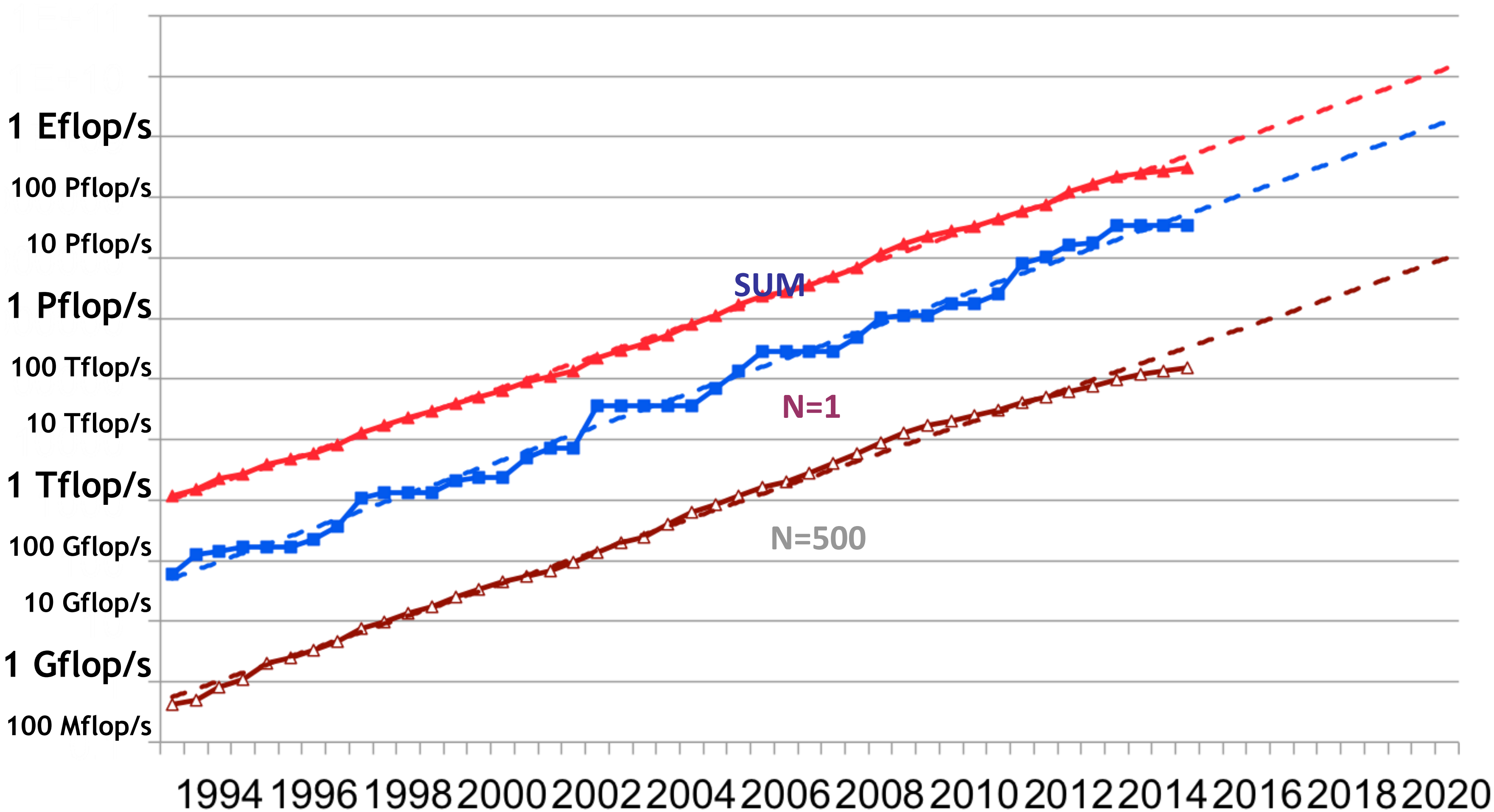
24	Lawrence Berkeley National Laboratory	Cray	**Edison** Cray XC30, Intel Xeon E5-2695v2, 2.4GHz	USA	133,824	1.65	
44	Lawrence Berkeley National Laboratory	Cray	**Hopper** Cray XE6, Opteron 12C 2.1 GHz, Gemini	USA	153,408	1.05	2.90

