Vector Load Balancing for High-Performance Parallel Applications

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Parallel Programming Laboratory
University of Illinois at Urbana-Champaign
Thesis Defense

Committee

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- Professor Luke Olson
- Professor David Padua
- Dr. Antonio Peña (Barcelona Supercomputing Center)

Outline

Background and Motivation

“Many hands make light work”

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Caveats

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- Work needs to be *divisible*

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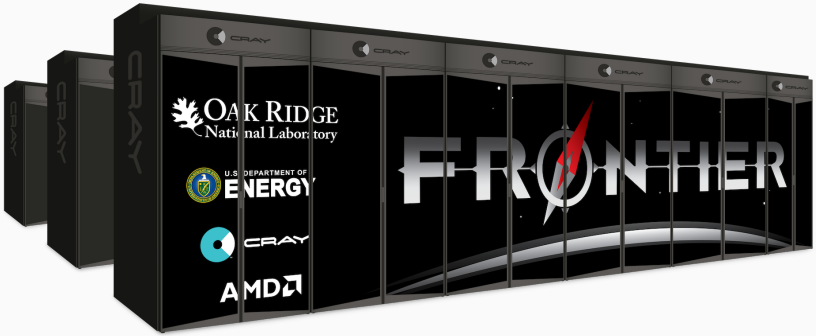
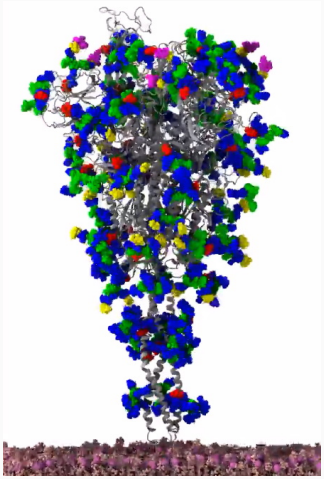
High Performance Computing



Supercomputers: many cores, many nodes, fast network, large memory, large storage

Why High Performance Computing?

- Necessary for science
  - No other way to do astrophysics, molecular dynamics, ...
  - Safety for storm surge, epidemic simulation, ...
  - Cost for iterative design, material analysis, ...



Using High Performance Computing

- By definition, HPC requires *high performance*
- Massive, powerful, systems, but hard to use
  - How to keep all the resources occupied?

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Aim for *equitable* division of labor

Dynamic Load Balancing

- Load may change as application runs

Dynamic Load Balancing

- Load may change as application runs
- Adaptively rearrange work amongst PEs to maximize performance as computation evolves
- Most loaded PE usually determines iteration time
- Necessary for scaling all but very regular, static applications

LB Prerequisites

Need three things to use LB:

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Load measurement Track execution of objects

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Migratability Move objects to different PEs

Overdecomposition More objects than PEs

Charm++ provides all three!

Charm++

- Charm++ is a task-based parallel programming framework for HPC
- Provides all requirements for LB:
  - Active runtime measures object loads
  - Serializable, migratable objects allows work to be moved
  - Supports many objects per PE for overdecomposition

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- Provides all requirements for LB:
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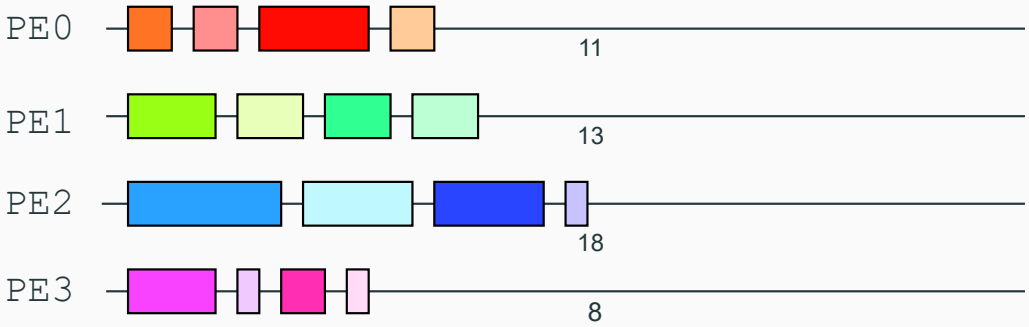
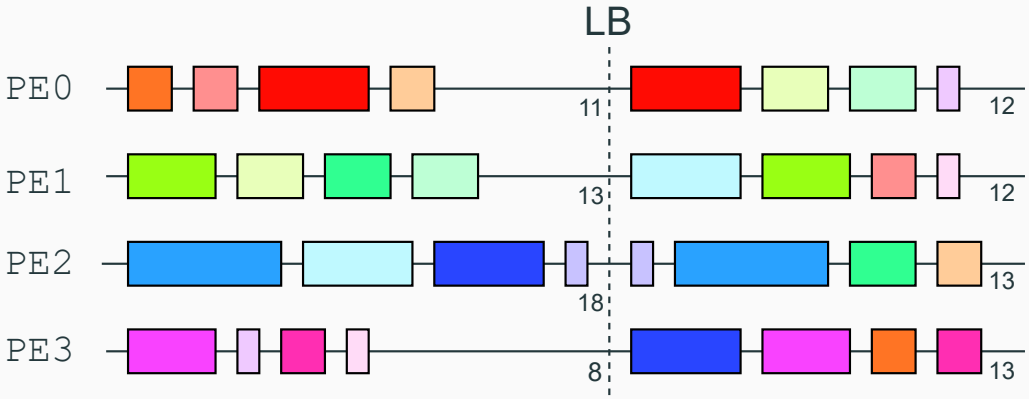
- Used throughout, but work **not Charm++ specific**

Before LB



After LB



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Deficient for many classes of applications!

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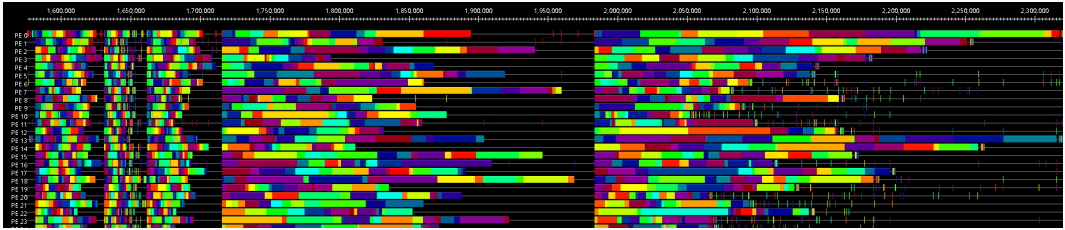

