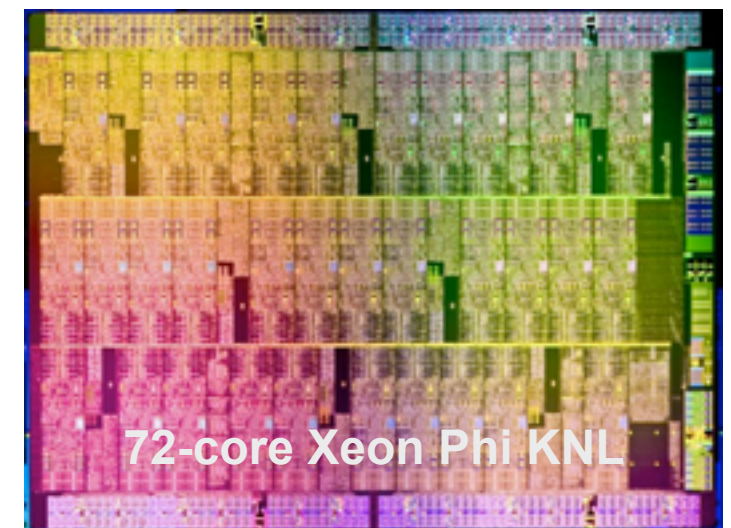
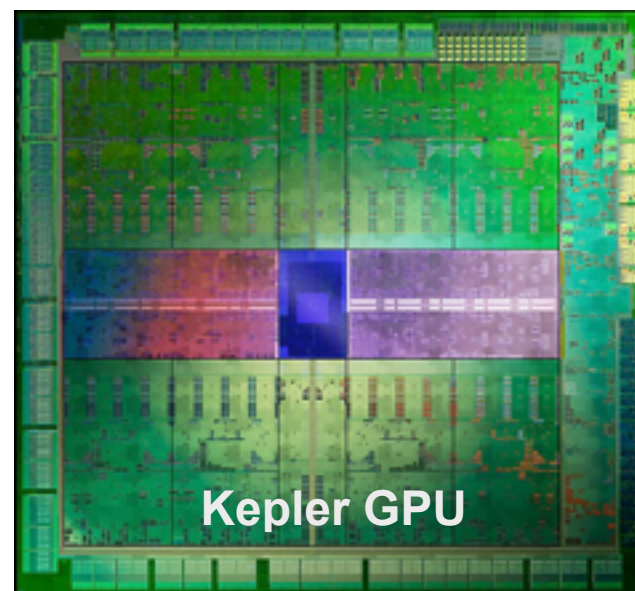
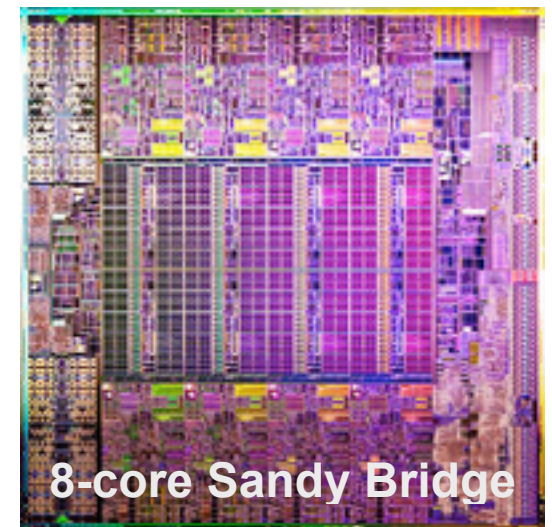


# Next-Generation Computing Architectures: Friend or Foe?

Salman Habib  
HEP and MCS Divisions  
Argonne National Laboratory

Computation Institute  
Argonne National Laboratory  
University of Chicago

Kavli Institute for Cosmological Physics  
University of Chicago



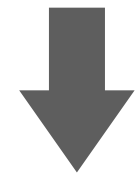
# LSST-DESC and Computing

- **LSST-DESC focus is on Level II/III analysis**

- Estimates of initial computing needs are unclear, ranging from 150-350 TFlops/year
- Initial storage needs are ~PB, growing linearly
- Based on this, we would want (at least) the #1 machine in the Top 500 in 2006
- In 2022 there may be  $O(1000-10,000)$  such machines in the US alone!
- Storage requirement is already 'trivial', LSST is NOT 'Big Data'

- **So what's the problem?**

- Analyses will be complex (and there will be many)
- These tasks will expand to fill available computational space
- Programming models may be very different from those in use today

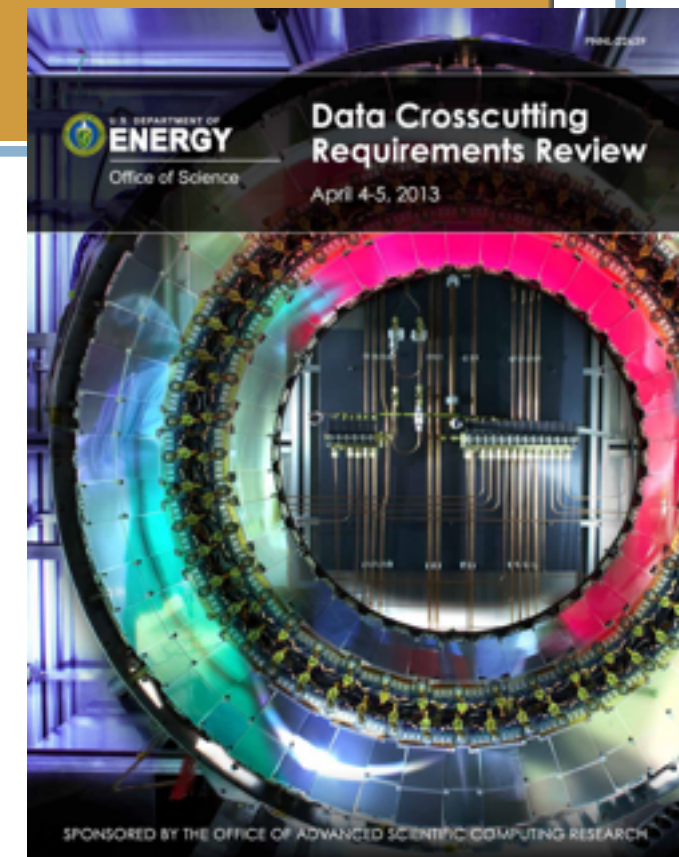
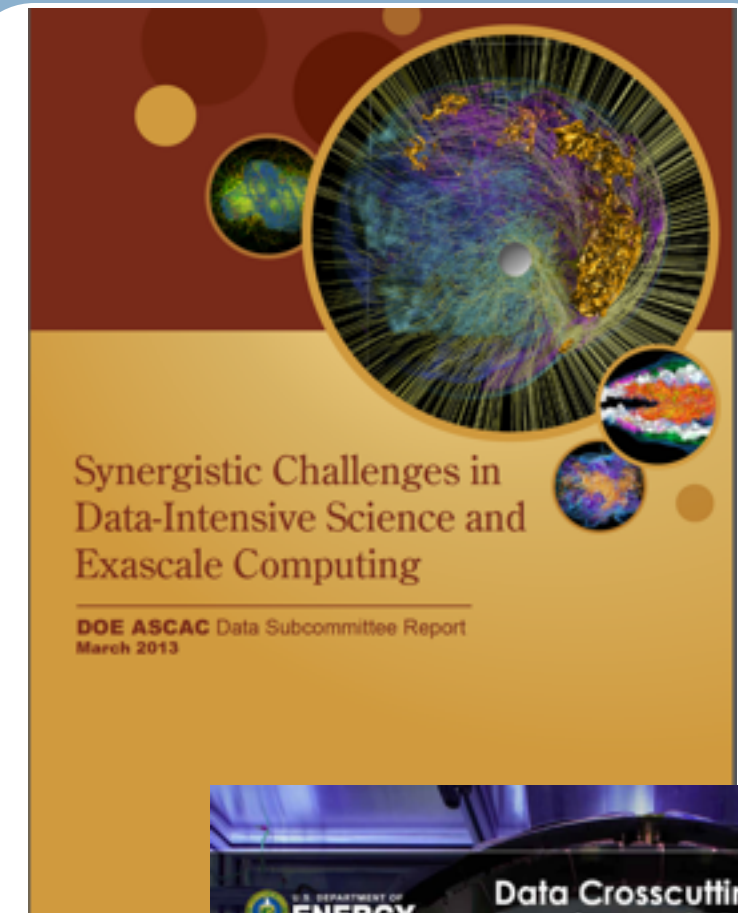