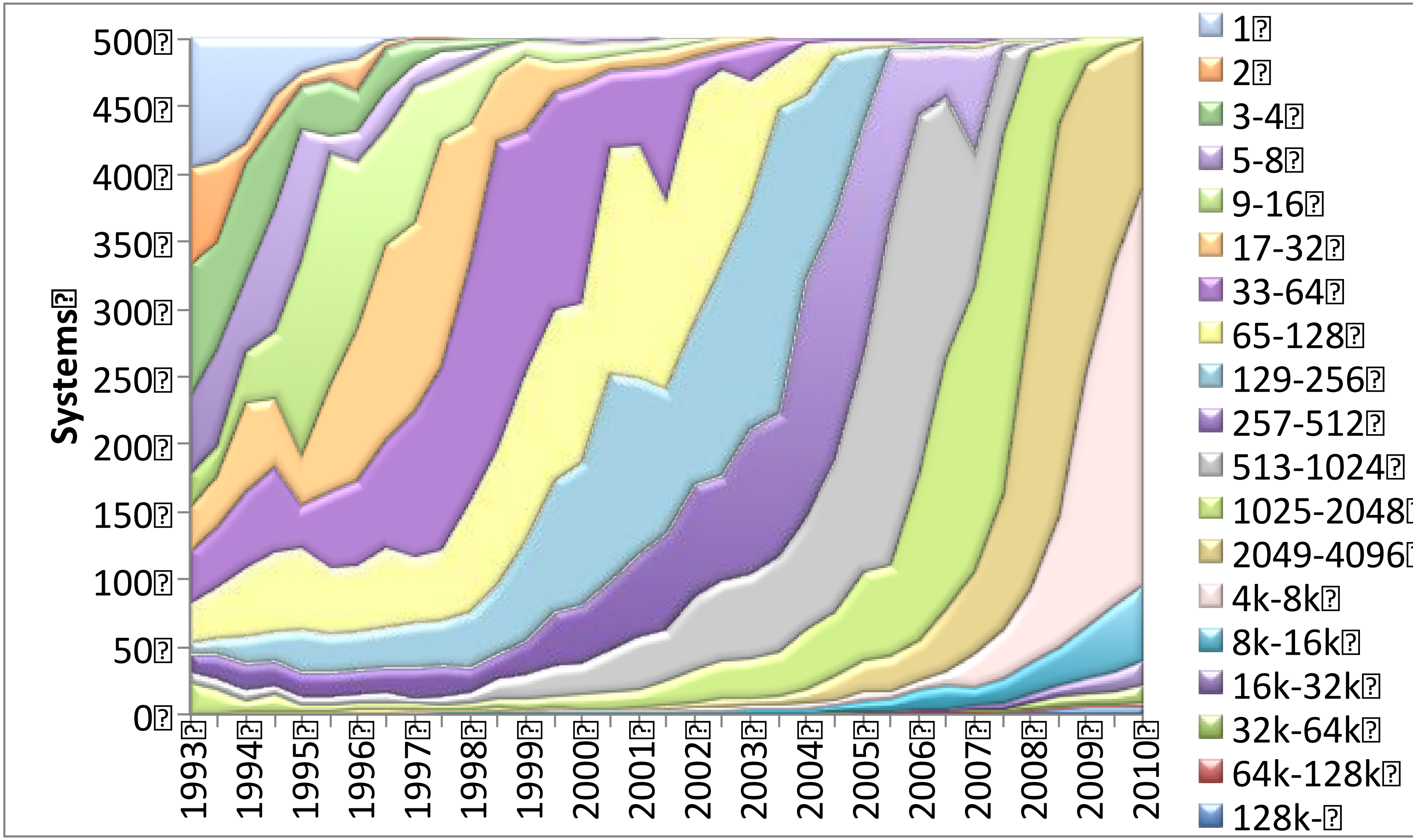
Performance Development (Nov 2014)



Projected Performance Development (Nov 2104)



Core Count



Systems
500
450
400
350
300
250
200
150
100
50
0
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
1
2
3-4
5-8
9-16
17-32
33-64
65-128
129-256
257-512
513-1024
1025-2048
2049-4096
4k-8k
8k-16k
16k-32k
32k-64k
64k-128k
128k-

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 ~~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