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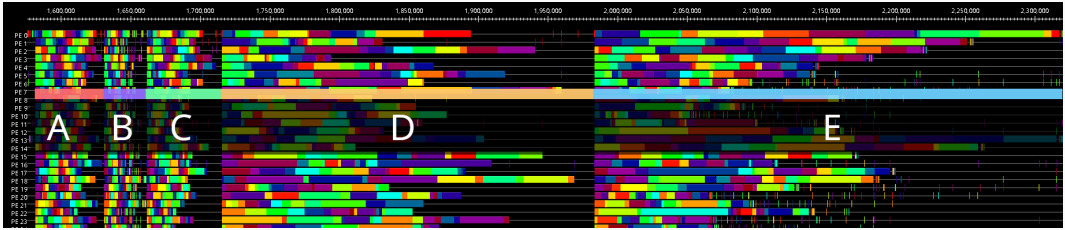

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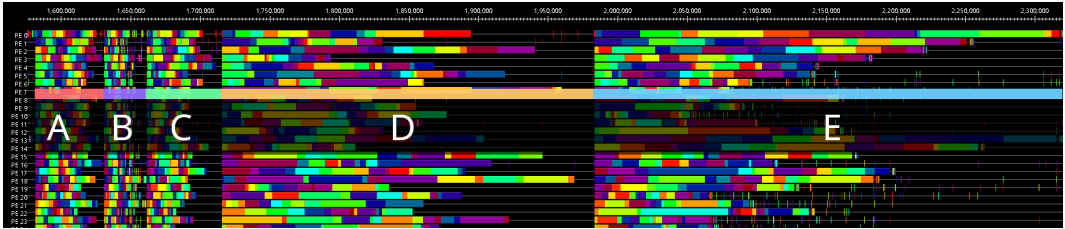

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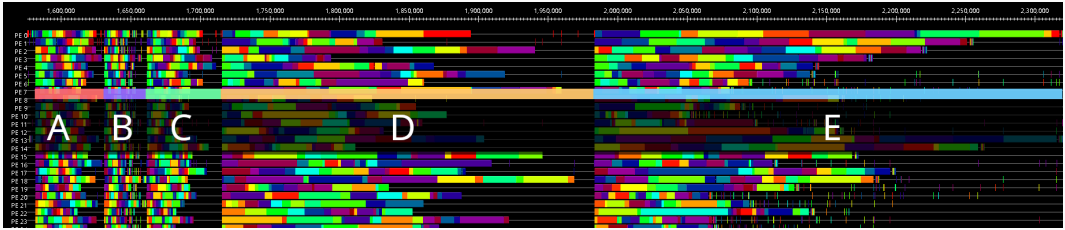

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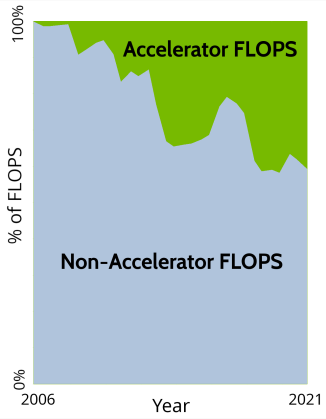

Share of Top500 FLOPS over Time

- Accelerators are large source of FLOPS in HPC

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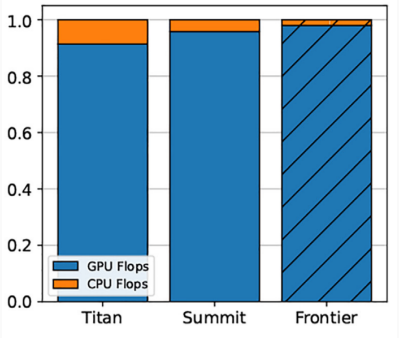

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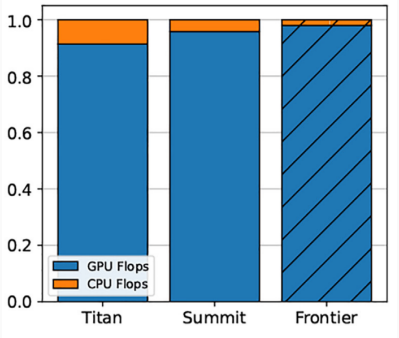

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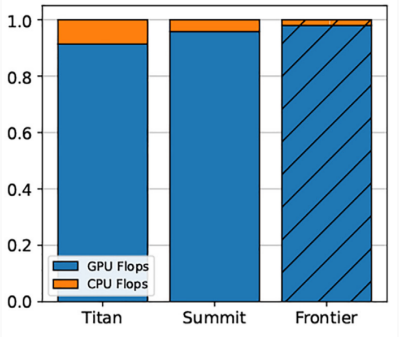

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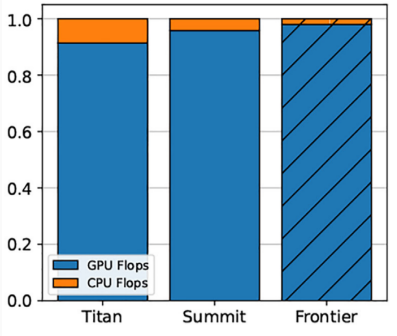

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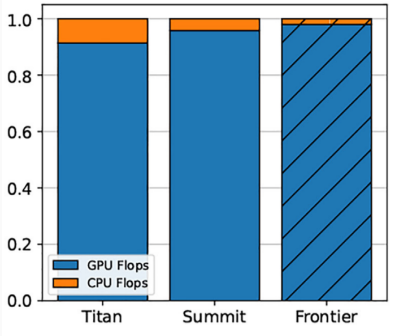

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- Scalar cannot retain *processor type* of load

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Scalar Load Deficiencies - Constraints

- Object mapping may be subject to some constraints
  - Required: Memory footprint, File descriptor count, ...
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- Cannot encode *constraints* and load into scalar

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  - In nutrition: fat, protein, carbohydrates, vitamins, ...
- The same applies to computer programs!

