

# Engineering Performance for Multiphysics Applications

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# Performance, then Productivity

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- Note the “then” – not “instead of”
  - ◆ For “easier” problems, it is correct to invert these
- For the very hardest problems, we must focus on getting the best performance possible
  - ◆ Rely on other approaches to manage the complexity of the codes
  - ◆ Performance can be understood and engineered (note I did not say predicted)
- We need to start now, to get practice
  - ◆ “Vector” instructions, GPUs, extreme scale networks
  - ◆ Because Exascale platforms will be even more complex and harder to use effectively



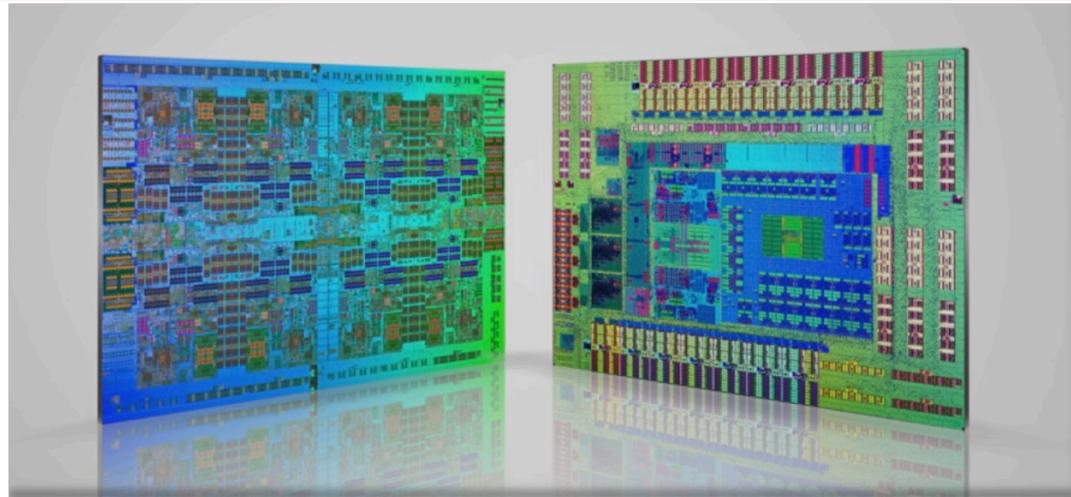
# Exascale Directions

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- Exascale systems are likely to have
  - ◆ Extreme power constraints, leading to
    - Clock Rates similar to today's systems
    - A wide-diversity of simple computing elements (simple for hardware but complex for software)
    - Memory per core and per FLOP will be much smaller
    - Moving data anywhere will be expensive (time and power)
  - ◆ Faults that will need to be detected and managed
    - Some detection may be the job of the programmer, as hardware detection takes power
  - ◆ Extreme scalability and performance irregularity
    - Performance will require enormous concurrency
    - Performance is likely to be variable
      - Simple, static decompositions will not scale
  - ◆ A need for latency tolerant algorithms and programming
    - Memory, processors will be 100s to 10000s of cycles away. Waiting for operations to complete will cripple performance



# IBM PERCS: Two New Chips



## Power7 Chip

*Up to 256 GF peak performance*

3.5–4.0 GHz

Up to 8 cores, 32 SMT threads

Caches

L1 (2x64 KB), L2 (256 KB),  
L3 (32 MB, complex policy)

Memory Subsystem

Two memory controllers

128 GB/s memory bandwidth

## PERCS Hub Chip

*1.128 TB/s total bandwidth*

Connections:

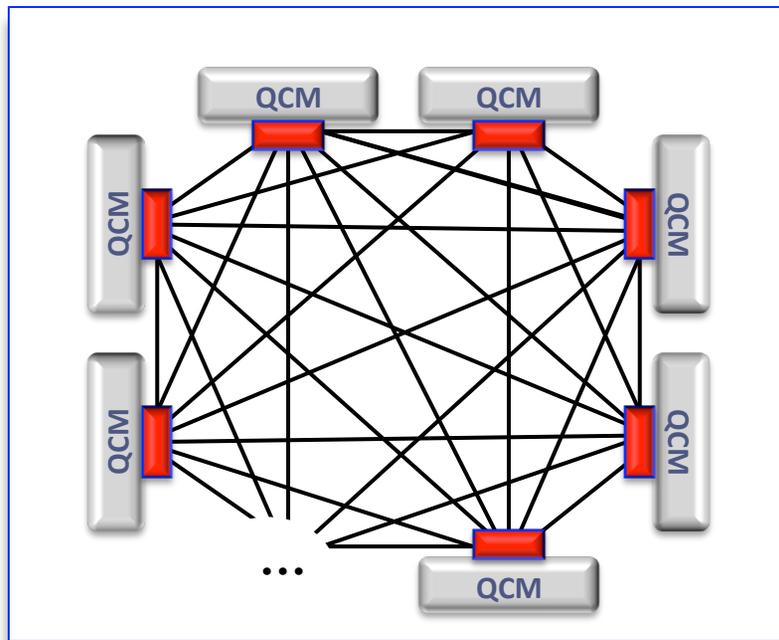
192 GB/s QCM connection

896 GB/s to other QCMs

40 GB/s general purpose I/O

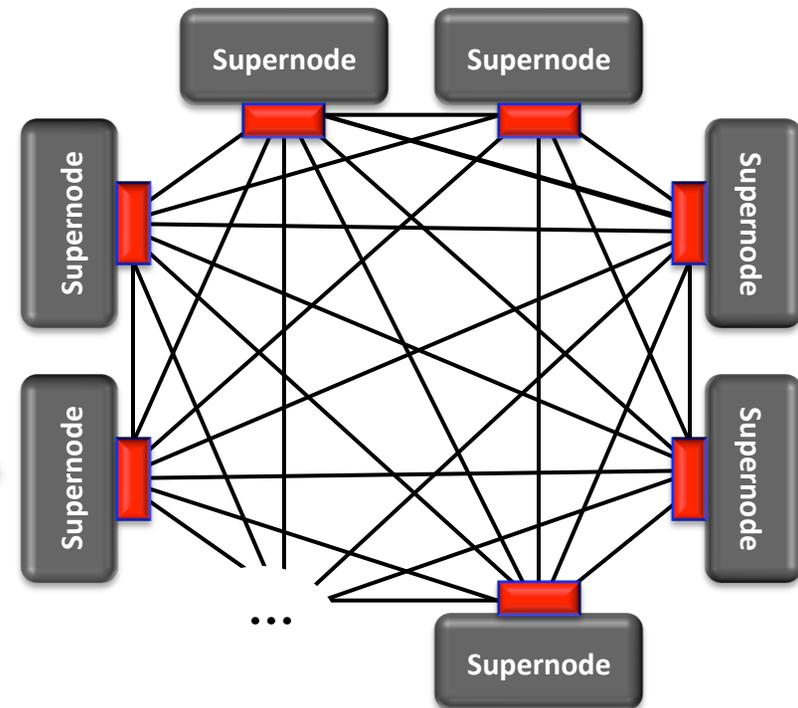


# Two-level (L, D) Direct-connect Network



**Each Supernode = 32 QCMs**  
(4 Drawers x 8 SMPs/Drawer)

**Fully Interconnected with**  
 $L_{\text{local}}$  and  $L_{\text{remote}}$  **Links**



**Blue Waters = 320 Supernodes**  
(40 BBs x 8 SNs/BB)

**Fully Interconnected with**  
**D Links**

But complex, nonuniform network [PARALLEL@ILLINOIS](mailto:PARALLEL@ILLINOIS)



★ **Result: Very low hardware latency**  
**Very high bandwidth**

# Another Example System

- 128 node GPU Cluster
- #3 on Green500
- Each node has
  - ◆ One Core i3 530 2.93 GHz dual-core CPU
  - ◆ One Tesla C2050 GPU per node
- 33.62 TFLOPS on HPL
- 934 MFLOPS/Watt
- How can we *engineer* codes for performance on these complex systems?
- And an exercise for the viewer: what do performance models tell you about the CPU/GPU comparisons you see?