300 TFlops/10PB,  
10kW in 2020  
(Projection)



# Different Flavors of Computing

- **High Performance Computing ('PDEs')**
  - Parallel systems with a fast network
  - Designed to run tightly coupled jobs
  - High performance parallel file system
  - Batch processing
- **Data-Intensive Computing ('Interactive Analytics')**
  - Parallel systems with balanced I/O
  - Designed for data analytics
  - System level storage model
  - Interactive processing
- **High Throughput Computing ('Events'/'Workflows')**
  - Distributed systems with 'slow' networks
  - Designed to run loosely coupled jobs
  - System level/Distributed data model
  - Batch processing



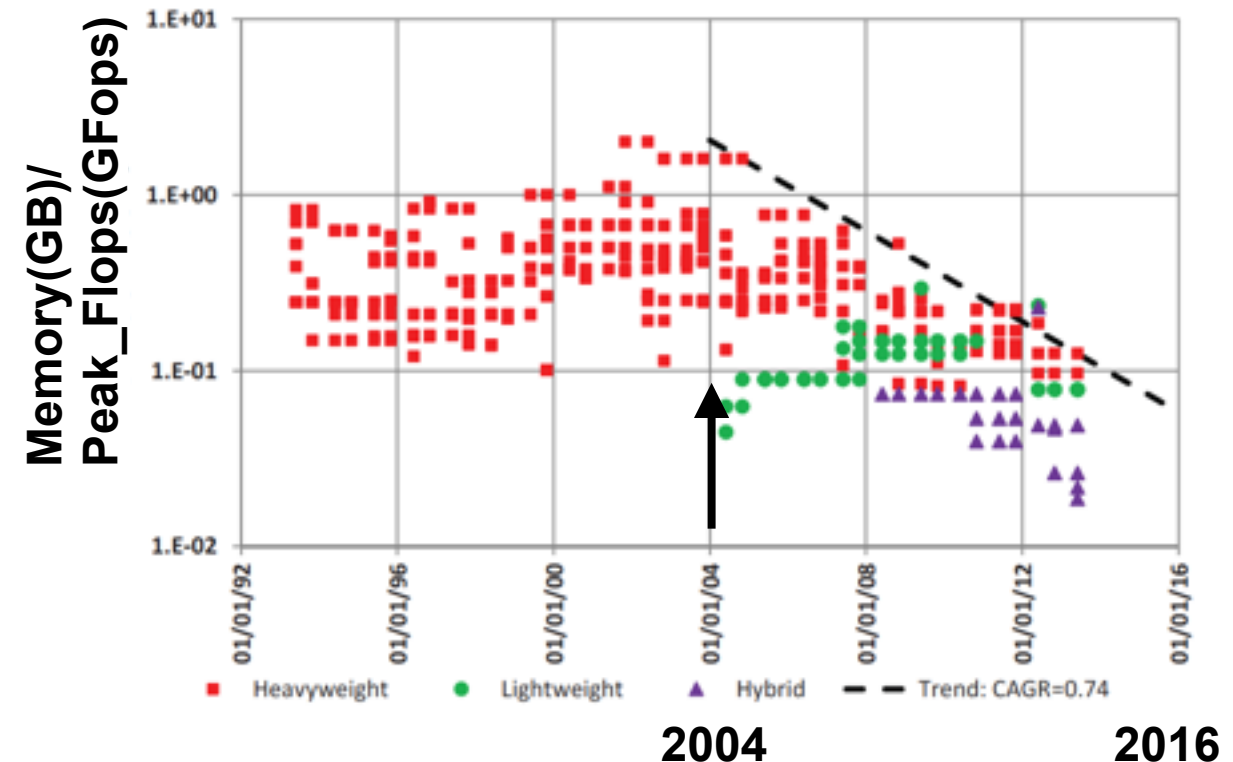
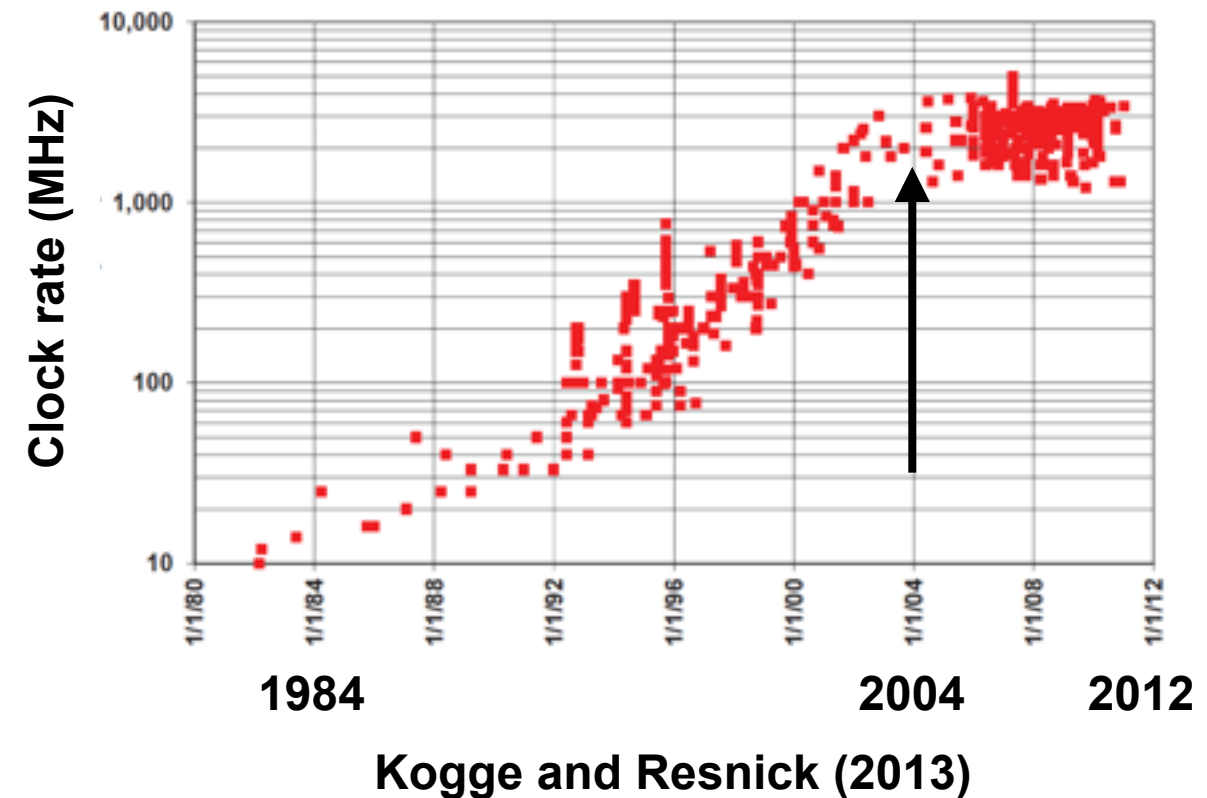
# Interactive Exercise I