Vector Load Balancing

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  - Resource constrained applications
    - Resource usage alongside CPU time: $< cpu, mem >$

Measuring Vector Loads

- Features and APIs to measure vector loads:
  - Applications can call function to indicate phase boundary, RTS automatically measures per-phase load
  - Runtime flags to automatically add communication load (# messages, bytes sent)
  - Memory footprint via `PUP`
  - GPU load via vendor timers
  - Users may manually specify load vector

Vector Load Balancing

Vector Load Balancing Strategies

Vector Balancing

- Existing LB strategies cannot use a load vector
  - Still compatible, vector converted to scalar via sum, max, etc.
- Multiple dimensions makes vector load balancing more complex
  - Objects can no longer be totally ordered
  - Want to minimize over all dimensions simultaneously
    - Single variable optimization is now multivariate
- New LB strategies are needed

Vector Strategies - Greedy

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  - Scalar version goes through objects from heaviest to lightest and assigns to the current least loaded processor

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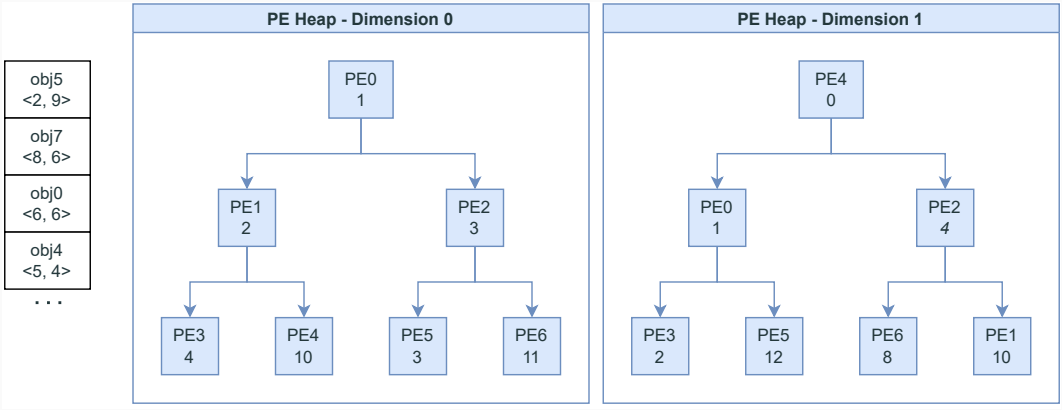
  - Scalar version goes through objects from heaviest to lightest and assigns to the current least loaded processor
- Vector version:
  - Create d PE minheaps, each keyed on a different dimension of the vector, add all PEs to each heap
  - Go through objects in descending $\max(\vec{l})$, assign to minimum PE in dimension of $\max(\vec{l})$ and update heaps
- Simple, but focuses on single dimension at a time

Vector Strategies - Greedy



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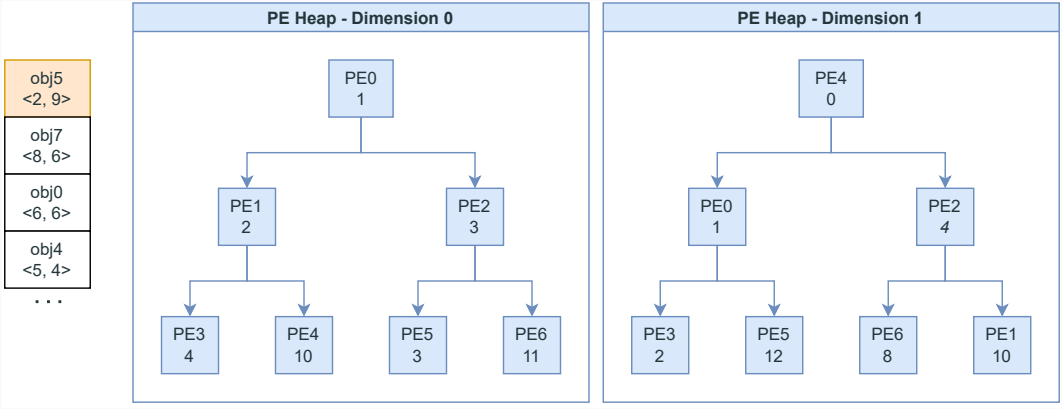

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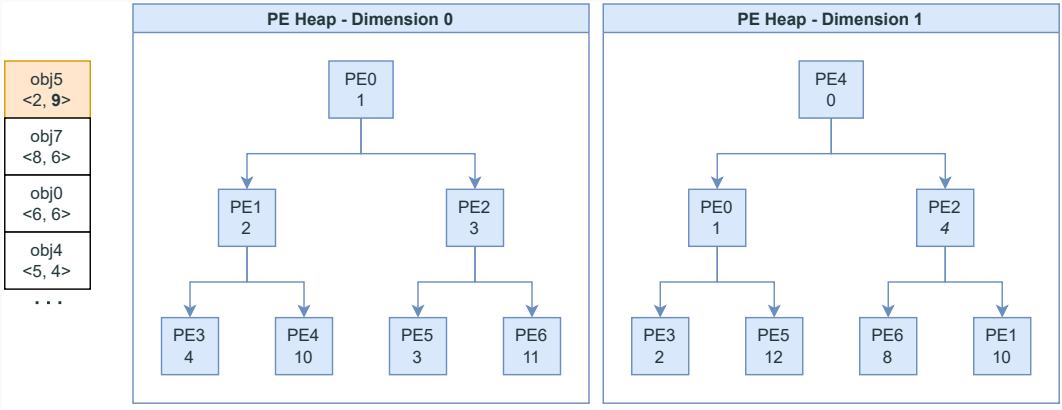

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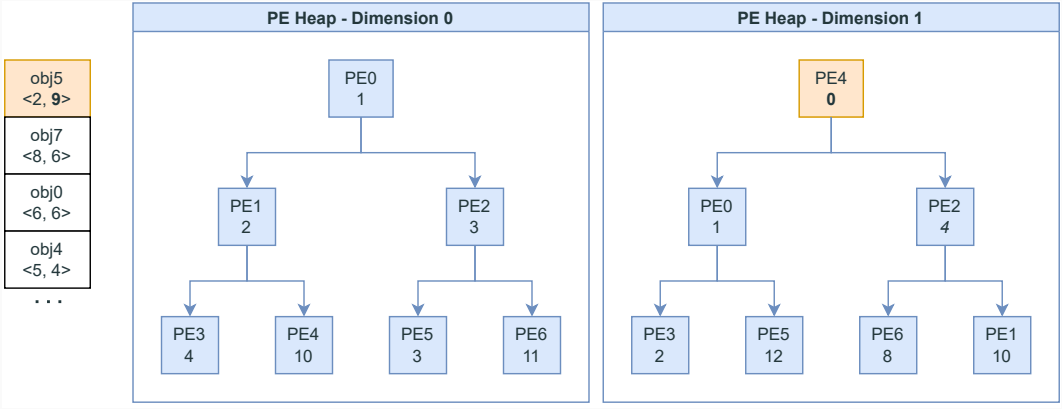