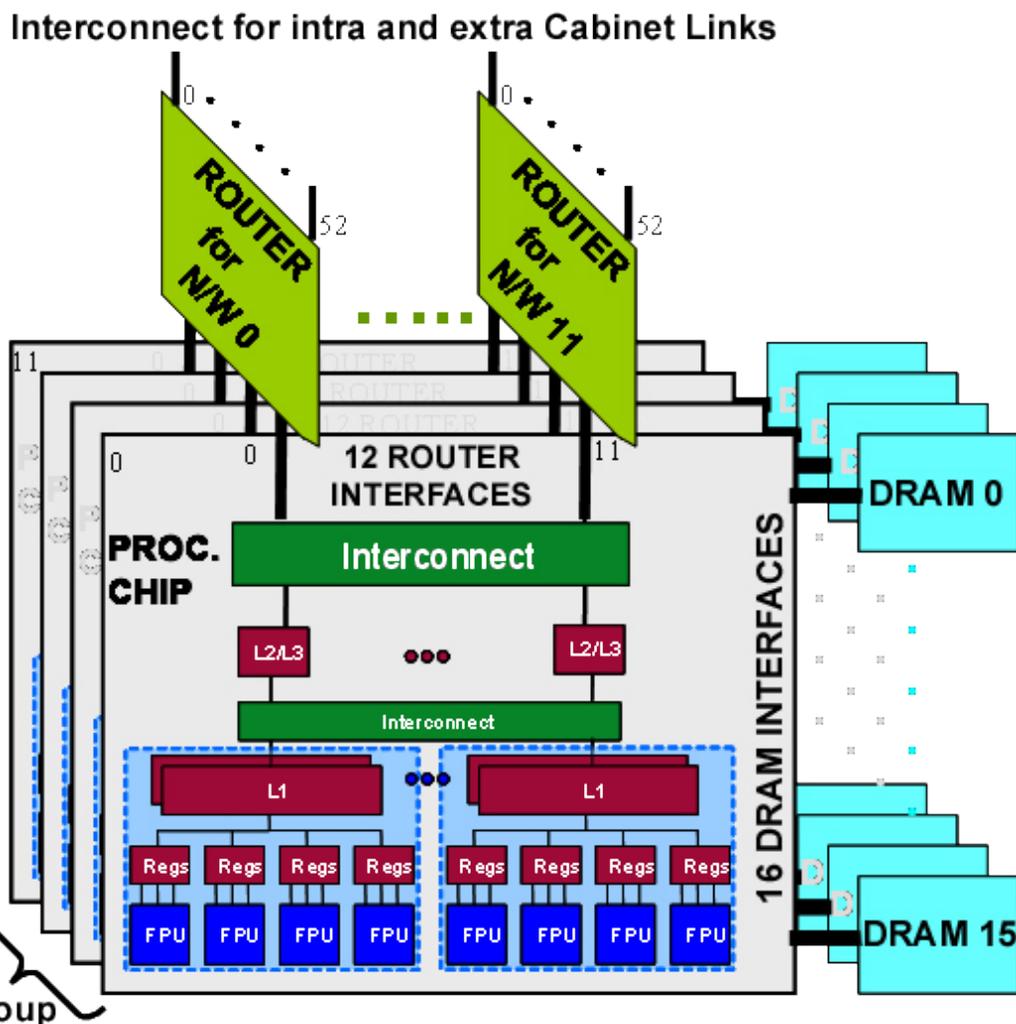


# 1 EFlop/s “Clean Sheet of Paper” Strawman

Sizing done by “balancing” power budgets with achievable capabilities

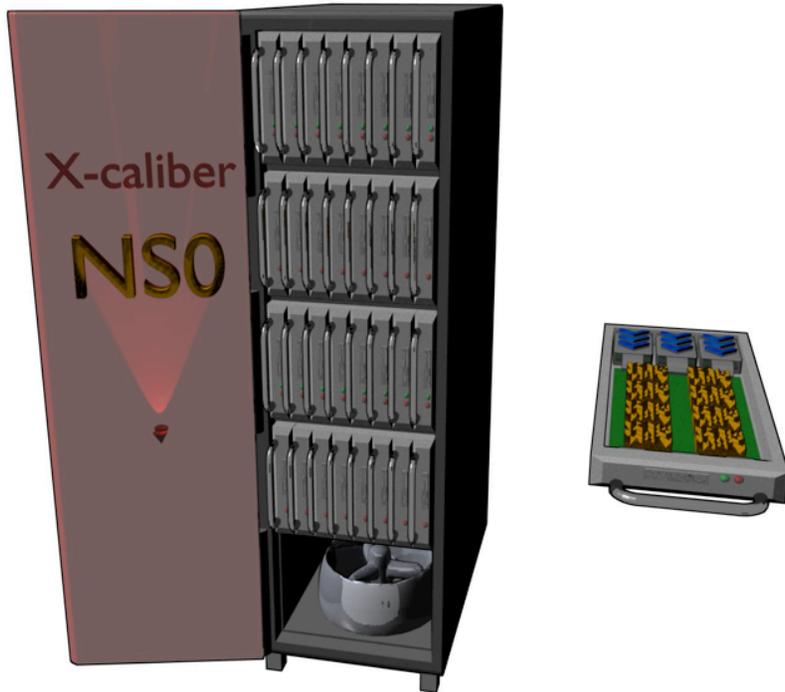
- 4 FPUs+RegFiles/Core (=6 GF @1.5GHz)
- **1 Chip = 742 Cores** (=4.5TF/s)
  - 213MB of L1I&D; 93MB of L2
- 1 Node = 1 Proc Chip + 16 DRAMs (16GB)
- 1 Group = 12 Nodes + 12 Routers (=54TF/s)
- 1 Rack = 32 Groups (=1.7 PF/s)
  - 384 nodes / rack
- 3.6EB of Disk Storage included
- 1 System = 583 Racks (=1 EF/s)
  - **166 MILLION cores**
  - **680 MILLION FPUs**
  - **3.6PB = 0.0036 bytes/flops**
  - **68 MW w'aggressive assumptions**

Largely due to Bill Dally, Stanford



Thanks to Peter Kogge for this slide, based on the DARPA report

# An Even More Radical System



- Rack Scale
  - ◆ Processing: 128 Nodes, 1 (+) PF/s
  - ◆ Memory:
    - 128 TB DRAM
    - 0.4 PB/s Aggregate Bandwidth
  - ◆ NV Memory
    - 1 PB Phase Change Memory (addressable)
    - Additional 128 for Redundancy/RAID
  - ◆ Network
    - 0.13 PB/sec Injection, 0.06 PB/s Bisection

Deployment	Nodes	Topology	Compute	Mem BW	Injection BW	Bisection BW
Module	1	N/A	8 TF/s	3 TB/s	1 TB/s	N/A
Deployable Cage	22	All-to-All	176 TF/s	67.5 TB/s	22.5 TB/s	31 TB/s
Rack	128	Flat. Butterfly	1 PF/s	.4 PB/s	0.13 PB/s	0.066 PB/s
Group Cluster	512	Flat. Butterfly	4.1 PF/s	1.6 PB/s	0.52 PB/s	0.26 PB/s
National Resource	128k	Hier. All-to-All	1 EF/s	0.4 EB/s	0.13 EB/s	16.8 PB/s
Max Configuration	2048k	Hier. All-to-All	16 EF/s	6.4 EB/s	2.1 EB/s	0.26 EB/s

