AMS 250: An Introduction to High Performance Computing

Overview

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Outline

- Course Overview
  - What is AMS 250
  - What is expected of you
  - What will you learn in AMS 250
- High Performance Computing (HPC)
  - What is HPC
  - What motivates HPC
  - Trends that shape the field
  - Large-scale problems and high-performance computing
  - Parallel architecture types
  - Scalable parallel computing and performance

What is AMS 250

- Successor to *AMS 290B: An Introduction to Parallel Computing and Large Computational Fluid Dynamics Codes*:

  https://classes.soe.ucsc.edu/ams290b/Winter08/

- AMS 250 is a graduate course that introduces students to the modern world of cutting-edge supercomputing
- AMS 250 was inaugurated by Prof. Nic Brummell in Spring 2015:

  https://courses.soe.ucsc.edu/courses/ams250/Spring15/01

- My lectures are also heavily influenced by the *Parallel Computing* course at University of Oregon:

  http://ipcc.cs.uoregon.edu/curriculum.html

What is expected of you

- Fledgling Computational Scientists
- Computer Scientists and Engineers can benefit from this course as well
- Have taken *AMS 209: Foundation of Scientific Computing*; or equivalent
  https://ams209-fall15-01.courses.soe.ucsc.edu/
- Reasonably proficient in any, preferably all, of the following languages:
  - C/C++
  - Modern Fortran
  - Python, particularly NumPy
  - Java

Course Web Sites

- Drupal Site:
  https://ams250-spring16-01.courses.soe.ucsc.edu/

- Google Classroom:
  http://classroom.google.com/c/OTgxNTk0NTg0
  Sign in with your Google Apps for Education account (*@ucsc.edu*)
  Join in with the code *gqrbdy*

Syllabus

- PART A: CONCEPTS
  - Parallel Computer Architectures
  - Parallel programming models
  - Parallel Programming Patterns & Algorithms
- PART B: TOOLS
  - Shared Memory Programming with OpenMP
  - Distributed Memory Programming with MPI
  - Debugging & Performance Optimization
  - Analysis & Visualization
- PART C: Advanced Topics
  - Manycore Computing (GPU & MIC)
  - Parallel Math Libraries
  - Parallel IO
  - MapReduce
- PART D: CASE STUDIES
  - N-Body Simulations
  - BoxLib: a block-structured AMR framework

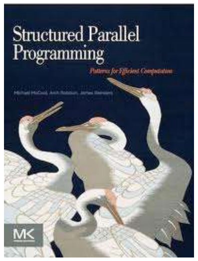
Course Materials

- Major reading materials are lectures notes and references therein
- Supplemental textbooks:
  - *Programming on Parallel Machines*, Norm Matloff, UC Davis

    Open Textbook: http://heather.cs.ucdavis.edu/parprocbook

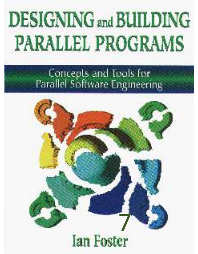
  - *Structured Parallel Programming: Patterns for Efficient Computation*, Michael McCool, Arch Robinson, James Reinders, Morgan Kaufmann, 2012

    PDF: http://www.sciencedirect.com/science/book/9780124159938



  - *Designing and Building Parallel Programs*, Ian Foster, Addison Wesley, 1995

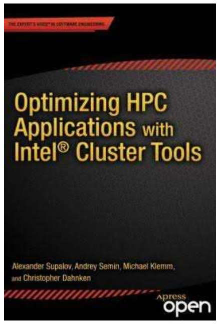
    http://www.mcs.anl.gov/~itf/dbpp/text/book.html



Course Materials

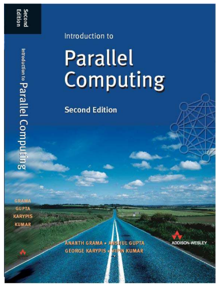
- Supplemental textbooks (cont'd):
  - *Optimizing HPC Applications with Intel Cluster Tools*, Alexander Supalov, Andrey Semin, Michael Klemm, Christopher Dahnken, Apress, 2014

    Free eBook: http://www.apress.com/9781430264965



  - *Introduction to Parallel Computing*, Ananth Grama, Anshul Gupta, George Karypis, Vipin Kumar, Addison Wesley, 2nd Ed., 2003

    http://www-users.cs.umn.edu/~karypis/parbook/



Grading Policy

- Homework (60%)
  - 4 simple programming assignments to help you understand the course materials
  - Homework will be assigned every 2 weeks on Tuesdays, starting from the 1st week
  - Homework will be due 2 weeks from the assignment date
  - Homework will be submitted to Google Classroom site
  - Penalty for late homework submission
    - You are going to receive a maximum of 80% if late by less than 1 day
    - 50% if late by more than a day
- Final Project (40%)

Parallel Programming Final Project

- Major programming project for the course
  - Non-trivial parallel application
  - Include performance analysis
  - Use the *Hyades* cluster
- Project teams
  - Up to 4 persons per team
  - Try to balance skills
- Project dates
  - Proposal due end of 4^{th} week
  - Project presentation during the final week
  - Project report due at the end of the quarter

Hyades Cluster

- Funded by a $1 million NSF-MRI award in 2012
- 180 Compute Nodes
- 8 GPU Node
- 1 MIC Node
- 1 Analysis Node
- 146 TB of parallel scratch space
- https://pleiades.ucsc.edu/hyades/

What will you get out of AMS 250

- In-depth understanding of parallel computer design
- Knowledge of how to program parallel computer systems
- Understanding of pattern-based parallel programming
- Exposure to different forms parallel algorithms
- Practical experience using a parallel cluster
- Background on parallel performance modeling
- Techniques for debugging, performance analysis and tuning

What is High Performance Computing

- We mostly use the following terms interchangeably:
  - *Parallel Computing*
  - *High Performance Computing*
  - *Supercomputing*
- *Parallel Computing* is all about *High Performance*
- A *parallel computer* is a computer system that uses multiple processing elements simultaneously in a cooperative manner to solve a computational problem
- *Parallel processing* includes techniques and technologies that make it possible to compute in parallel
  - Hardware, networks, operating systems, parallel libraries, languages, compilers, algorithms, tools, …
- Parallel computing is an evolution of serial computing
  - Parallelism is natural
  - Computing problems differ in level / type of parallelism

Concurrency

- Consider multiple tasks to be executed in a computer
- Tasks are concurrent with respect to each if
  - They *can* execute at the same time (*concurrent execution*)
  - Implies that there are no dependencies between the tasks
- Dependencies
  - If a task requires results produced by other tasks in order to execute correctly, the task's execution is *dependent*
  - If two tasks are dependent, they are not concurrent
  - Some form of synchronization must be used to enforce (satisfy) dependencies
- Concurrency is fundamental to computer science
  - Operating systems, databases, networking, …

Concurrency and Parallelism

- Concurrent is not the same as parallel! Why?
- Parallel execution
  - Concurrent tasks *actually* execute at the same time
  - Multiple (processing) resources have to be available
- **Parallelism = concurrency + parallel hardware**
  - Both are required
  - Find concurrent execution opportunities
  - Develop application to execute in parallel
  - Run application on parallel hardware
- Is a parallel application a concurrent application?
- Is a parallel application run with one processor parallel? Why or why not?

Parallelism

- There are granularities of parallelism (parallel execution) in programs
  - Processes, threads, routines, statements, instructions, …
  - Think about what are the software elements that execute concurrently
- These must be supported by hardware resources
  - Processors, cores, … (execution of instructions)
  - Memory, DMA, networks, … (other associated operations)
  - All aspects of computer architecture offer opportunities for parallel hardware execution
- Concurrency is a necessary condition for parallelism
  - Where can you find concurrency?
  - How is concurrency expressed to exploit parallel systems?

Why use parallel processing?

- Two primary reasons (both performance related)
  - Faster time to solution (response time)
  - Solve bigger computing problems (in same amount of time)
- Other factors motivate parallel processing
  - Effective use of machine resources
  - Cost efficiencies
  - Overcoming memory constraints
- Serial machines have inherent limitations
  - Processor speed, memory bottlenecks, …
- Parallelism has become the mainstream of computing
- Performance is still the driving concern
- **Parallelism = concurrency + parallel hardware = performance**

Perspectives on Parallel Processing

- Parallel computer architecture
  - Hardware needed for parallel execution?
  - Computer system design
- (Parallel) Operating system
  - How to manage systems aspects in a parallel computer
- Parallel programming
  - Libraries (low-level, high-level)
  - Languages
  - Software development environments
- Parallel algorithms
- Parallel performance evaluation
- Parallel tools
  - Performance, debugging, analytics, visualization, …

Why study parallel computing today?

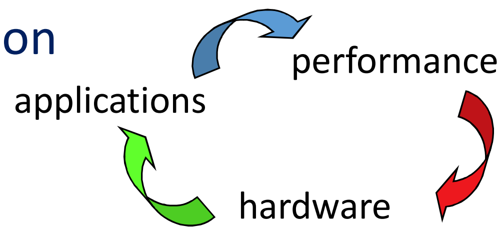
- Computing architecture
  - Innovations often drive to novel programming models
- Technological convergence
  - The “killer micro” is ubiquitous
  - Laptops and supercomputers are fundamentally similar!
  - Trends cause diverse approaches to converge
- Technological trends make parallel computing inevitable
  - Multi-core processors are here to stay!
  - Practically every computing system is operating in parallel
- Understand fundamental principles and design tradeoffs
  - Programming, systems support, communication, memory, …
  - Performance
- Parallelism is the mainstream and future of computing

Inevitability of Parallel Computing

- Application demands
  - Insatiable need for computing cycles
- Technology trends
  - Processor and memory
- Architecture trends
- Economics
- Current trends:
  - Today's microprocessors have multiprocessor support
  - Servers and workstations available as multiprocessors
  - Tomorrow's microprocessors are multiprocessors
  - Multi-core is here to stay and #cores/processor is growing
  - Accelerators (GPUs, gaming systems)

Application Characteristics

- Application performance demands hardware advances
- Hardware advances generate new applications
- New applications have greater performance demands
  - Exponential increase in microprocessor performance
  - Innovations in parallel architecture and integration



- Range of performance requirements
  - System performance must also improve as a whole
  - Performance requirements demand computer engineering
  - Costs addressed through technology advancements

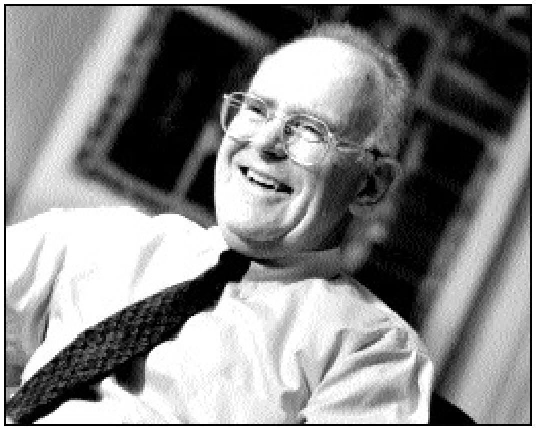
Broad Parallel Architecture Issues

- Resource allocation
  - How many processing elements?
  - How powerful are the elements?
  - How much memory?
- Data access, communication, and synchronization
  - How do the elements cooperate and communicate?
  - How are data transmitted between processors?
  - What are the abstractions and primitives for cooperation?
- Performance and scalability
  - How does it all translate into performance?
  - How does it scale?