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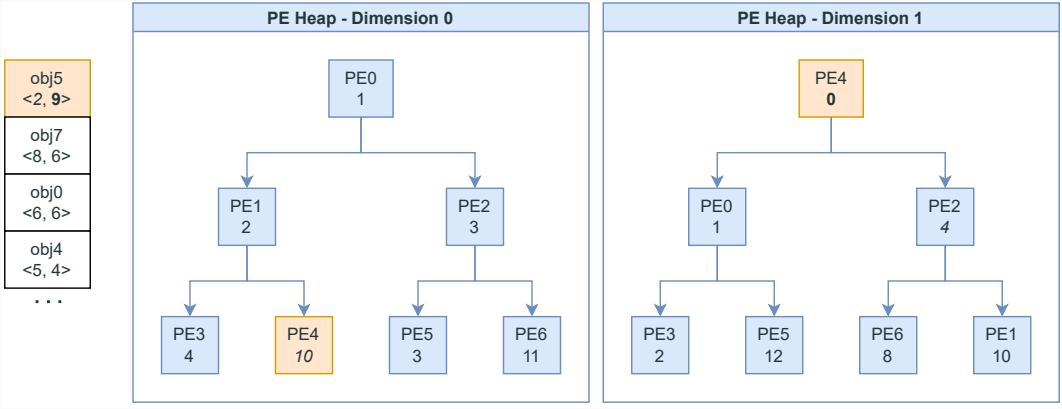

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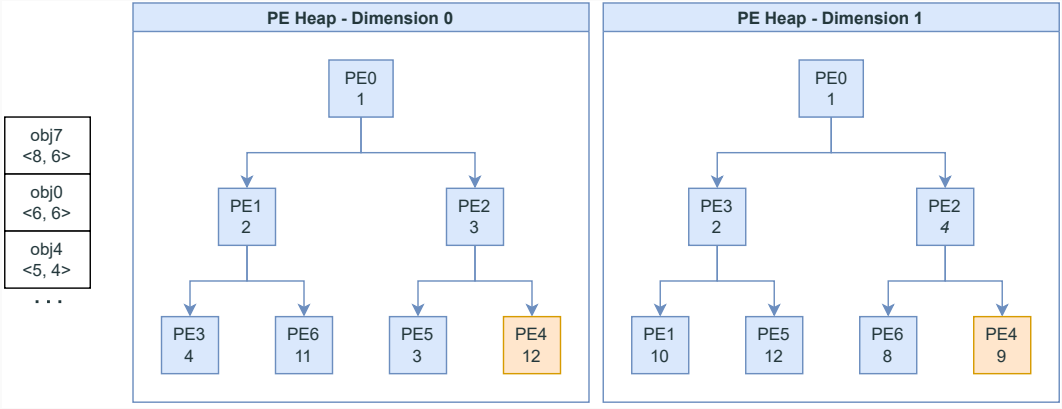

Vector Strategies - METIS

- METIS supports giving vertices vector weights
- Reframe LB problem as graph, objects map to vertices and output partitions map to PEs
  - No edges, but could use with comm graph
- Implemented via bipartitioning objects based on $\max(\vec{l})$ like Greedy, but adds refinement phase to consider rest of vector
- Generally works pretty well, but gives poor results for some configurations

Vector Strategies - Norm

- Go through objects in descending order and place on the PE such that the post-placement PE load vector norm is globally minimized
  - Works well, but computationally expensive
  - Norm inequalities are not preserved under vector addition:
    - $\|(2,0)\|_2 < \|(0,3)\|_2$
    - $\|(2,0)+(3,0)\|_2 > \|(0,3)+(3,0)\|_2$
  - Makes it non-trivial to reduce search space
- Choice of underlying norm (2, 4, ∞, etc.)

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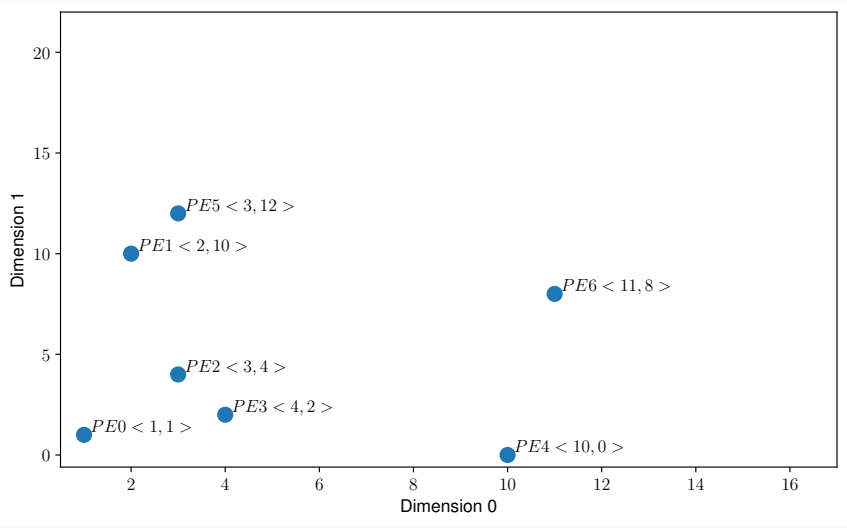

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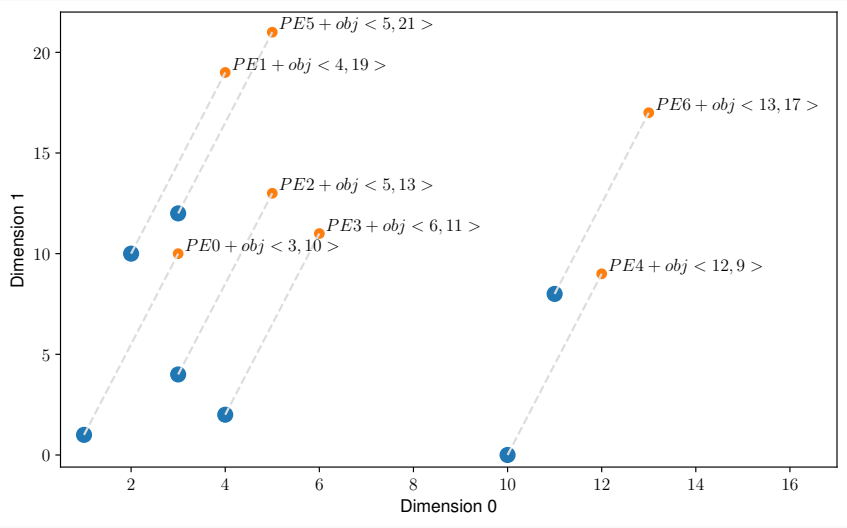