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

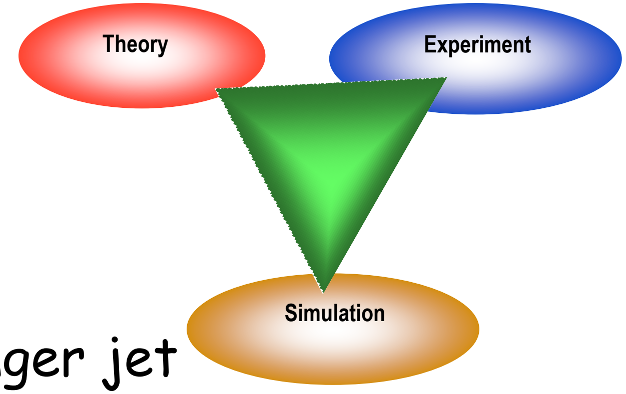
Nature, March 23, 2006

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 data

Simulation: The Third Pillar of Science

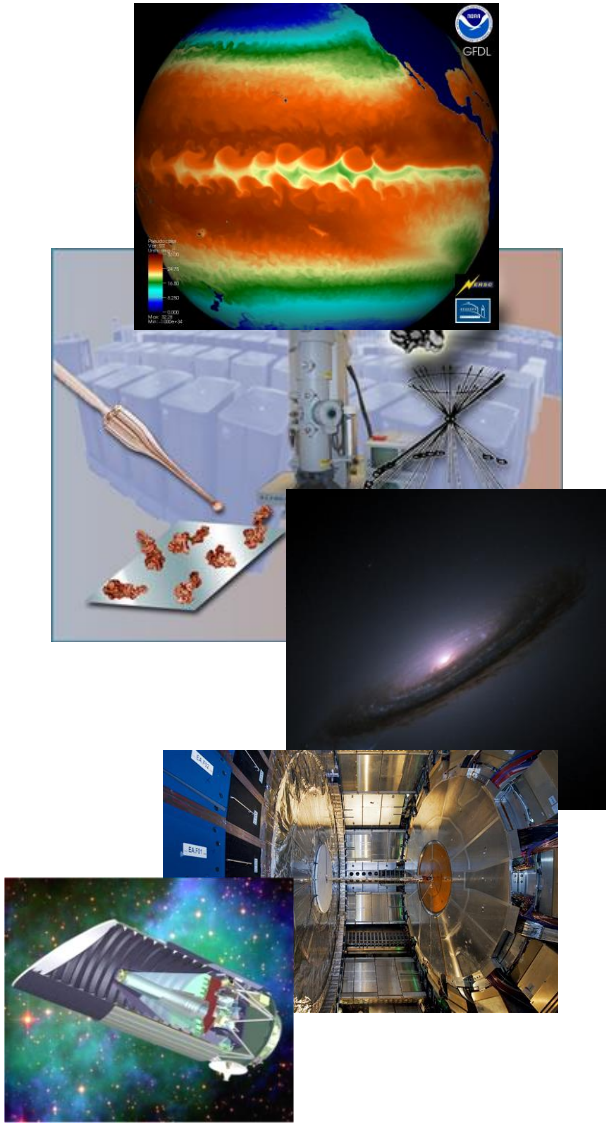
- **Traditional scientific and engineering method:**
  - (1) Do theory or paper design
  - (2) Perform experiments or build system



- **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**



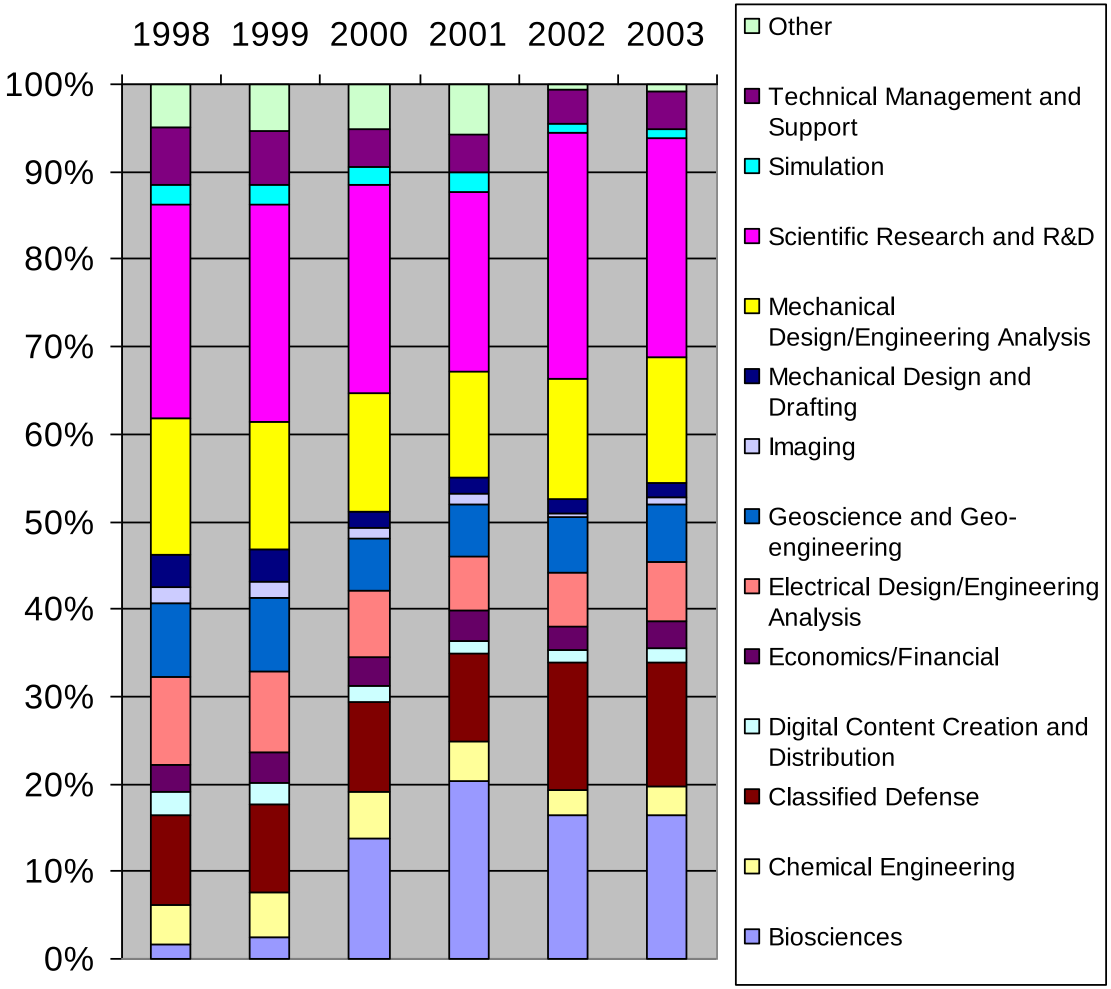
Some Particularly Challenging Computations