- **Do you care about computational architectures (what's in the processor/system) in your current work?**
  - If so, why?
  - If not, why not?
- **Types of computing**
  - Do you exploit parallelism in your codes?
  - If so, are your use cases HPC, DISC, or HTC?
  - If you don't exploit parallelism, why not?
  - I don't have any codes
- **Programming expertise**
  - Do you consider yourself to be primarily a code 'consumer', i.e., you primarily stitch together programs/workflows based on functional units written by others?
  - Or do you consider yourself to be an application developer, i.e., you actually design/understand/implement the key algorithms?
  - None of the above (if so, explain what you do)



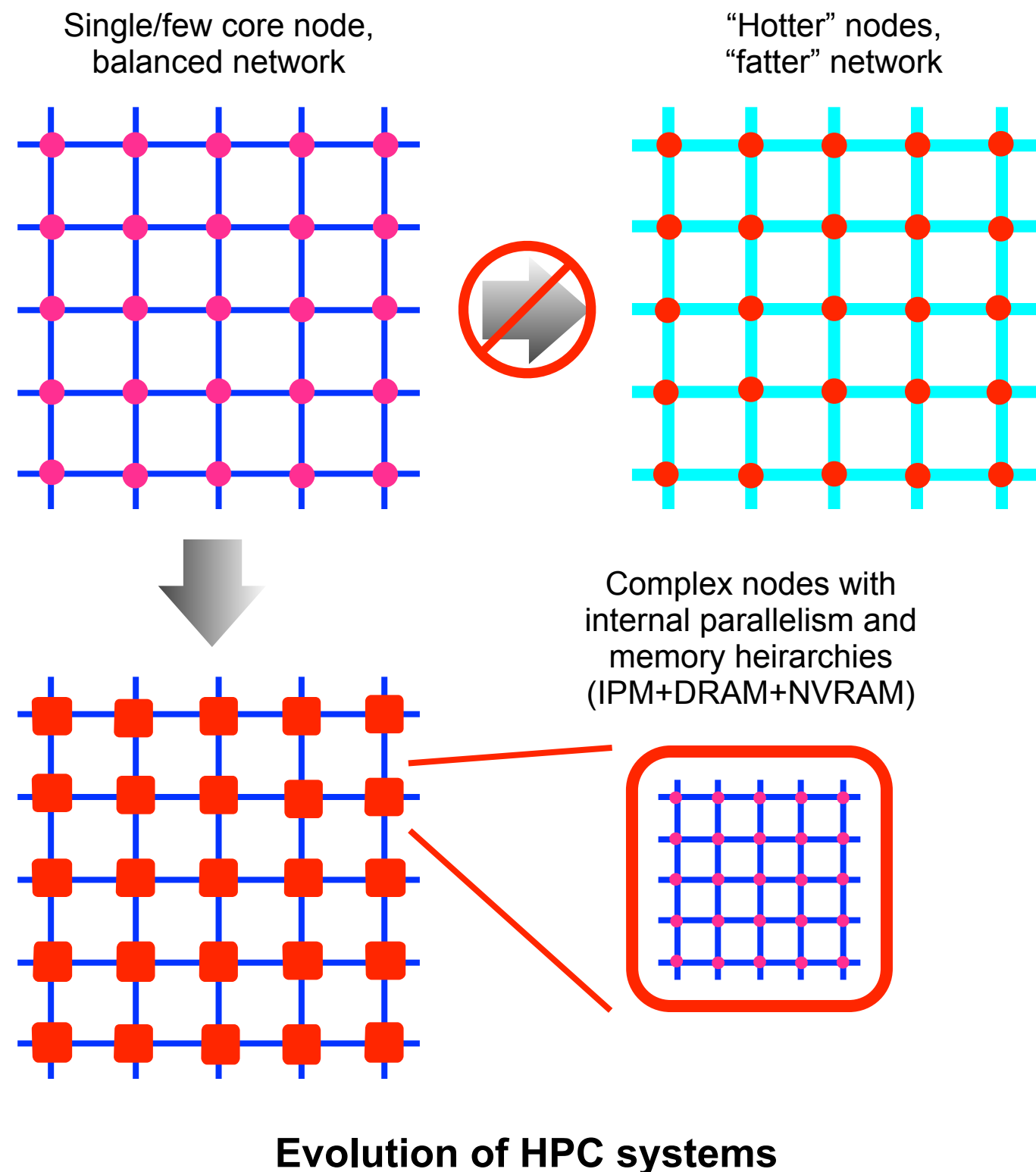
# The Problem: Hardware Evolution

- **Power is the main constraint**
  - Target: 30X performance gain by 2020
  - ~10-20MW per large system
  - Power/Socket roughly const.
- **Only way out: more cores**
  - Several design choices (e.g., cache vs. compute vs. interconnect)
  - All lead to more complexity
- **Micro-architecture gains sacrificed**
  - Accelerate specific tasks
  - Restrict memory access structure (SIMD/SIMT)
- **Machine balance sacrifice**
  - Memory/Flops; comm BW/Flops — all go in the “wrong” direction



