
CS267 / E233

Applications of Parallel

Computers

<https://sites.google.com/lbl.gov/cs267-spr2019/>

Video of lectures available the day after classroom lecture

Lecture 1: Introduction

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Course Staff

Instructors



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Jim Demmel
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GIs



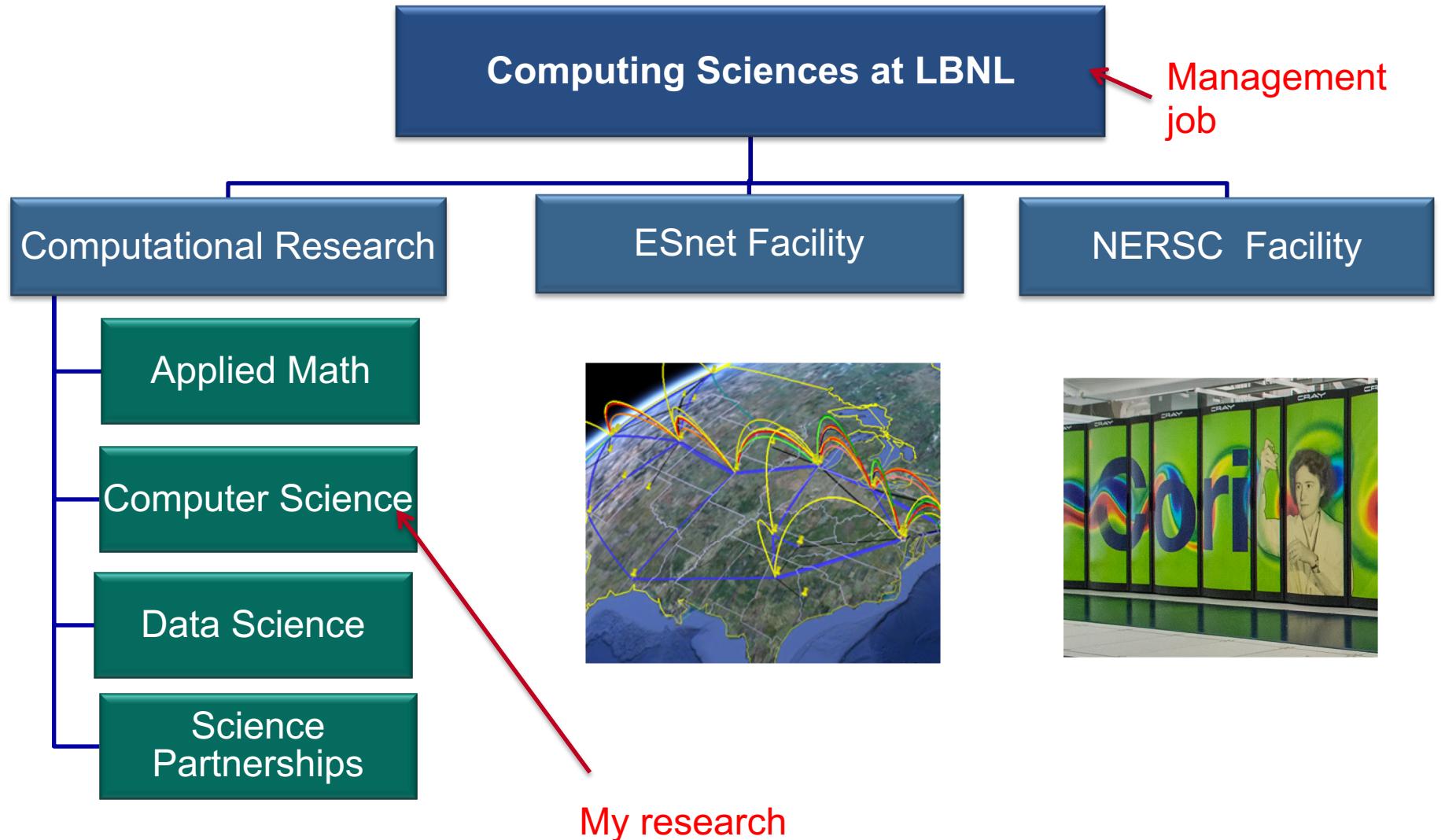
Ben Brock
EECS and LBNL



Kevin Laeufer
EECS

See website for contact information and office hours. Email us at cs267.sp19@gmail.com

My day job



Who is in this class?

- Applied Mathematics
- Applied Science & Tech
- Astrophysics
- Biostatistics
- Business Administration
- Chemical Engineering
- Chemistry
- Civil & Environmental
- Computer Science
- Earth & Planetary Sci
- EECS
- Environ. Sci, Pol & Mgmt
- Industrial Eng & Ops Res
- Info Mgmt & Sys (MIMS)
- Landscape Architecture
- Materials Science & Eng
- Mathematics
- Mechanical Engineering

26% CS
50% EECS
24% other

22% UG
35% MS/MEng
43% PhD

Universities Offering CS267 in Spring 2018

NSF XSEDE Program (using 2018 Berkeley lectures / material)

- Austin Peay
- Florida Polytechnic
- Franklin and Marshall
- George Mason University
- Indiana University Southeast
- Lamar University
- McNeese State University
- Morgan State
- North Carolina Central
- Oneonta University
- Penn State
- Prairie View A&M
- Rutgers University
- San Francisco State
- South Dakota State
- University of Houston- Clear Lake
- University of Kentucky

Some of the World's Fastest Computer

The Top500 List

Units of Measure for HPC

- 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...

Kilo	$Kflop/s = 10^3 \text{ flop/sec}$	$Kbyte = 10^3 \sim 2^{10} = 1024 \text{ bytes (KiB)}$
Mega	$Mflop/s = 10^6 \text{ flop/sec}$	$Mbyte = 10^6 \sim 2^{20} \text{ bytes (MiB)}$
Giga	$Gflop/s = 10^9 \text{ flop/sec}$	$Gbyte = 10^9 \sim 2^{30} \text{ bytes (GiB)}$
Tera	$Tflop/s = 10^{12} \text{ flop/sec}$	$Tbyte = 10^{12} \sim 2^{40} \text{ bytes (TiB)}$
Peta	$Pflop/s = 10^{15} \text{ flop/sec}$	$Pbyte = 10^{15} \sim 2^{50} \text{ bytes (PiB)}$
Exa	$Eflop/s = 10^{18} \text{ flop/sec}$	$Ebyte = 10^{18} \sim 2^{60} \text{ bytes (EiB)}$
Zetta	$Zflop/s = 10^{21} \text{ flop/sec}$	$Zbyte = 10^{21} \sim 2^{70} \text{ bytes (ZiB)}$
Yotta	$Yflop/s = 10^{24} \text{ flop/sec}$	$Ybyte = 10^{24} \sim 2^{80} \text{ bytes (YiB)}$

- Current fastest (public) machines are petaflop systems
 - Up-to-date list at www.top500.org

The TOP500 Project

- Listing the 500 most powerful computers in the world
- Yardstick: Rmax of Linpack
 - Solve $Ax=b$, Matrix A is dense with random entries
 - 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 TOP12 of the Top500, November 2018



#	Site	Manufacturer	Computer	Country	Cores	Rmax [Pflops]	Power [MW]
1	Oak Ridge National Laboratory	IBM	Summit IBM Power System, P9 22C 3.07GHz, Mellanox EDR, NVIDIA GV100	USA	2,397,824	143.5	9.8
2	Lawrence Livermore National Laboratory	IBM	Sierra IBM Power System, P9 22C 3.1GHz, Mellanox EDR, NVIDIA GV100	USA	1,572,480	94.6	7.4
3	National Supercomputing Center in Wuxi	NRCPC	Sunway TaihuLight NRCPC Sunway SW26010, 260C 1.45GHz	China	10,649,600	93.0	15.4
4	National University of Defense Technology	NUDT	Tianhe-2A ANUDT TH-IVB-FEP, Xeon 12C 2.2GHz, Matrix-2000	China	4,981,760	61.4	18.5
5	Swiss National Supercomputing Centre (CSCS)	Cray	Piz Daint Cray XC50, Xeon E5 12C 2.6GHz, Aries, NVIDIA Tesla P100	Switzerland	387,872	21.23	2.38
6	Los Alamos NL / Sandia NL	Cray	Trinity Cray XC40, Intel Xeon Phi 7250 68C 1.4GHz, Aries	USA	979,072	20.16	7.58
7	National Institute of Advanced Industrial Science and Technology	Fujitsu	AI Bridging Cloud Infrastructure (ABCi) PRIMERGY CX2550 M4, Xeon Gold 20C 2.4GHz, IB-EDR, NVIDIA V100	Japan	391,680	19.9	1.65
8	Leibniz Rechenzentrum	Lenovo	SuperMUC-NG ThinkSystem SD530, Xeon Platinum 8174 24C 3.1GHz, Intel Omni-Path	Germany	305,856	19.5	
9	Oak Ridge National Laboratory	Cray	Titan Cray XK7, Opteron 16C 2.2GHz, Gemini, NVIDIA K20x	USA	560,640	17.6	8.21
10	Lawrence Livermore National Laboratory	IBM	Sequoia BlueGene/Q, Power BQC 16C 1.6GHz, Custom	USA	1,572,864	17.2	7.89
11	Lawrence Livermore National Laboratory	IBM	Lassen Cray XC40	USA	248,976	15.4	
12	Lawrence Berkeley National Laboratory / NERSC	Cray	Cori Cray XC40, Intel Xeons Phi 7250 68C 1.4 GHz, Aries	USA	622,336	14.0	3.94

System Performance

- Peak performance of 200 petaflops for modeling & simulation
- Peak of 3.3 ExaOps for data analytics and artificial intelligence

Each node has

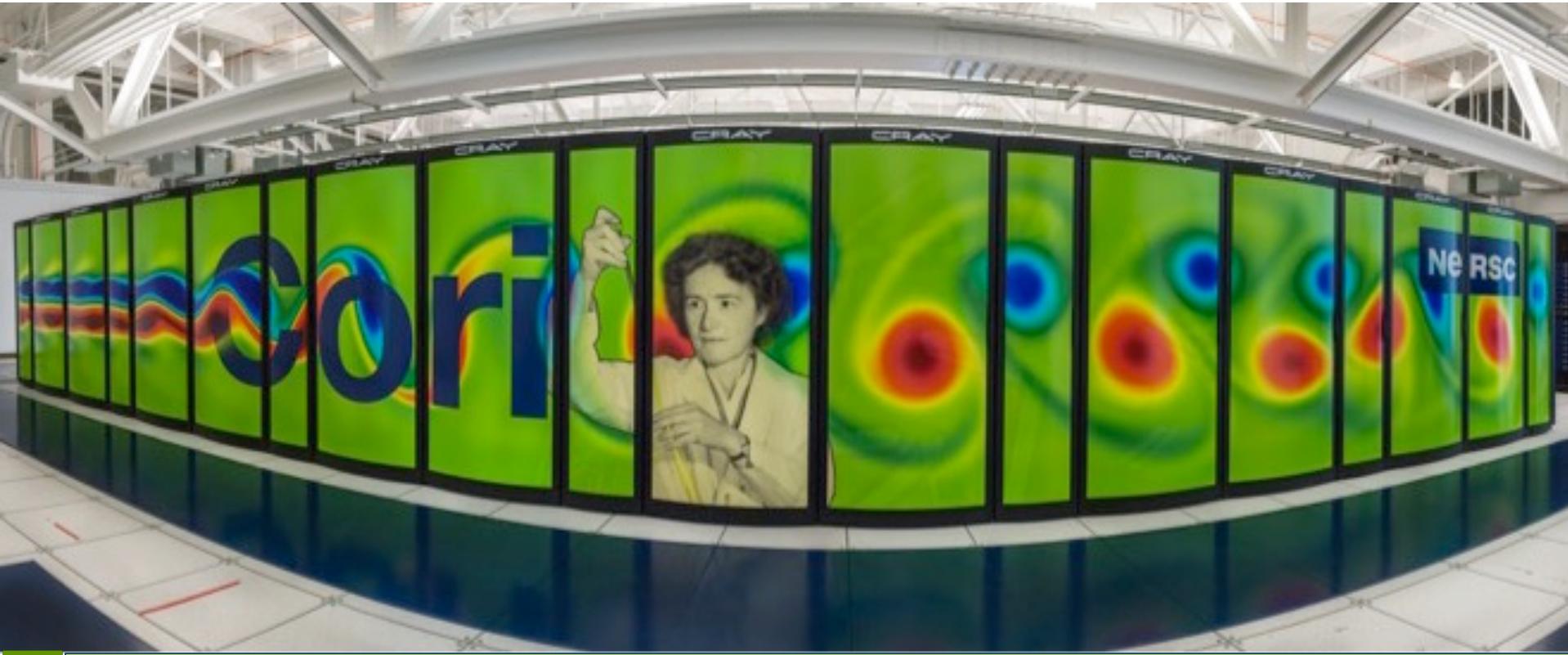
- 2 IBM POWER9 processors
- 6 NVIDIA Tesla V100 GPUs
- 608 GB of fast memory
- 1.6 TB of NVMe memory

The system includes

- 4608 nodes
- Dual-rail Mellanox EDR InfiniBand network
- 250 PB IBM Spectrum Scale file system transferring data at 2.5 TB/s