- **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



- IDC 2004, from NRC Future of Supercomputing Report

What Supercomputers Do

Global Climate Modeling Problem

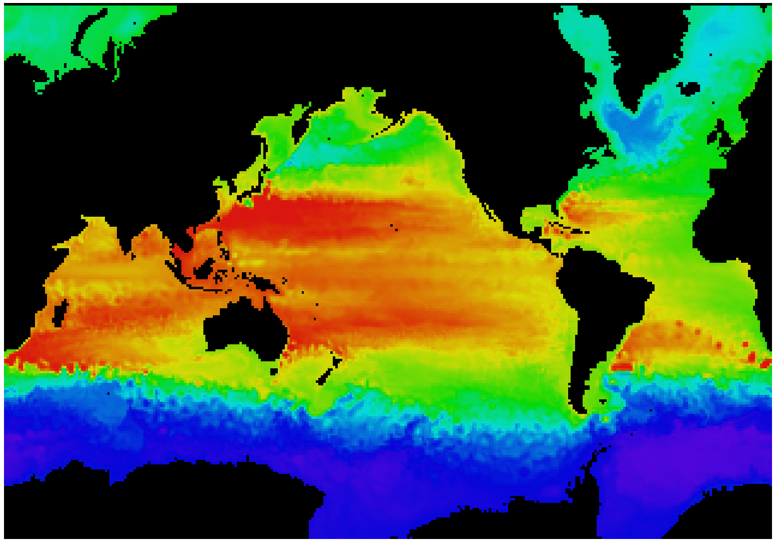
- **Problem is to compute:**

  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

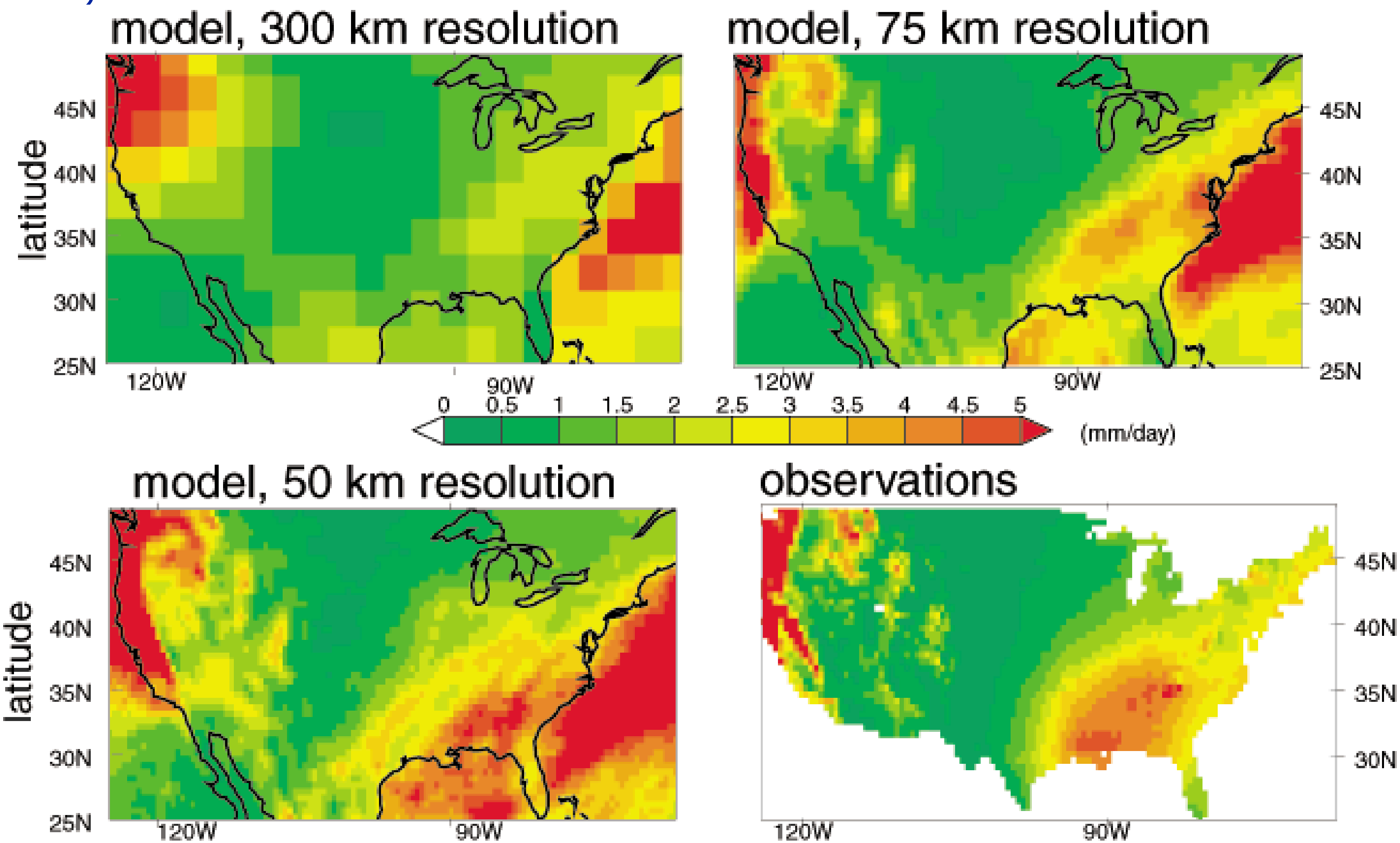
Global Climate Modeling Computation