# Hardware Evolution: Implications

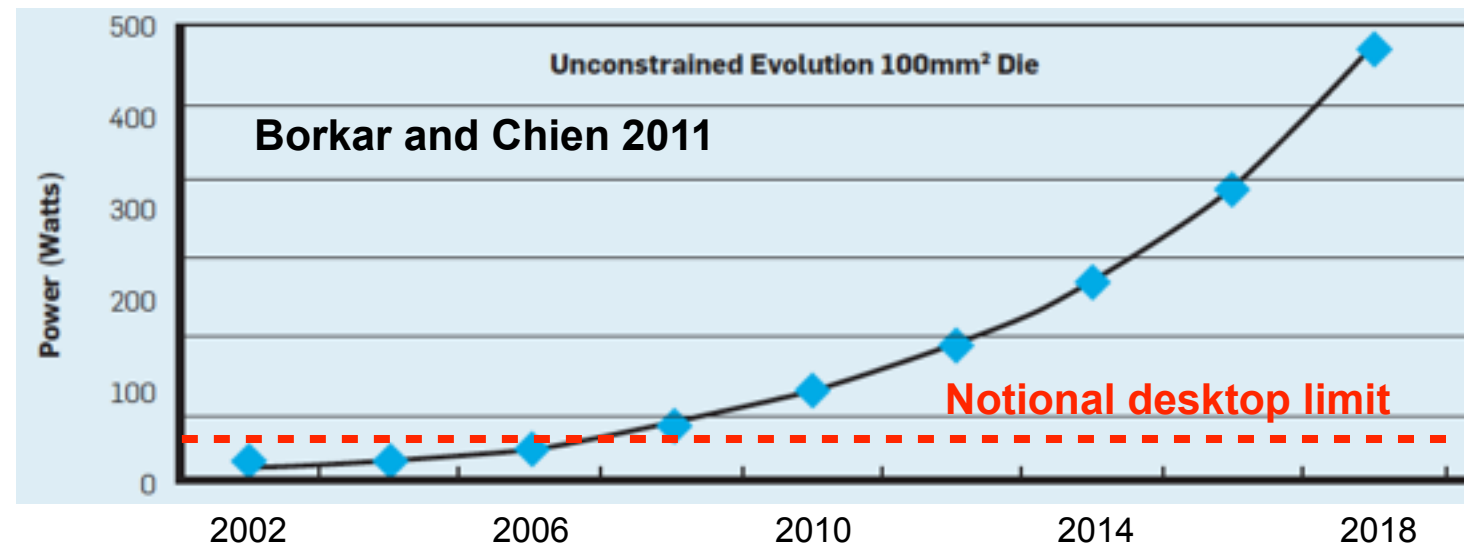
- **Programming view (current)**
  - Processor properties hidden
  - Simple control flow
  - Single memory image
  - (Mostly) portable code
- **How to handle complex nodes?**
  - Magic compiler unlikely, problem is too complex
  - “Problem + Task Decomposition + Hardware” — single problem
  - Portability is a serious issue
- **Possible approaches**
  - Rely on someone else (e.g. NumPy)
  - Bite the bullet



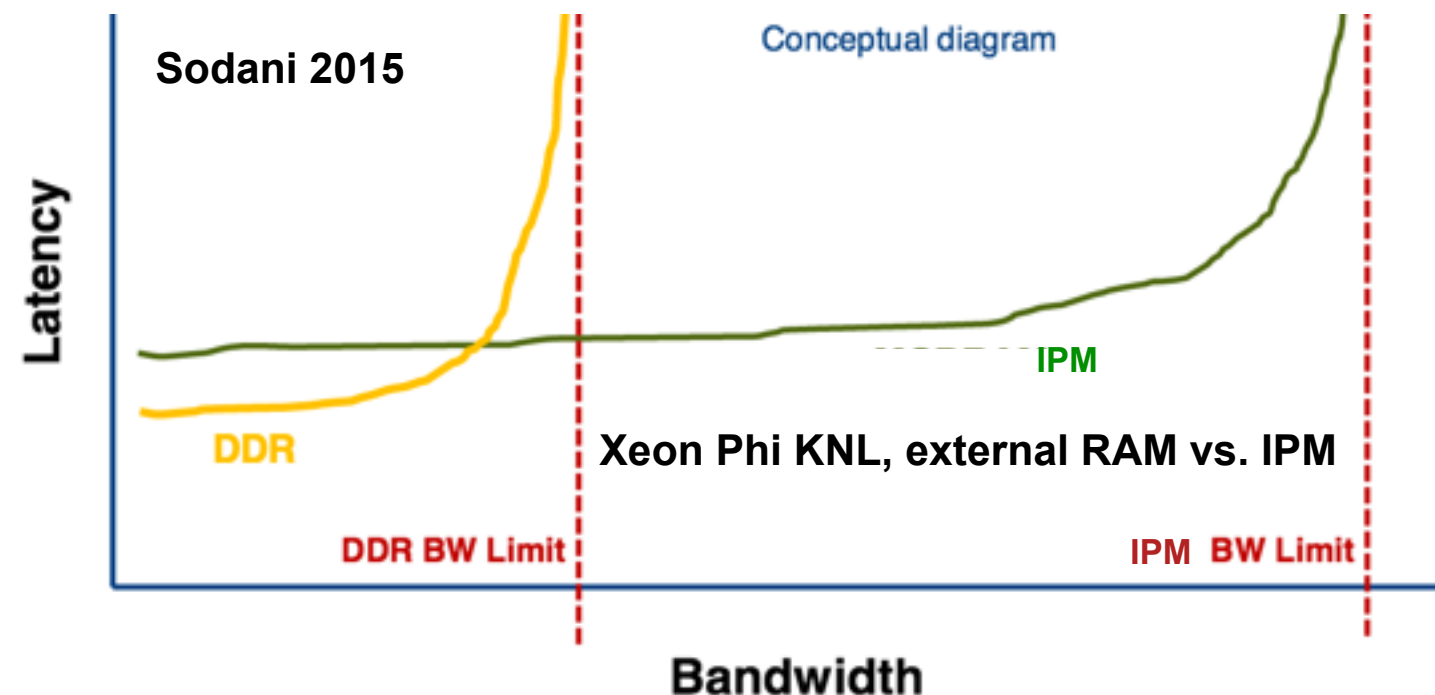


# Processor Complexity

- **Example: Xeon Phi KNL**
  - ▶ 72 out-of-order cores
  - ▶ 512 bit vector registers (X2)
  - ▶ 4 threads/core
  - ▶ 16GB IPM at 400GB/s
  - ▶ 3+ TFlops in DP
  - ▶ Multiple memory modes (flat, cache, hybrid)
  - ▶ In principle, what runs on a standard Xeon will run on KNL, but extracting performance will require work
- **CPU/GPU**
  - ▶ Also possible but not covered here, likely to have only a niche application in the current context