Cori at NERSC in Berkeley, CA

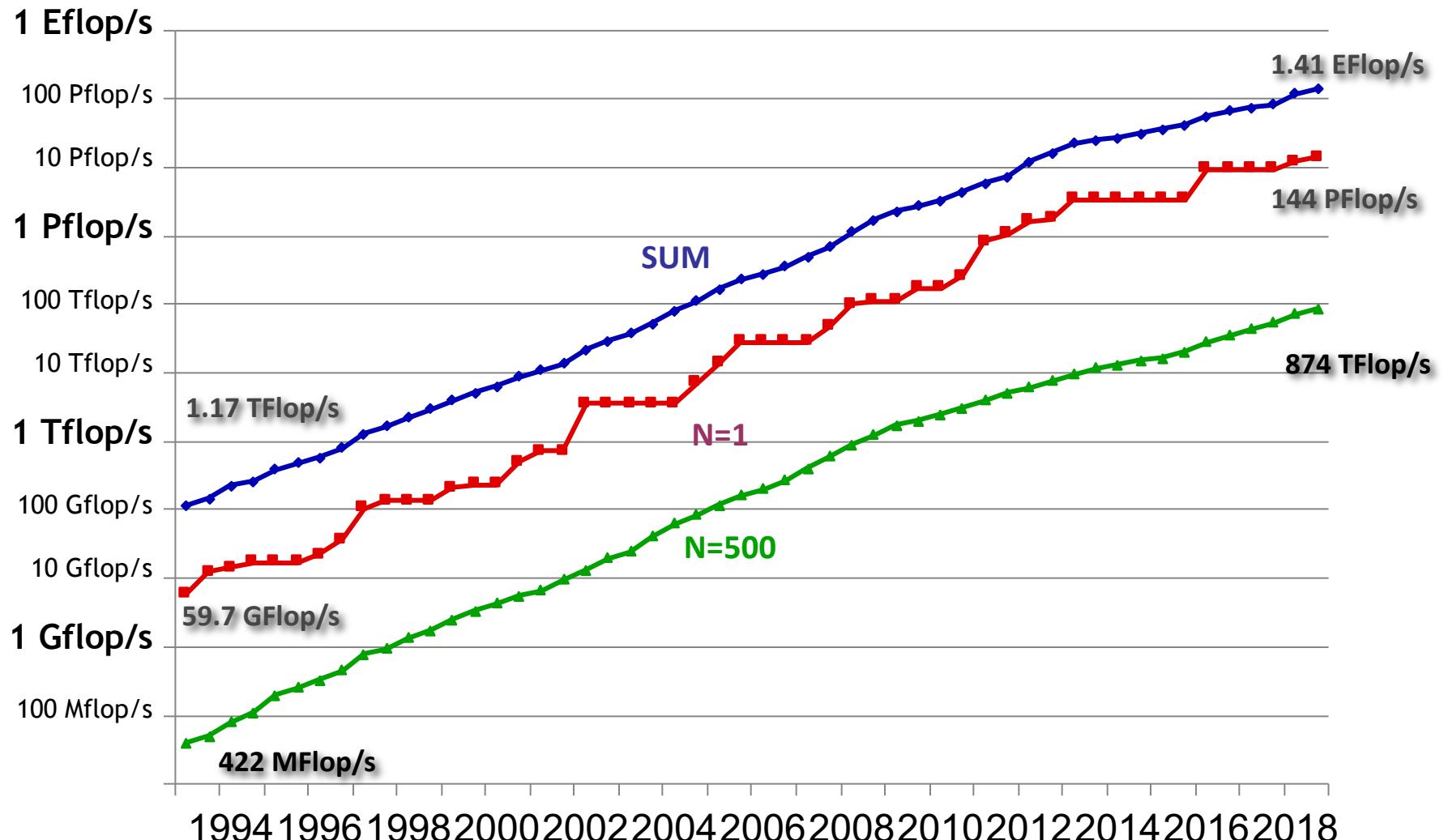


Phase 1

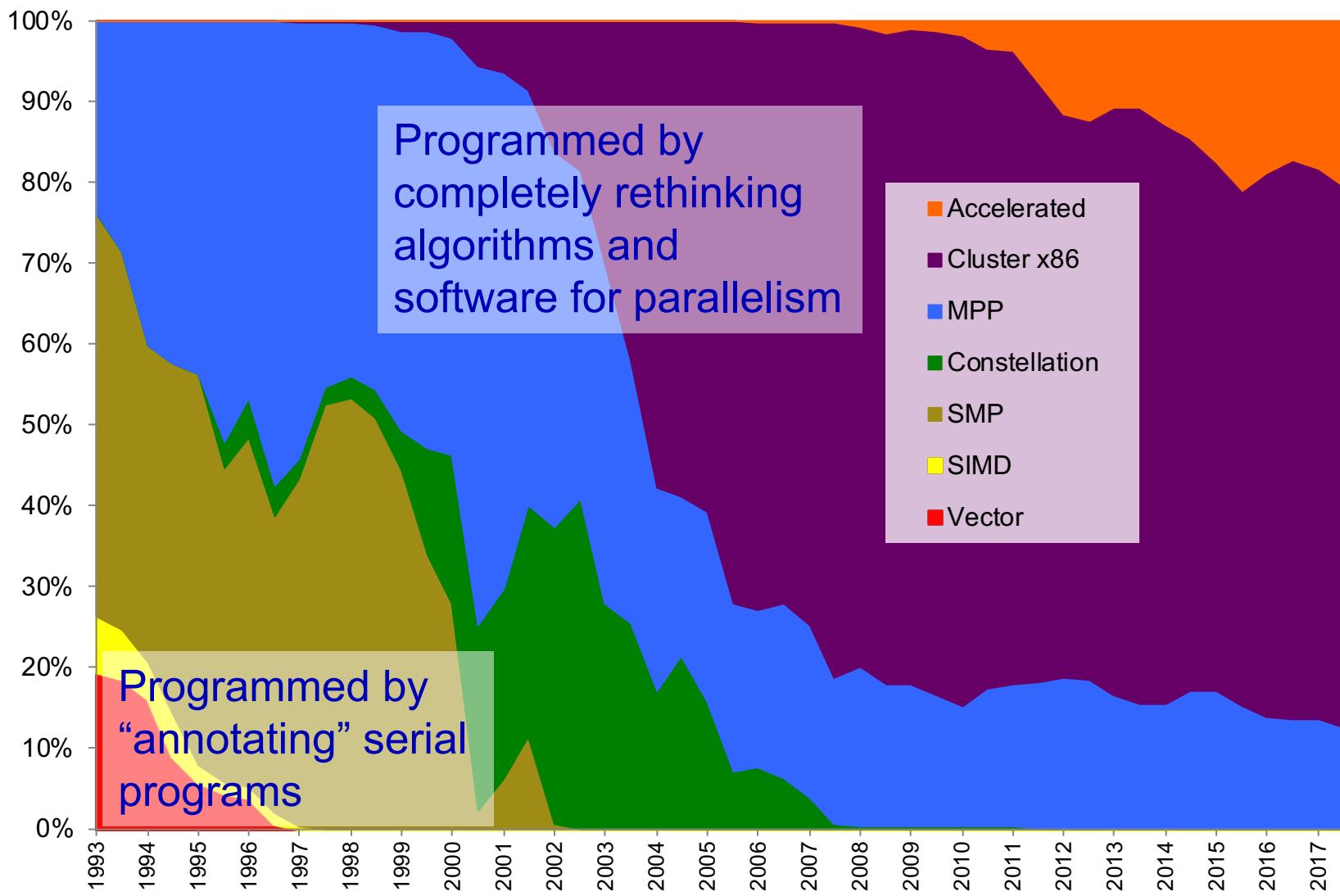
Peak: 2.8 PFlop/s	Proc: 3800 Haswell (ph 1)	Memory:	0.3 PB
	Cores: 2.3 GHz, 16/proc	Storage:	shared
	Proc Peak: 0.6 TFlop/s		

Peak: 28PFlop/s	Processor: 9300 KNL	Memory:	1.31 PB
LinPack: 14 Pflops/s	Cores: 1.4 GHz, 68/proc	MemBW:	1 PB/s HBM,DDR
Power: 4 MW	Node Peak: 3 TFlop/s	Storage:	28 PB

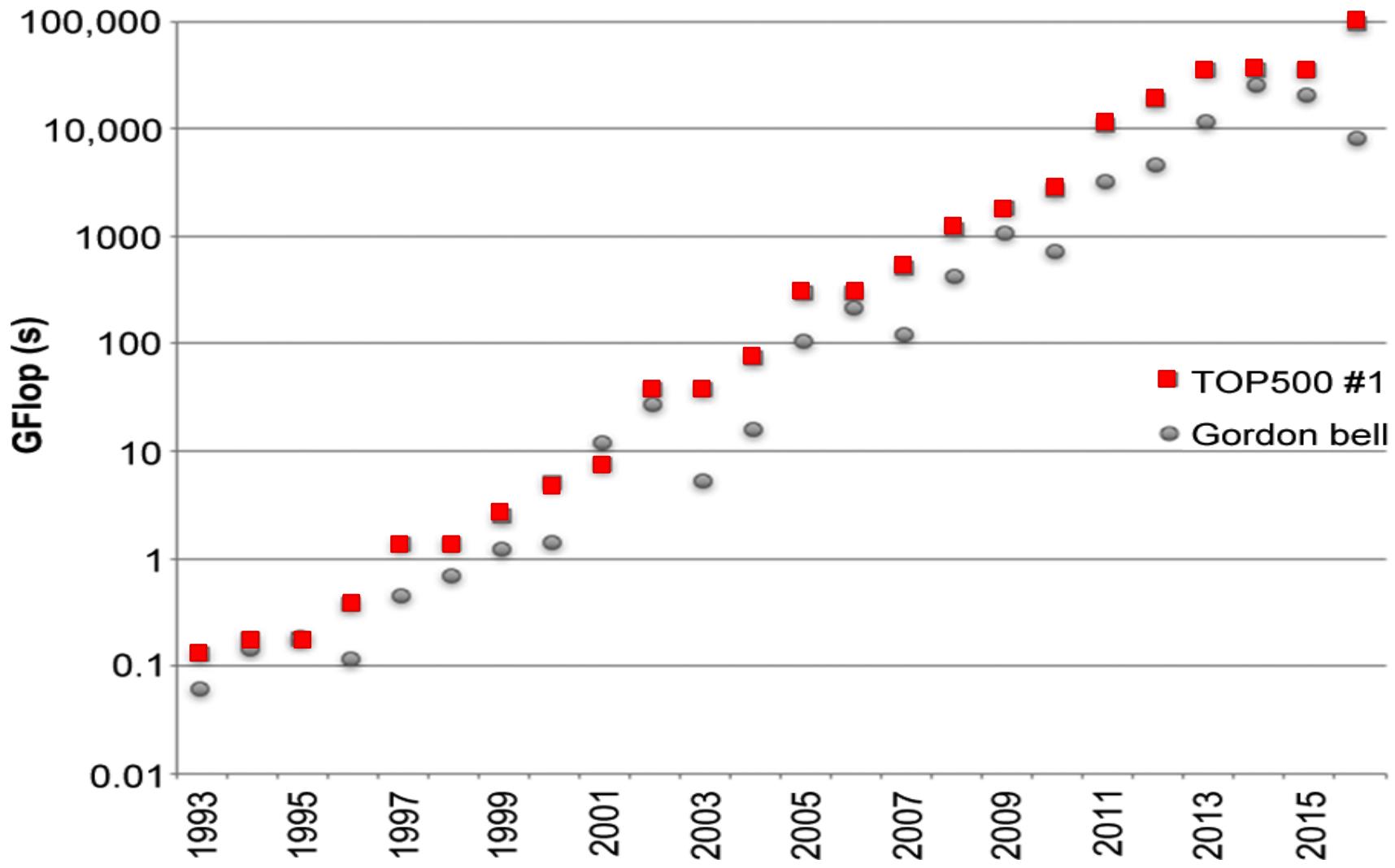
Performance Development (2018)