# Need for Adaptivity

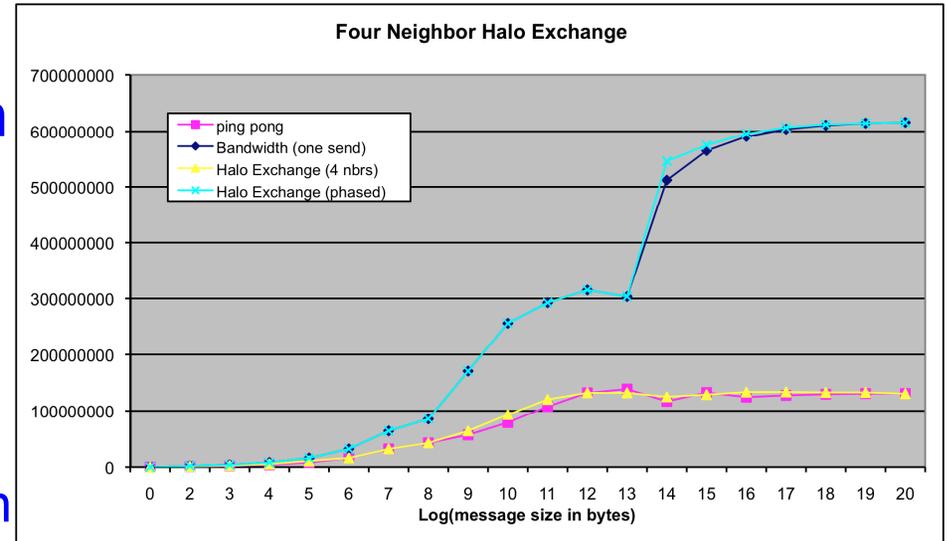
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- Uniform meshes rarely optimal
  - ◆ More work than necessary
  - ◆ Note that minimizing floating-point operations will not minimize running time – perfect irregular mesh is also not optimal
- Once adaptive meshing/model approximations used, need to address load balance, avoid the use of synchronizing operations
  - ◆ No barriers
  - ◆ Nothing that looks like a barrier (MPI\_Allreduce)
    - See MPI\_Iallreduce, likely to appear in MPI 3
  - ◆ Care with operations that are weakly synchronizing– e.g., neighbor communication (it synchronizes, just not as tightly)
    - Using MPI\_Send synchronizes



# Consequences of Unnecessary Synchronization

- How relevant is ping-pong bandwidth and real system
- What are the correct parameters?
  - ◆ Model the real system, but abstractly
  - ◆ For Blue Gene, must model independent communication
  - ◆ Impacts choice of communication algorithm (many benchmarks do not provide a relevant measurement)
- Using one MPI\_Send at a time prevents use of concurrent communication
  - ◆ Similar effects even if there is one communication path out of node, but contention in the network. Performance can suffer 2x or more slow down
  - ◆ Unnecessary in many cases
  - ◆ Benchmarks that use MPI\_Send are not "fair"



# Processes and SMP nodes

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- HPC users typically believe that their code “owns” all of the cores all of the time
  - ◆ The reality is that was never true, but they did have all of the cores the same fraction of time when there was one core /node
  - ◆ Given this belief, load balancing is unnecessary for regular grid codes
  - ◆ Is this true?
- We can use a simple performance model to check the assertion and then use measurements to identify the problem and suggest fixes.
- Consider a simple Jacobi sweep on a regular mesh, with every core having the same amount of work. How are run times distributed?

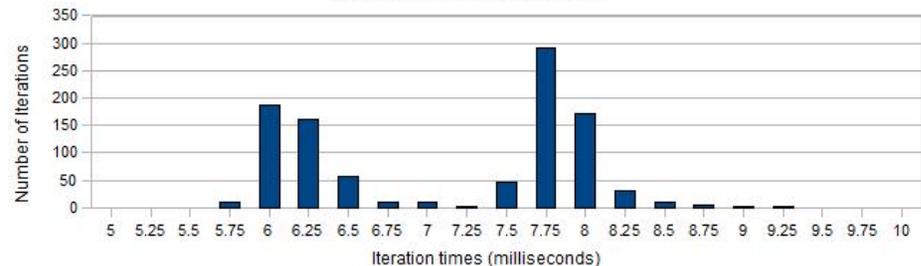


# Sharing an SMP

- Having many cores available makes everyone think that they can use them to solve other problems (“no one would use all of them all of the time”)
- However, compute-bound scientific calculations are often *written* as if all compute resources are owned by the application
- Such *static* scheduling leads to performance loss
- Pure dynamic scheduling adds overhead, but is better
- Careful mixed strategies are even better
- Recent results give 10-16% performance improvements on large, scalable systems
- Thanks to Vivek Kale

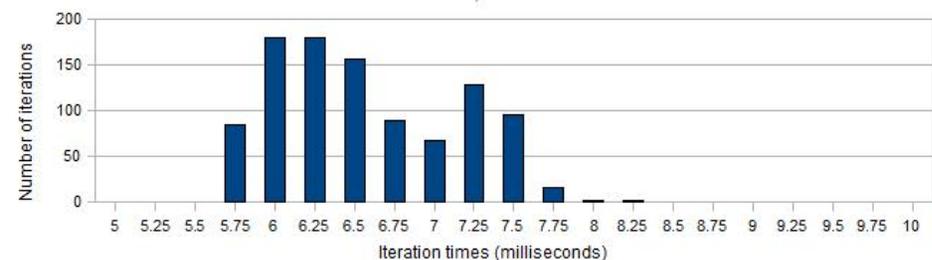
Distribution of Iteration Times for fully Static scheduling

1000 iterations , 64 x 512 x 64



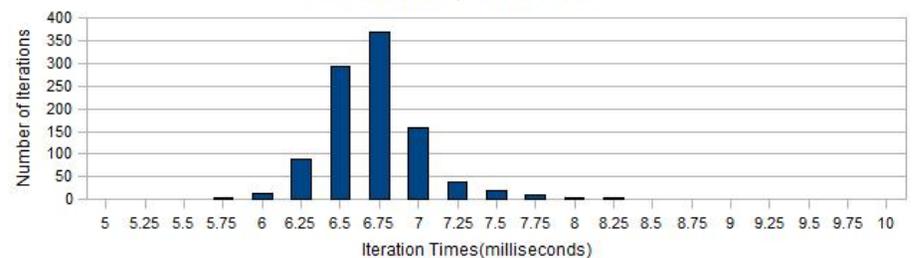
Distribution of Iteration times for 50% dynamic , with 64 tasklets