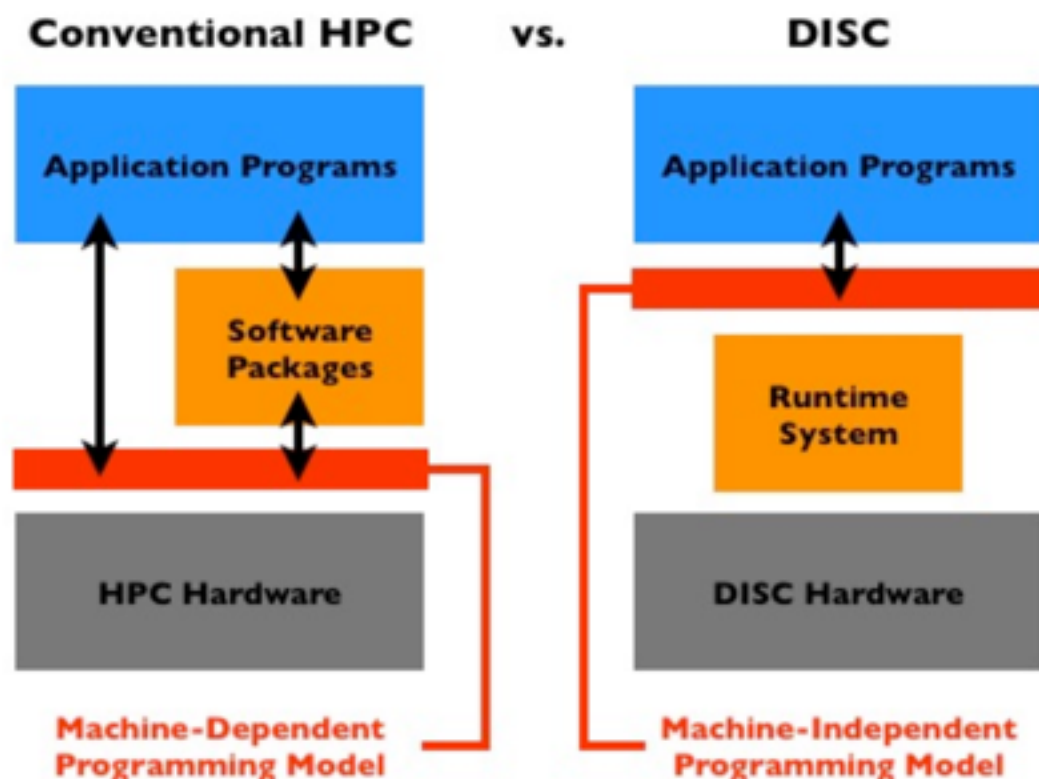


Performance requires many cores but each core cannot run at high clock frequencies (power limit), therefore performance requires vectorization; keeping the cores fed requires a fast on-chip communication fabric; to avoid the “memory wall”, need fast on-chip storage (IPM) — to maximize performance code must be able to exploit parallelism (288-way) and be highly vectorized

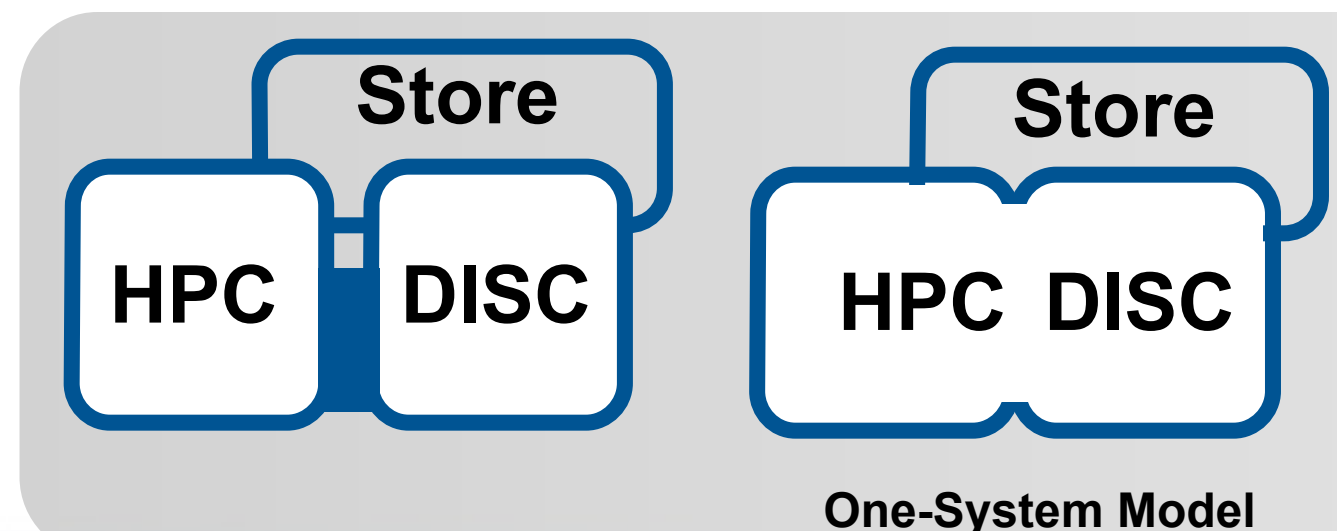
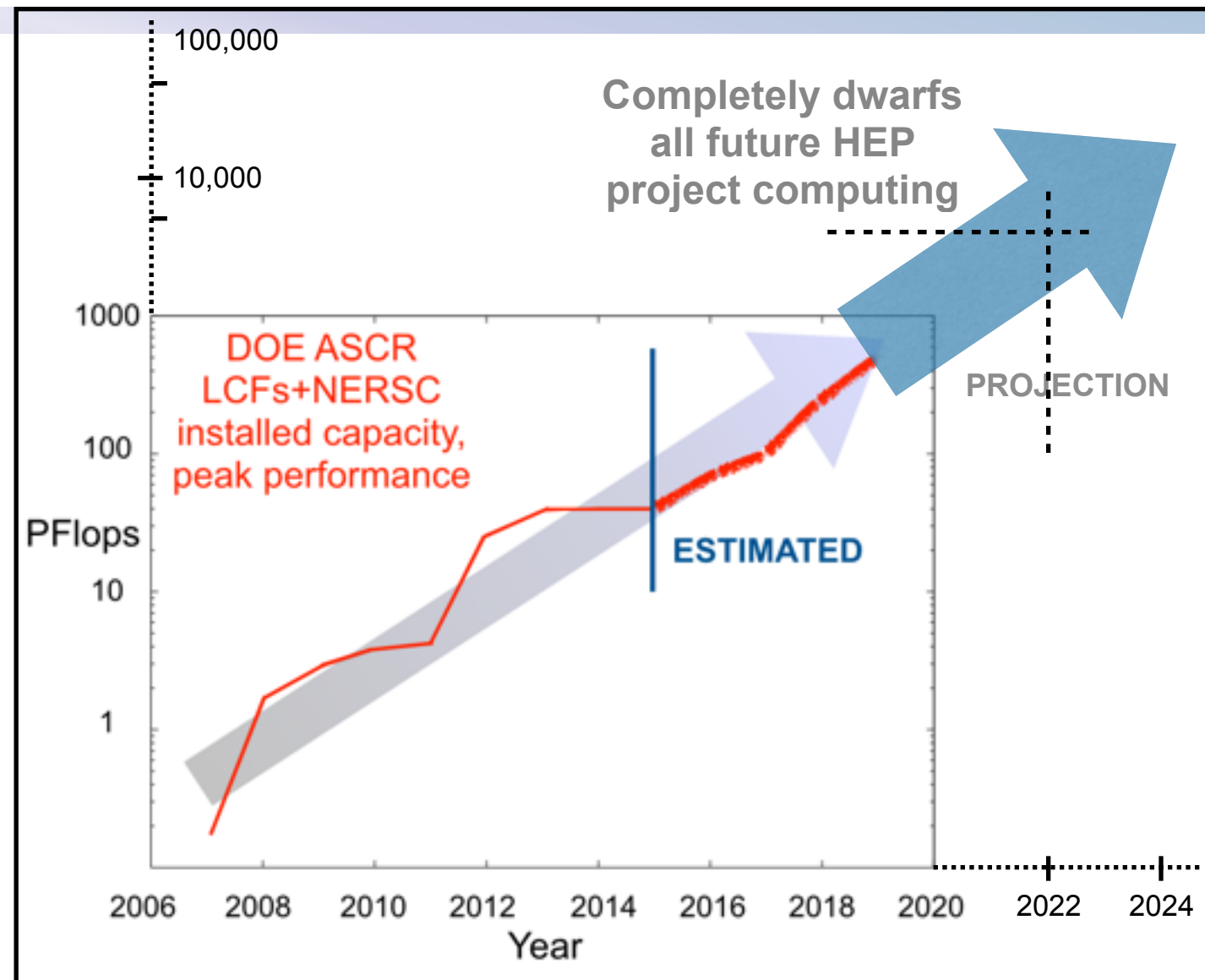