From Vector Supercomputers to Massively Parallel Accelerator Systems



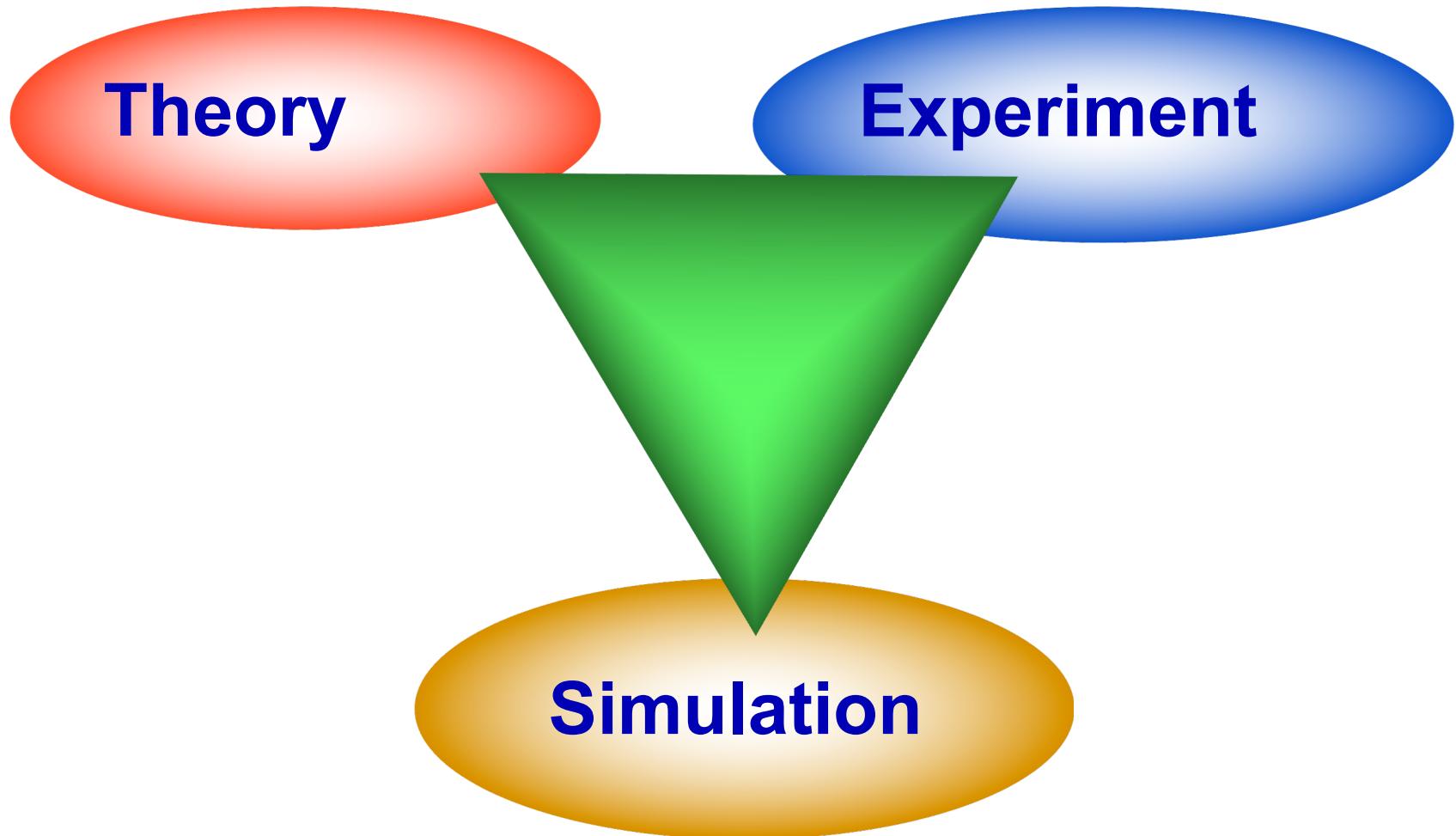
Science: Gordon Bell Prizes vs Top 500



Science using High Performance Computing

Today and tomorrow, mostly from the
DOE Exascale Project

The “Third Pillar” of Science

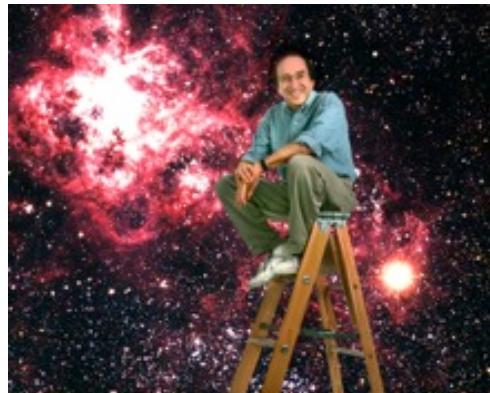


Simulation in Science and Engineering

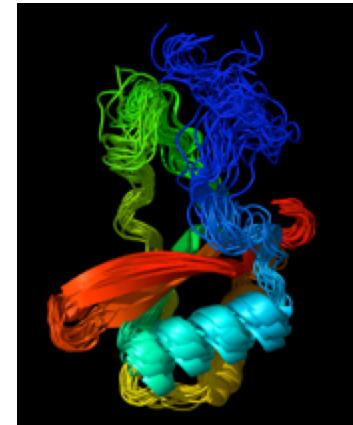
High performance computing (HPC) simulation to understand things that are:

- too big
- too small
- too fast
- too slow
- too expensive or
- too dangerous

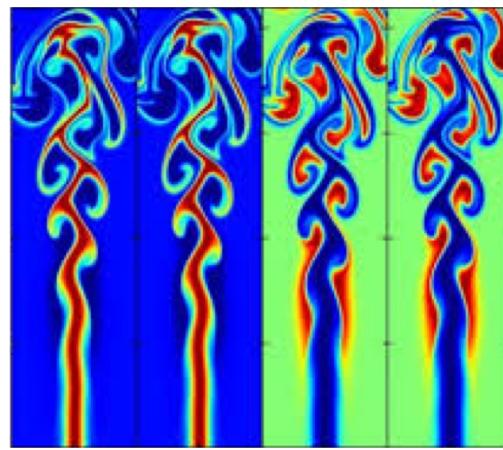
for experiments



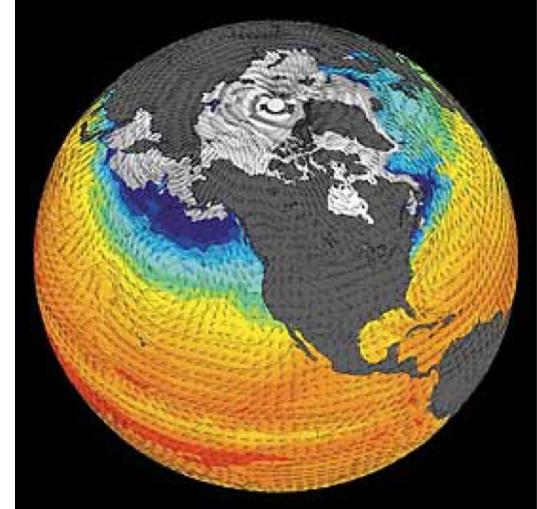
Understanding the universe



Proteins and diseases

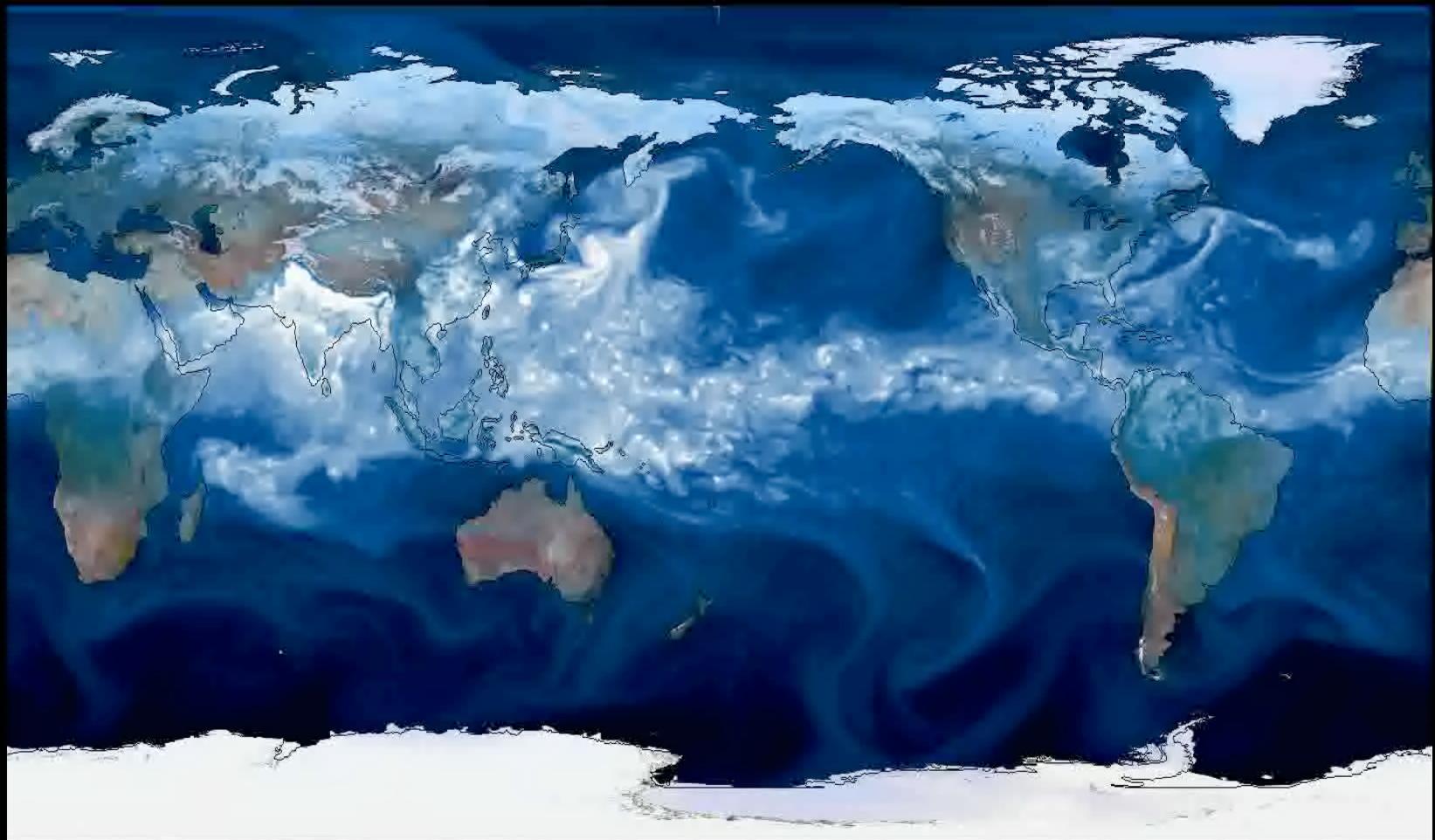


Energy-efficient jet engines



Climate change

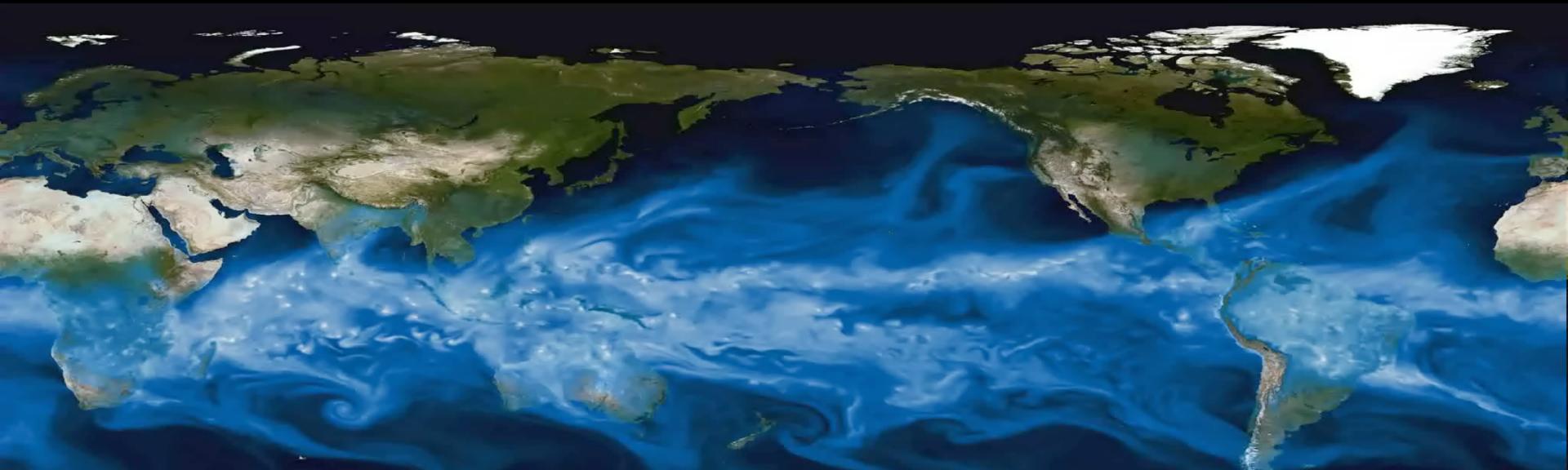
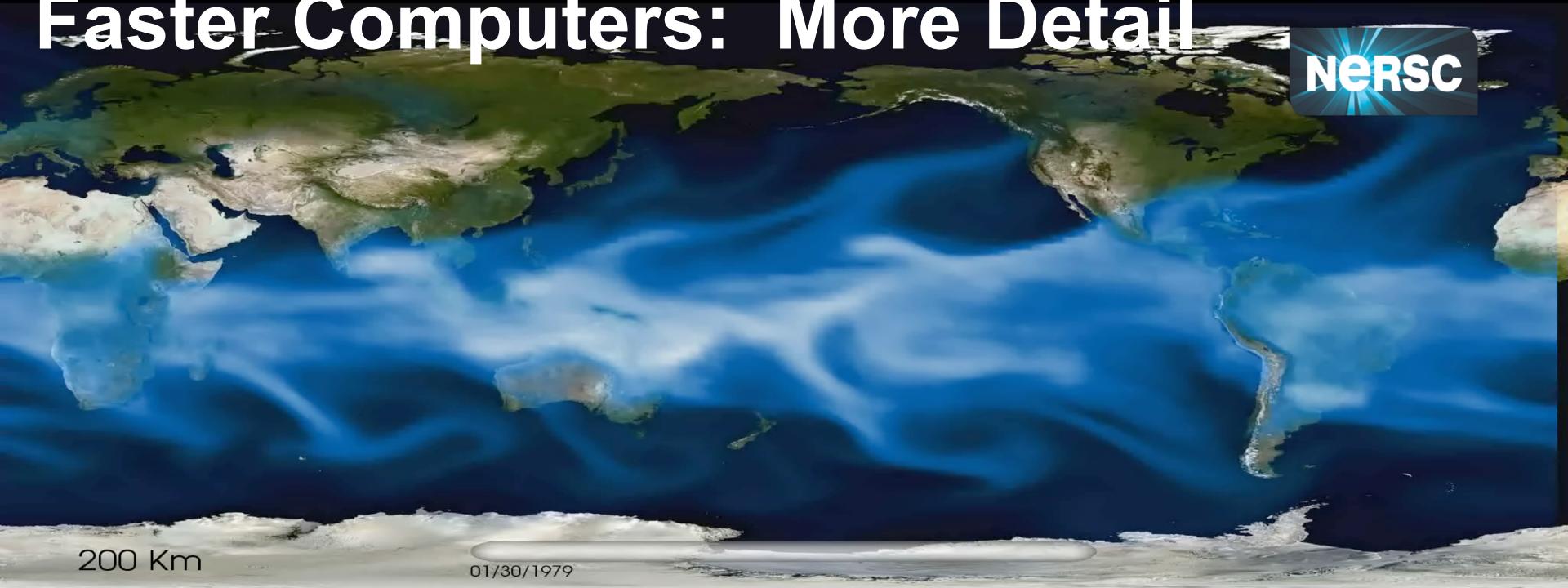
Simulations Show the Effects of Climate Change in Hurricanes