1000 iterations, 64 x 512 x 64



Distribution of iteration times for 50% dynamic scheduling (skewed tasklet workload)

1000 iterations, 64 x 512 x 64



# Need for Aggregation

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- Functional units are cheap
  - ◆ Small amount of area, relatively small amount of power
  - ◆ Memory motion is expensive
  - ◆ Easy to arrange many floating point units, in different patterns
    - Classic vectors (Cray, NEC SX)
    - Commodity vectors (2 or 4 elements)
    - Streams
    - GPU
  - ◆ All have different requirements on both the algorithms (e.g., work with full vectors) and programming (e.g., satisfy alignment rules)
  - ◆ Compilers will be able to help but will not solve the problem
    - The following compares three compilers success at producing good commodity vector code from loops in applications



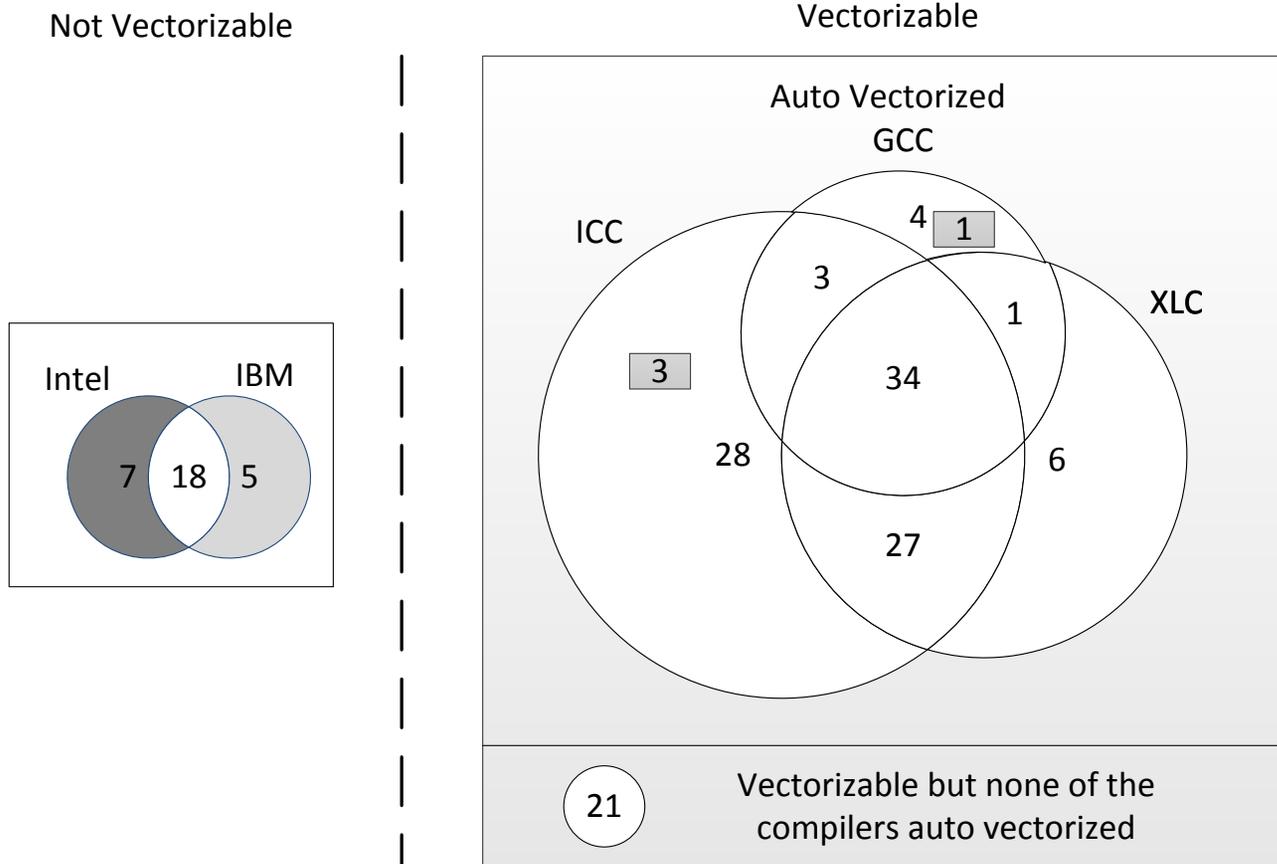
# Utilizing the Processor

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- Note rapidly growing numbers of functional units – Power7 has 2 multiply-add units per core; x86 increasingly long; accessed through “vector” instructions
- How do we know how well we are doing?
- How do we know how well the compiler is doing?
- We can model the expected performance, including vectorization!
- Using the model, we can also identify where manually applying well-known transformations will help
- Also identifies where extra constraints, such as alignment restrictions, may inhibit use of vectorization



# How Good are Compilers at Vectorizing Codes?



S. Maleki, Y. Gao, T. Wong, M. Garzarán, and D. Padua. An Evaluation of Vectorizing Compilers. In preparation. 2011.

# Media Bench II Applications

Appl	XLC	ICC	GCC	XLC	ICC	GCC
	Automatic			Manual		
JPEG Enc	-	1.33	-	1.39	2.13	1.57
JEPG Dec	-	-	-	-	1.14	1.13
H263 Enc	-	-	-	1.25	2.28	2.06
H263 Dec	-	-	-	1.31	1.45	-
MPEG2 Enc	-	-	-	1.06	1.96	2.43
MPEG2 Dec	-	-	1.15	1.37	1.45	1.55
MPEG4 Enc	-	-	-	1.44	1.81	1.74
MPEG4 Dec	-	-	-	1.12	-	1.18

