Task mapping, job placements and routing strategies



Abhinav Bhatele Center for Applied Scientific Computing

LLNL: Peer-Timo Bremer, Todd Gamblin, Katherine E. Isaacs, Steven H. Langer, Kathryn Mohror, Martin Schulz

Illinois: Ronak Buch, Nikhil Jain, Harshitha Menon, Laxmikant V. Kale, Michael Robson

Utah: Amey Desai, Aaditya G. Landge, Valerio Pascucci

Purdue: Ahmed Abdel-Gawad, Mithuna Thottethodi

LBL: Brian Austin, Nicholas J.Wright

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Floating point operation	< 0.25	30-45
Time to access DRAM	50	128
Get data from another node	> 1000	128-576

P. Kogge et al., Exascale computing study: Technology challenges in achieving exascale systems, *Technical Report*, 2008.





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IBM		Cr	ay
Blue Gene/L	0.375	XT3	8.77
Blue Gene/P	0.375	XT4	1.36
Blue Gene/Q	0.117	XT5	0.23

Network bytes to flop ratios

A. Bhatele et al., Automated mapping of regular communication graphs on mesh interconnects, Intl. Conf. on High Performance Computing (HiPC), 2010.





- High costs for data movement in terms of time and energy
- Newer platforms stressing communication further (more cores, bigger networks)
- Imperative to minimize data movement and maximize locality



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TASK MAPPING











- What is mapping layout/placement of tasks/processes in an application on the physical interconnect
- Does not require any changes to the application







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- Goals:
 - Balance computational load
 - Minimize contention (optimize latency or bandwidth)



- Traditionally, research has focused on bringing tasks closer to reduce the number of hops
 - Minimizes latency, but more importantly link contention
- For applications that send large messages this might not be optimal







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Rubik

- We have developed a mapping tool focusing on:
 - structured applications that are bandwidth-bound, use collectives over sub-communicators
 - built-in operations that can increase effective bandwidth on torus networks based on heuristics
- Input:
 - Application topology with subsets identified
 - Processor topology
 - Set of operations to perform
- Output: map file for job launcher





Application example

app = box([9,3,8]) # Create app partition tree of 27-task planes
app.tile([9,3,1])

network = box([6,6,6]) # Create network partition tree of 27-processor cubes
network.tile([3,3,3])

network.map(app) # Map task planes into cubes





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Mapping pF3D

- A laser-plasma interaction code used at the National Ignition Facility (NIF) at LLNL
- Three communication phases over a 3D virtual topology:
 - Wave propagation and coupling: 2D FFTs within XY planes
 - Light advection: Send-recv between consecutive XY planes
 - Hydrodynamic equations: 3D near-neighbor exchange





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<image/>	

	2048 cores		16384	cores
MPI call	Total %	MPI %	Total %	MPI %
Send	4.90	28.45	23.10	57.21
Alltoall	8.10	46.94	7.30	18.07
Barrier	2.78	16.10	8.13	20.15



Performance benefits



A. Bhatele et al. Mapping applications with collectives over sub-communicators on torus networks. In Proceedings of the ACM/IEEE International Conference for High Performance Computing, Networking, Storage and Analysis, SC '12. IEEE Computer Society, November 2012.





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Visualizing network traffic using **Boxfish**



MODELING & SIMULATION









Predicting execution time without executing the code

- Goal: find which mapping gives the best performance
- Offline metrics: maximum hops, average bytes, maximum bytes
- Use network hardware counters to propose new metrics
- Supervised learning algorithms to predict performance

N. Jain et al. Predicting application performance using supervised learning on communication features. In Proceedings of the ACM/IEEE International Conference for High Performance Computing, Networking, Storage and Analysis, SC '13. IEEE Computer Society, November 2013.









 Wasted allocation hours

	2012	2013
Intrepid	4.16M	0.73M
Mira	0.17M	7.67M
Total	4.33M	8.40M





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13 million core hours!





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- Wasted allocation hours
- Wasted time in the queue
- All we need is which is the best mapping?