Moore's Law

Gordon E Moore, Intel Cofounder
Electronics, 35th anniversary issue, 1965

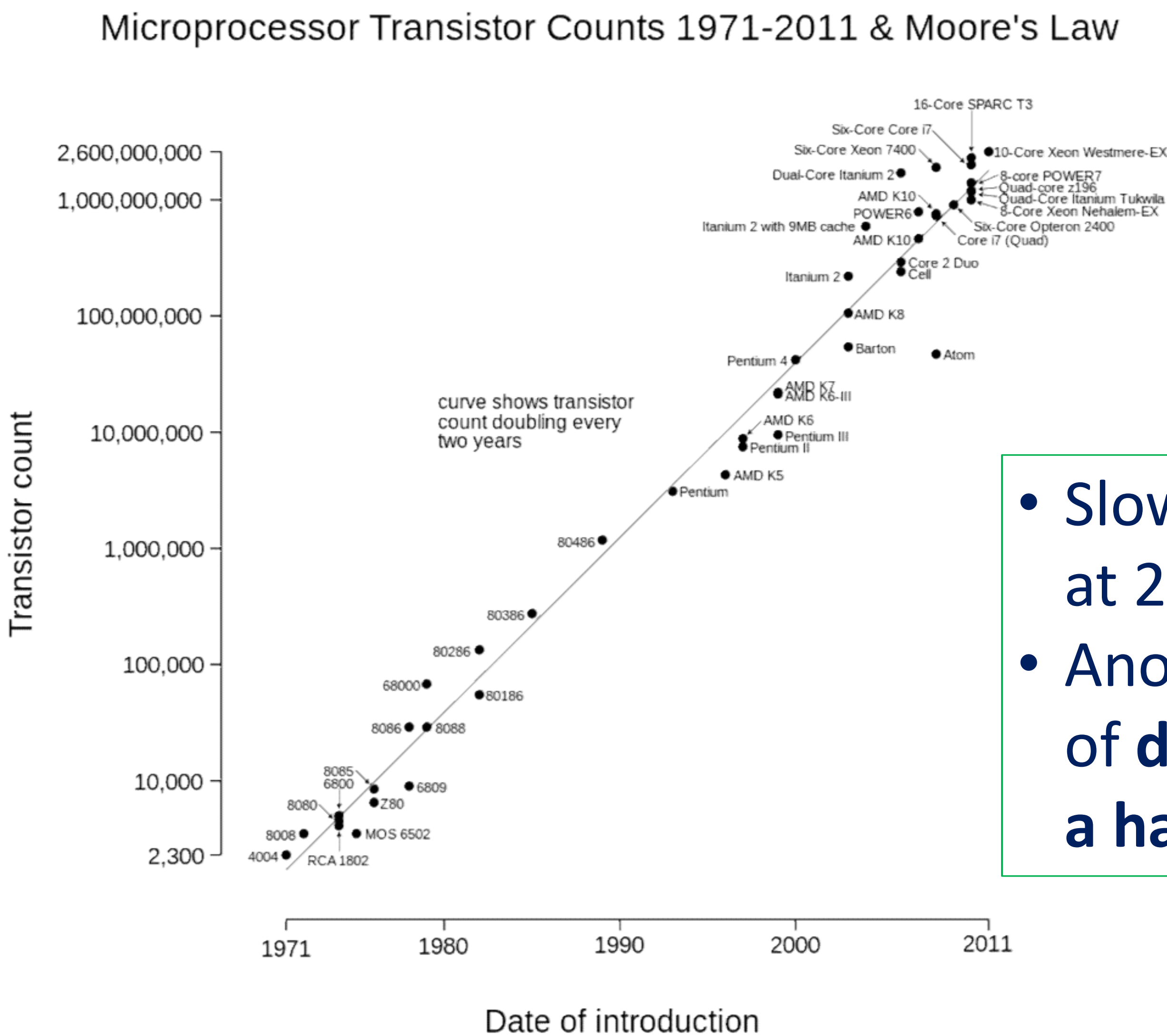
> *"The complexity for minimum component costs has increased at a rate of* ***roughly a factor of two per year****. Certainly over the short term this rate can be expected to continue, if not to increase. Over the longer term, the rate of increase is a bit more uncertain, although there is no reason to believe it will not remain nearly constant for at least 10 years."*



1975 revision

> *"The number of transistors than can be cheaply placed on integrated circuit board will* ***double every two years****."*

≈ Chip performance **doubles every 18 months**

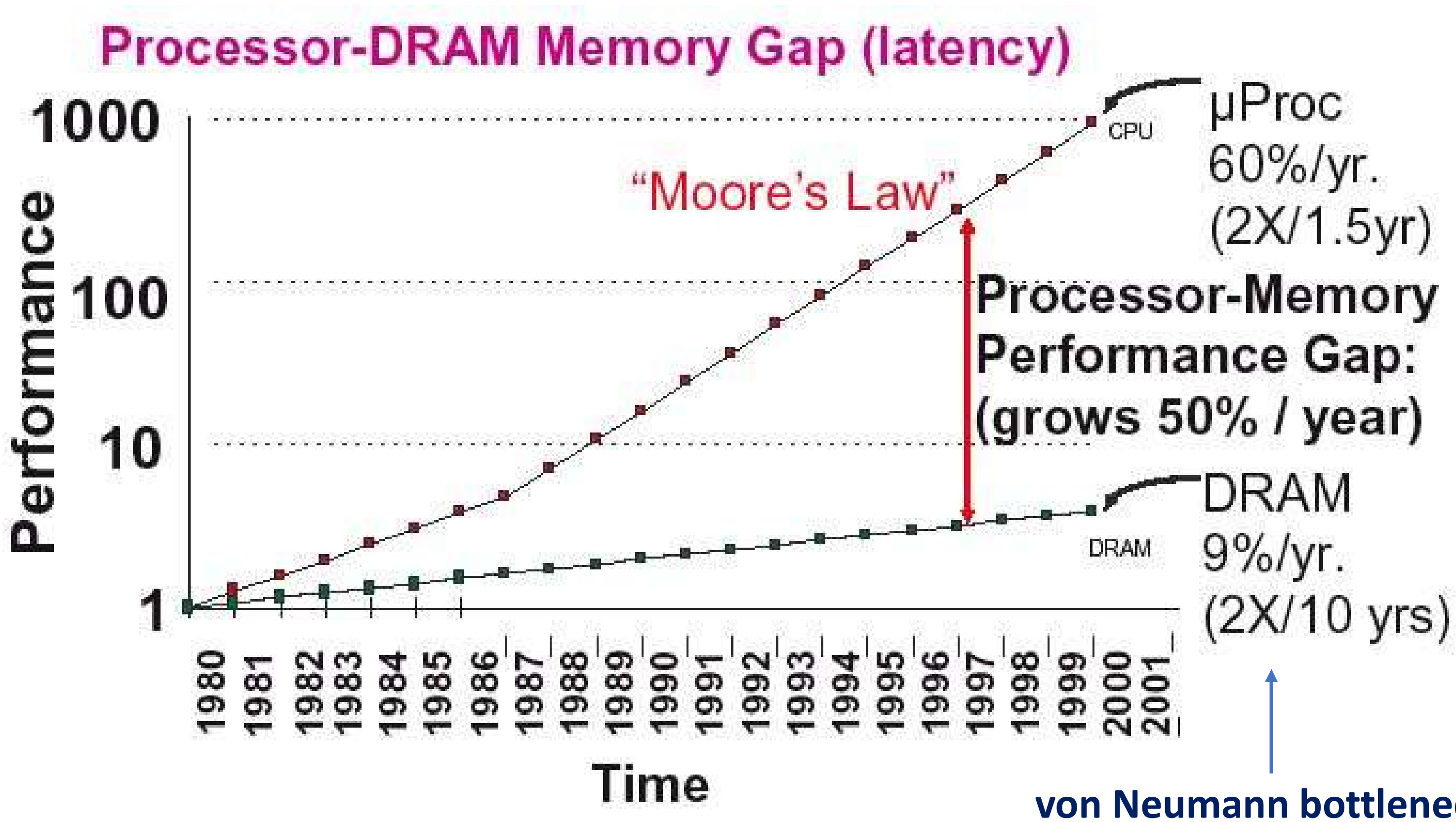


- Slowing down since 2012 at 22nm feature width
- Another revision to a rate of **doubling every two and a half years**?

Leveraging Moore's Law

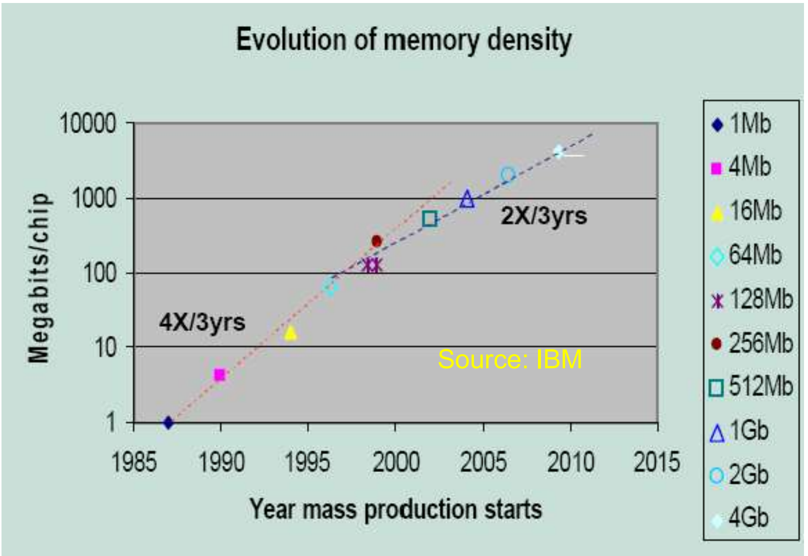
- More transistors = more parallelism opportunities
- Microprocessors
  - Implicit parallelism
    - pipelining
    - multiple functional units
    - superscalar
  - Explicit parallelism
    - SIMD instructions
    - long instruction works

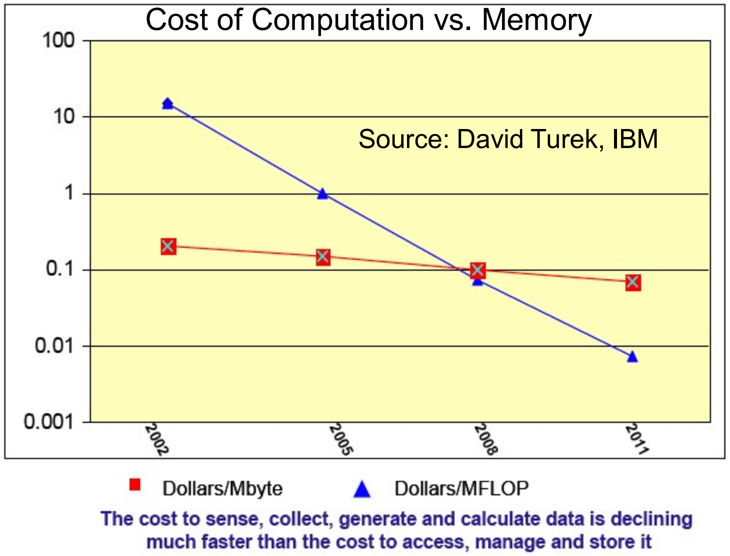
What's Driving Parallel Computing Architecture?



von Neumann bottleneck!
(memory wall)