Michael Wehner and Prabhat, Berkeley Lab

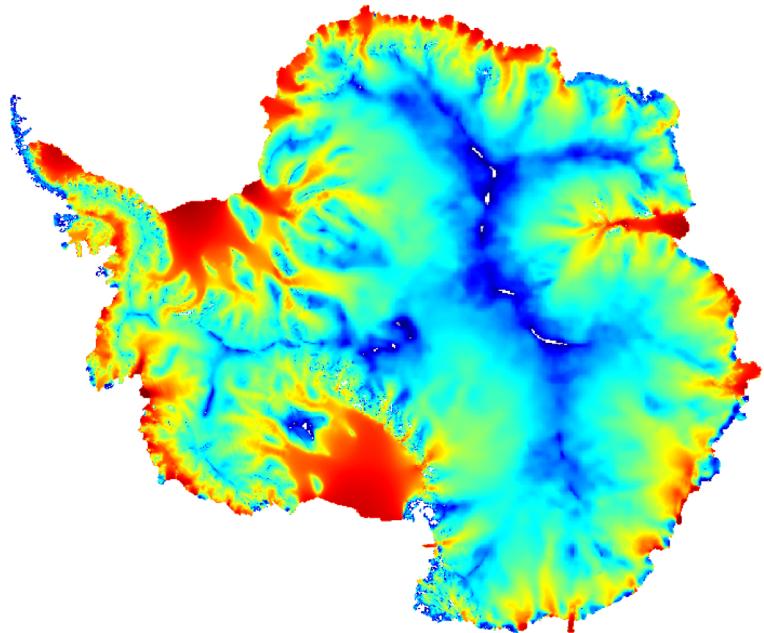
Easter Computers: More Detail

NERSC



Michael Wehner, Prabhat, Chris Algieri, Fuyu Li, Bill Collins, Lawrence Berkeley National Laboratory; Kevin Reed, University of Michigan; Andrew Gettelman, Julio Bacmeister, Richard Neale, National Center for Atmospheric Research

Extreme Scale Climate Science



*Melting of West Antarctic Ice Sheet
using Adaptive Mesh Refinement (AMR)
Dan Martin, LBNL (BISICLES/E3SM)*

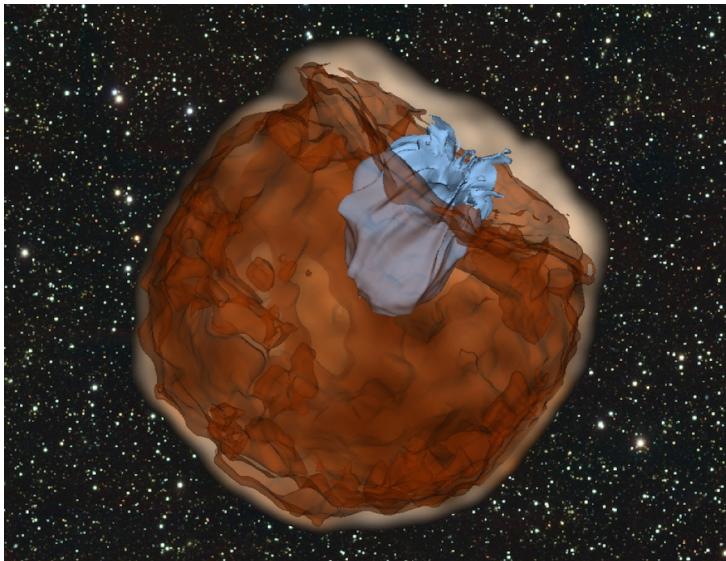


*Mathematical model for clouds
David Romps et al, UCB*

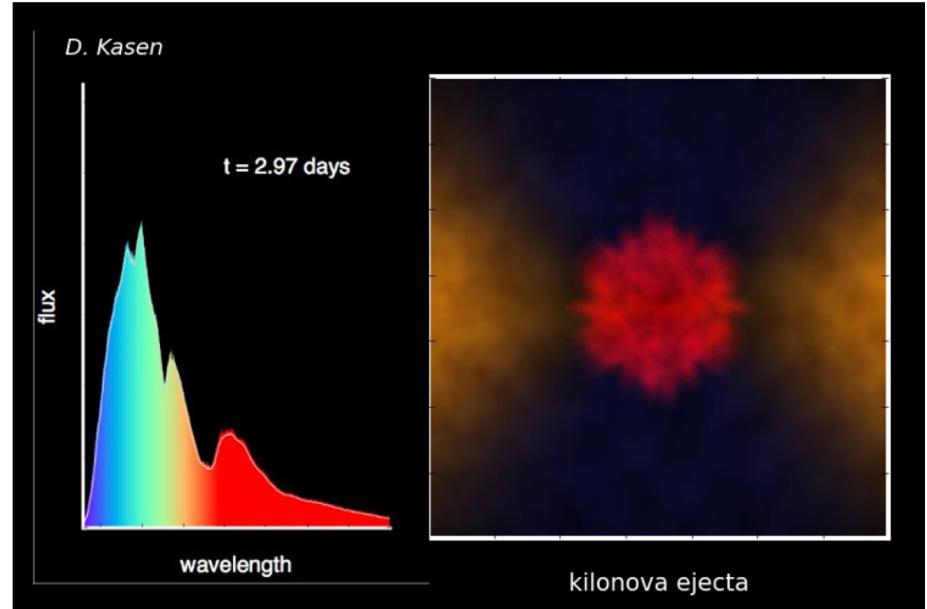
Exascale is needed to simulate climate and analyze impacts

Resolve clouds, predict sea level rise, quantify extreme events and model precipitation and ground water levels

Extreme Scale Astrophysics (Dan Kasen, LBNL/UCB)



Expanding debris from a supernova explosion (red) running over and shredding a nearby star (blue)

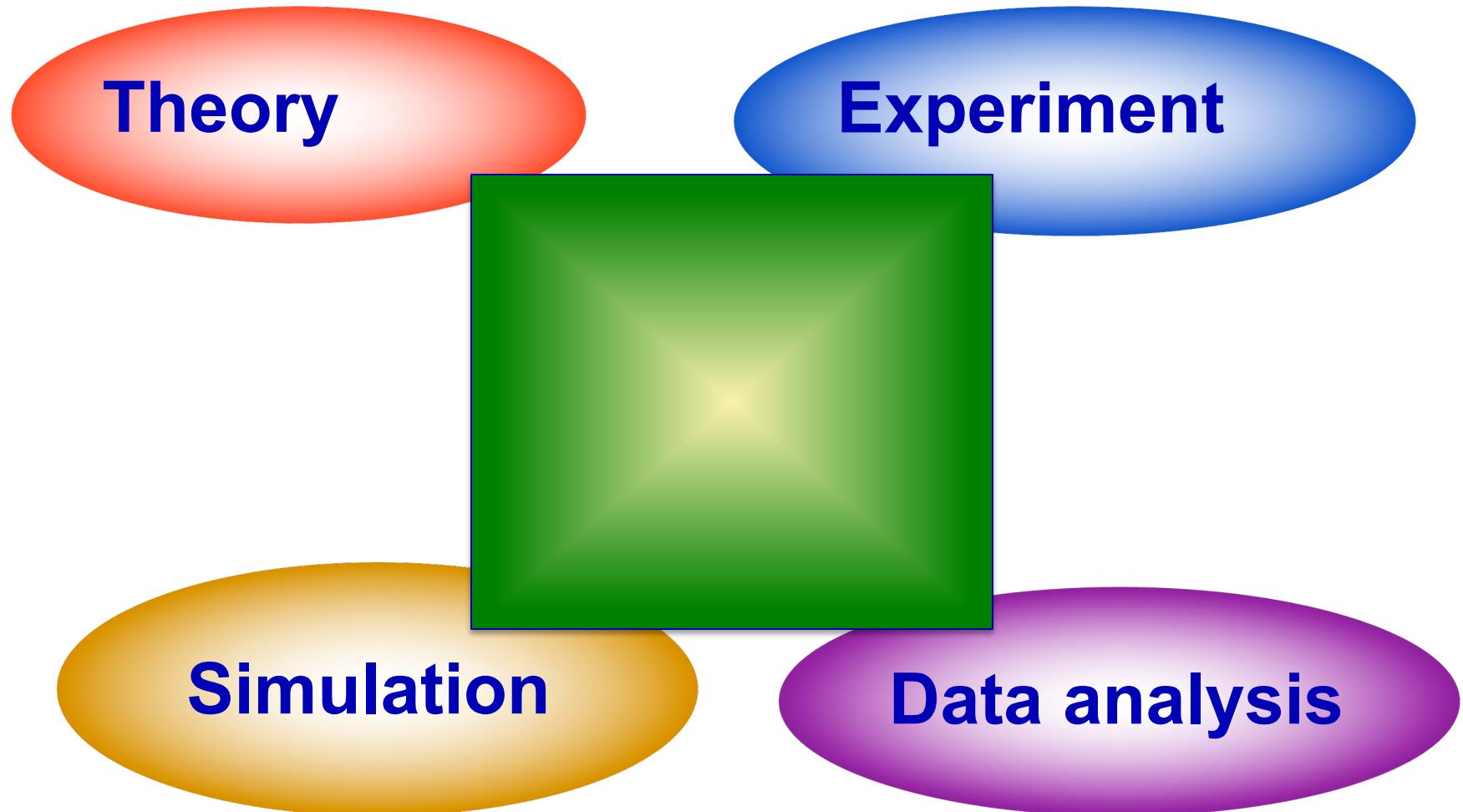


Ligo and Virgo observations match earlier simulations of gravitational waves from neutron star merger. Simulations predict ~200 earth masses of gold; ~500 of platinum

Exascale is needed to identify the source of the heaviest elements

Understand rapid neutron capture process (r-process) by simulating scenarios: core-collapse supernovae, neutron star mergers, and accreting black holes

The Fourth Paradigm of Science



Data analytics in science and engineering

High Performance Data Analytics (HPDA) is used for data sets that are:

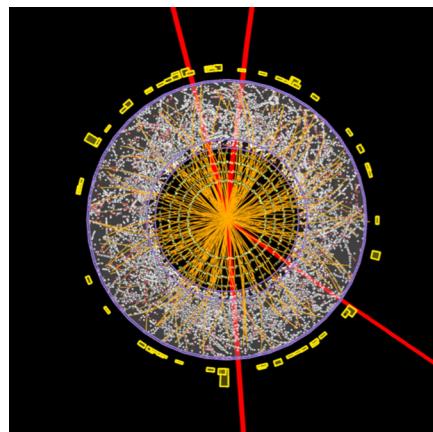
- too big
- too complex
- too fast (streaming)
- too noisy
- too heterogeneous for measurement alone



Images from telescopes



Genomes from sequencers

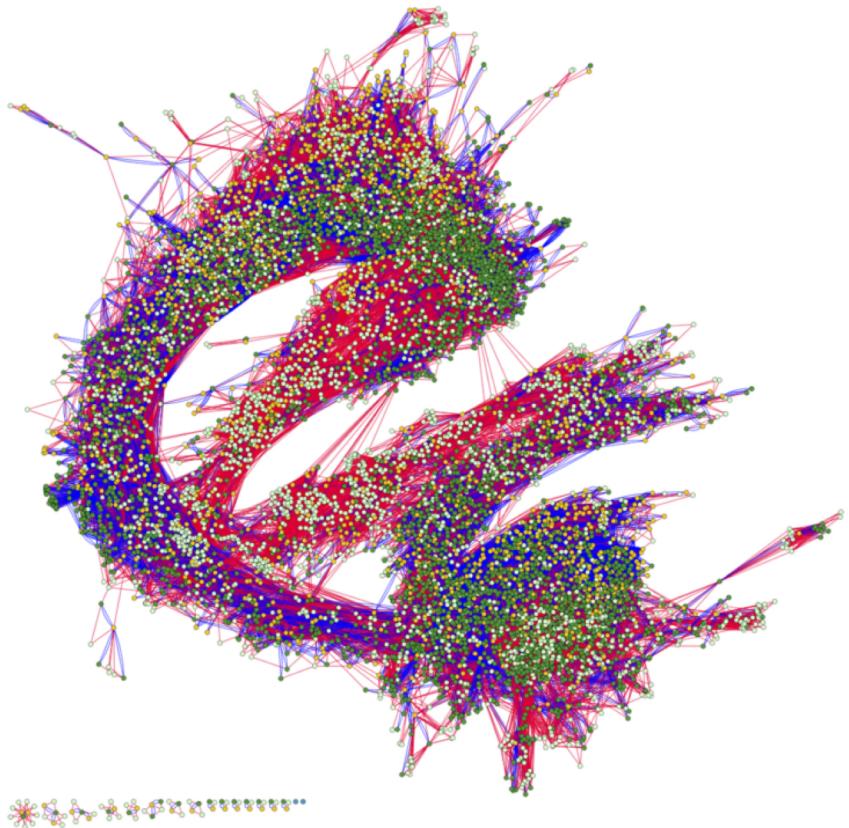


Particle from detectors



Sensor data

Analysis of Genomic Data



Dark green nodes: Kalanchoë genes

Yellow nodes: pineapple genes

Light green: model plant that uses a different photosynthesis strategy.