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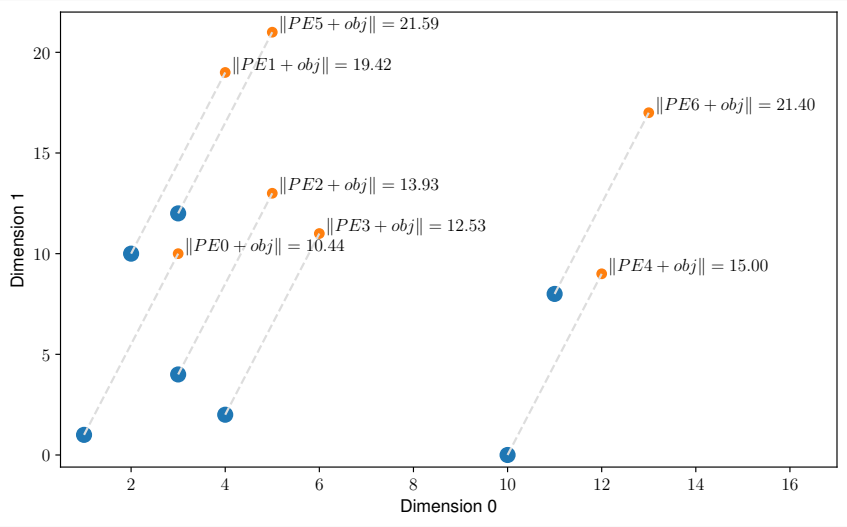

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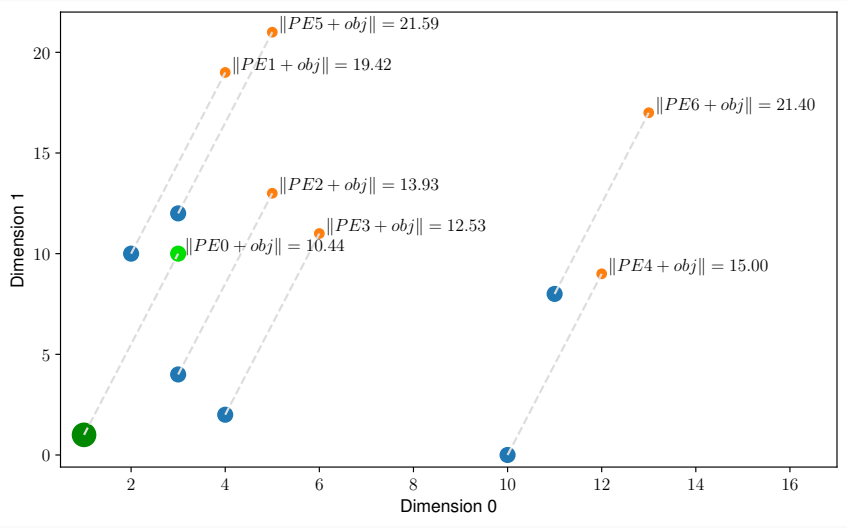


NormLB - k-d Implementation

- Represent PEs as points in a k-d tree
  - Arbitrary dimensional space partitioning tree
  - Can prune search space as candidates are found
- k-d works well for searching in static point set, but here, tree updated after every assignment
  - Costly update operations
  - Structured pattern of updates results in unbalanced tree
- Can be worse than the naïve exhaustive version!

Random Relaxed k-d (rk-d)

- Random Relaxed k-d trees help solve these problems; two key differences from standard k-d:

  Random Discriminant is uniformly randomly chosen and each insertion has some probability of becoming the root, or root of subtree, ...

  Relaxed Instead of cycling through discriminants, $1, 2, \ldots, k, 1, \ldots$, each node stores arbitrary discriminant $j \in \{1, 2, \ldots, k\}$

- Stochasticity keeps tree balanced, makes updates fast

Random Relaxed k-d

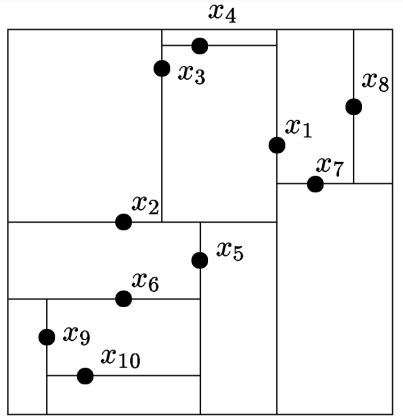


Figure 1: k-d

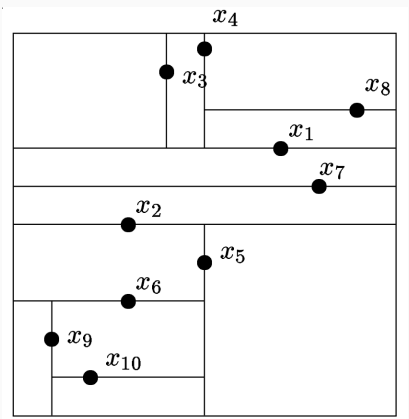
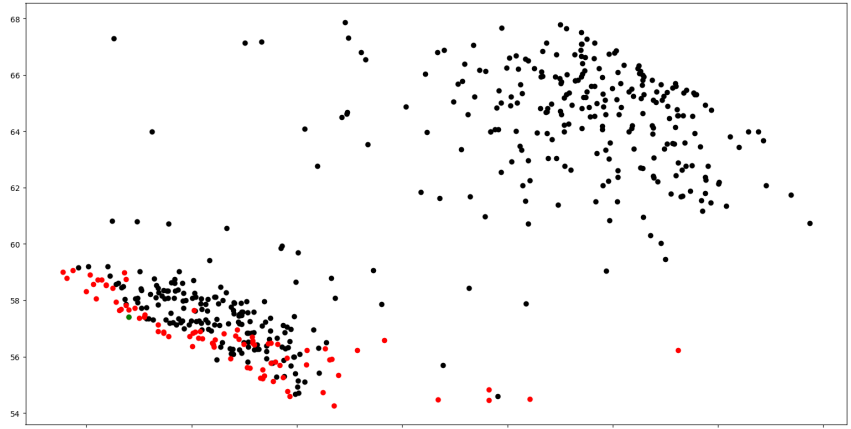


Figure 2: rk-d

k-d - Search Pruning



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- In vector world, only partially ordered
  - Is $\langle 4, 4 \rangle$ or $\langle 5, 2 \rangle$ better?
- Have to choose correct objective function for scenario!