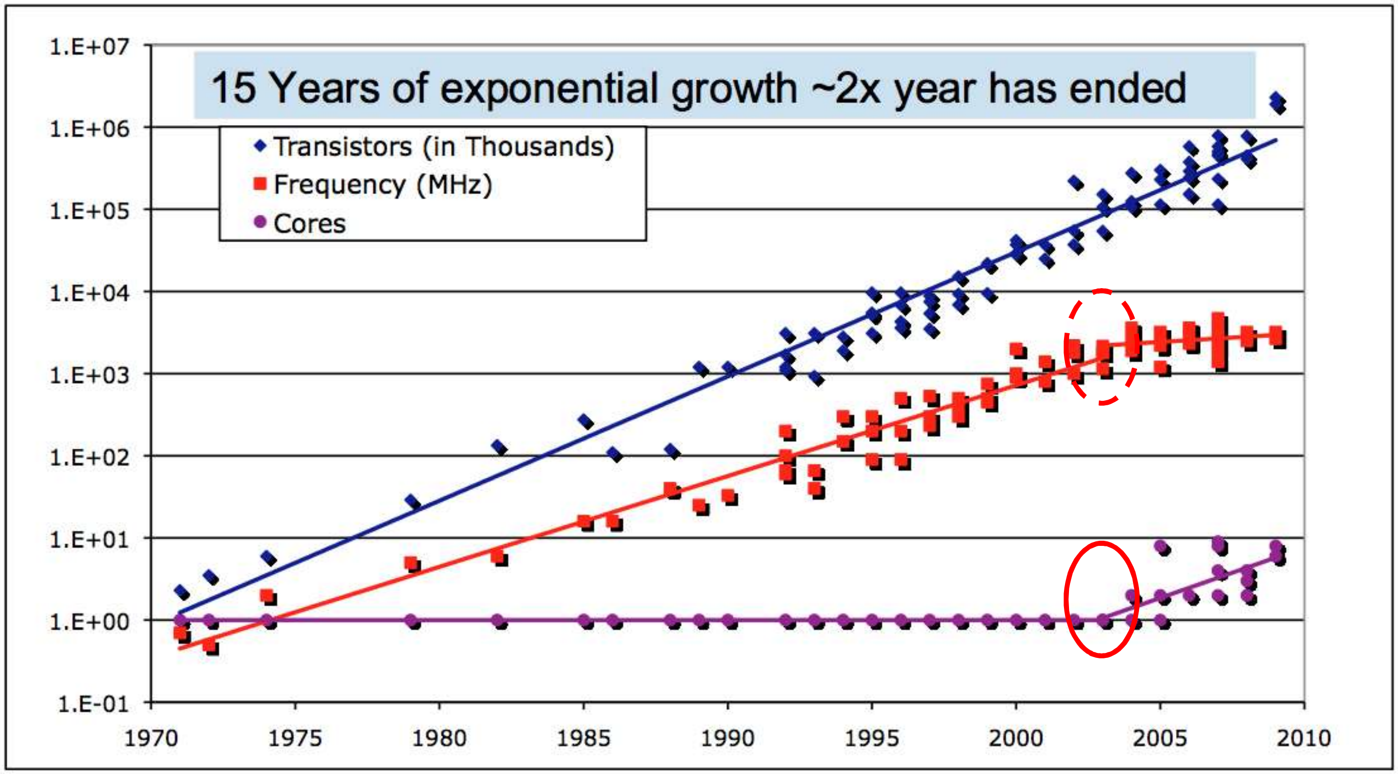
Memory Wall





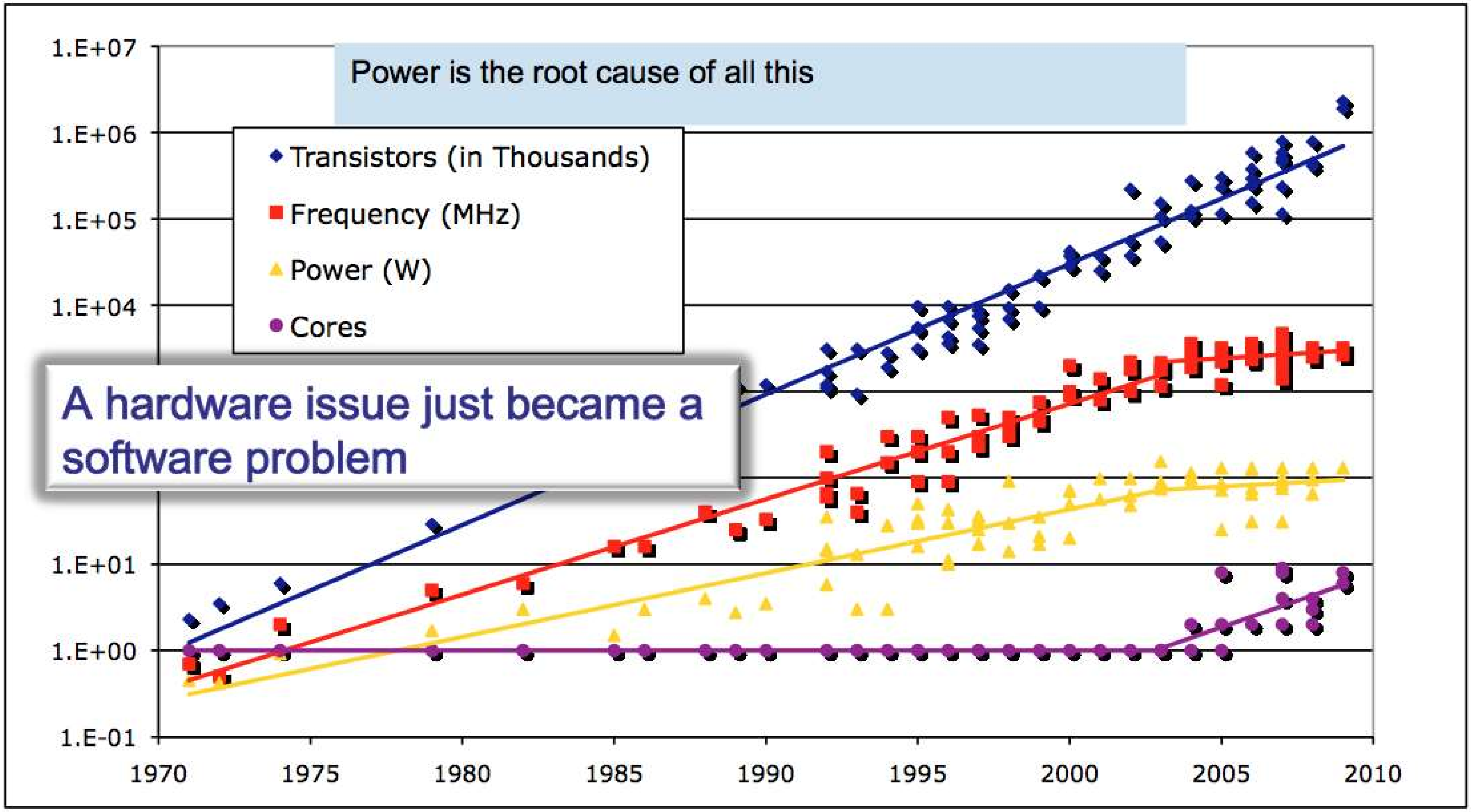
- Memory density is doubling every three years
- Processor logic (computation) is doubling every two years
- Memory are gradually getting more expensive, relative to computation
- Can we double concurrency without doubling memory?

What's Driving Parallel Computing Architecture?

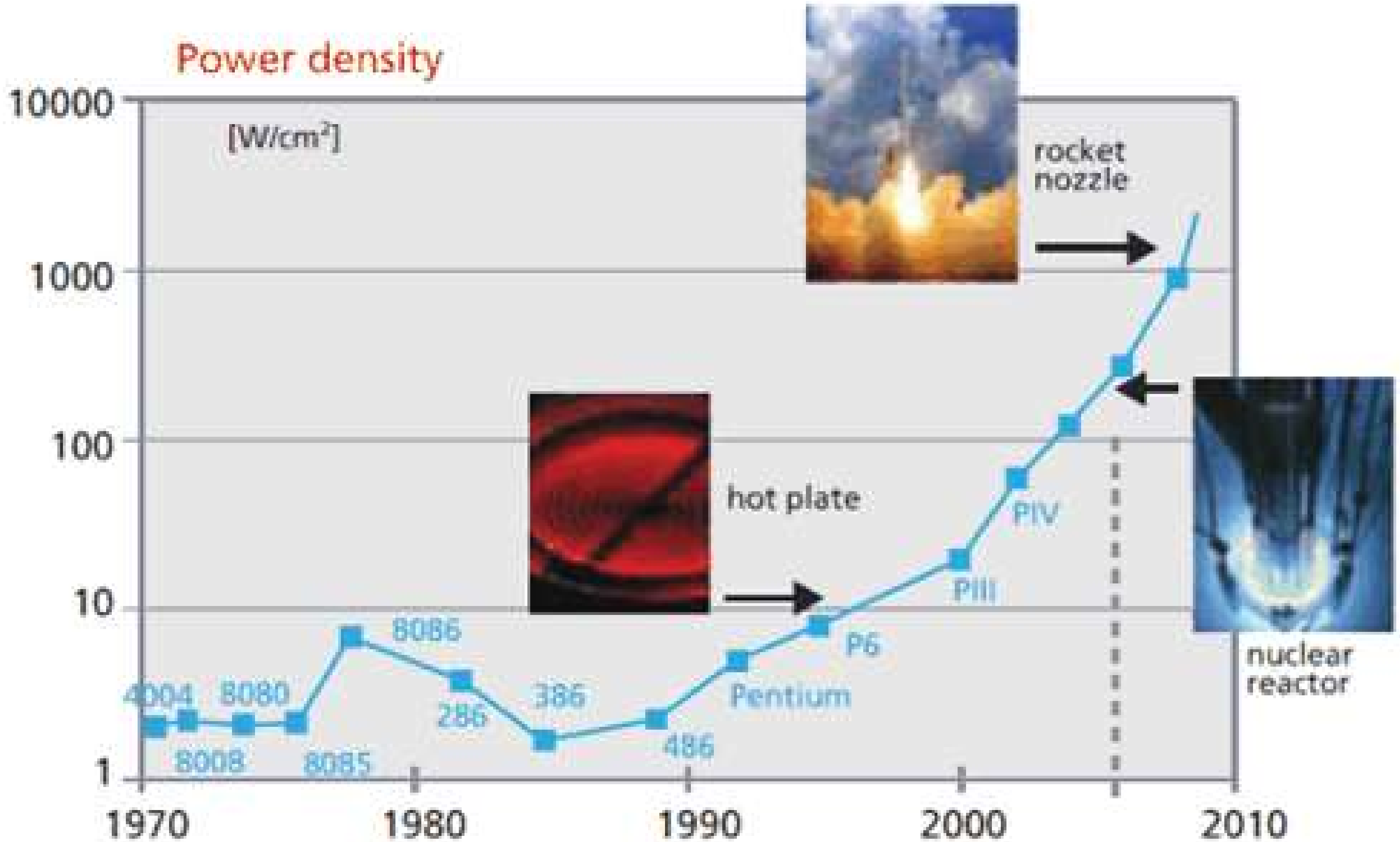


Data from Kunle Olukotun, Lance Hammond, Herb Sutter, Burton Smith, Chris Batten, and Krste Asanoviç
Slide from Kathy Yelick

What's Driving Parallel Computing Architecture?



Power Density Growth



Power Wall

- Processing chip manufacturers had increased processor performance by increasing CPU clock frequency
- Until the chips got too hot!

$$P = CV^2 f$$

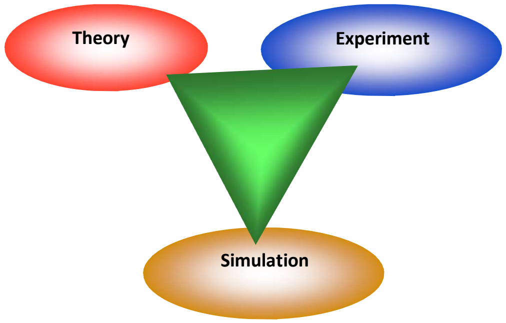
  P is dynamic power consumed by a CPU, *C* is capacitance, *V* is voltage, *f* is frequency

- Then they add more and more cores to increase performance
  - Keep clock frequency same or reduced
  - Keep lid on power requirements

What does the Technology Enable?

- Continued exponential increase in computational power
  - Simulation is becoming third pillar of science, complementing theory and experiment
- Continued exponential increase in experimental data
  - Techniques and technology in data analysis, visualization, analytics, networking, and collaboration tools are becoming essential in all data rich scientific applications

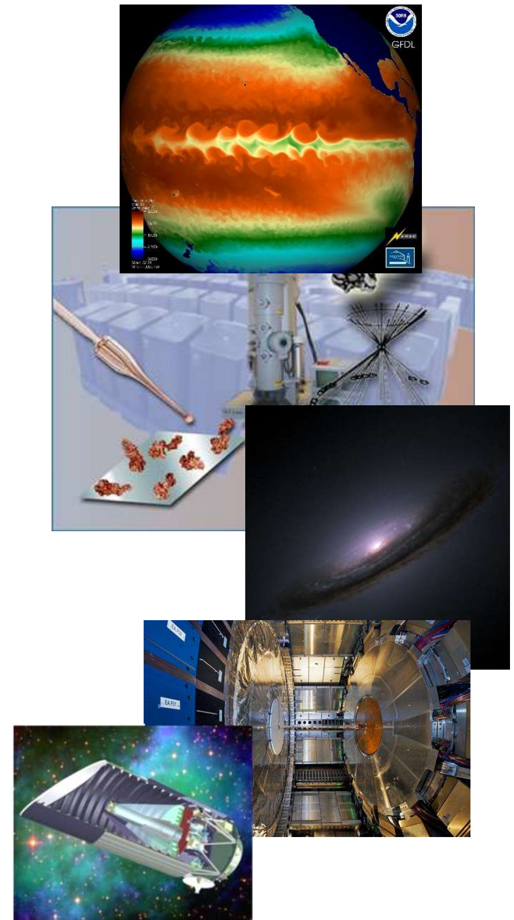
Third Pillar of Science



- 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 (CSE) 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 experimentally

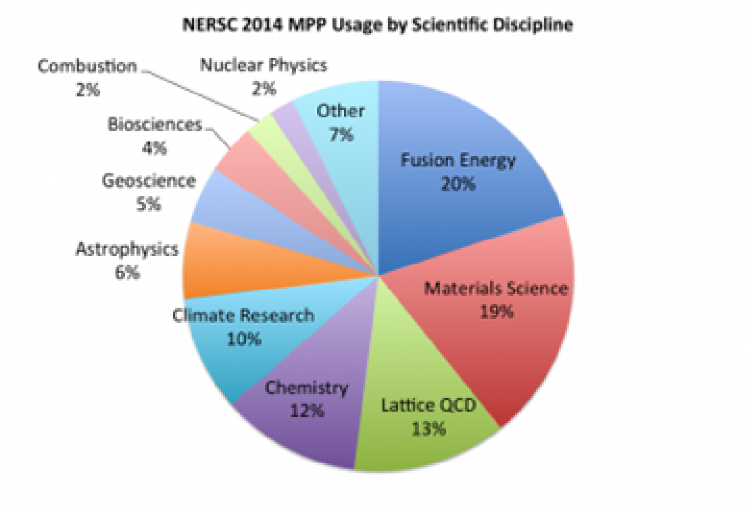
Data-Driven Science

- 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:*** estimate of the next IPCC (Intergovernmental Panel on Climate Change) data is in 10s of petabytes
  - ***Genome:*** JGI (Joint Genome Institute) alone will have .5 petabyte of data this year and double each year
  - ***Particle physics***: LHC (Large Hadron Collider) is projected to produce 16 petabytes of data per year
  - ***Astrophysics***: LSST (Large Synoptic Survey Telescope) will produce 15 terabytes of raw scientific image data per night (via 3.2 Gigapixel camera)



Particularly Challenging Problems

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



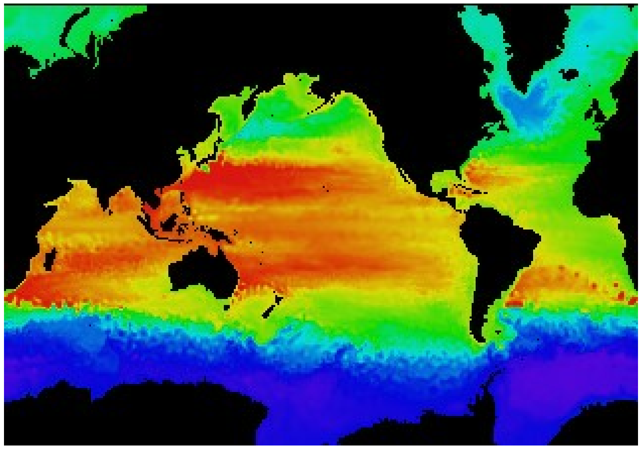
Example: Climate Modeling

- Problem is to compute:

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

  (temperature, pressure, humidity, wind velocity)