Blue edges: positive correlations

Red edges show negative correlations a

- Correlations of gene expression in plants that use different photosynthesis strategies.

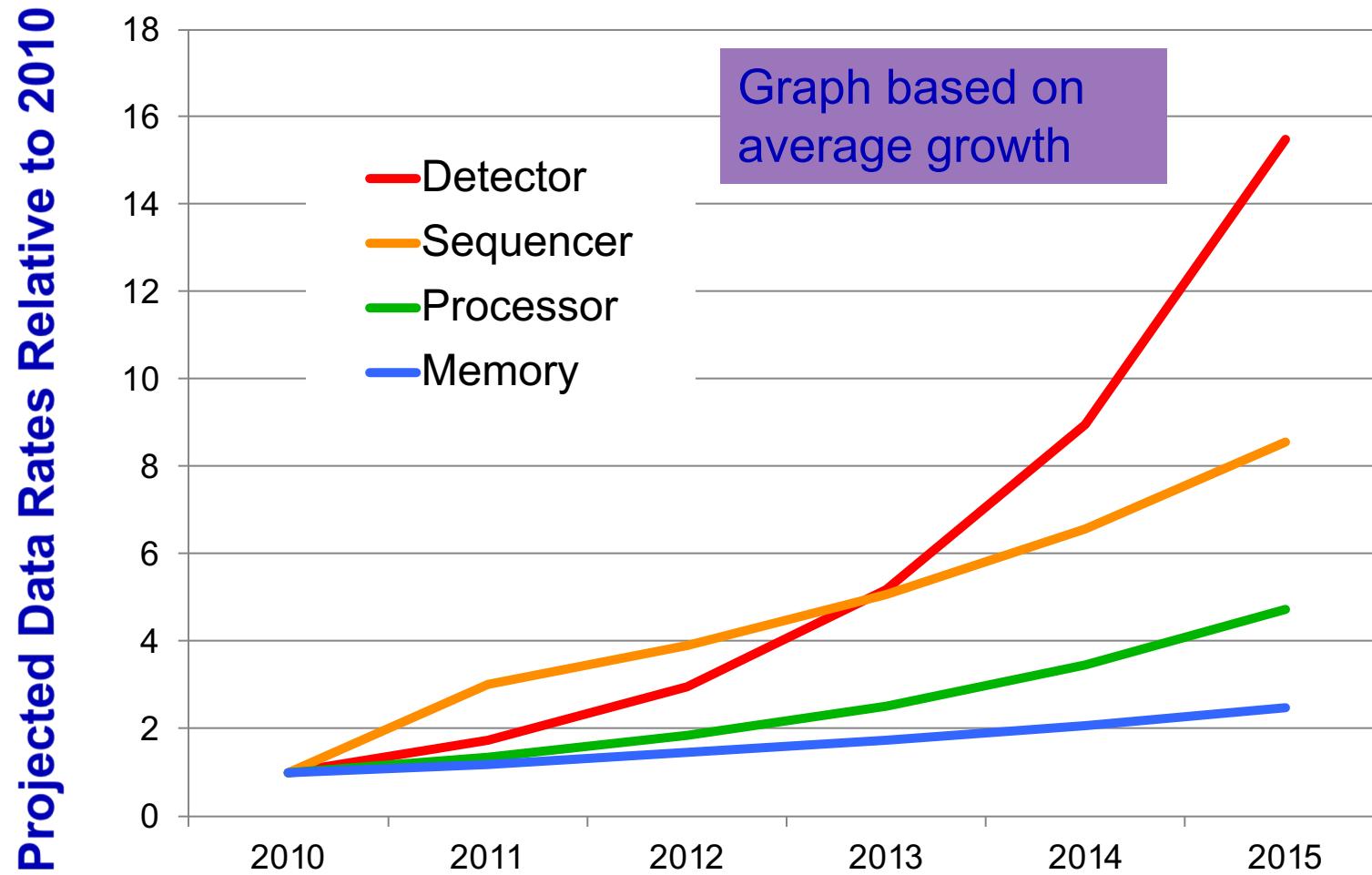
- Kalanhoë and pineapple both use water-sparing photosynthesis

- 2.36 exaops / second on Summit computer

- ($\text{exaop} = 10^{18}$ 16-bit ops)

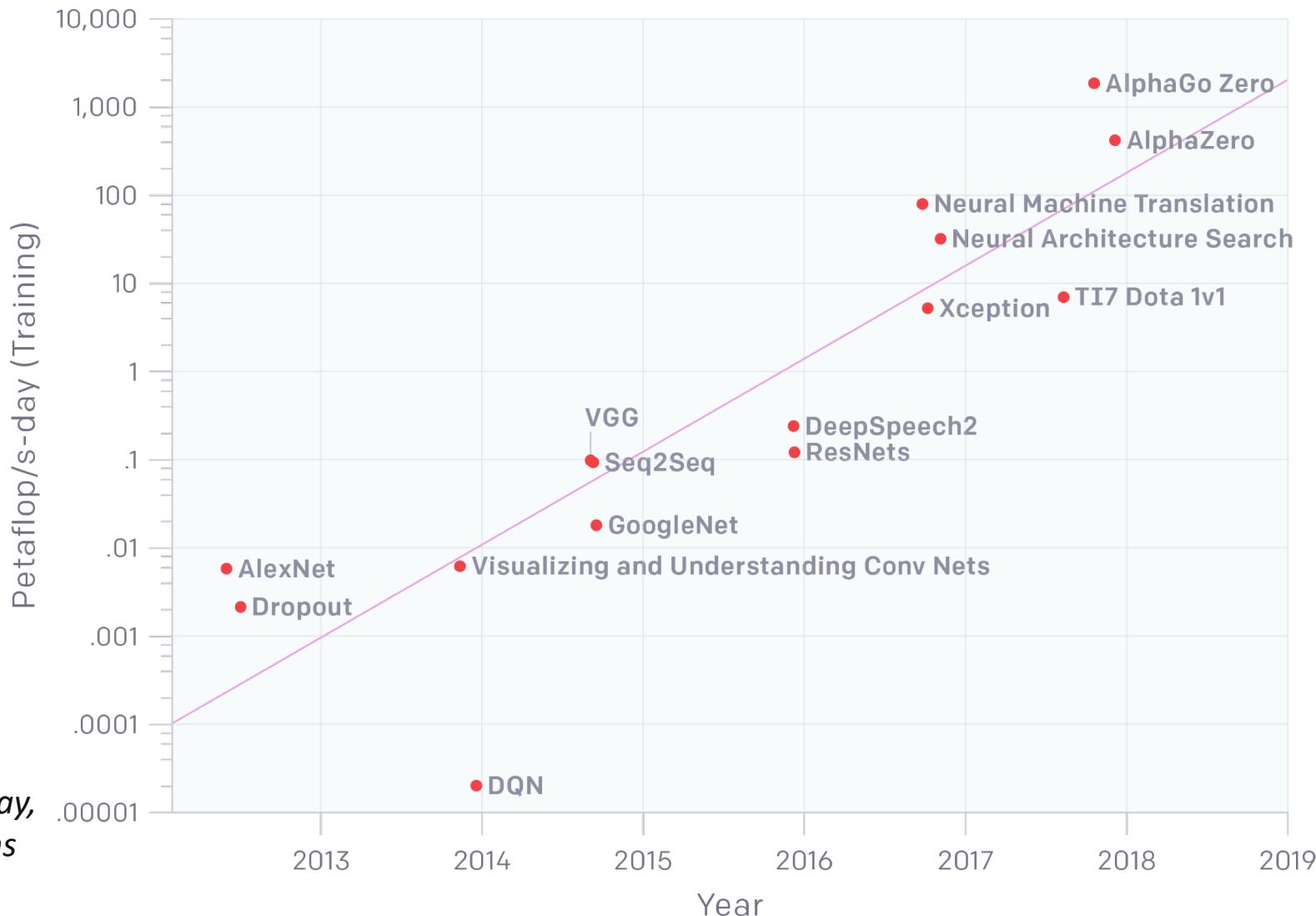
Wayne Joubert, Dan Jacobson
et al, Gordon Bell Prize (1 of 2) 25
at SC18

Data Growth is Outpacing Computing Growth



Growth of Computing in Machine Learning

AlexNet to AlphaGo Zero: A 300,000x Increase in Compute



Machine Learning in Climate Data

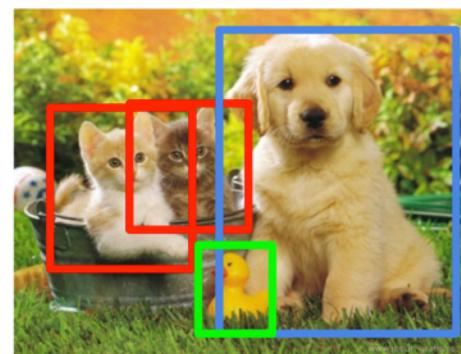
Classification



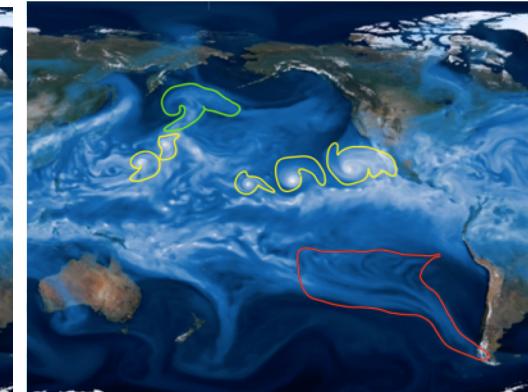
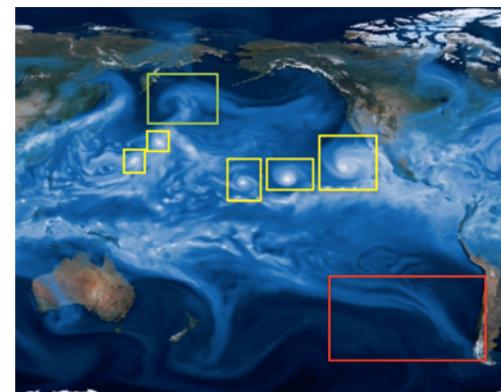
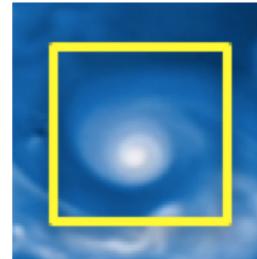
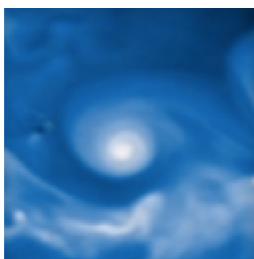
Classification + Localization



Object Detection

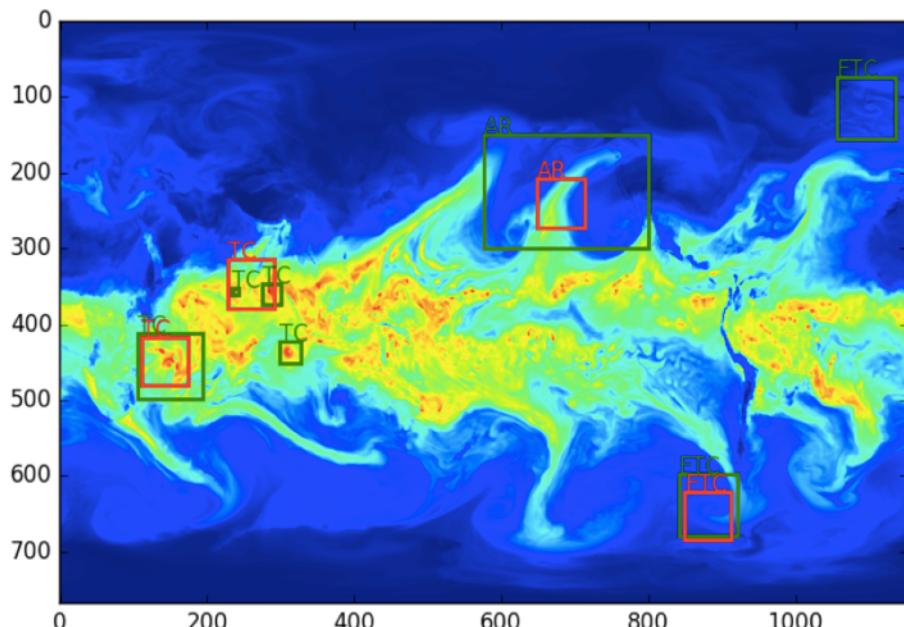


Instance Segmentation

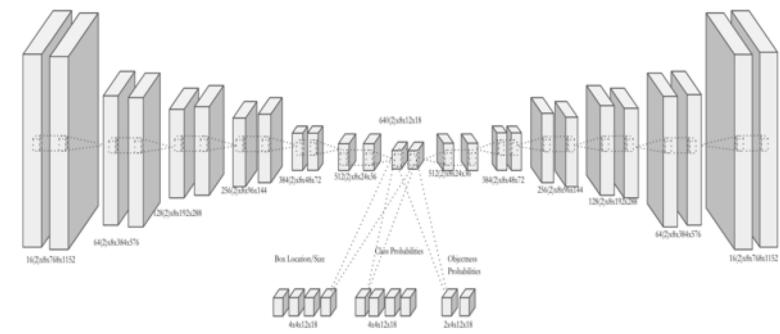


Contributors: Prabhat, Thorsten Kurth, Jian Yang, Ioannis Mitliagkas, Chris Pal, Nadathur Satish, Narayanan Sundaram, Amir Khosrowshahi, Michael Wehner, Bill Collins.