- **One piece is modeling the fluid flow in the atmosphere**
  - Solve Navier-Stokes equations
  - Roughly 100 Flops per grid point with 1 minute timestep
- **Computational requirements:**
  - To match real-time, need 5×10^{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

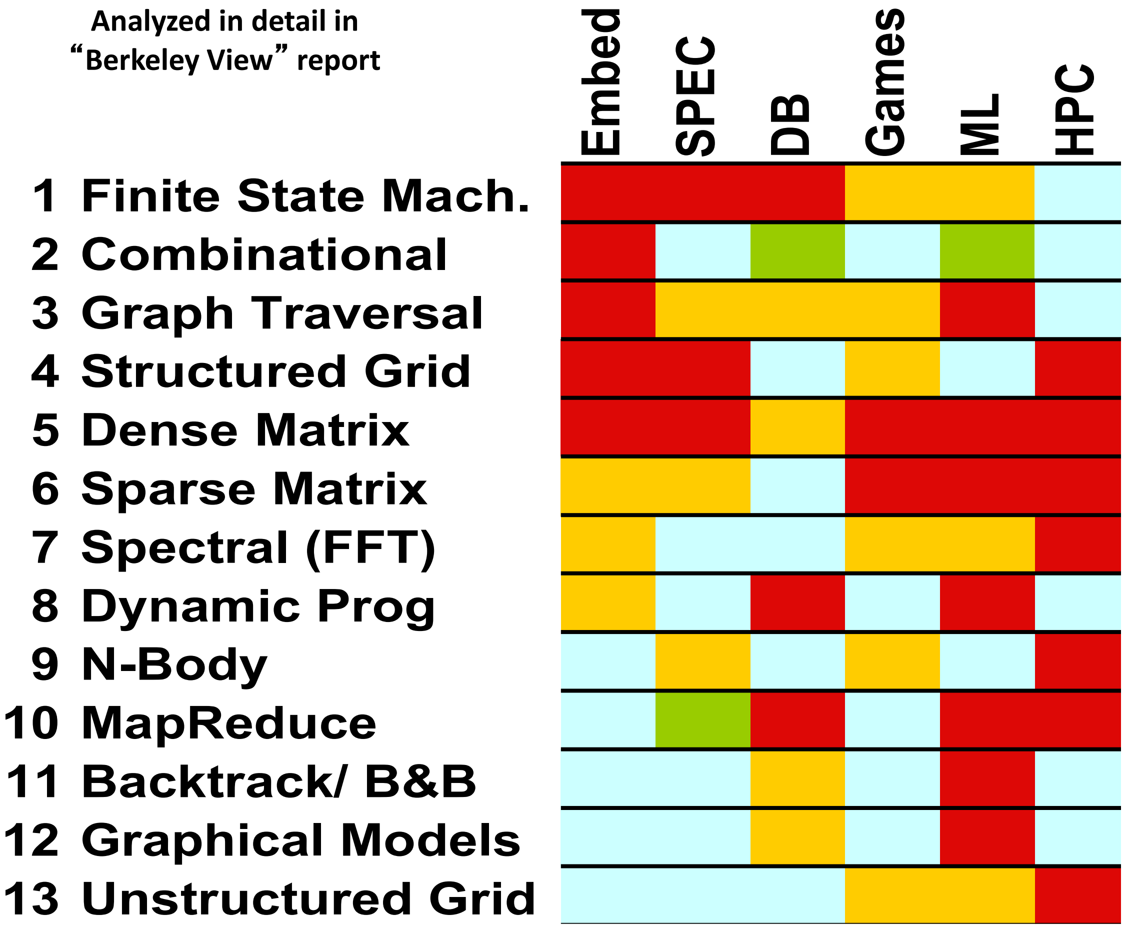
Wintertime Precipitation (millimeters/day)