- Approach:
  - *Discretize* the domain - a measurement point every 10 km (0.1 deg)?
  - Devise an algorithm to predict weather at time *t+dt* given *t*
- Importance:
  - Predict major events, e.g., El Nino, hurricanes
  - Evaluate global warming scenarios



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

Example: Climate Modeling

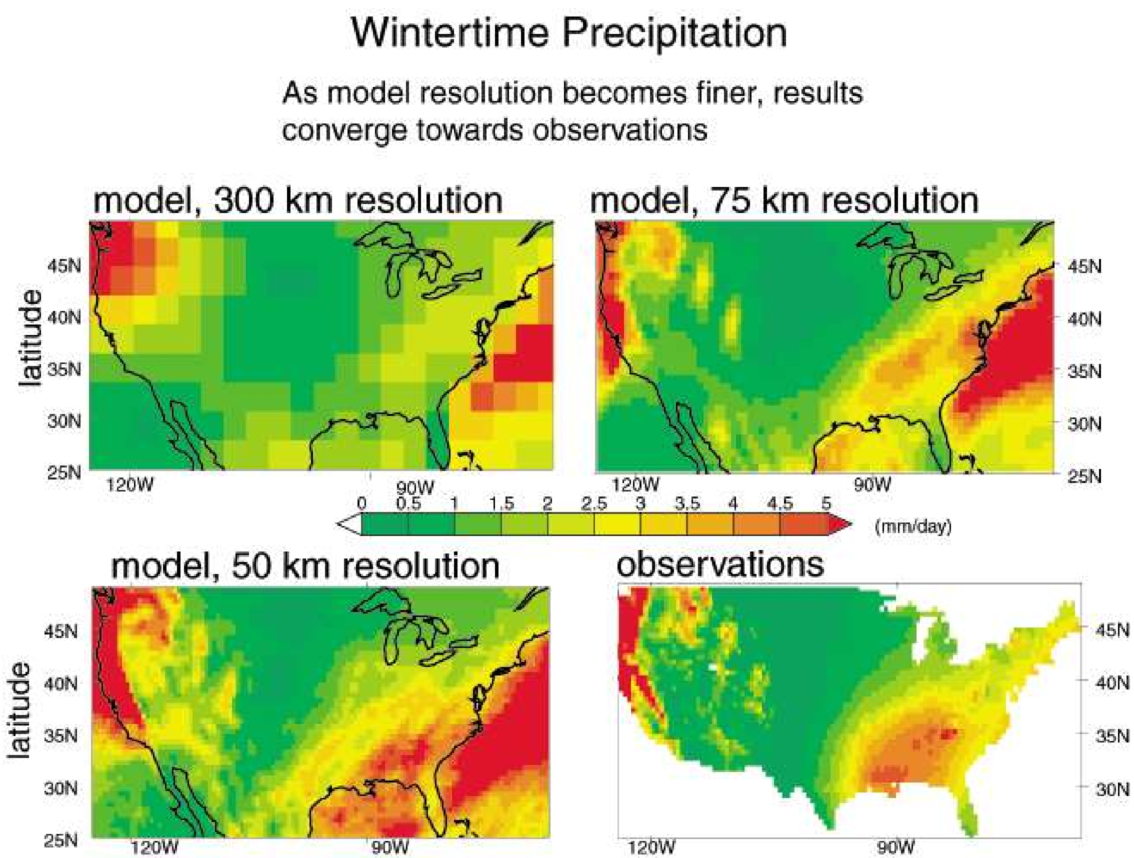
- State of the art models require integration of atmosphere, ocean, clouds, sea-ice, land models, plus possibly carbon cycle, geochemistry and more
- One piece is modeling the fluid flow in the atmosphere by solving the Navier-Stokes equations
  - Takes roughly 100 flops per grid point with 1-minute timestep
  - # points = Area/resolution * #height_levels = 4*pi*$(6000km/10km)^2$ * 1000 ~ 5 x 10^9

Example: Climate Modeling

- Computational requirements:
  - **Speed:** ~ 5 x 10^9 x 100 flops → 5 x 10^{11} flops/timestep (min)
  - 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
  - **Data**:
    - **Per timestep (min):** 5 x 10^9 (points) x 8 bytes (double precision) x 5 (variables) → 200 GB
    - **Per sim hour**: 200 GB x 60 (mins) → 12 Terabytes
    - **Per climate prediction**: 12 TB x 50 (years) x 365 x 24 → 5 Exabytes
- To double the grid resolution, computation is 8x to 16x !!

Example: Climate Modeling

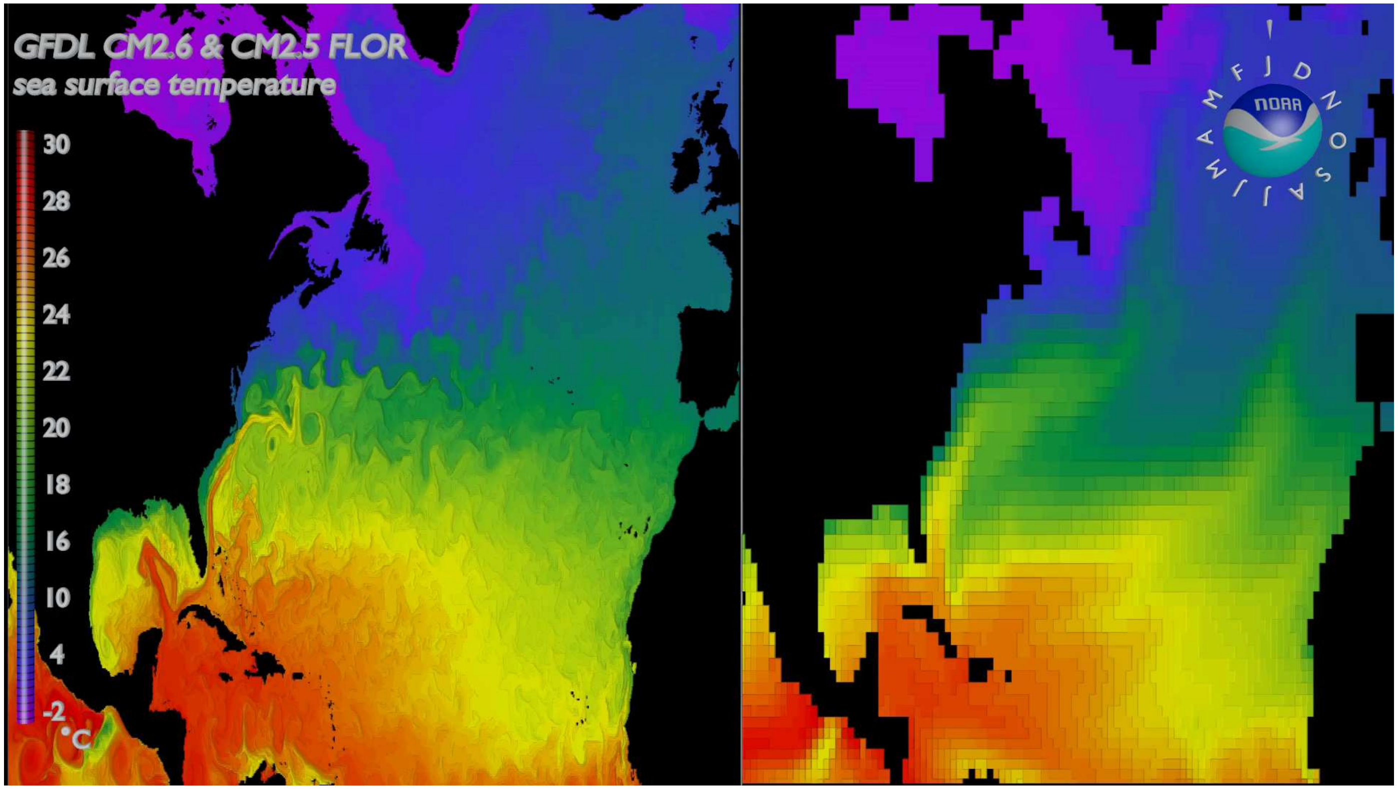
Effect of resolution:



Ref: P. Duffy et al, LLNL

Example: Climate Modeling

Effect of resolution:



Ref: NOAA GFDL

Classifying Parallel Systems – Flynn's Taxonomy

- Distinguishes multi-processor computer architectures along the two independent dimensions
  - ***Instruction*** and ***Data***
  - Each dimension can have one state: ***Single*** or ***Multiple***
- SISD: Single Instruction, Single Data
  - Serial (non-parallel) machine
- SIMD: Single Instruction, Multiple Data
  - Processor arrays and vector machines
  - SIMT (*T: threads*) for GPUs
- MISD: Multiple Instruction, Single Data (weird)
- MIMD: Multiple Instruction, Multiple Data
  - Most common parallel computer systems
  - SPMD & MPMD (*P: program*)

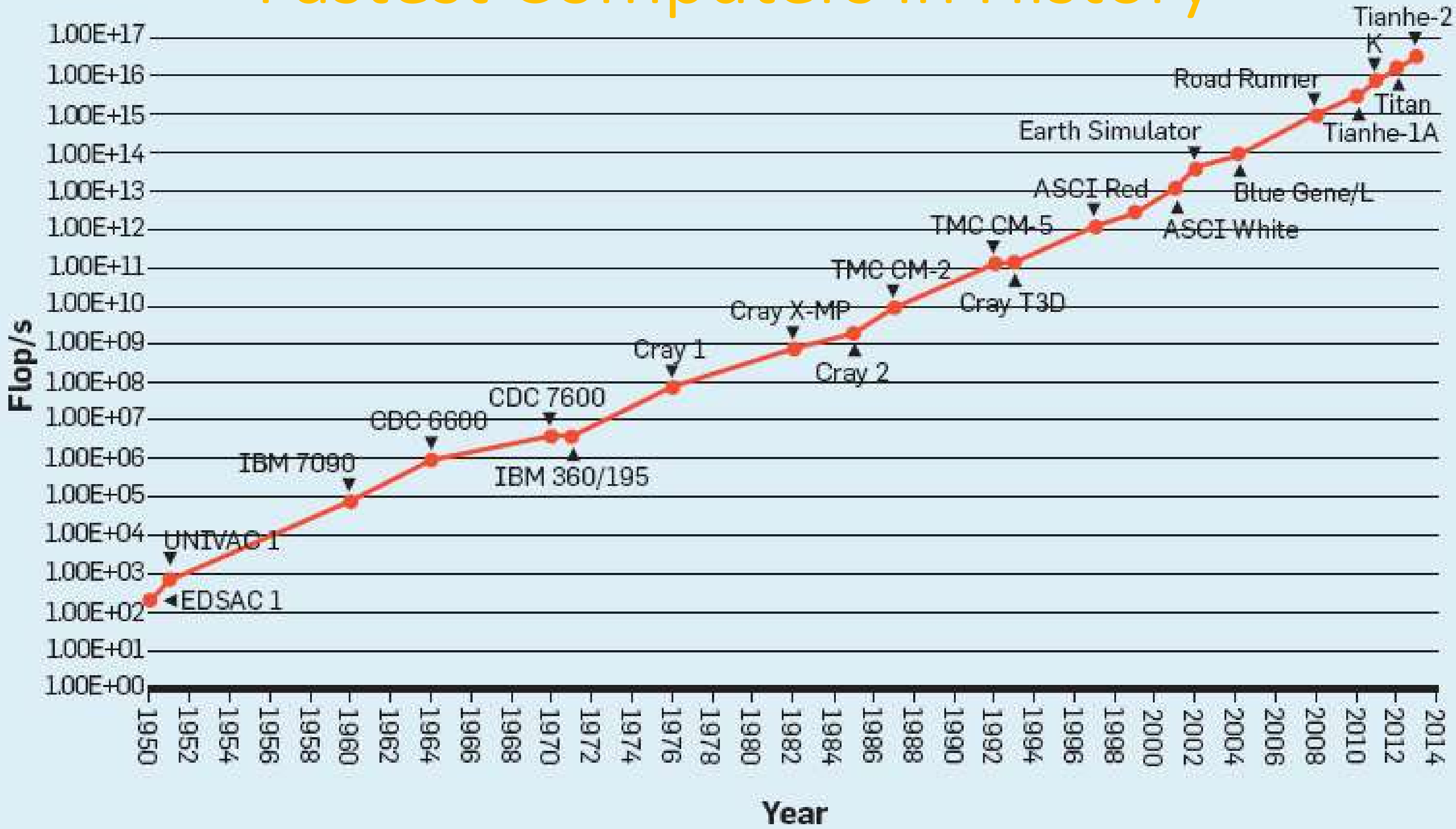
Parallel Architecture Types

- Instruction-Level Parallelism
  - Parallelism captured in instruction processing
- Vector processors
  - Operations on multiple data stored in vector registers
- Shared-memory Multiprocessor (SMP)
  - Multiple processors sharing memory
  - Symmetric Multiprocessor (SMP)
- Multicomputer
  - Multiple computer connect via network
  - Distributed-memory cluster
- Massively Parallel Processor (MPP)