Table shows **whole program speedups** measured against unvectorized application



S. Maleki, Y. Gao, T. Wong, M. Garzarán, and D. Padua. An Evaluation of Vectorizing Compilers. In preparation. 2011.

# Need for Appropriate Data Structures

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- Choice of data structure strongly affects ability of the system to provide good performance (duh!)
  - ◆ Key is to work *with* the hardware provided for improving memory system performance, rather than using it as a crutch
  - ◆ This choice often requires a large scale view of the problem and is not susceptible to typical autotuning approaches



# Processes and Memory

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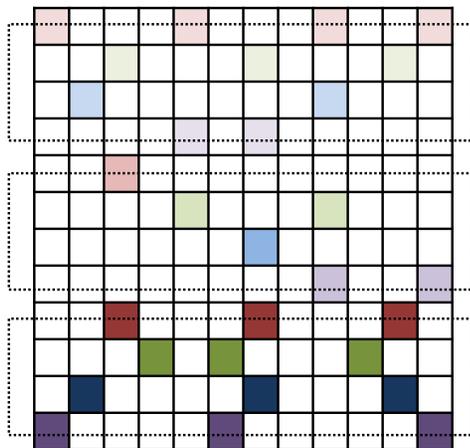
- For many computations, sustained memory performance is the limiting resource
  - ◆ As in sparse matrix-vector multiply
- What is the appropriate sustained rate?
  - ◆ Memory bus bandwidth is nearly irrelevant – it is the sustained rate that is usually important
  - ◆ What about other ways to increase effective sustained performance, such as prefetch?
- Prefetch hardware can detect regular accesses and prefetch data, making use of otherwise idle memory bus time.
  - ◆ However, the hardware must be presented with enough independent data streams



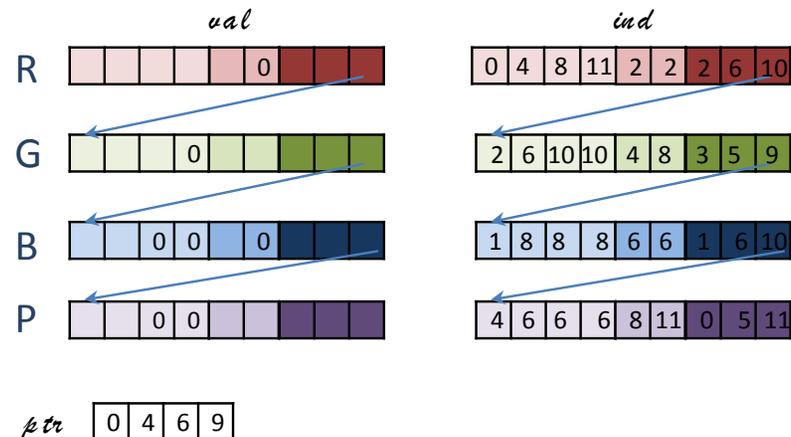
# Streamed Compressed Sparse Row (S-CSR) format

- S-CSR format partitions the sparse matrix into blocks along rows with size of  $bs$ . Zeros are added in to keep the number of elements the same in each row of a block. The first rows of all blocks are stored first, then second, third ... and  $bs$ -th rows.
- For the sample matrix in the following Figure,  $NNZ = 29$ . Using a block size of  $bs = 4$ , it generates four equal length streams  $R$ ,  $G$ ,  $B$  and  $P$ . This new design only adds 7 zeros every 4 rows.

A sparse matrix ( $N = 12$ ,  $NNZ = 29$ )