# Hardware Co-Evolution: HPC and DISC

- HPC systems on “Two Swim-Lane Track” (CPU-GPU and Manycore)
  - 30X performance gain by 2020
  - ~10-20MW per large system
  - power/socket roughly const.
- HPC and DISC convergence
  - Not a matter of hardware — convergence at the node level
  - Configurational flexibility



After Bryant (2007)





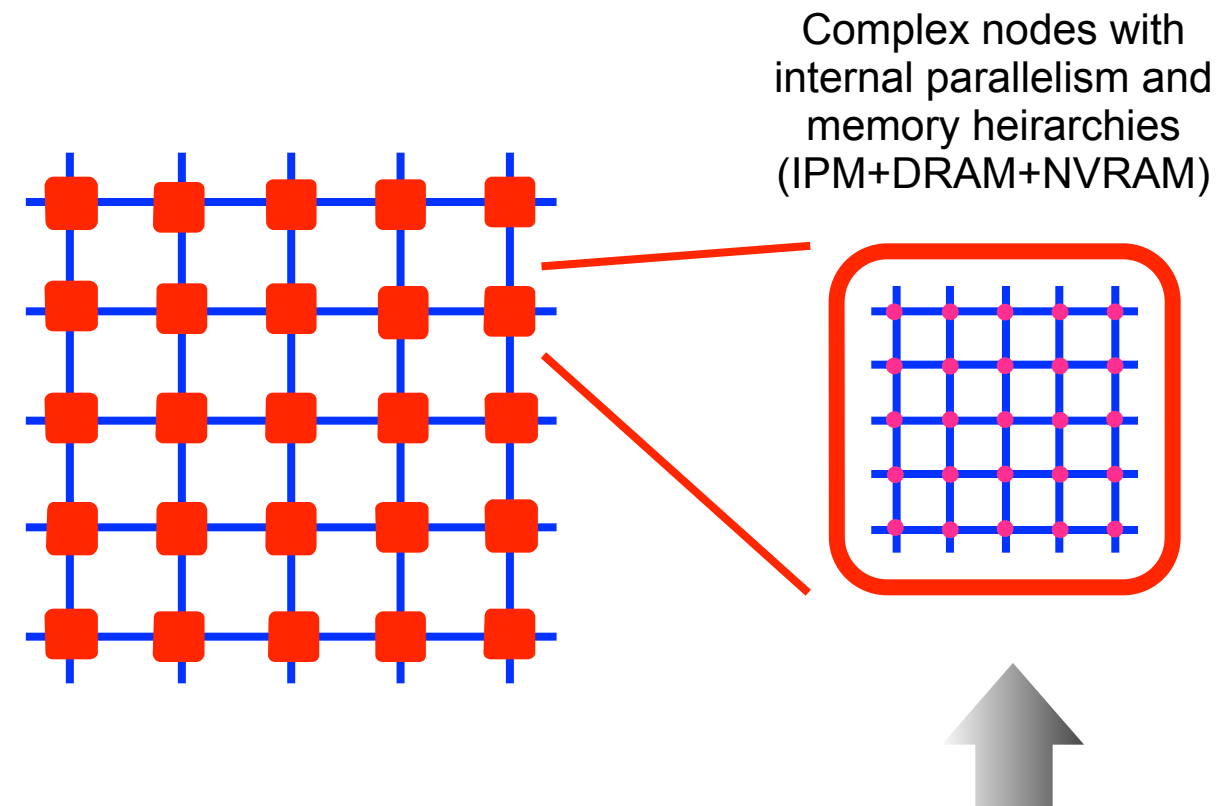
# Interactive Exercise II

- **Do you NOW care about computational architectures in your future work?**
  - If so, why?
  - If not, why not?
- **Types of computing**
  - Would you exploit parallelism in your codes in the future?
  - If so, are your use cases HPC, DISC, or HTC?
  - If you won't exploit parallelism, why not?
  - I don't have any codes, so —
- **Programming expertise**
  - Do you wish to learn more about computational architectures?
  - Or have you seen enough — someone else should deal with this?