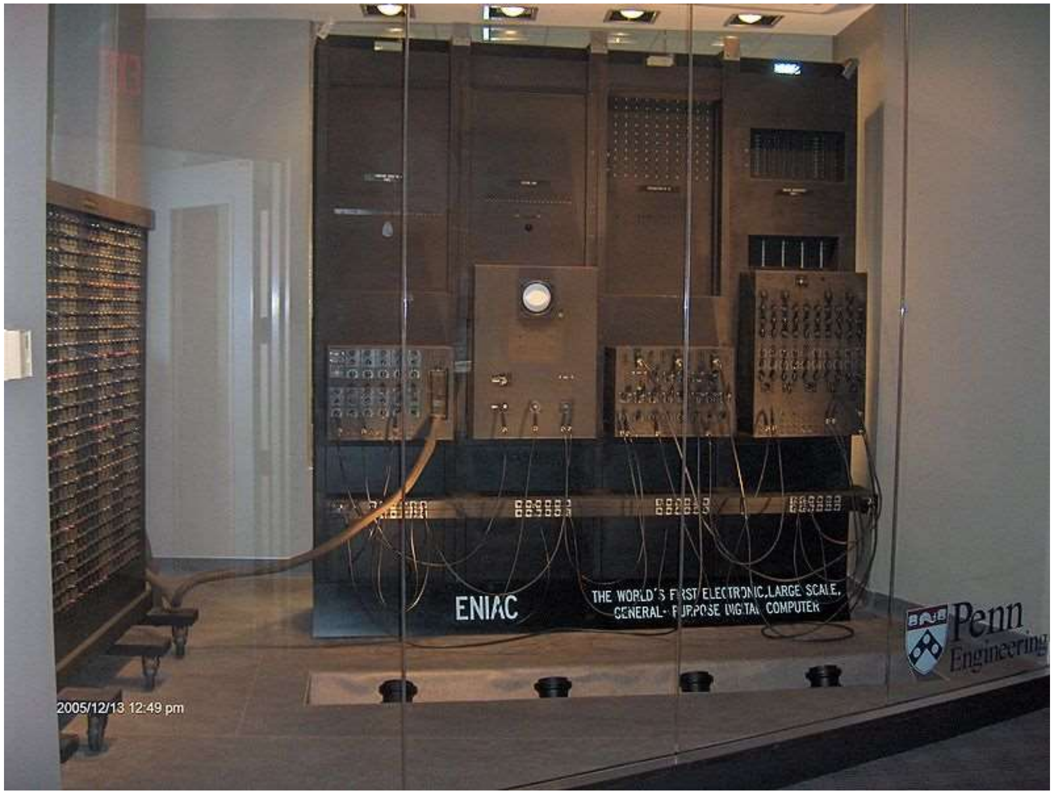
Phases of Supercomputing (Parallel) Architecture

- Phase 1 (1950s): sequential instruction execution
- Phase 2 (1960s): sequential instruction issue
  - Pipeline execution, reservations stations
  - Instruction Level Parallelism (ILP)
- Phase 3 (1970s): vector processors
  - Pipelined arithmetic units
  - Registers, multi-bank (parallel) memory systems
- Phase 4 (1980s): SIMD and SMPs
- Phase 5 (1990s): MPPs and clusters
  - Communicating sequential processors
- Phase 6 (>2000): many cores, accelerators, scale, …

Fastest Computers in History



ENIAC



- 1946
- 1st *electronic general-purpose* computer
- Vacuum tube circuitry
- Could make a 10-digit by 10-digit multiplication in 2800 µs
- ~ 357 *single-precision* FLOPS
  (floating-point operations per second)
- https://en.wikipedia.org/wiki/ENIAC

UNIVAC I

- 1951
- 1st commercial computer in US
- Multiplication time was 2150 μs
- ~ 465 *single-precision* FLOPS
- Originally priced at $159,000
- Raised to $1.25 - $1.5 million
- https://en.wikipedia.org/wiki/UNIVAC_I

IBM 704

- 1954
- 1st mass-produced computer with floating-point arithmetic hardware
- Fortran & Lisp were 1st developed for IBM 704
- ~ 12 kFLOPS
- $2 million
- https://en.wikipedia.org/wiki/IBM_704

IBM 7090

- 1959
- *Transistorized* version of IBM 709 vacuum tube mainframe
- Double-precision floating-point instructions were introduced on IBM 7094
- ~ 100 kFLOPS
- $2.9 million
- https://en.wikipedia.org/wiki/IBM_7090

CDC 6600

- 1965
- 1st successful supercomputer
- Designed by Seymour Cray
- CPU, peripheral processors (PPs) and I/O operated *in parallel*
- 6600 CPU had multiple functional units that could operate *in parallel*
- ~ 3 MFLOPS
- $6 - $10 million
- https://en.wikipedia.org/wiki/CDC_6600

CDC 7600

- Fastest from 1969 to 1975
- Designed by Seymour Cray
- An architecture landmark
  - Instruction pipeline
  - Reduced Instruction Set Computer (RISC)
- ~ 10 MFLOPS on hand-compiled code
- 36 MFLOPS peak performance
- $5 million
- https://en.wikipedia.org/wiki/CDC_7600

Cray-1

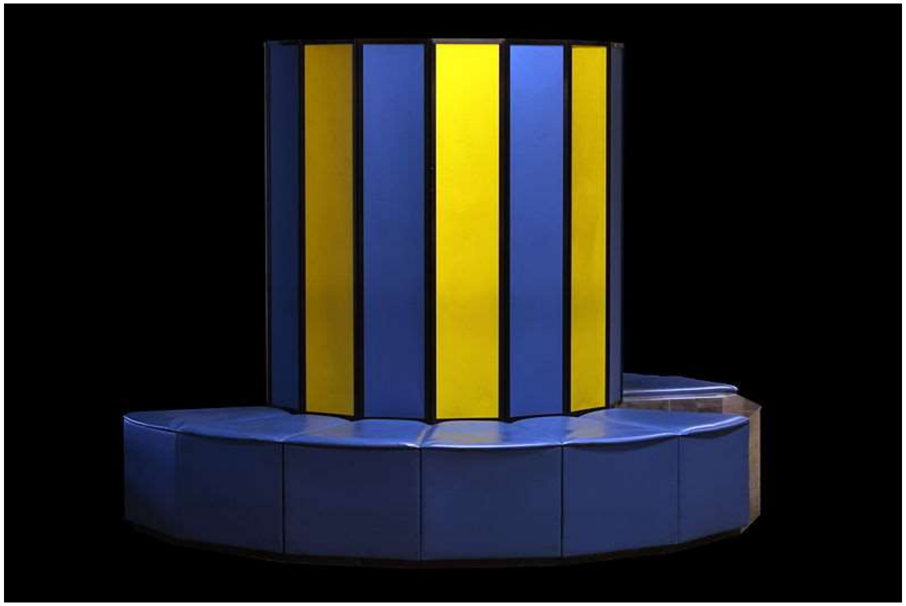
- 1975
- One of the best known and most successful supercomputers in history
- 1st Cray design to use *integrated circuits* (ICs)
- 64-bit
- Vector processor, with 12 pipelined functional units
- ~ 160 MFLOPS, with 250 MFLOPS peak
- $8.86 million (1977)
- https://en.wikipedia.org/wiki/Cray-1

IBM PC

- IBM PC 5150 was released in 1981
- Intel 8088 CPU at 4.77 MHz
- 16 kB – 256 kB of memory
- ~ 50 kFLOPS with Intel 8087 floating-point coprocessor
- $1,565 ~ $3,000

$$\frac{R_{max}(\text{Cray}-1)}{R_{max}(\text{IBM 5150})} = \frac{250\ MFLOPS}{50\ kFLOPS} = 5000$$

Cray X-MP



- 1982
- Shared-memory parallel vector processor supercomputer
- 2 vector processors at 105 MHz
- 400 MFLOPS peak performance
- $15 million
- https://en.wikipedia.org/wiki/Cray_X-MP

Cray Y-MP

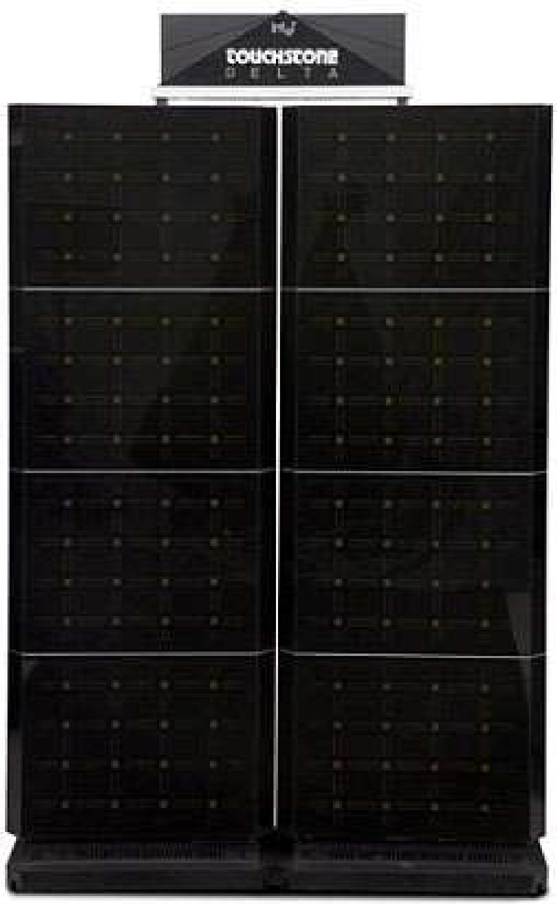
- 1988
- 2, 4, or 8 vector processors (with 2 functional units each) at 167 MHz
- 2.144 GFLOPS (measured) & 2.667 GLOPS (peak)
- $10 million
- https://en.wikipedia.org/wiki/Cray_Y-MP
- Cray C90 was a development of the Y-MP architecture, launched in 1991

Thinking Machines CM-1

- 1985
- SIMD supercomputer
- 65,536 simple single-bit processors
- Each CM-1 processor had its own 4 kilobits of RAM
- Connected in a hypercubic routing network
- ~ 1 GFLOPS
- $5 million
- https://en.wikipedia.org/wiki/Connection_Machine

Intel Paragon

- Massively parallel supercomputers by Intel in the 1990s
- Based on the Intel i860 RISC microprocessors
- Up to 2048 (later, up to 4000) i860s are connected in a 2D grid
- The prototype was the Touchstone Delta, funded by DARPA and installed at Caltech in 1990
  - 16x32 mesh of i860 processors with a wormhole routing interconnection network
  - 40 GFLOPS



Performance Expectations

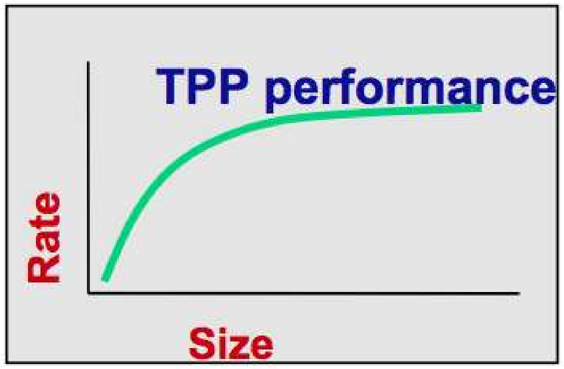
- If each processor is rated at k MFLOPS and there are p processors, we should expect to see k*p MFLOPS performance?
- If it takes 100 seconds on 1 processor, it should take 10 seconds on 10 processors?
- Several causes affect performance
  - Each must be understood separately
  - But they interact with each other in complex ways
    - solution to one problem may create another
    - one problem may mask another
- Scaling (system, problem size) can change conditions
- Need to understand performance space

Scalability

- A program can scale up to use many processors
  - What does that mean?
- How do you evaluate scalability?
- How do you evaluate scalability goodness?
- Comparative evaluation
  - If double the number of processors, what to expect?
  - Is scalability linear?
- Use parallel efficiency measure
  - Is efficiency retained as problem size increases?
- Apply performance metrics

Top 500 Benchmarking Methodology

- http://top500.org/
- Ranks and details of 500 fastest supercomputers in the world
- HPL (High Performance Linpack) benchmark
  - Solving dense linear system of equations (Ax = b)
- Data listed
  - R_{max} : maximal performance
  - R_{peak} : theoretical peak performance
  - N_{max} : problem size needed to achieve R_{max}
  - $N_{1/2}$: problem size needed to achieve 1/2 of R_{max}
  - Manufacturer and computer type
  - Installation site, location, and year
- Updated twice a year at ISC and SC conferences