Phase Objective Function

M mapping, O set of objects, P set of PEs, d dimensions

$$\arg\min_{M} \sum_{0 \le i < d} \left(\max_{p \in P} \left(\sum_{\forall o \in O : M(o) = p} (\vec{l_o})_i \right) \right) \quad (1)$$

Phase Objective Function

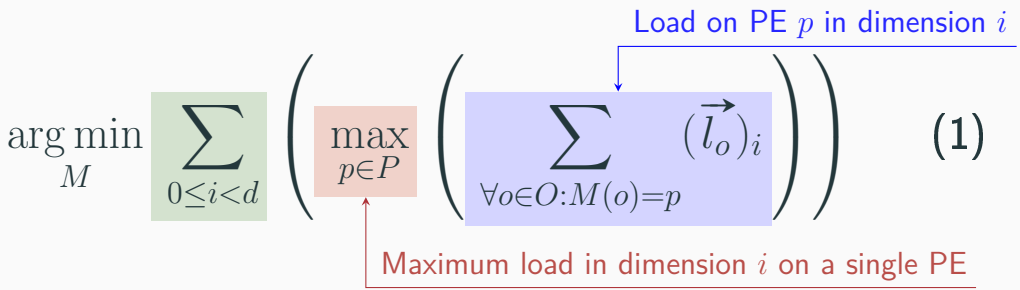
M mapping, O set of objects, P set of PEs, d dimensions

Load on PE p in dimension i

$$\arg\min_{M} \sum_{0 \le i < d} \left(\max_{p \in P} \left(\sum_{\forall o \in O : M(o) = p} (\vec{l_o})_i \right) \right) \quad (1)$$

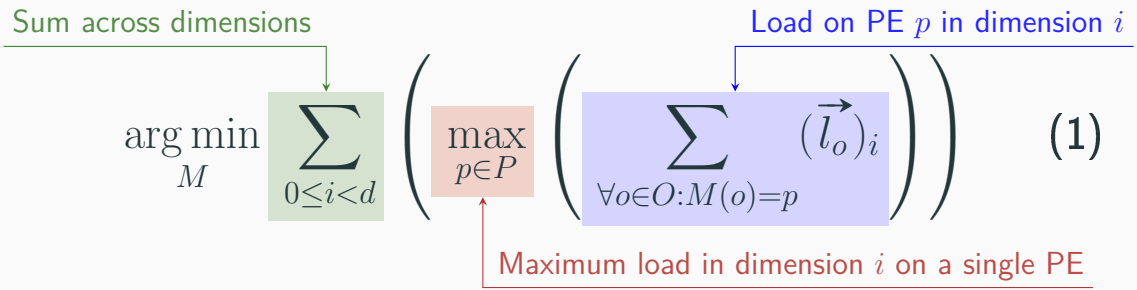
Phase Objective Function

M mapping, O set of objects, P set of PEs, d dimensions



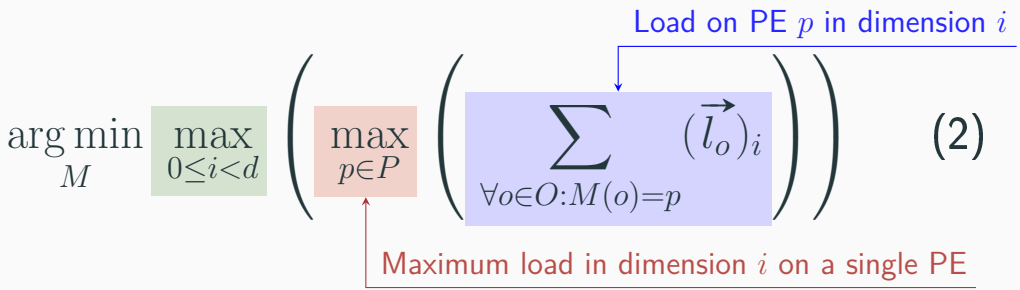
Phase Objective Function

M mapping, O set of objects, P set of PEs, d dimensions



Overlapped Objective Function

M mapping, O set of objects, P set of PEs, d dimensions



Overlapped Objective Function

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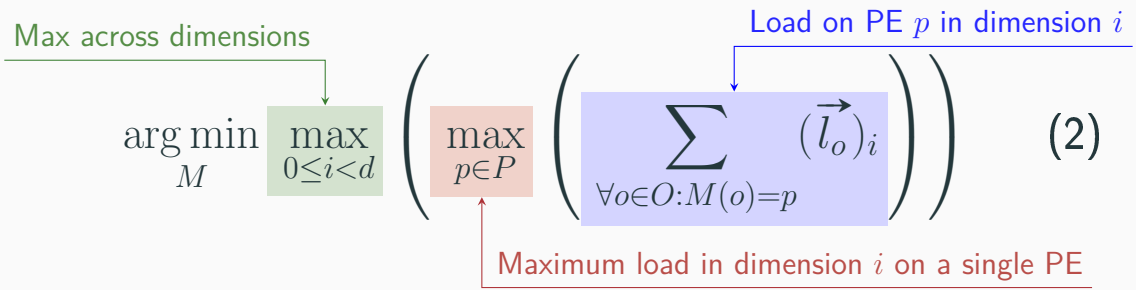

Generalized Objective Function

Take $\overrightarrow{l_M}$ to be the maximum load vector:

$$\overrightarrow{l_M} = \left\langle \max_{p \in P} \left(\sum_{\forall o \in O : M(o) = p} (\vec{l_o})_1 \right), \ldots, \max_{p \in P} \left(\sum_{\forall o \in O : M(o) = p} (\vec{l_o})_d \right) \right\rangle \quad (3)$$

Generalized Objective Function

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Then the general objective function is:

$$\arg\min_{M} \left\| \overrightarrow{l_M} \right\|_k \tag{4}$$

Generalized Objective Function

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Then the general objective function is:

$$\arg\min_{M} \left\| \overrightarrow{l_M} \right\|_k \tag{4}$$

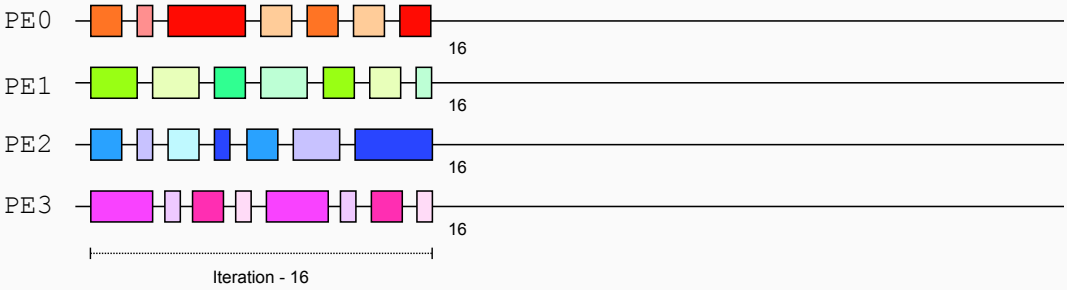
The phase case is $k = 1$, overlap is $k = \infty$