Deep Learning for Extreme Weather Events



Ground Truth vs Prediction



Use of deep learning (CNNs)

- Supervised and semi-supervised learning on CAM5 data
- 85-99% accuracy at identifying extreme climate events
- 1 ExaOp (16-bit) on Summit at ORNL; trained in 100 minutes

Outline

- ✓ Some of the World's Fastest (Parallel) Computers
 - Top500 List highlights
- ✓ Why science needs high performance computing (HPC)
 - Simulation and data analysis
- Why high performance machines are parallel
 - Including your laptops and handhelds
- Performance from parallelism (and locality)
 - Measuring, understanding, and reporting performance
- About this course
 - Topics, structure and objectives

all (since 2005)

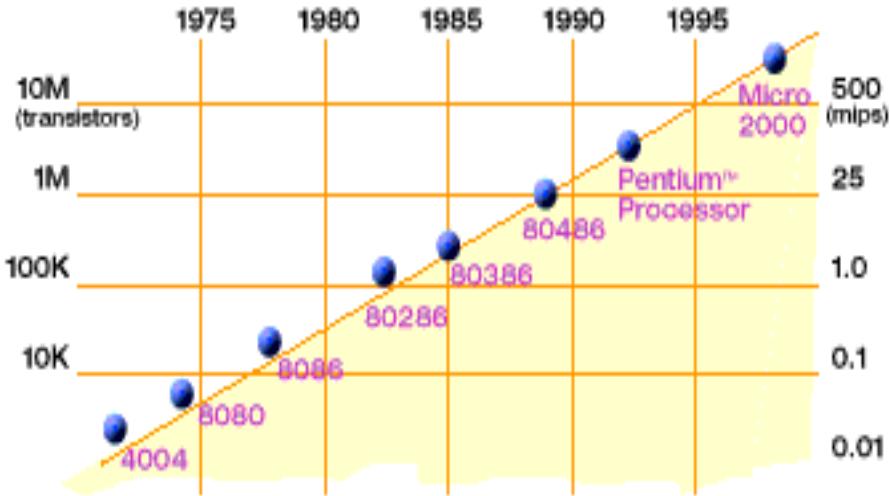
Why the ~~Fastest~~ Computers are Parallel Computers

Including laptops and handhelds

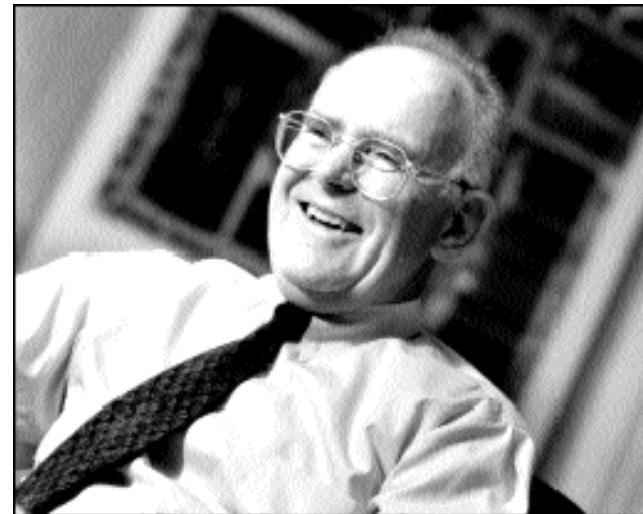
Tunnel Vision by Experts

- “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



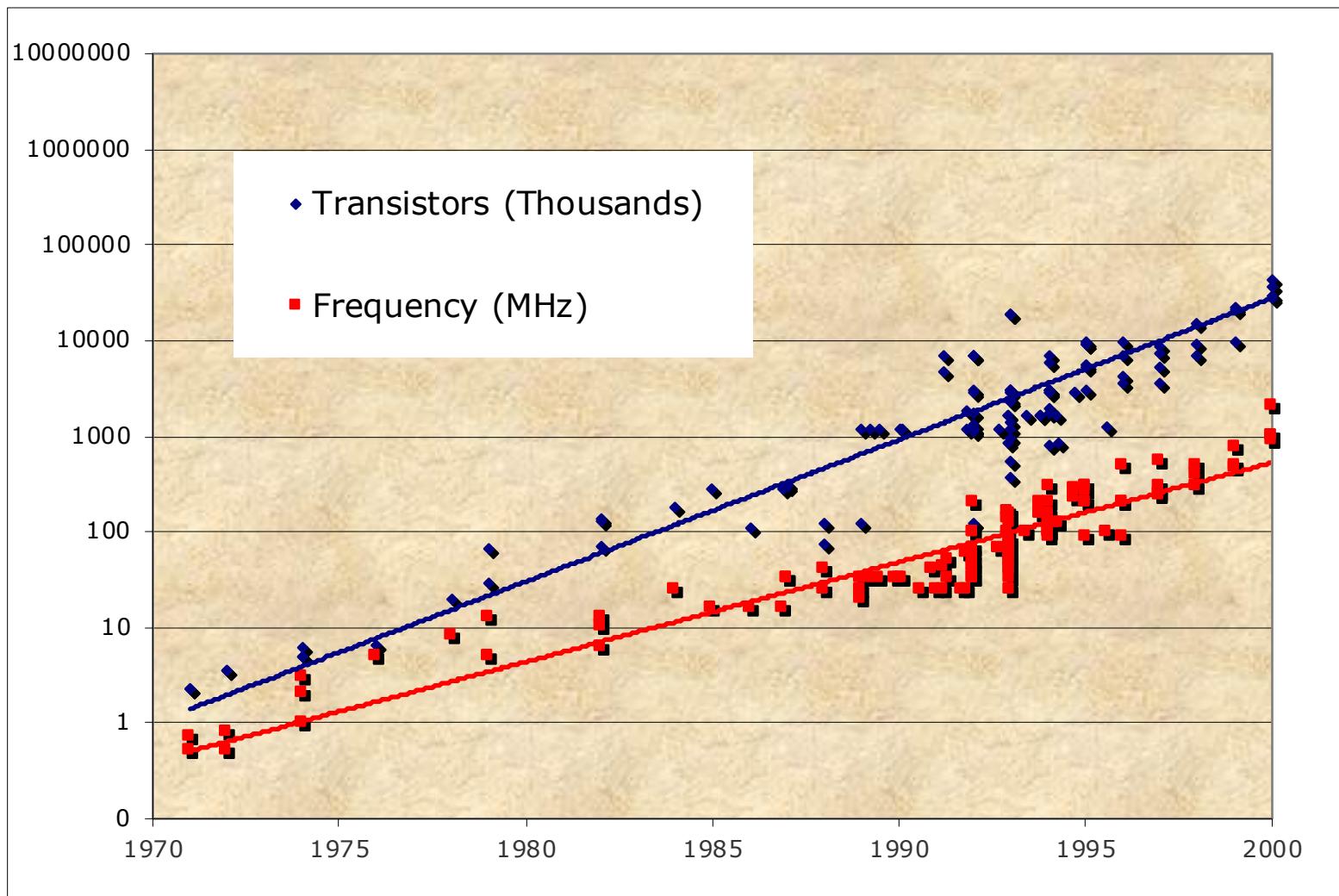
2X transistors/Chip Every 1.5 years
Called "Moore's Law"



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

Slide source: Jack Dongarra

Microprocessor Transistors / Clock (1970-2000)



Historical 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 has also increased
 - typically another factor of $\sim x$
- Raw computing power of the chip goes up by $\sim x^4$!
 - 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

Limits: How fast can a serial computer be?

1 Tflop/s, 1
Tbyte sequential
machine



$r = 0.3$
mm

- Consider the 1 Tflop/s sequential machine:
 - Data must travel some distance, r , to get from memory to processor.
 - To get 1 data element per cycle, this means 10^{12} times per second at the speed of light, $c = 3 \times 10^8$ m/s. Thus $r < c/10^{12} = 0.3$ mm.
- Now put 1 Tbyte of storage in a 0.3 mm x 0.3 mm area:
 - Each bit occupies about 1 square Angstrom, or the size of a small atom.
- No choice but parallelism