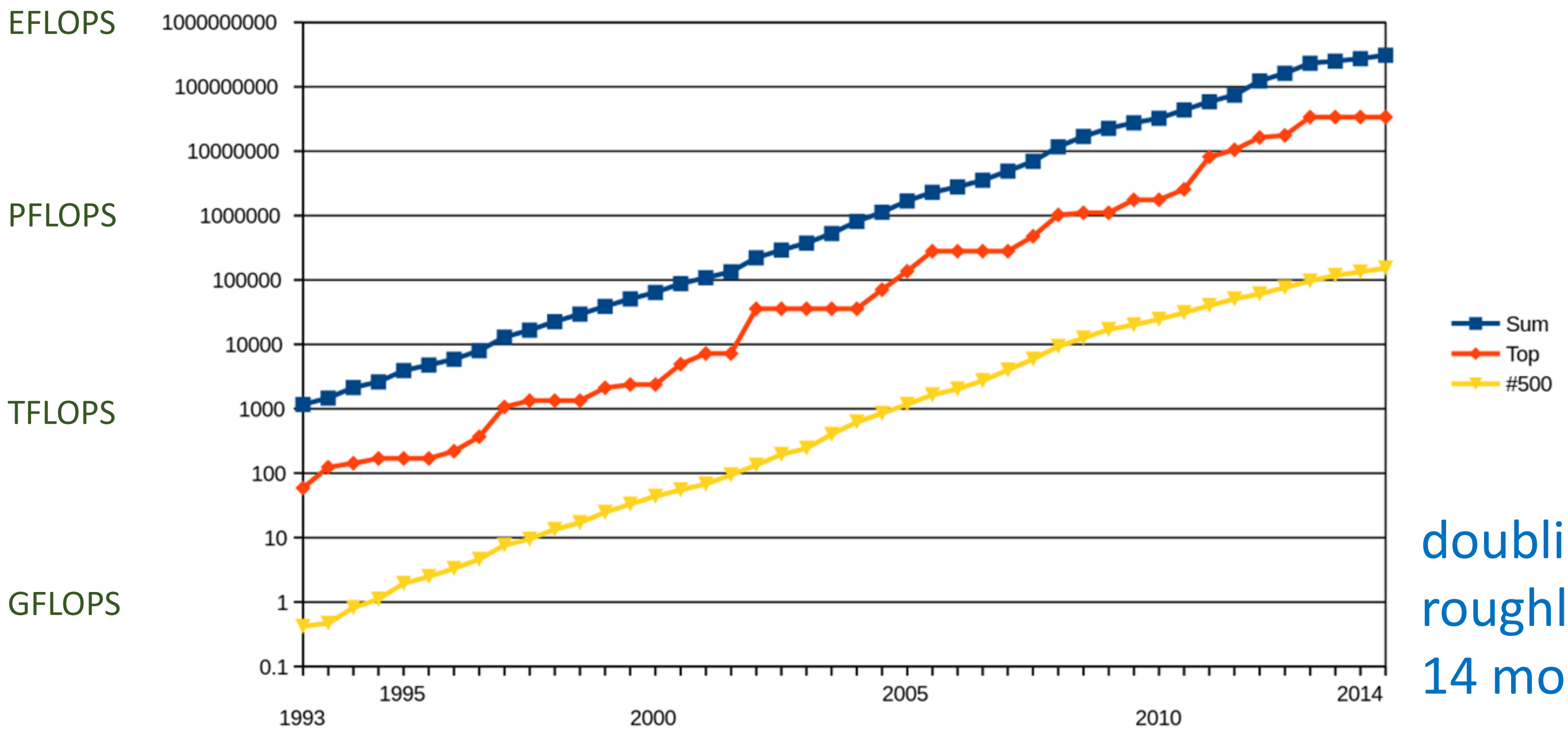
Top 10 positions of the 46th TOP500 in November 2015

Rank	Rmax Rpeak (PFLOPS)	Name	Computer design Processor type, interconnect	Vendor	Site Country, year	Operating system
1	33.863 54.902	*Tianhe-2*	**NUDT** Xeon E5–2692 + Xeon Phi 31S1P, TH Express-2	NUDT	National Supercomputing Center in Guangzhou China, 2013	Linux (Kylin)
2	17.590 27.113	*Titan*	**Cray XK7** Opteron 6274 + Tesla K20X, Cray Gemini Interconnect	Cray Inc.	Oak Ridge National Laboratory United States, 2012	Linux (CLE, SLES based)
3	17.173 20.133	*Sequoia*	**Blue Gene/Q** PowerPC A2, Custom	IBM	Lawrence Livermore National Laboratory United States, 2013	Linux (RHEL and CNK)
4	10.510 11.280	*K computer*	**RIKEN** SPARC64 VIIIfx, Tofu	Fujitsu	RIKEN Japan, 2011	Linux
5	8.586 10.066	*Mira*	**Blue Gene/Q** PowerPC A2, Custom	IBM	Argonne National Laboratory United States, 2013	Linux (RHEL and CNK)
6	8.101 11.079	Trinity	**Cray XC40** Xeon E5-2698v3, Cray Aries Interconnect	Cray Inc.	DOE/NNSA/LANL/SNL United States, 2015	Linux (CLE)
7	6.271 7.779	*Piz Daint*	**Cray XC30** Xeon E5–2670 + Tesla K20X, Aries	Cray Inc.	Swiss National Supercomputing Centre Switzerland, 2013	Linux (CLE)
8	5.640 7.404	Hazel Hen	**Cray XC40** Xeon E5-2680v3, Cray Aries Interconnect	Cray Inc.	HLRS - Höchstleistungsrechenzentrum, Stuttgart Germany, 2015	Linux (CLE)
9	5.537 7.235	*Shaheen II*	**Cray XC40** Xeon E5–2698v3, Aries	Cray Inc.	King Abdullah University of Science and Technology Saudi Arabia, 2015	Linux (CLE)
10	5.168 8.520	*Stampede*	**PowerEdge C8220** Xeon E5–2680 + Xeon Phi, Infiniband	Dell	Texas Advanced Computing Center United States, 2013	Linux (CentOS)[13]

Tops of the Top 500

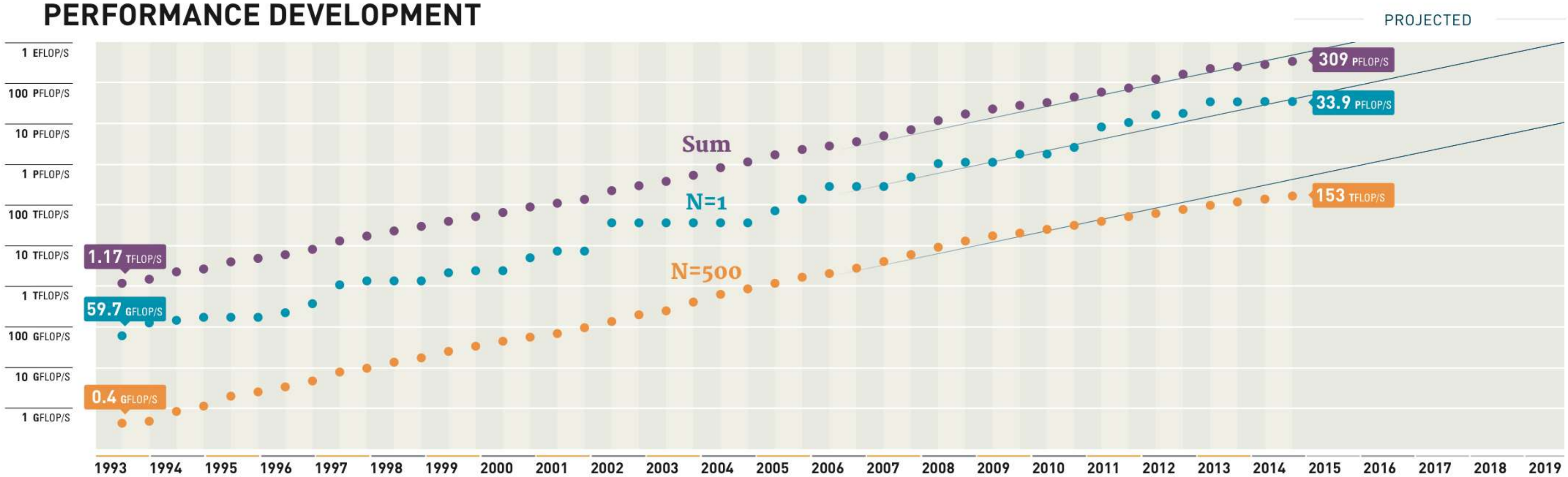
Year	Supercomputer	Peak speed (Rmax)	Location
1993	Fujitsu Numerical Wind Tunnel	124.50 GFLOPS	National Aerospace Laboratory, Tokyo, Japan
1993	Intel Paragon XP/S 140	143.40 GFLOPS	DoE-Sandia National Laboratories, New Mexico, USA
1994	Fujitsu Numerical Wind Tunnel	170.40 GFLOPS	National Aerospace Laboratory, Tokyo, Japan
1996	Hitachi SR2201/1024	220.4 GFLOPS	University of Tokyo, Japan
	Hitachi CP-PACS/2048	368.2 GFLOPS	University of Tsukuba, Tsukuba, Japan
1997	Intel ASCI Red/9152	1.338 TFLOPS	DoE-Sandia National Laboratories, New Mexico, USA
1999	Intel ASCI Red/9632	2.3796 TFLOPS	
2000	IBM ASCI White	7.226 TFLOPS	DoE-Lawrence Livermore National Laboratory, California, USA
2002	NEC Earth Simulator	35.86 TFLOPS	Earth Simulator Center, Yokohama, Japan
2004	IBM Blue Gene/L	70.72 TFLOPS	DoE/IBM Rochester, Minnesota, USA
2005		136.8 TFLOPS	DoE/U.S. National Nuclear Security Administration, Lawrence Livermore National Laboratory, California, USA
		280.6 TFLOPS	
2007		478.2 TFLOPS	
2008	IBM Roadrunner	1.026 PFLOPS	DoE-Los Alamos National Laboratory, New Mexico, USA
		1.105 PFLOPS	
2009	Cray Jaguar	1.759 PFLOPS	DoE-Oak Ridge National Laboratory, Tennessee, USA
2010	Tianhe-IA	2.566 PFLOPS	National Supercomputing Center, Tianjin, China
2011	Fujitsu K computer	10.51 PFLOPS	RIKEN, Kobe, Japan
2012	IBM Sequoia	16.32 PFLOPS	Lawrence Livermore National Laboratory, California, USA
2012	Cray Titan	17.59 PFLOPS	Oak Ridge National Laboratory, Tennessee, USA
2013	NUDT Tianhe-2	33.86 PFLOPS	Guangzhou, China