# Likely Exploits

- **Most use cases likely to be DISC/HTC**
  - Note HPC systems can easily handle these in the very near future
  - Will possibly fall into two classes —  
**1)** many runs of a simple, not highly optimizable code, **2)** smaller, but still sizable number of runs of a potentially optimizable code
- **‘Single node’ application span**
  - Nodes are big enough: >100GB RAM + NVRAM
  - Main parallelism exploit will be at the node level
- **Exceptions**
  - Large-scale spatio-temporal statistics (will need system level parallelism — HPC application)



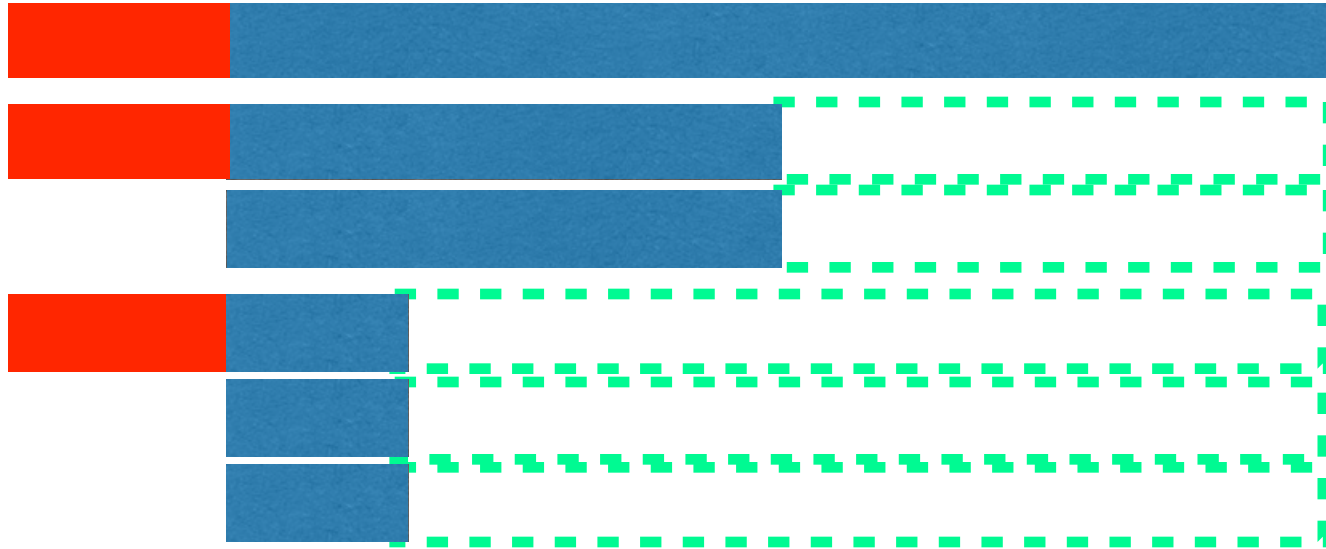
**Focus on node-level parallelism: Quasi-independent tasks run on individual nodes; intermittent communication (if at all) across nodes**

## **Main themes:**

- 1. Locality, locality, locality, —**
- 2. Threading**

# Serial and Parallel Workloads

$$T_1 = t_{ser} + t_{par}$$



$$T_N \geq t_{ser} + t_{par}/N$$

**But Amdahl's Law is most often not directly relevant for a number of reasons:**

1. As problem size increases (possible as N increases), the amount of parallel work increases relative to the serial work and the bound can be exceeded (**Gustafson's law**)
2. In reality, there is a complex question of dependencies, overheads, communication, memory access, memory limitations, that can make life complicated (results could be worse than Amdahl's prediction)

- **Amdahl's Law**

- ▶ Suppose N+1 computational units are available and all serial work is done by one of them (N=1), then the speedup is bounded:

$$S = T_1/T_N \leq \frac{t_{ser} + t_{par}}{t_{ser} + t_{par}/N}$$

$$t_{ser} = fT_1$$

$$t_{par} = (1 - f)T_1$$

$$S \leq \frac{1}{f + (1 - f)/N}$$

- ▶ Note that even with infinite N, the speedup is finite
- ▶ Assignment — plot S as a function of N at fixed values of f

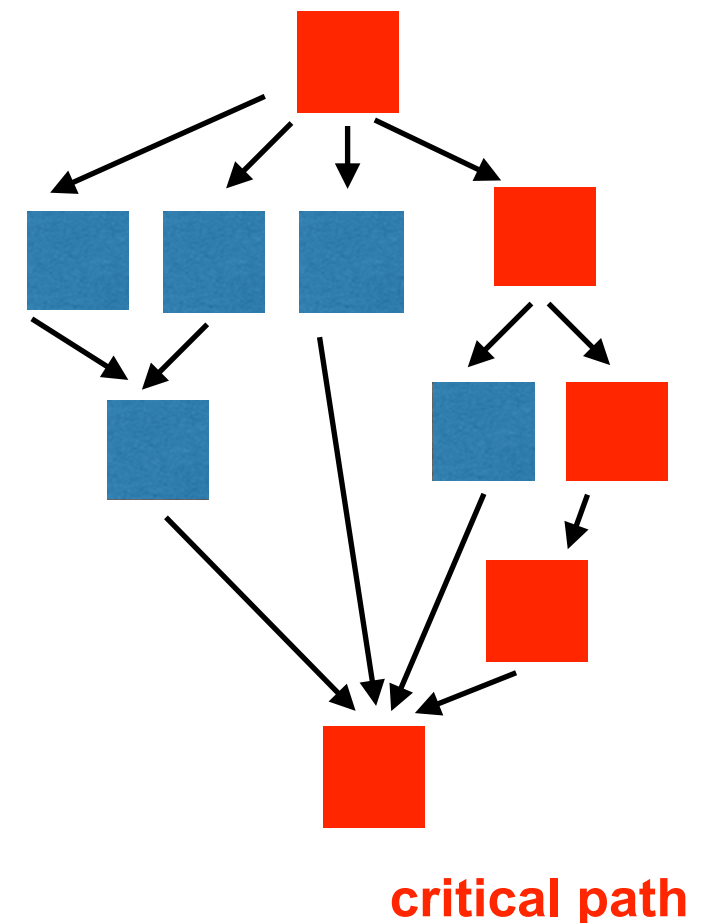


# Work-Span Model

- **Work and Span**

- ▶ Suppose all computations can be broken up into unit work chunks, the tasks form a directed acyclic graph (DAG), and a task runs when all its precursors have been completed
- ▶ Example — we have 10 tasks so the **work** = 10; the **span** is the time taken on an ideal parallel machine; there is a 5-path chain (critical path) here that cannot be parallelized further because of dependencies, so **span**=5
- ▶ The speedup  $S$  is always less than work/span, in our case, 2, but usually we would like to be in a situation where work  $\gg$  span
- ▶ In this case, a good practical estimate for the run time is

$$T_N \sim T_1/N + T_\infty$$



For more details, see  
McCool, Robison, Reinders,  
Structured Parallel  
Programming (2012)