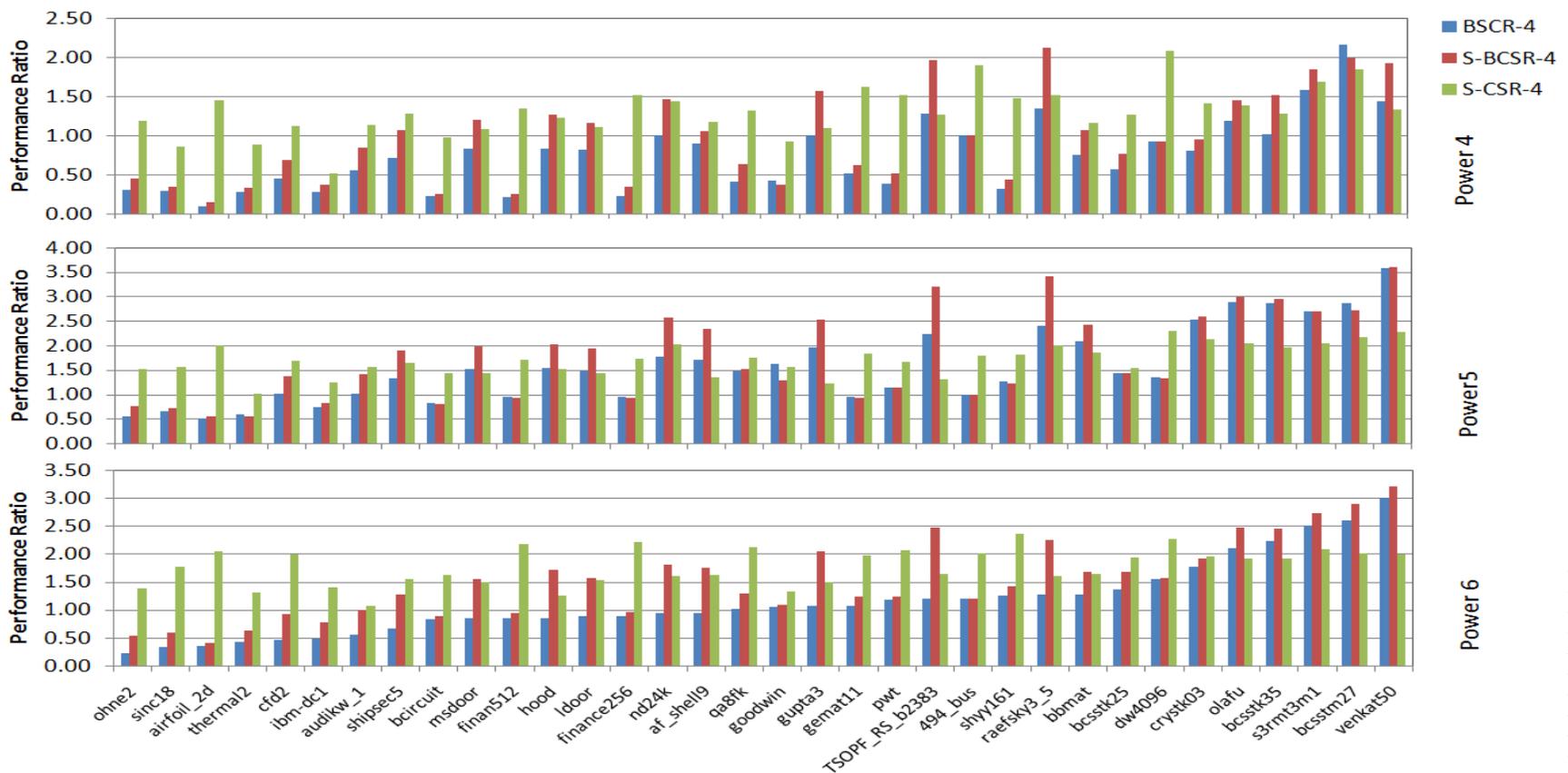


Streamed Compressed Sparse Row format (S-CSR)



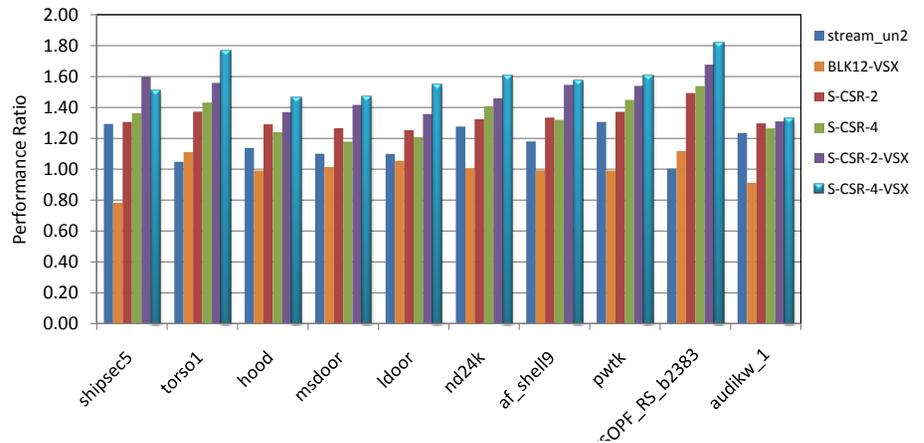
# Performance Ratio Compared to CSR Format

- S-CSR format is better than CSR format for all (on Power 5 and 6) or Most (on Power 4) matrices
- S-BCSR format is better than BCSR format for all (on Power 6) or Most (on Power 4 and 5) matrices
- Blocked format performance from 1/2 to 3x CSR.

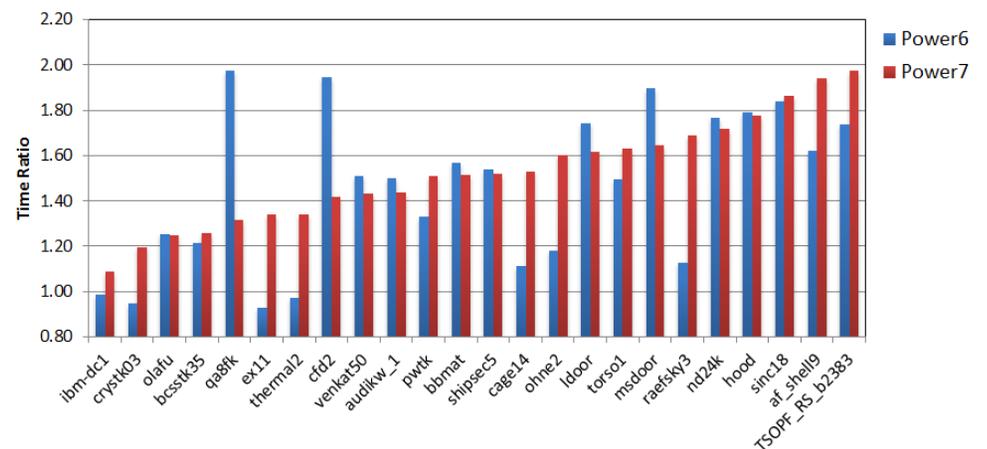


# Combining With Other Optimizations

- We can further modify the S-CSR and S-BCSR to match the requirements for vectorization
- We can use OSKI to optimize “within the loops”