Top 500 Performance Development

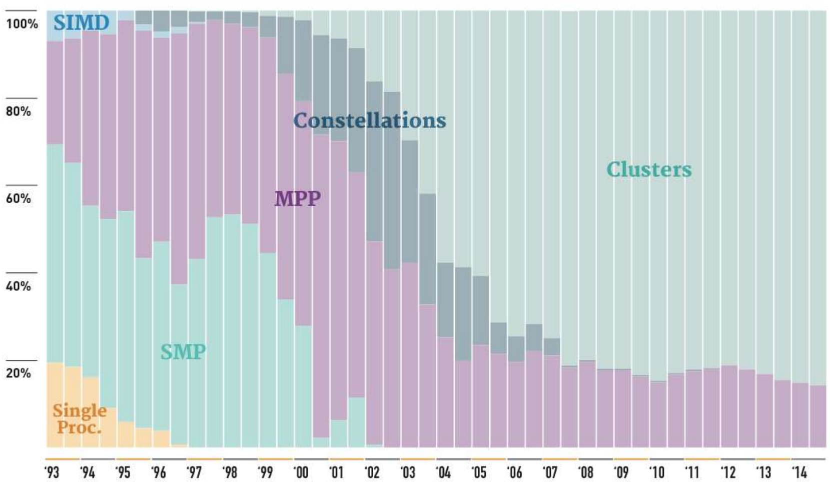


doubling roughly every 14 months

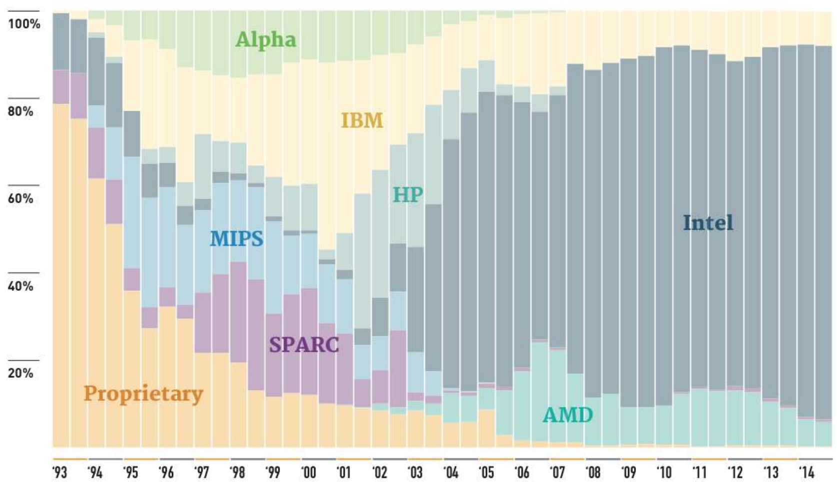
PERFORMANCE DEVELOPMENT



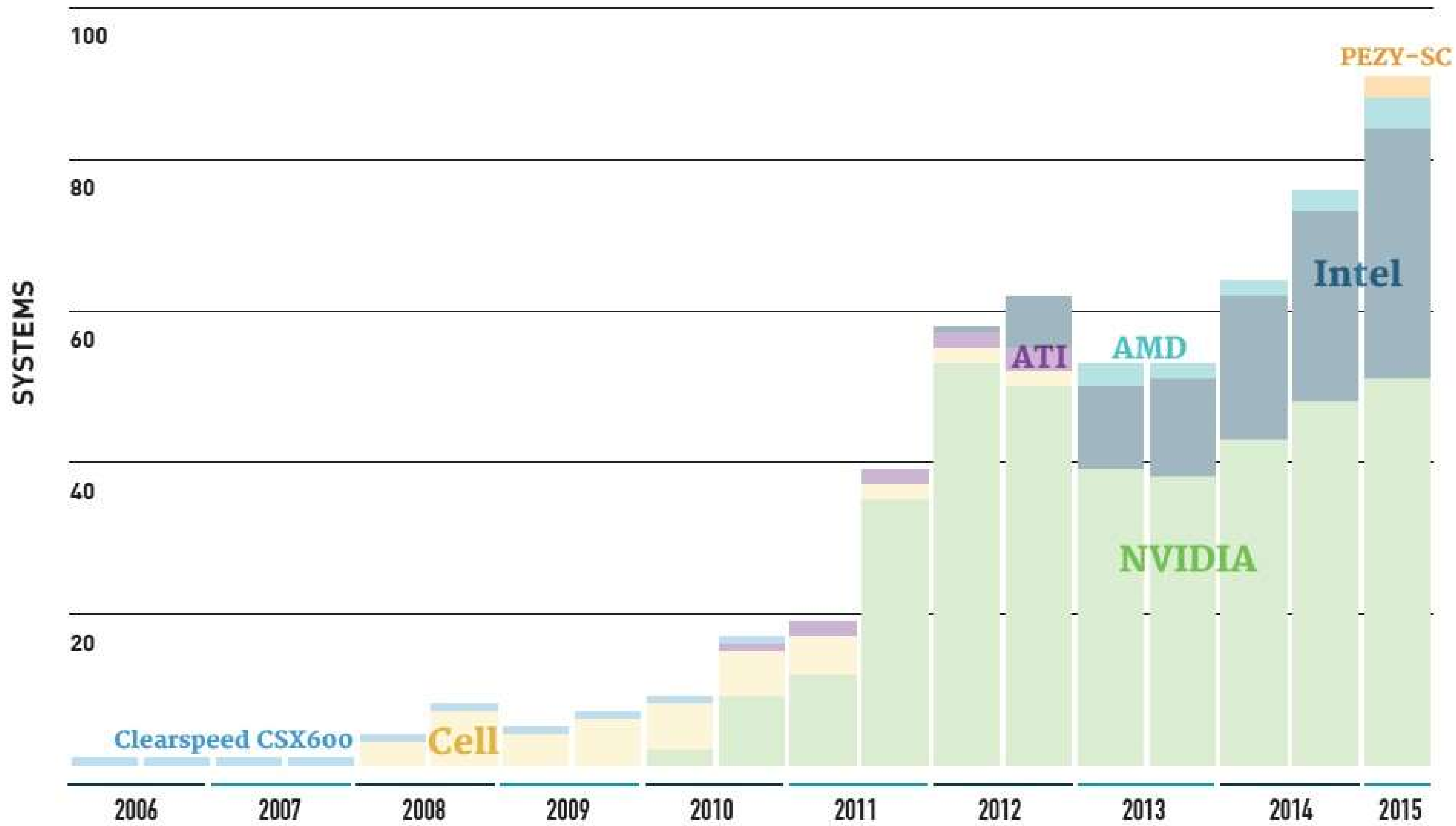
ARCHITECTURES



CHIP TECHNOLOGY



ACCELERATORS/CO-PROCESSORS



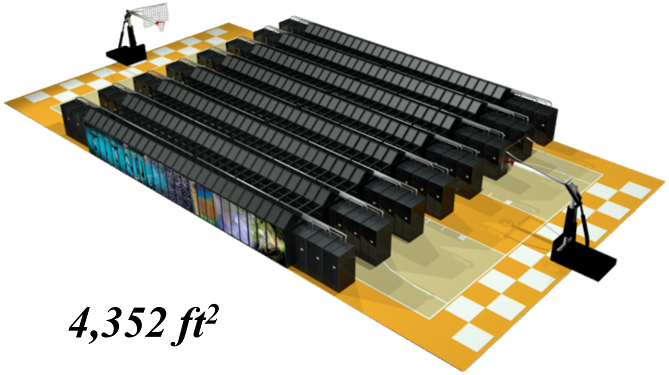
#1: NUDT Tianhe-2 (Milky Way 2)

- 16,000 Compute Nodes, each with:
  - Two Intel Ivy Bridge Xeon E5-2692v2 12C 2.2GHz
  - Three Intel Xeon Phi 31S1P
  - Memory: 64 GB host + 24 GB devices (3 x 8GB)
  - 3.432 TFLOPS
- Front-End Node
  - 4096 Galaxy FT-1500 CPUs (a SPARC derivative)
  - Each FT-1500 has 16 cores, and runs @ 1.8 GHz
- Proprietary interconnect
  - TH2 express, in a fat tree topology
- 12.4PB of global shared parallel storage
- # 1 since June 2013

R_{peak} = 54.902 PFLOPS
R_{max} = 33.863 PFLOPS
Power = 17.6 MW (24 MW)
Cost = 2.4 billion Yuan = $390m

#2: ORNL Titan

- 18,688 Compute Nodes (Cray XK7), each with:
  - One AMD Opteron 6274 16-core CPU @ 2.2 GHz
  - One NVIDIA Tesla K20X GPU
  - Memory: 32 GB host + 6GB device
- 512 Service and I/O nodes
- Cray Gemini 3D Torus Interconnect
- 40 PB of Lustre storage, with an aggregate transfer rate of 1.4 TB/s
- 200 Cabinets
- #1 in November 2012; #2 since June 2013

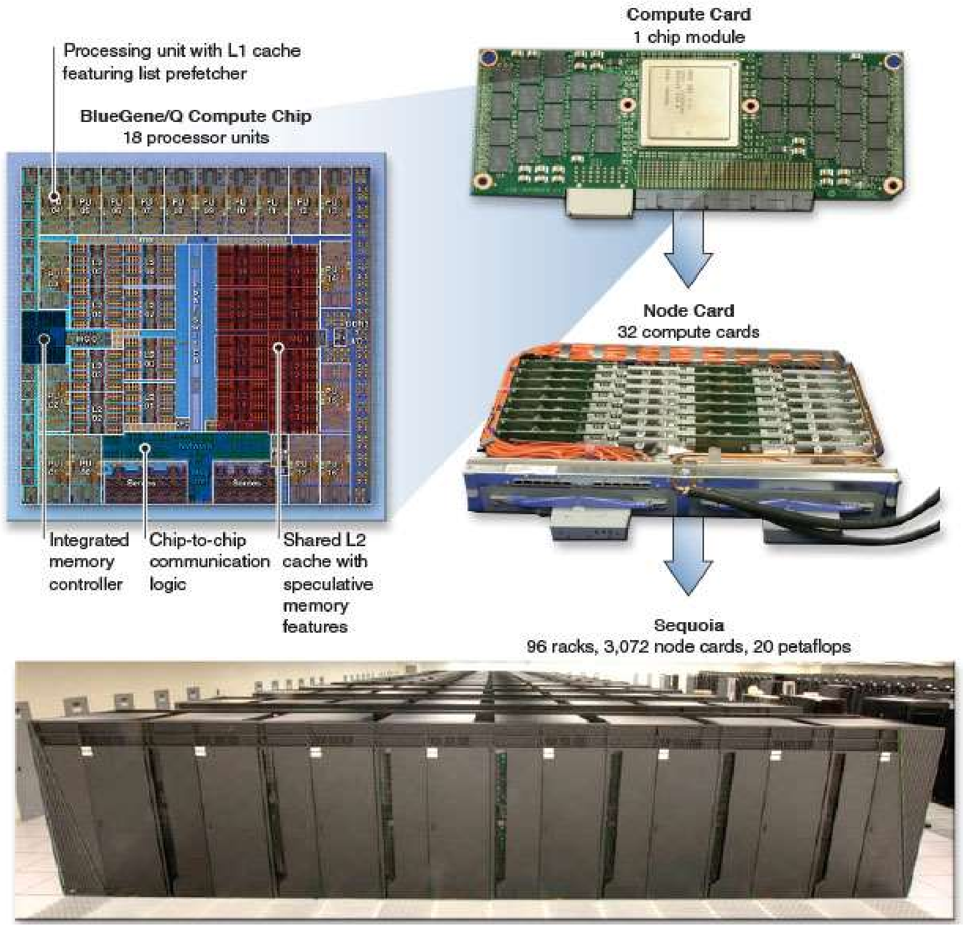


R_{peak} = 27.1 PFLOPS = 24.5 GPU + 2.6 CPU
R_{max} = 17.590 PFLOPS
Power = 8.2 MW
Cost = $97 million

#3: LLNL Sequoia

- IBM Blue Gene/Q design
- 98,304 (1024/rack x 96 racks) Compute Cards, each with:
  - 18-core PowerPC A2 processor @ 1.6 GHz, with 16 cores used for computing
  - 16 GB of DDR3 memory
- 5-dimensional torus interconnect
- 55 PB of Lustre storage (with ZFS backend)
- #1 in June 2012; #3 since June 2013

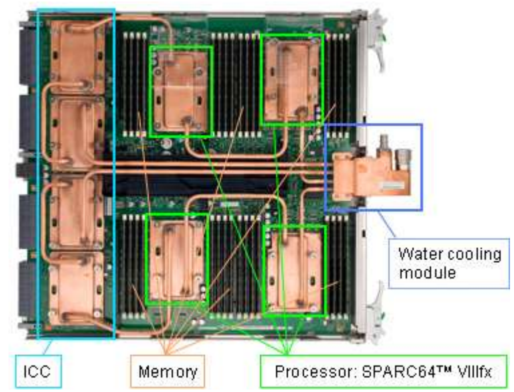
R_{peak} = 20.133 PFLOPS
R_{max} = 17.173 PFLOPS
Power = 7.9 MW
Cost = $655.4 million



3,000 ft²

#4: RIKEN K Computer

- 82,944 (96/cabinets x 864 cabinets) Compute Nodes, each with:
  - One 8-core SPARC64 VIIIfx @ 2.0 GHz
  - 16 GB of memory
- 5,184 (6/cabinets x 864 cabinets) I/O Nodes
- 6-dimensional torus interconnect (*Tofu*)
- Fujitsu Exabyte File System (*FEFS*), based on Lustre
- #1 in June 2011; #4 since June 2013



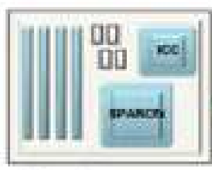
R_{peak} = 11.280 PFLOPS
R_{max} = 10.510 PFLOPS
Power = 12.6 MW
Cost > 100 billion Yen ($1.25b)

K computer Specifications

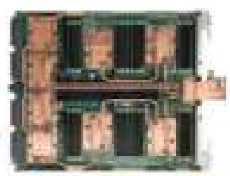
CPU (SPARC64 VIIIfx)	Cores/Node	8 cores (@2GHz)
	Performance	128GFlops
	Architecture	SPARC V9 + HPC extension
	Cache	L1(I/D) Cache : 32KB/32KB L2 Cache : 6MB
	Power	58W (typ. 30 C)
	Mem. bandwidth	64GB/s.
Node	Configuration	1 CPU / Node
	Memory capacity	16GB (2GB/core)
System board(SB)	No. of nodes	4 nodes /SB
Rack	No. of SB	24 SBs/rack
System	Nodes/system	> 80,000

Inter-connect	Topology	6D Mesh/Torus
	Performance	5GB/s. for each link
	No. of link	10 links/ node
	Additional feature	H/W barrier, reduction
	Architecture	Routing chip structure (no outside switch box)
Cooling	CPU, ICC*	Direct water cooling
	Other parts	Air cooling

CPU
128GFlops
SPARC64™ VIIIfx
8 Cores@2.0GHz

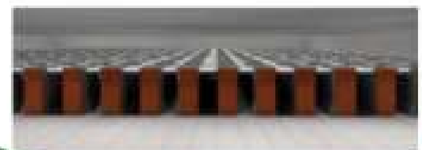


Node
128 GFlops
16GB Memory
64GB/s Memory band width



System Board
512 GFlops
64 GB memory

Rack
12.3 TFlops
15TB memory



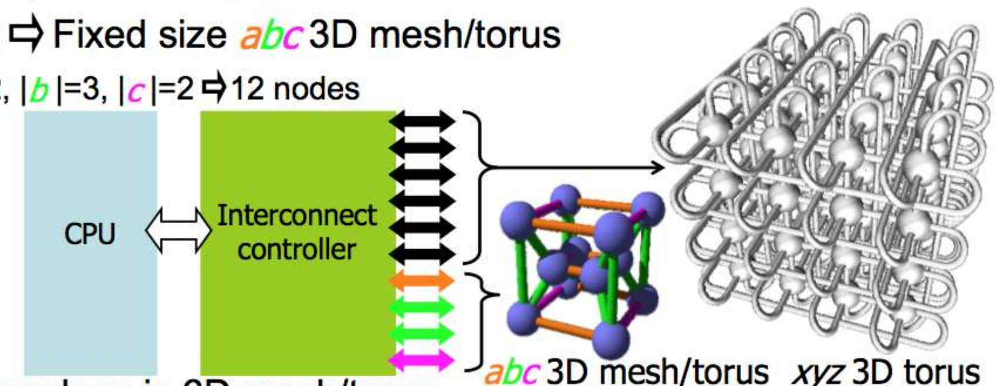
System
LINPACK 10 PFlops
over 1PB mem.
800 racks
80,000 CPUs
640,000 cores