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Supervised learning: scikit-learn

- Use simulation and other tools to obtain network counters and other contention parameters
- Exploit supervised learning algorithms for performance prediction
 - forests of randomized decision trees



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Decision surfaces of a random forest





Existing and new metrics

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Maximum Dilation

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- Existing metrics
 - maximum hops
 - average bytes
 - maximum bytes
- New metrics:
 - Buffer length (on intermediate node)
 - FIFO length (packets in injection FIFOs)
 - Delay per link (packets in buffers / #received packets)

Fime per iteration (ms)

60

50

40

30

20

0







Message life cycle on Blue Gene/Q







Results

- Three communication kernels
 - Five-point 2D Stencil
 - 14-point 3D Stencil
 - All-to-all over subcommunicators





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Absolute performance correlation





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Absolute performance correlation





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Blue Gene/Q (16,384 cores)





 Better correlation than with existing metrics such as average or maximum bytes





- Better correlation than with existing metrics such as average or maximum bytes
- Hybrid metric:
 - average bytes + maximum bytes + average buffer length + maximum FIFO length





- Better correlation than with existing metrics such as average or maximum bytes
- Hybrid metric:
 - average bytes + maximum bytes + average buffer length + maximum FIFO length
- Crazy things:
 - combine all training sets
 - use 16k training set to predict 64k performance





Predicting the performance of pF3D

Production application

- has computation
- and multiple phases of communication
- Hybrid metric:
 - average bytes + average buffer length + average delay + sum of hops + maximum FIFO length





Blue Gene/Q (16,384 cores)



JOB PLACEMENT & ROUTING







Performance variability

Average messaging rates for batch jobs running a laser-plasma interaction code





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Performance variability

Average messaging rates for batch jobs running a laser-plasma interaction code



Total number of bytes sent on the network

Time spent sending the messages



Leads to several problems ...

- Individual jobs run slower:
 - More time to complete science simulations
 - Increased wait time in job queues
 - Inefficient use of machine time allocation/core-hours
- Overall lower throughput
- Increase energy usage/costs





Also affects software development

- Debugging performance issues
- Quantifying the effect of various software changes on performance
 - code changes
 - compiler/software stack changes
- Requesting time for a batch job
- Writing allocation proposals





pF3D characterization

Time spent in communication and computation in pF3D







pF3D characterization



Time spent in MPI calls on 512 nodes





Sources of variability

• Operating system noise (OS jitter)

- OS daemons running on some cores of each node
- Placement/location of the allocated nodes for the job (Allocation shape)
- Contention for shared resources (Inter-job contention)
 - Sharing network links with other jobs





April I 16



April II

April 16

https://scalability.llnl.gov/performance-analysis-through-visualization/software.php







April I I 6



April I I MILC job in green

April 16 25% higher messaging rate

https://scalability.llnl.gov/performance-analysis-through-visualization/software.php





April I 16



April II

April 16b





April I 16



April I I MILC job in green

April 16b

27.8% higher messaging rate, LSMS is not communication-heavy









March 15 April 04



March 15

April 04







March 15 April 04



March 15

Three conflicting jobs, two MILC



April 04

2.29X higher messaging rate



Effect of MILC on pF3D





Effect of MILC on pF3D





Effect of MILC on pF3D





Performance tip!

- Variability insignificant on IBM Blue Gene systems
- OS noise and allocation shape have a weak correlation with performance

 The placement of other jobs around a job can affect its performance significantly

http://www.hpcwire.com/2013/11/16/sc13-research-highlight-goes-performance-neighborhood/



Modeling job placements and message routing

- Dragonfly topology: a two-level hierarchical topology
- Routing choices: static (deterministic) vs. dynamic (adaptive), direct vs. indirect (random jumps)
- Placement options: random, round-robin, blocked



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Single jobs



Job placements grouped based on Routing



Parallel job workload

- Representative of NERSC workloads
- Static routing out of the question
- Routings with indirect jumps preferred



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COMPUTΛTION









Summary

- Optimizing communication is the #1 priority
 - Minimize off-node communication
 - Map remaining off-node communication carefully
- Job placements and mapping are non-intrusive methods for improving performance
- Going forward: modeling and simulation will be crucial for:
 - designing future networks
 - predicting application performance





http://computation-rnd.llnl.gov/extreme-computing/ interconnection-networks.php

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