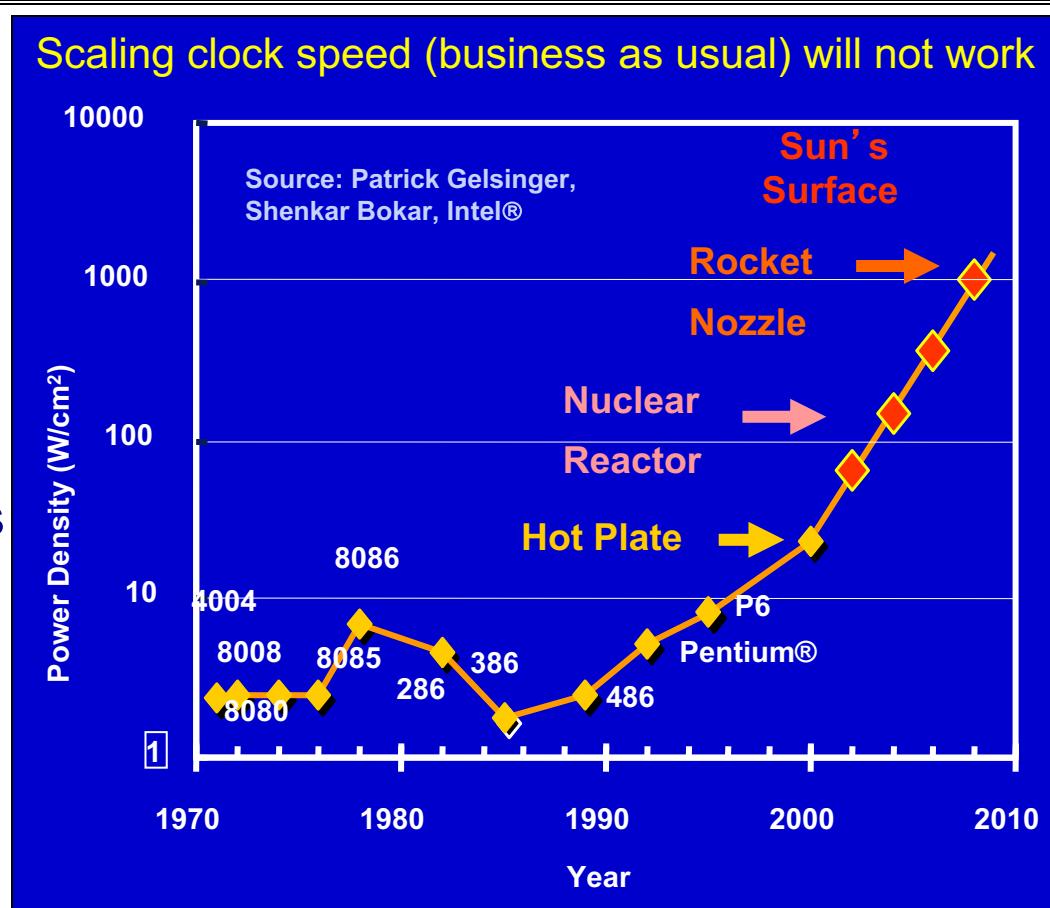
But What about Heat Density



SAM SPRATT - GIZMODO

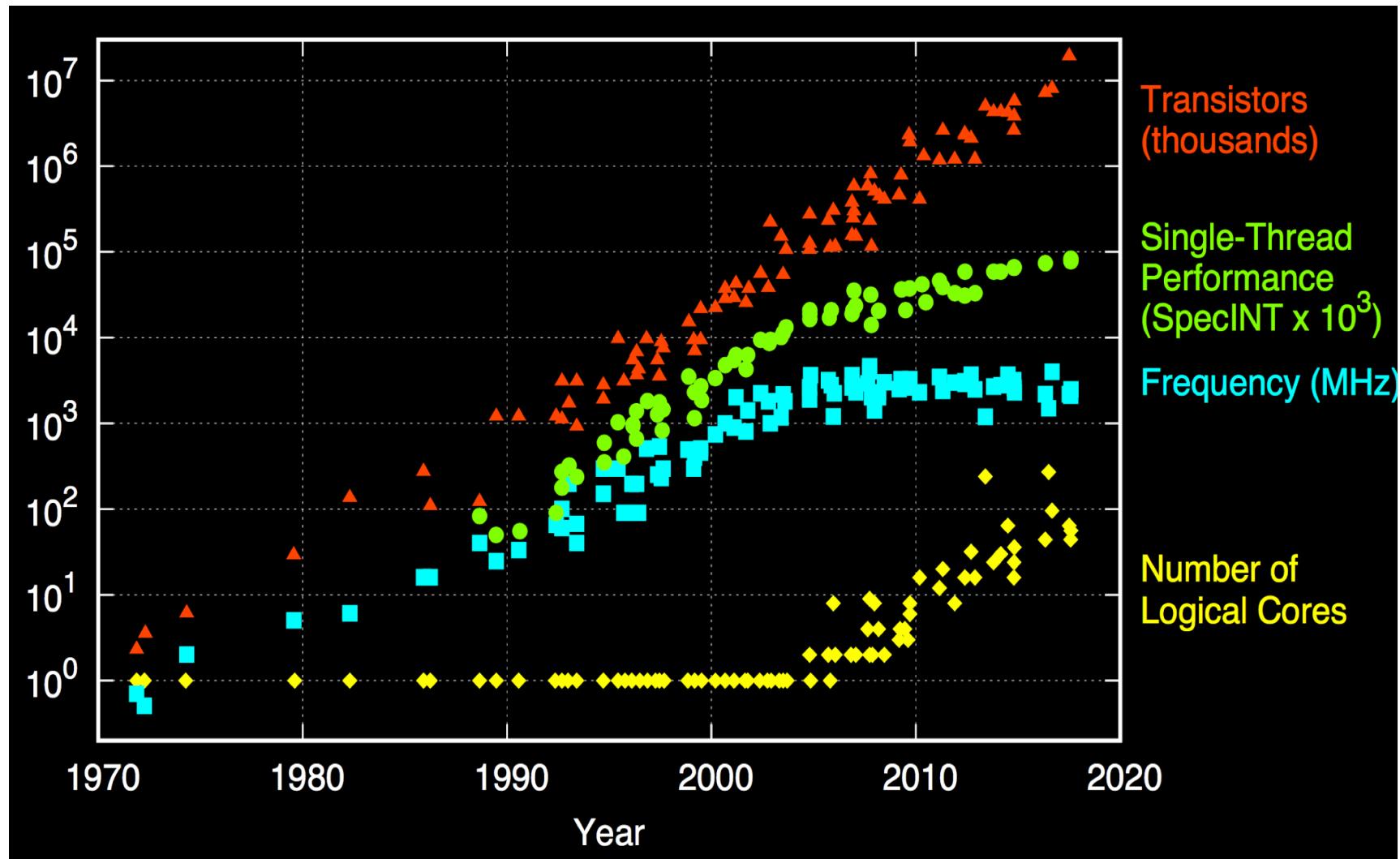
Power Density Limits Serial Performance

- 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

The Rest of the World Adopts Parallelism

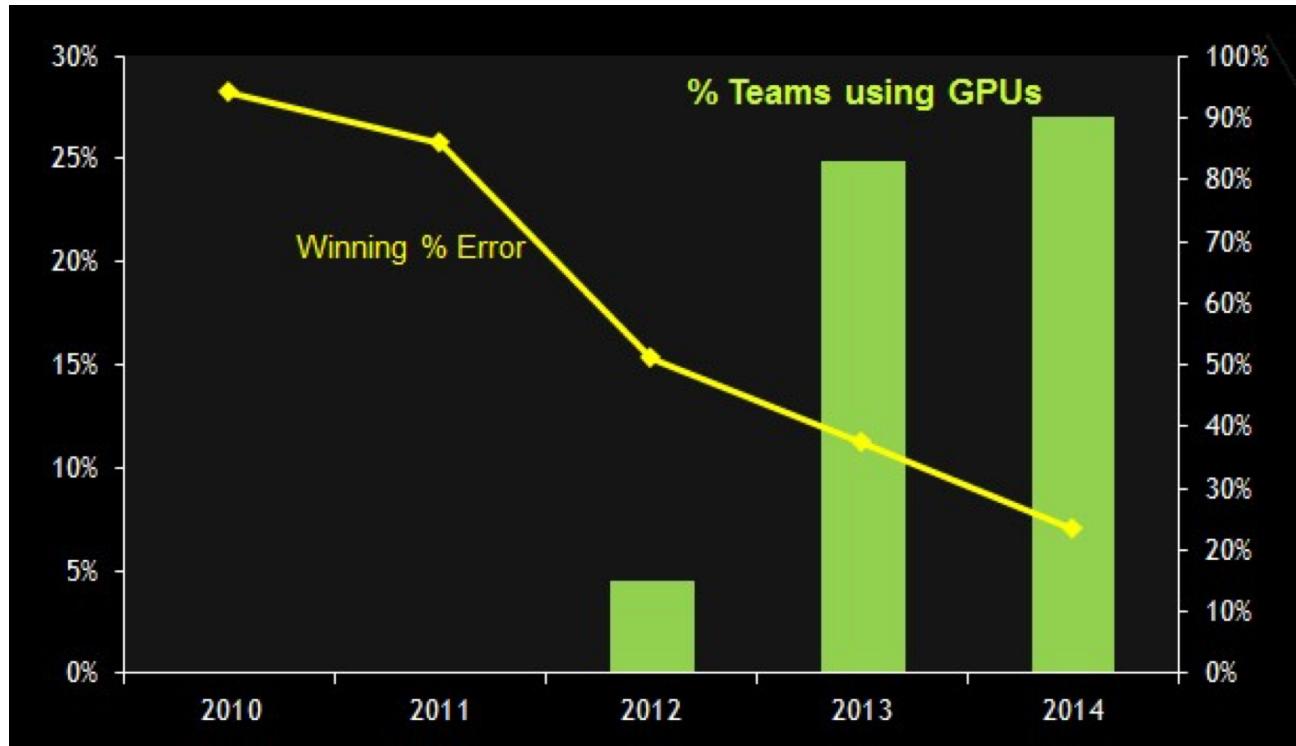


M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, C. Batten, and K. Rupp

Cores rather than clock frequency is doubling

Disruptions from commercial data analytics

ImageNet Large Scale Visual Recognition Challenge (image from NVIDIA)



In the second quarter of 2016, NVIDIA attributed nearly half its \$151 million in datacenter sales to GPUs intended for deep learning.

Applications in self-driving cars, etc.

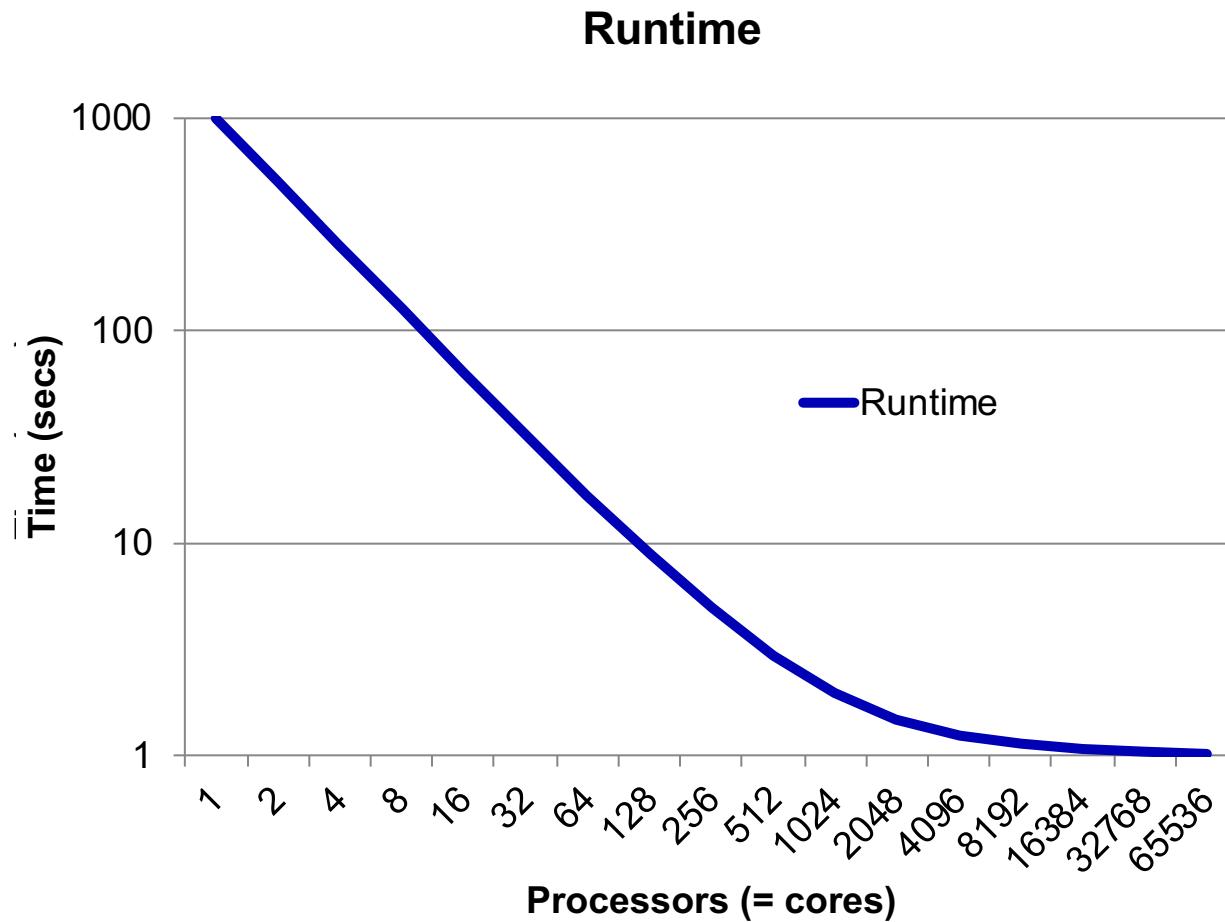
Moore's Law reinterpreted

- 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
- But Moore's Law is not forever... industry consortium predicts end in 2021

Measuring Performance

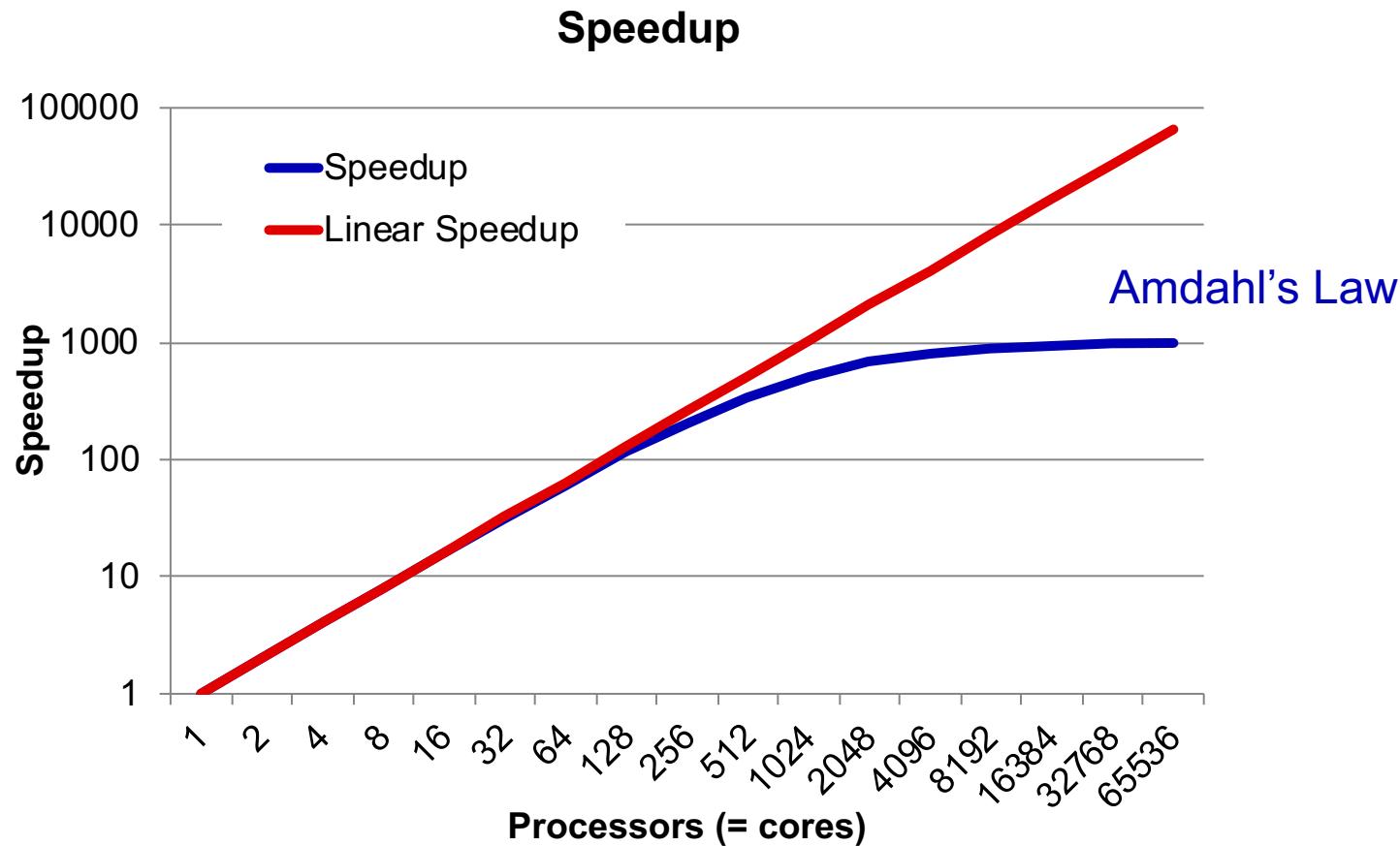
Tips, tricks, and cheats

Goal of Parallelism: Decrease Running Time



A bit better, but the point of this is to show the value of parallelism

Reporting Speedup (Strong Scaling)