* ICC : Interconnect Chip

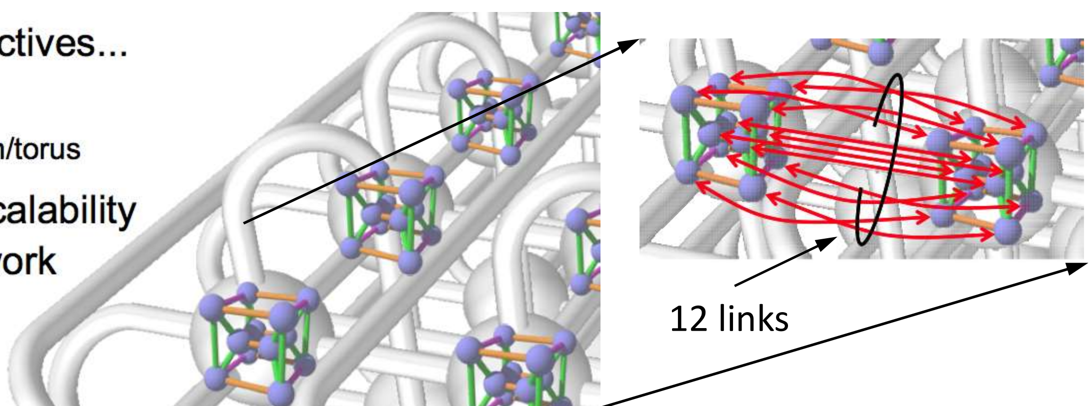
New Linpack run with 705,024 cores at 10.51 Pflop/s (88,128 CPUs)

K Computer – Interconnect

- 6 links ⇨ Scalable *xyz* 3D torus
- 4 links ⇨ Fixed size *abc* 3D mesh/torus
  - |*a*|=2, |*b*|=3, |*c*|=2 ⇨ 12 nodes



- Total topology is 6D mesh/torus
  - Cartesian product of *xyz* and *abc* mesh/torus
- From the other perspectives...
  - Overlaid twelve *xyz* torus
  - X x Y x Z array of *abc* mesh/torus
- Twelve times higher scalability than the 3D torus network



Contemporary HPC Architectures

Date	System	Location	Chip	Interconnect	Peak (PF)	Power (MW)
2009	Jaguar; Cray XT5	ORNL	AMD	Seastar2	2.3	7.0
2010	Tianhe-1A	NSC Tianjin	Intel + NVIDIA	Proprietary	4.7	4.0
2010	Nebulae	NSCS Shenzhen	Intel + NVIDIA	InfiniBand	2.9	2.6
2010	Tsubame 2	TiTech	Intel + NVIDIA	InfiniBand	2.4	1.4
2011	K Computer	RIKEN/Kobe	SPARC64 VIIIfx	Tofu	10.5	12.7
2012	Titan; Cray XK7	ORNL	AMD + NVIDIA	Gemini	27	9
2012	Mira; BlueGeneQ	ANL	IBM SoC	Proprietary	10	3.9
2012	Sequoia; BlueGeneQ	LLNL	IBM SoC	Proprietary	20	7.9
2012	Blue Waters; Cray	NCSA/UIUC	AMD + (partial) NVIDIA	Gemini	11.6	
2013	Stampede	TACC	Intel + MIC	InfiniBand	9.5	5
2013	Tianhe-2	NSCC-GZ (Guangzhou)	Intel + MIC	Proprietary	54	~20

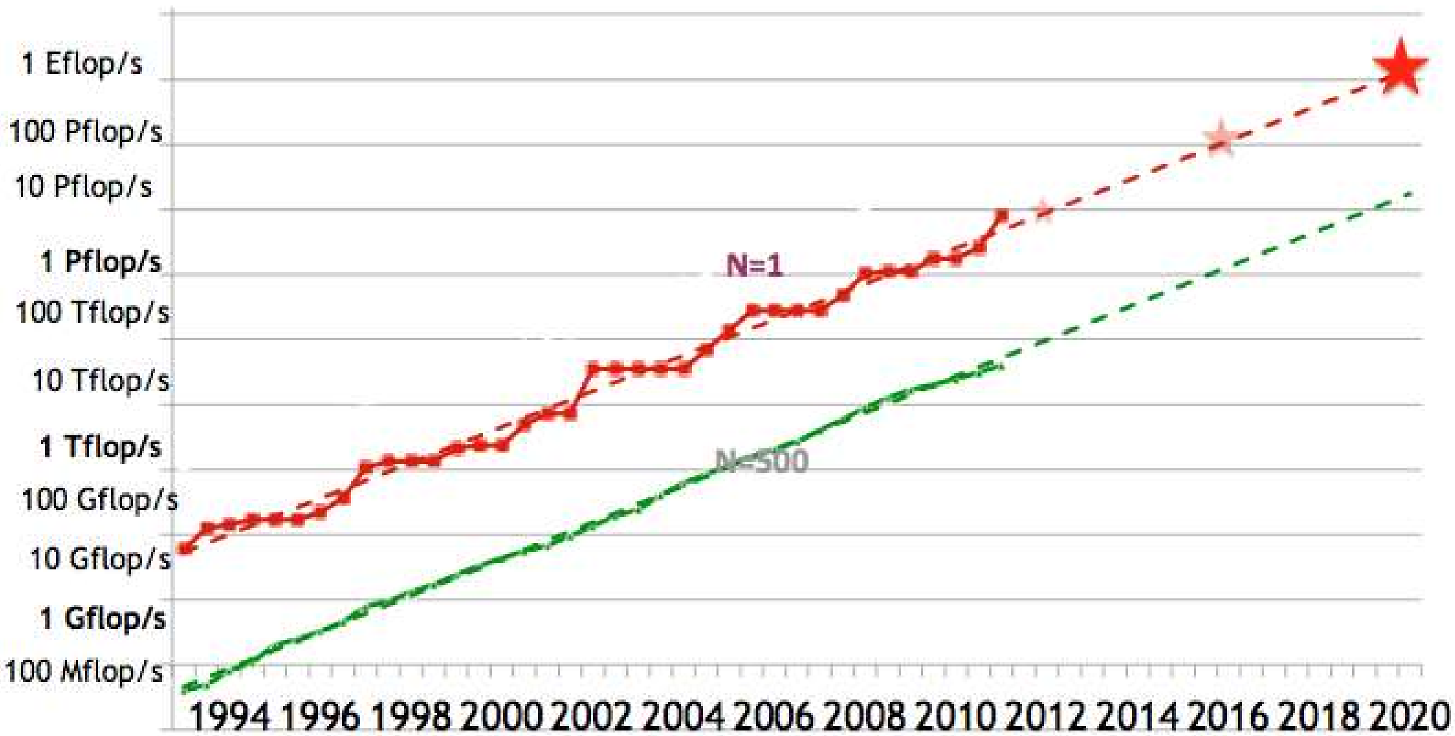
Graph 500

- http://www.graph500.org/
- Rating of supercomputers, focused on ***data intensive loads***
- Graph 500 benchmark
  - breadth-first search in a large undirected graph (model of Kronecker graph with average degree of 16)
- 6 problem classes defined by their input size:
  - **toy** : 17 GB (2^{26} vertices, scale 26; 10^{10} bytes, level 10)
  - **mini** : 140 GB (2^{29} vertices, scale 29; 10^{11} bytes, level 11)
  - **small** : 1 TB (2^{32} vertices, scale 32; 10^{13} bytes, level 13)
  - **medium** : 17 TB (2^{36} vertices, scale 36; 10^{14} bytes, level 14)
  - **large** : 140 TB (2^{39} vertices, scale 39; 10^{15} bytes, level 15)
  - **huge** : 1.1 PB (2^{42} vertices, scale 42; 10^{11} bytes, level 16)
- The main performance metric is ***GTEPS*** (10^9 traversed edges per second)

Graph 500 Top 10 (November 2015)

Rank	Site	Machine (Architecture)	Number of nodes	Number of cores	Problem scale	GTEPS
1	RIKEN Advanced Institute for Computational Science	K computer (Fujitsu custom)	65536	524288	40	17977.1
2	Lawrence Livermore National Laboratory	IBM Sequoia (Blue Gene/Q)	65536	1048576	40	16599
3	Argonne National Laboratory	IBM Mira (Blue Gene/Q)	49152	786432	40	14328
4	Forschungszentrum Jülich	JUQUEEN (Blue Gene/Q)	16384	262144	38	5848
5	CINECA	Fermi (Blue Gene/Q)	8192	131072	37	2567
6	Changsha, China	Tianhe-2 (NUDT custom)	8192	196608	36	2061.48
7	CNRS/IDRIS-GENCI	Turing (Blue Gene/Q)	4096	65536	36	1427
7	Science and Technology Facilities Council - Daresbury Laboratory	Blue Joule (Blue Gene/Q)	4096	65536	36	1427
7	University of Edinburgh	DIRAC (Blue Gene/Q)	4096	65536	36	1427
7	EDF R&D	Zumbrota (Blue Gene/Q)	4096	65536	36	1427
7	Victorian Life Sciences Computation Initiative	Avoca (Blue Gene/Q)	4096	65536	36	1427

Top 500 Performance Development



http://www.netlib.org/utk/people/JackDongarra/SLIDES/korea-2011.pdf

Exascale Initiative

- Exascale machines are targeted for 2020
- What are the potential differences and problems?

Systems	2011 K Computer	2019	Difference Today & 2019
System peak	8.7 Pflop/s	1 Eflop/s	O(100)
Power	10 MW	~20 MW	
System memory	1.6 PB	32 - 64 PB	O(10)
Node performance	128 GF	1,2 or 15TF	O(10) - O(100)
Node memory BW	64 GB/s	2 - 4TB/s	O(100)
Node concurrency	8	O(1k) or 10k	O(100) - O(1000)
Total Node Interconnect BW	20 GB/s	200-400GB/s	O(10)
System size (nodes)	68,544	O(100,000) or O(1M)	O(10) - O(100)
Total concurrency	548,352	O(billion)	O(1,000)
MTTI	days	O(1 day)	- O(10)

Table 1. Computational science platform requirements for the OLCF

	2012	2017	2020	2024
Peak flops	10–20 PF	100–200 PF	500–2000 PF	2000–4000 PF
Memory	0.5–1 PB	5–10 PB	32–64 PB	50–100 PB
Burst storage bandwidth	NA	5 TB/s	32 TB/s	50 TB/s
Burst capacity (cache)	NA	500 TB	3 PB	5 PB
Mid-tier capacity (disk)	20 PB	100 PB	1 EB	5 EB
Bottom-tier capacity (tape)	100 PB	1 EB	10 EB	50 EB
I/O servers	400	500	600	700

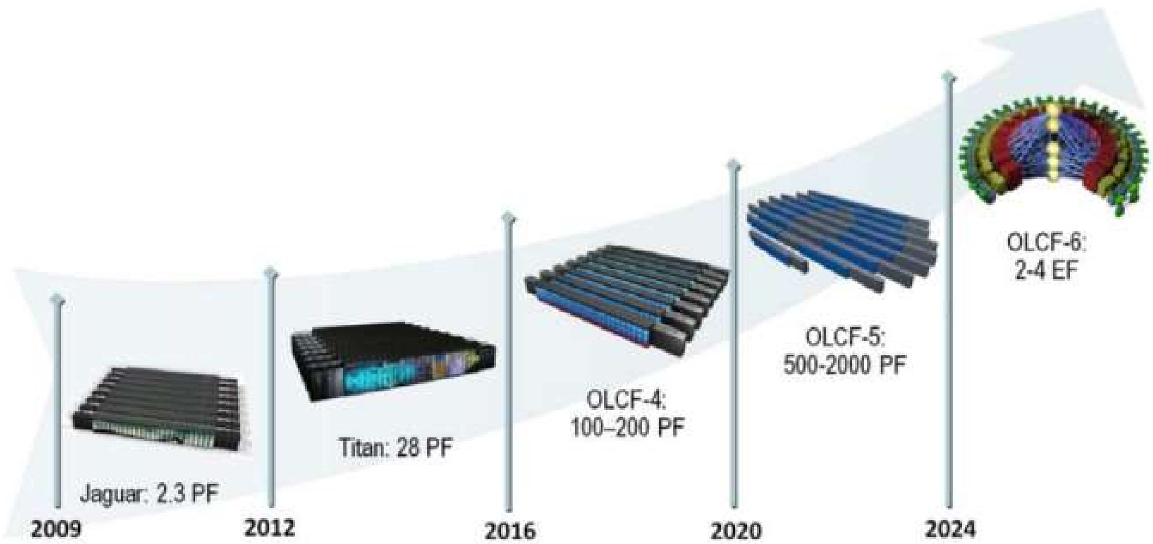


Figure 1. OLCF 2024 roadmap.

https://www.olcf.ornl.gov/wp-content/uploads/2013/01/OLCF_Requirements_TM_2013_Final.pdf

Major Changes to Software and Algorithms

- What were we concerned about before and now?
- Must rethink the design for exascale
  - Data movement is expensive (Why?)
  - Flops per second are cheap (Why?)
- Need to reduce communication and synchronization
- Need to develop fault-resilient algorithms
- How do with deal with massive parallelism?
- Software must adapt to the hardware (autotuning)

Scalable Parallel Computing

- Scalability in parallel architecture
  - Processor numbers
  - Memory architecture
  - Interconnection network
  - Avoid critical architecture bottlenecks
- Scalability in computational problem
  - Problem size
  - Computational algorithms
    - Computation to memory access ratio
    - Computation to communication ration
- Parallel programming models and tools
- Performance scalability