Time comparison between updated OSKI and original OSKI



# Implications

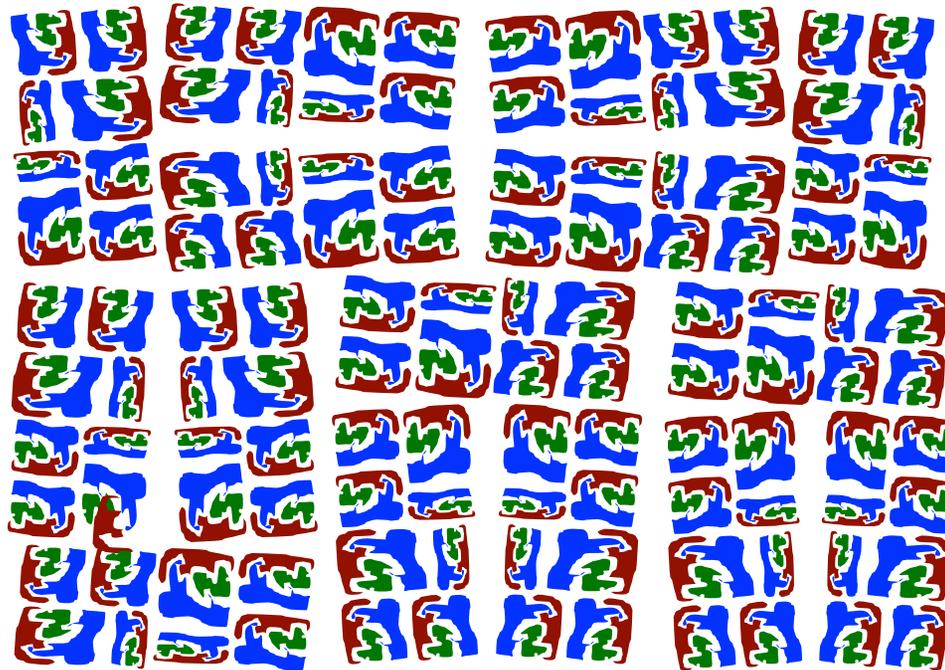
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- Vertically integrated (all modules within same “locality domain”)
  - ◆ Not horizontally in processor blocks
  - ◆ Adapt for load balance
    - Challenges
      - Minimize memory motion
      - Work within limited memory
    - ◆ Likely approach: interleave components in regions (nodes, if nodes have 1000’s of cores)



# Locality Domains

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- In hardware, the memory is in a hierarchy – core, memory stick, chip, node, module, rack, ..
- Algorithm/implementation needs to respect this hierarchy

# Implications 2

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- Restrict the use of separate computational and communication “phases”
  - ◆ Need more overlap of communication and computation to achieve latency tolerance (and energy reduction)
  - ◆ Adds pressure to be memory efficient



# Implications 3

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- Use aggregates that match the hardware
- Limit scalars to limited, essential control
  - ◆ Data must be in a hierarchy of small to large
- Fully automatic fixes unlikely
  - ◆ No vendor compiles the simple code for DGEMM and uses that for benchmarks
  - ◆ No vendor compiles simple code for a shared memory barrier and uses that (e.g., in OpenMP)
  - ◆ Until they do, the best case is a human-machine interaction, with the compiler helping



# Possible Solution Directions

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- Use mathematics as the organizing principle
  - ◆ Continuous representations, possibly adaptive, memory-optimizing representation, lossy (within accuracy limits) but preserves essential properties (e.g., conservation)
- Manage code by using data-structure-specific languages to handle operations and vertical integration across components
  - ◆ So-called “domain specific languages” are really data-structure specific languages – they support more applications but fewer algorithms.
  - ◆ Difference is important because a “domain” almost certainly require flexibility with data structures and algorithms



# Possible Solution Directions

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- Adaptive program models with a multi-level approach
  - ◆ Lightweight, locality-optimized for fine grain
  - ◆ Within node/locality domain for medium grain
  - ◆ Regional/global for coarse grain
  - ◆ May be different programming models (hierarchies are ok!) but they must work well together
- Performance annotations to support a complex compilation environment
- Asynchronous algorithms
- Integrated Development Environment (IDE) to ease vertical code development, maintenance, and refactoring



# Conclusions

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- Planning for extreme scale systems requires rethinking both algorithms and programming approaches (duh!)
- Key requirements include
  - ◆ Minimizing memory motion at all levels
  - ◆ Avoiding unnecessary synchronization at all levels
- Decisions must be informed by performance modeling / understanding
  - ◆ Not necessarily performance estimates – the goal is to guide the decisions



# Conclusions

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- Practical issues require separating algorithm, data structure, and implementation
  - ◆ Libraries will need to be supplemented by generated code
  - ◆ They may be data-structure-specific languages or annotations
    - Most proposals are not for domain specific, as they make assumptions about data structure and algorithm
    - Matlab is, after all, not domain specific – it is primarily data structure specific



# Thanks

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- Torsten Hoefler
  - ◆ Performance modeling lead, Blue Waters; MPI datatype
- David Padua, Maria Garzaran, Saeed Maleki
  - ◆ Compiler vectorization
- Dahai Guo
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- Vivek Kale
  - ◆ SMP work partitioning
- Hormozd Gahvari
  - ◆ AMG application modeling
- Marc Snir and William Kramer
  - ◆ Performance model advocates
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  - ◆ Process/node mapping
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