Balancing Phase-Based Applications

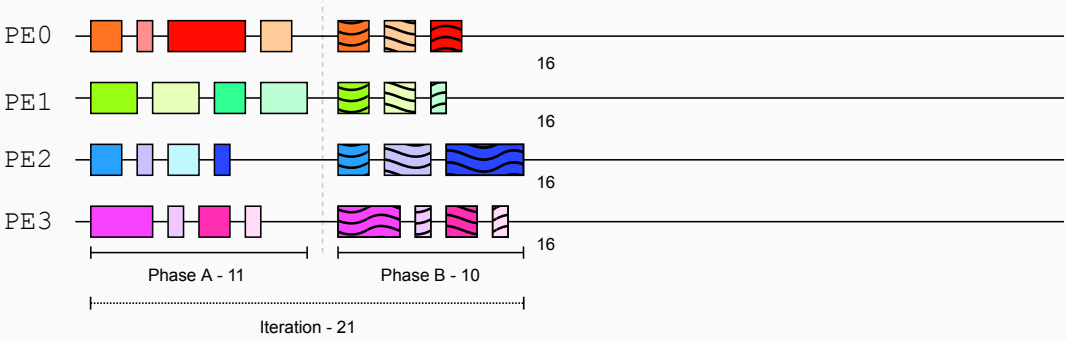
Why Phase-Based Applications?

- Multiphysics
  - Interaction of n different physical processes
- Multiscale
  - Update parts of domain at different frequencies
- Data Dependent Computation
  - Update everything, but different techniques for different distances, e.g. EM vs PME

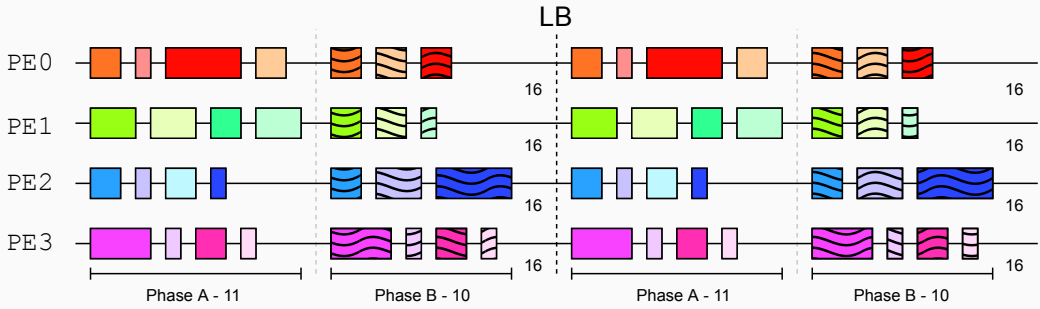
Non-Phase-Based Application



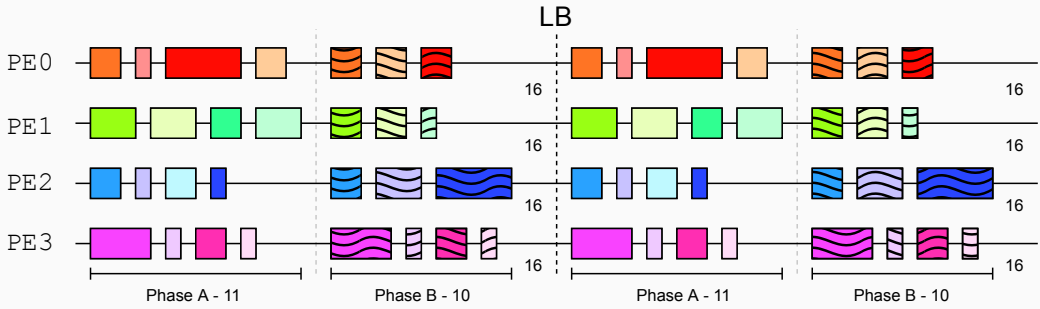
Phase-Based Application



Scalar LB

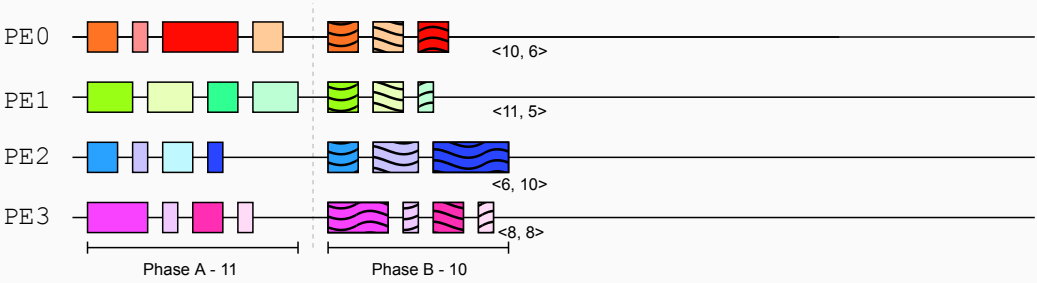

LB
PE0
PE1
PE2
PE3
16
16
16
16
16
16
16
16
Phase A - 11
Phase B - 10
Phase A - 11
Phase B - 10

Scalar LB

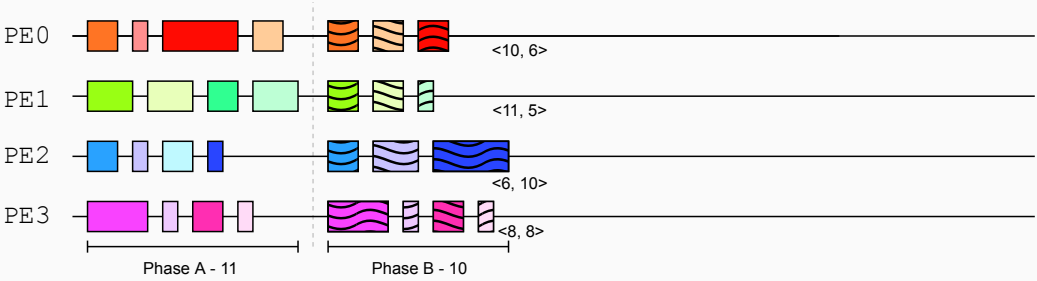


Scalar loads cannot identify imbalance!