As model resolution becomes finer, results converge towards observations



Which commercial applications *require* parallelism?

Analyzed in detail in
“Berkeley View” report

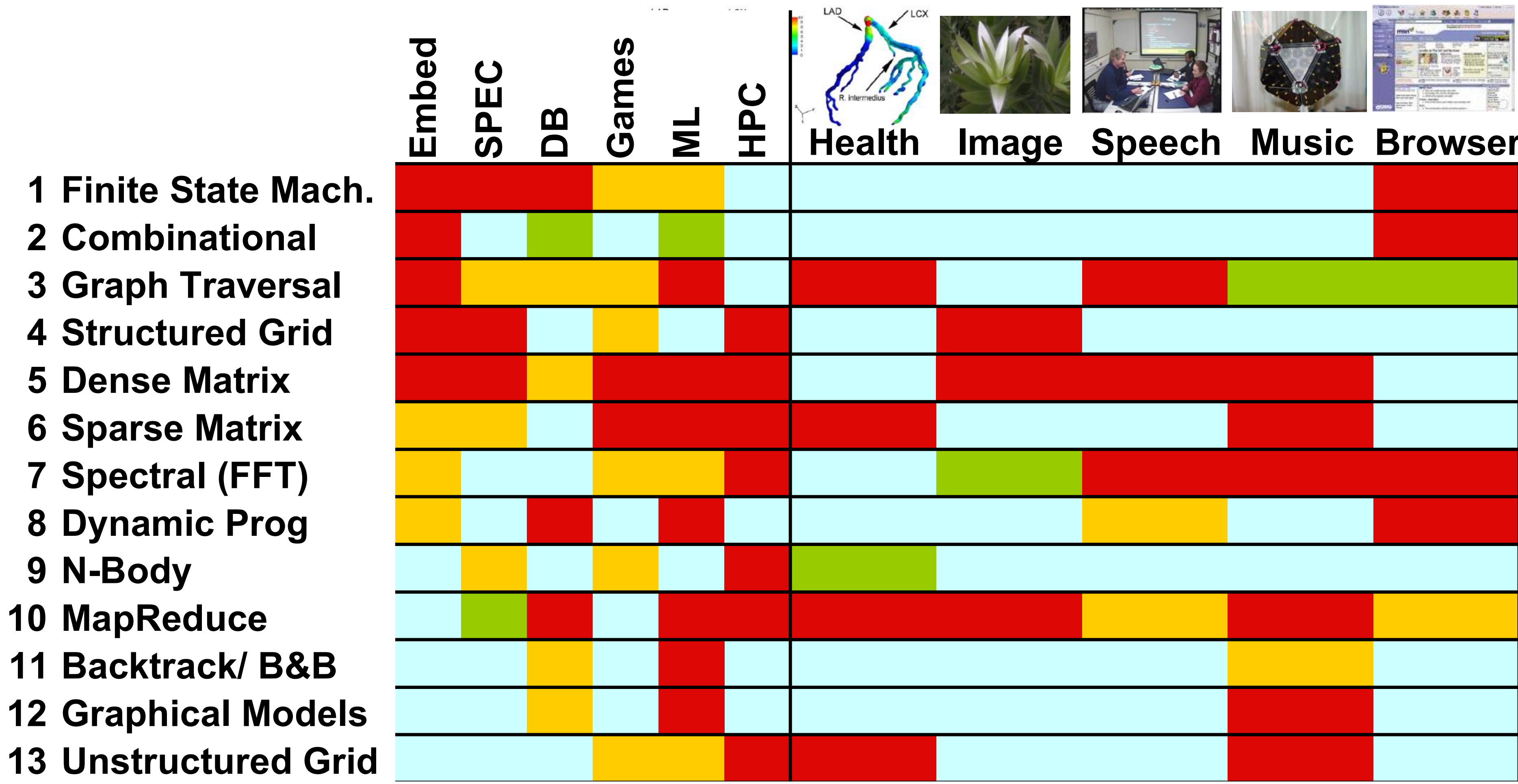


Analyzed in detail in “Berkeley View” report www.eecs.berkeley.edu/Pubs/TechRpts/2006/EECS-2006-183.html

What do commercial and CSE applications have in common?

Motif/Dwarf: Common Computational Methods

(Red Hot → Blue Cool)



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  - Including your laptops and handhelds
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  - Commercial problems too
- Why writing (fast) parallel programs is hard
  - But things are improving