# Communication Avoidance

- But “compute is free”? (Locality, once again)
  - ▶ One of the key problems in modern systems is not that we are compute bound, but that we are often communication-bound (slow networks and memory access limitations); note that the work-span model assumed communication costs were zero!
  - ▶ Model: words are packed into a contiguous block of memory, i.e., the message, which is then sent to the destination processor; the packing induces a **latency cost** and the size of the message induces a **bandwidth cost**, these have to be added to the **computational cost**

$$\begin{array}{c} \text{latency cost} \rightarrow \alpha S + \beta W + \gamma F \\ \begin{array}{l} \text{\# of messages} \nearrow \alpha S \\ \text{total words in message} \nearrow \beta W \\ \text{arithmic operations} \nearrow \gamma F \end{array} \end{array}$$

bandwidth cost      computational cost

$$\alpha \gg \beta \gg \gamma$$

For lower bounds this may be sufficient, for upper bounds, one would need to sum along the critical path; for more on this see Ballard et al. Acta Numerica 2014



# Lessons so Far

- **Life is complicated**

- ▶ In case real performance gains are required, simple “code ports” may not work
- ▶ Rethinking of algorithms in ways that align with modern architectures will be likely needed; in many cases, this is an art, yet to become a science
- ▶ But we don’t all have to become performance experts if extreme performance is not required; fortunately this is rarely the case
- ▶ Embarrassingly parallel applications with low compute intensity should be easy to implement on all platforms
- ▶ Portability on multi/manycore systems is important (likely to be primarily via the use of OpenMP)



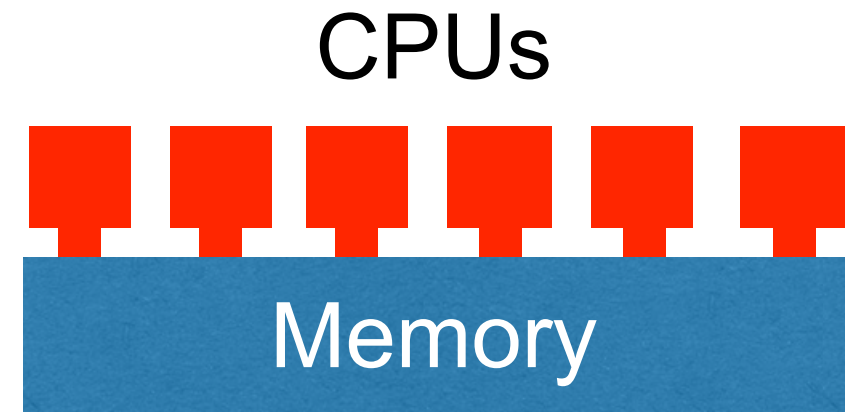
# Parallel Programming: MPI and OpenMP

- **MPI (Message Passing Interface)**

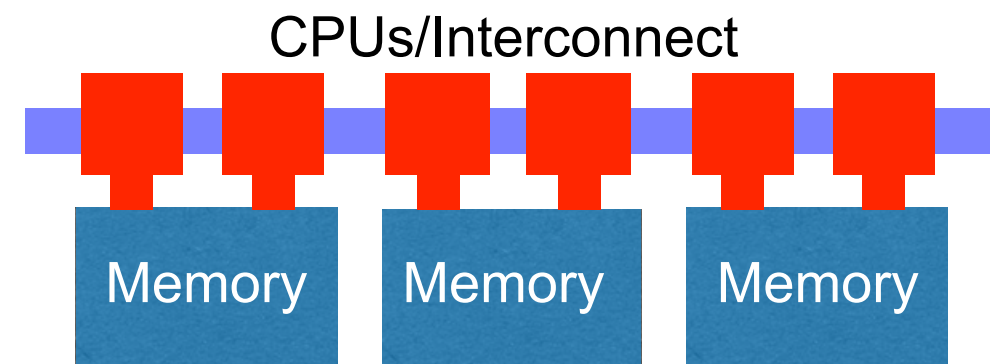
- ▶ We won't cover it today; MPI is essentially a distributed memory model approach independent of the actual architecture

- **OpenMP (Open Multi-Processing)**

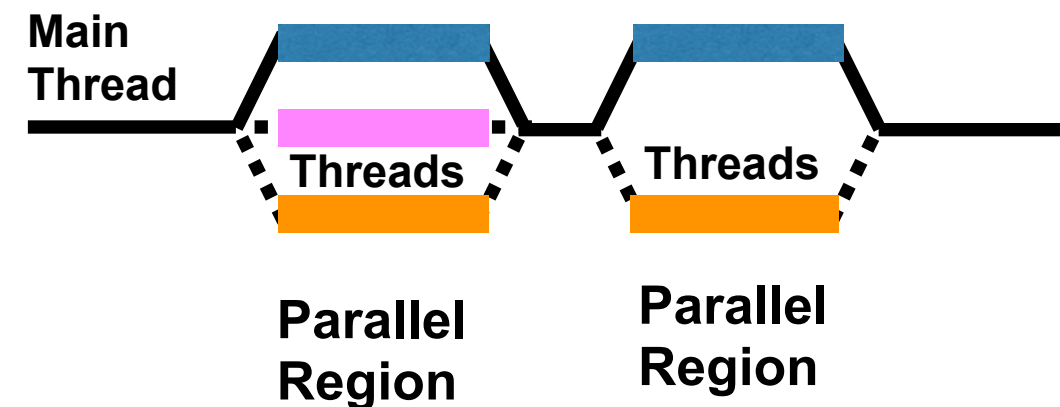
- ▶ Designed for shared memory systems
- ▶ Explicit programming model (parallelization is not automatic)
- ▶ Parallelism expressed solely through threads ('atom' of processing)
- ▶ Parallel execution model is **fork-join**
- ▶ Mostly works through compiler directives (C/C++, Cython, Fortran, —)
- ▶ **Adrian Pope** will take you through some simple examples; you can run them on your NERSC accounts



Uniform Memory Access



Non-Uniform Memory Access (NUMA)



# Where to Run?

- **Options**

- ▶ LSST repo at NERSC will probably allow people to try things out, but allocations may not be enough for serious production (however, no such need appears to exist currently)
- ▶ A recently started project across Argonne and LBNL will have LSST software targets; NCSA will likely partner (software containers to allow data-intensive tasks to run on HPC resources, to stay in touch send email to Salman Habib or Peter Nugent)
- ▶ Portability on multi/manycore systems is important (likely to be primarily via the use of OpenMP)
- ▶ Cloud as a resource will work for many use cases that don't require major compute intensity