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

This is a **strong scaling** plot: fixed problem size, vary number of processors

Amdahl's Law

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

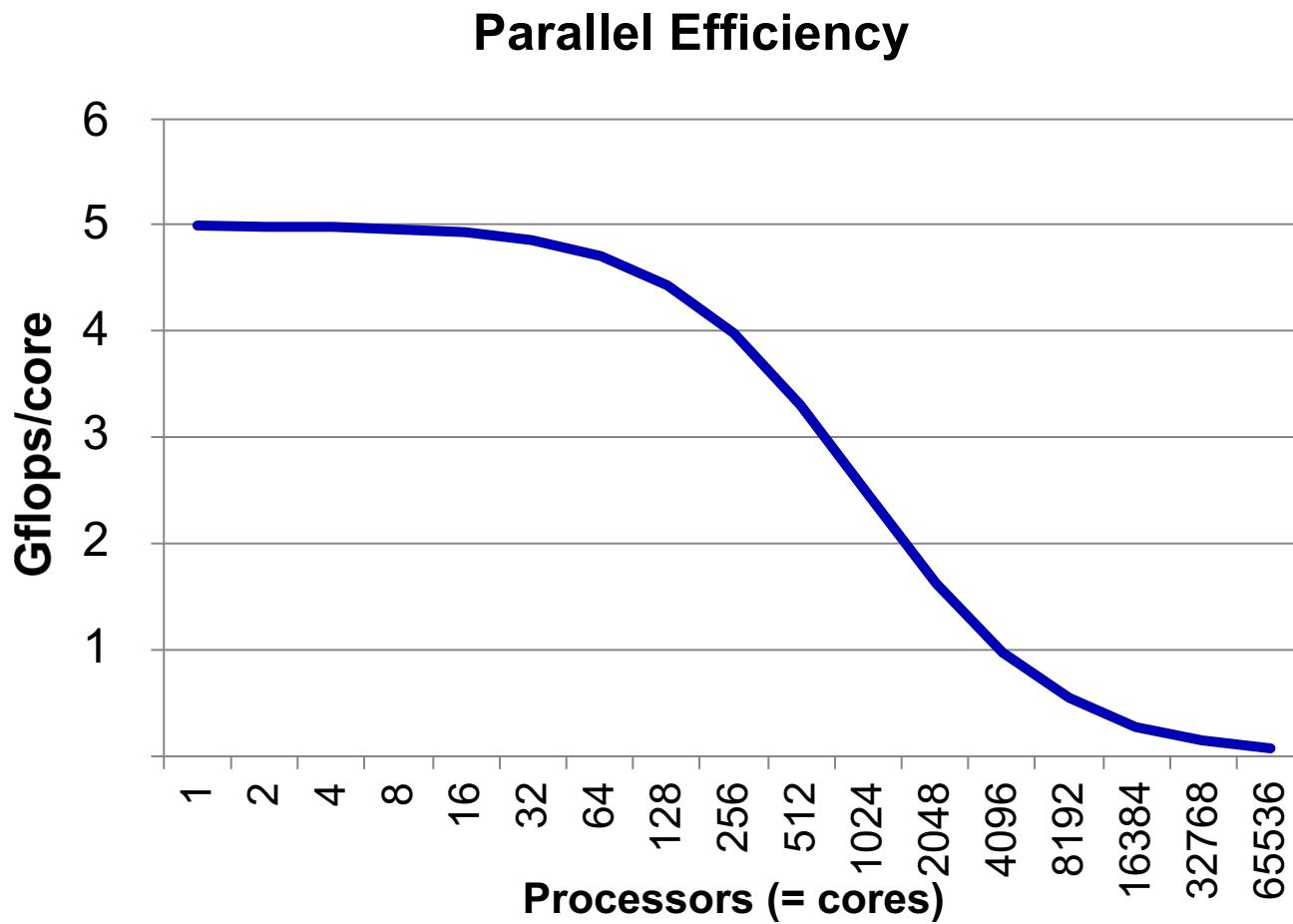
$$\text{Speedup}(P) = \text{Time}(1)/\text{Time}(P)$$

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

$$<= 1/s$$

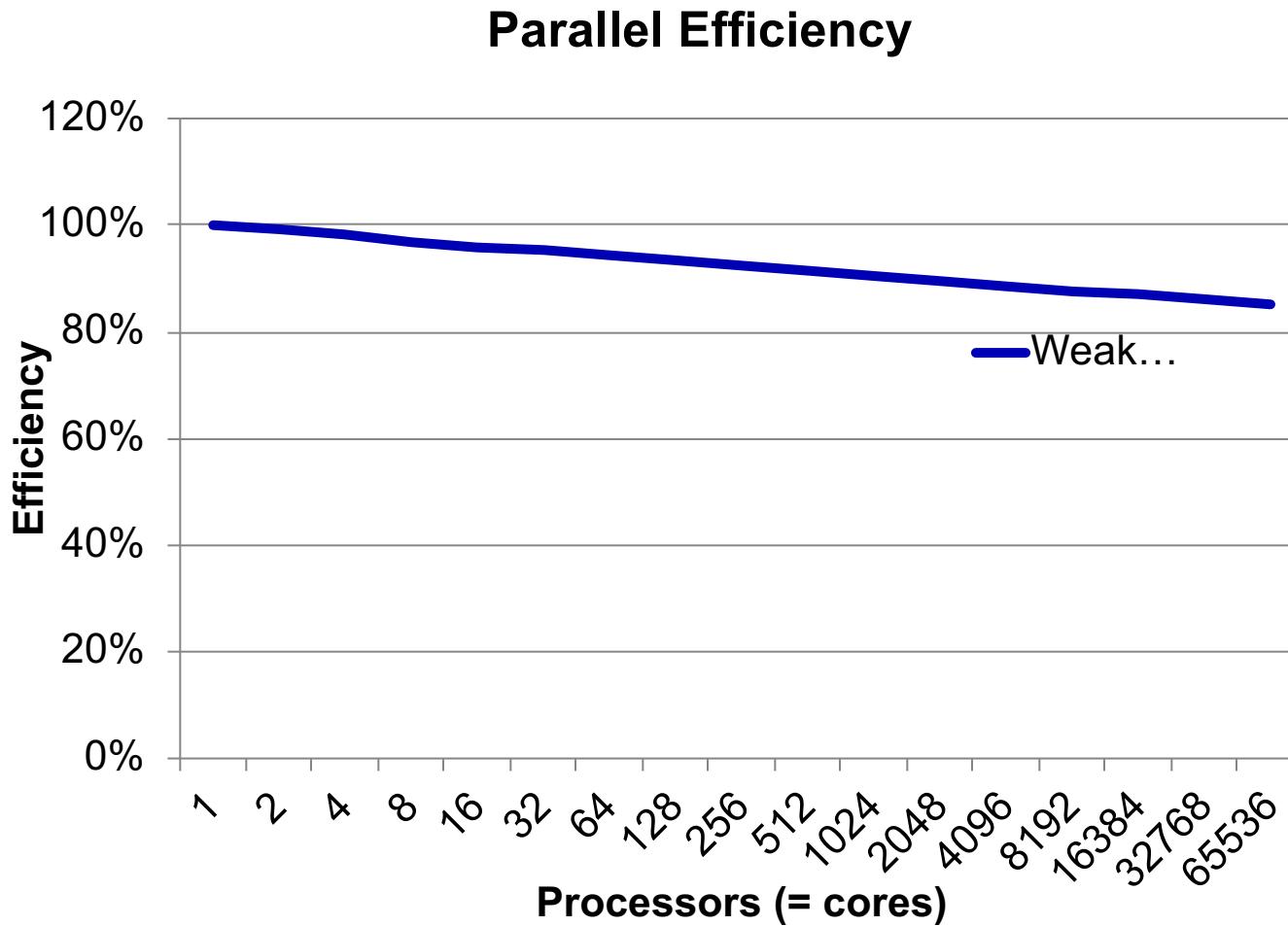
- Even if the parallel part speeds up perfectly performance is limited by the sequential part
- $1/10^{\text{th}}$ of your code's runtime is serial \rightarrow max speedup is 10x (Cori has 65K cores)

Parallel Efficiency



Same **strong scaling** results shown as efficiency

Parallel Efficiency (Weak Scaling)



Weak scaling uses a fixed problem size **per processor**. Can report as:

- Flop/s (or other rate) per processor; Efficiency based on rate per processor
- Time (if algorithm is linear in data size)

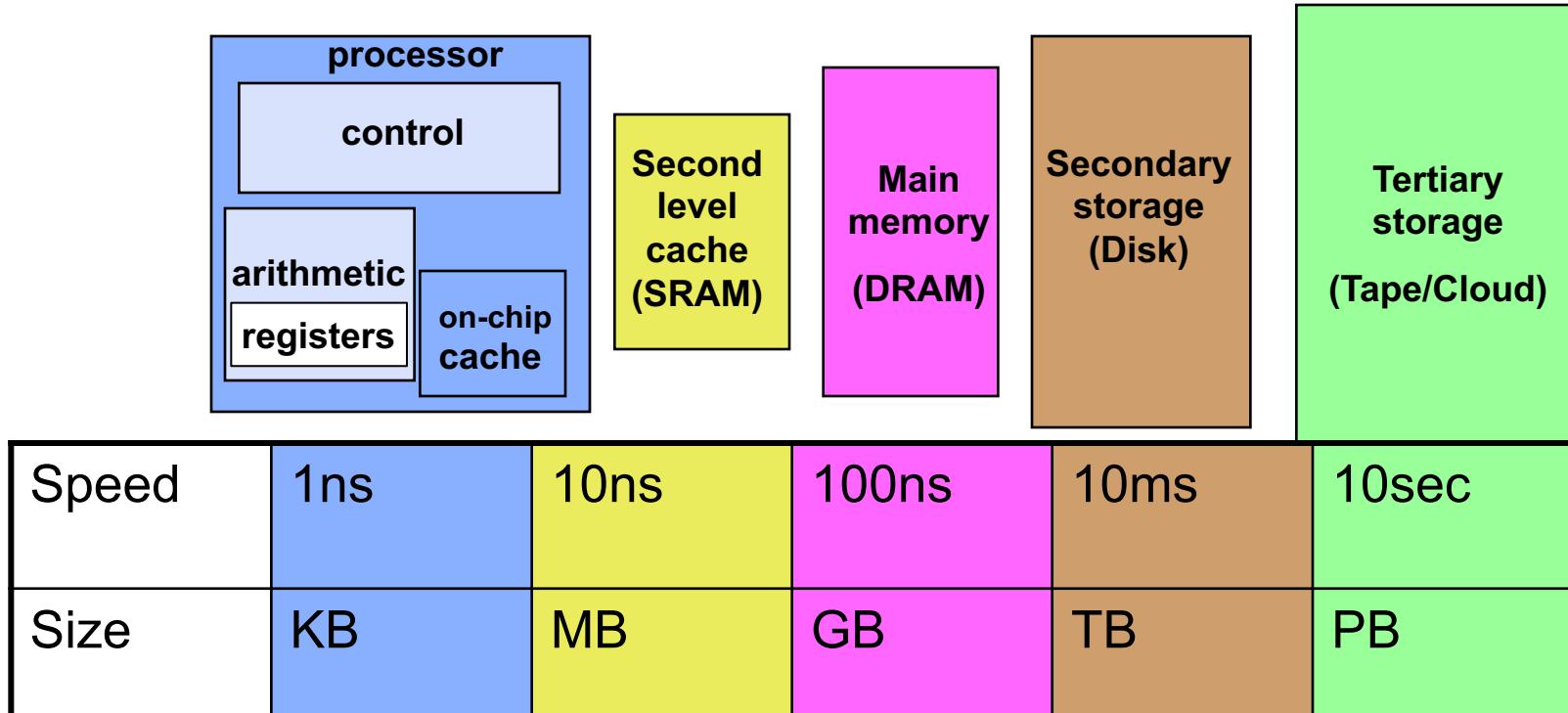
Limits to Parallelism

- Besides Amdahl's Law, here are some other limits
- Parallelism overheads include:
 - cost of creating parallelism (starting a thread/process)
 - cost of communicating shared data
 - cost of synchronizing
 - extra (redundant) computation
- Overheads can be in milliseconds..
- 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

Limits to Performance Start at Home

(Single Processor Memory Hierarchy)

- Large memories are slow; fast memories are small
- Most programs have a things nearby previous accesses
 - **temporal locality**: reusing an item that was previously accessed
- Memory hierarchy use this to improve *average case*





What's in this course?

What should you learn + some mechanics

Overview of the course (not in order)

- Parallel Programming Models and Machines (plus some architecture, e.g., caches)

Algorithm/machine model	Language / Library skills
Shared memory	OpenMP
	PGAS
Distributed memory	MPI
Data parallel	SPARK
	CUDA

- Parallelization Strategies for the “Motifs” of Scientific Computing (and Data)

Dense Linear Algebra	Monte Carlo
Sparse Linear Algebra	Spectral Methods
Particle Methods	Graphs
Structured Grids	Sorting
Unstructured Grids	Hashing

- Performance models: Roofline, α - β (latency/bandwidth), LogP
- Cross-cutting: Communication avoiding, load balancing, hierarchical algorithms, autotuning, Moore’s Law, Amdahl’s Law, Little’s Law

Course Mechanics

- **Web page:** <https://sites.google.com/lbl.gov/cs267-spr2019/>
 - Office hours will be posted there
- **Bcourses:** <https://bcourses.berkeley.edu/courses/1480197>
 - for homework submissions and grades
- **Piazza:** <https://piazza.com/class/jr7v03k3lcd62s>
 - for questions (XSEDE students should use Moodle)
- **Grading:**
 - Three team-based programming assignments (50% of grade)
 - HW0 (1%) Write a description of a parallel application of interest (see Website)
 - HW1 (10%), HW2 (10+10+9%), HW3 (10%)
 - Final projects (50% of grade)
 - Could be parallelizing an application, building or evaluating a tool, etc.
 - We encourage interdisciplinary teams, as with much parallel scientific software
- **Fill out survey** (see Piazza) To Do
- **Computer accounts at NERSC** (Edison and Cori) To Do
 - https://nim.nersc.gov/nersc_account_request.php
 - Description: Course work in CS267; institution University of California, Berkeley)

Reading Materials

- 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, also linked to 1996 html notes.
 - 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 Goedecker and Hoisie
 - Practical guide to performance optimization
 - *Petascale Computing, Algorithms and Applications*, Bader et al, Chapman & Hall/CRC, 2007
 - *Parallel Processing for Scientific Computing*, ed. by Heroux, Ragahvan, Simon, SIAM, 2006.

What you should get out of the course

Understanding of:

- Motivation for parallel computing
- Performance analysis and performance programming
- Parallel computing hardware options
- Importance of locality in performance and parallelism
- Overview of programming models (software) and tools, and experience using some of them
- Overview of parallel applications in simulation and data analysis
- Exposure to various open research questions

Terminology from Today:

- Speedup, Strong/Weak Scaling, Amdahl, Top500