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

$$\text{Speedup}(P) = \text{Time}(1)/\text{Time}(P)$$

$$\le 1/(s + (1-s)/P)$$

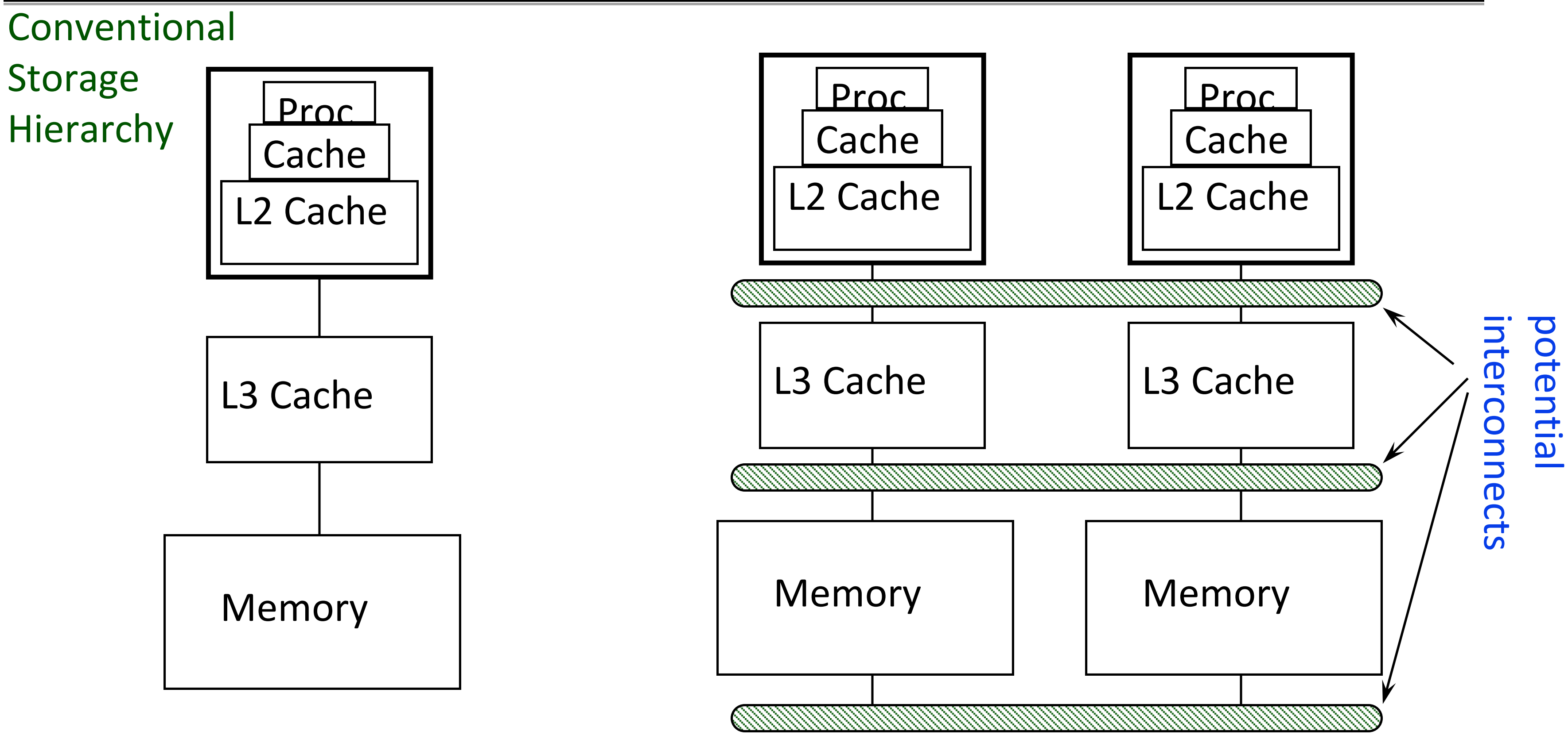
$$\le 1/s$$

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

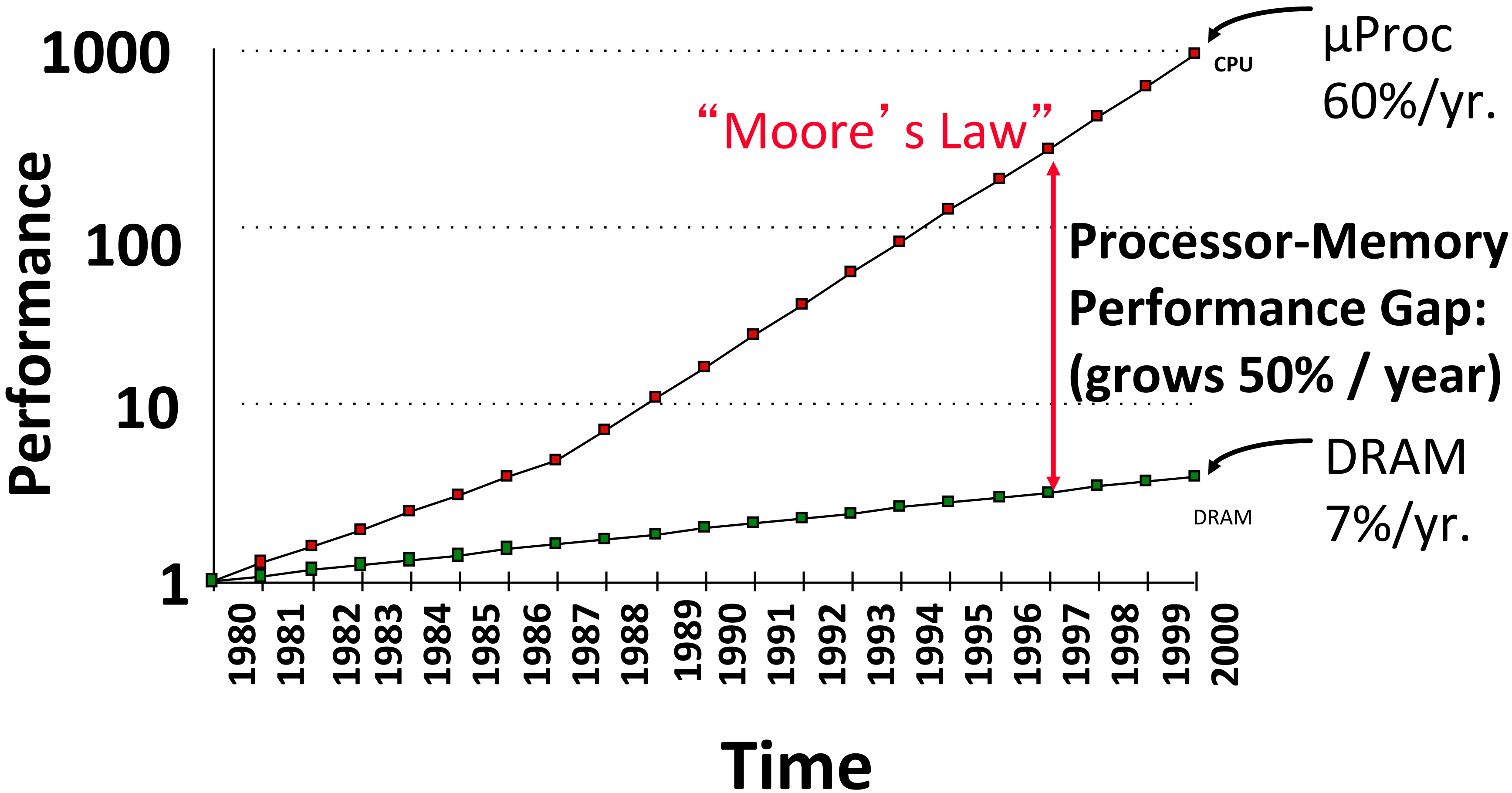
Locality and Parallelism



- **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

- **2 types of programmers → 2 layers of software**
- **Efficiency Layer (20% of programmers)**
  - Expert programmers build Libraries implementing kernels, "Frameworks", OS, ...
  - Highest fraction of peak performance possible
- **Productivity Layer (80% 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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all

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  - But things are improving