Vector LB

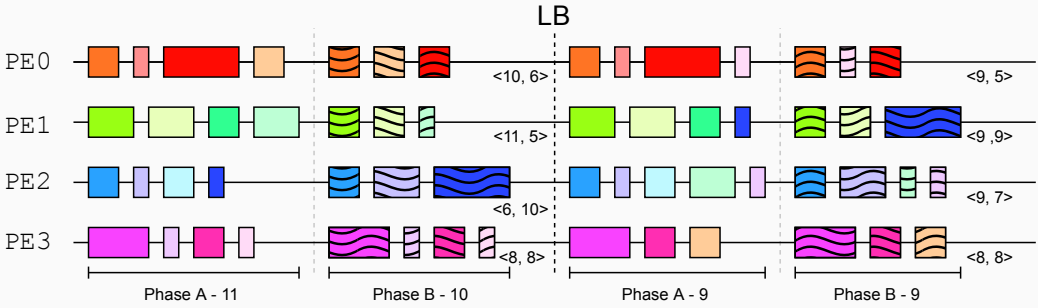


Vector LB

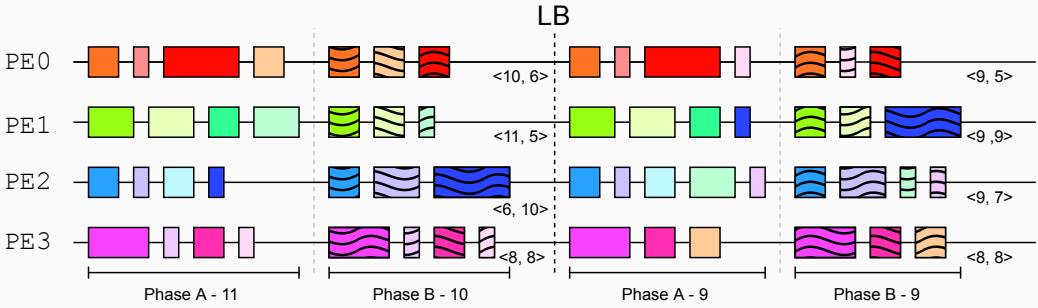


Identifies imbalance!

Vector LB


LB
PE0
PE1
PE2
PE3
<10, 6>
<11, 5>
<6, 10>
<8, 8>
<9, 5>
<9 ,9>
<9, 7>
<8, 8>
Phase A - 11
Phase B - 10
Phase A - 9
Phase B - 9

Vector LB

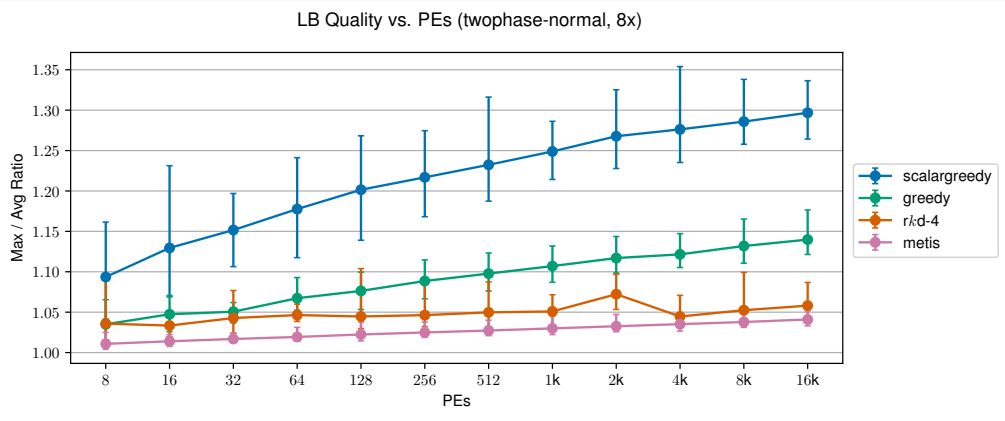


Identifies and *mitigates* imbalance!

LB Simulations

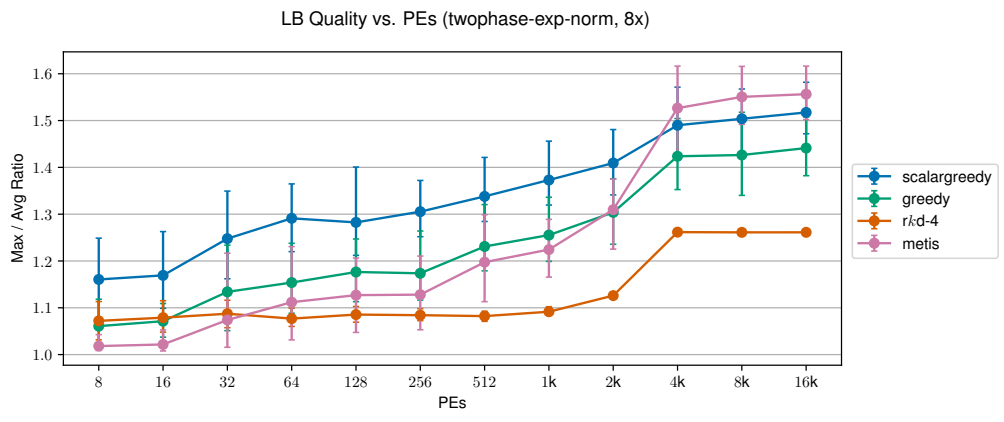
- Built LB simulator for testing and evaluation
  - Uses same LB strategy code as production use
- Allows testing large scale without burning many SUs
- Synthetic loads or production loads from logs
- Evaluates results by $Max : Avg$ ratio for chosen objective function
  - For phase-based case, use the sum-based objective

Vector LB Simulations - Phase



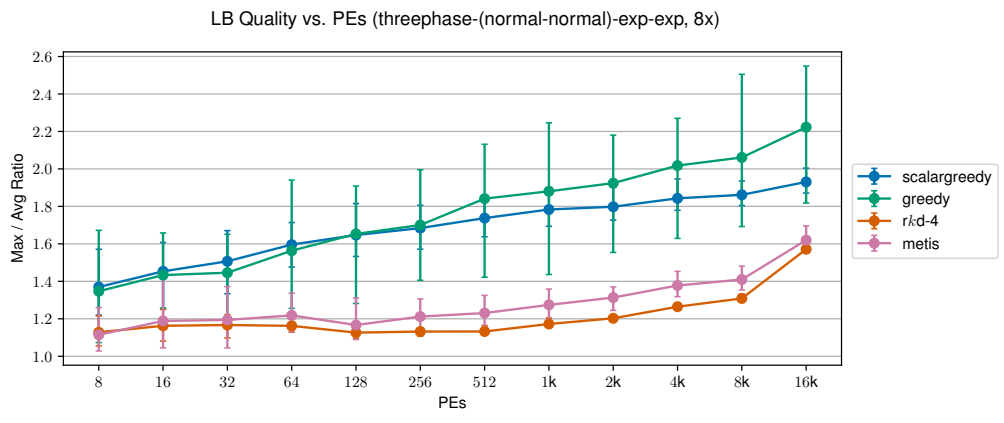
100 trials, Synthetic data: 2 phase (normal $\mu = 10, \sigma = 3$, normal $\mu = 10, \sigma = 3$)

Vector LB Simulations - Phase



100 trials, Synthetic data: 2 phase (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Vector LB Simulations - Phase

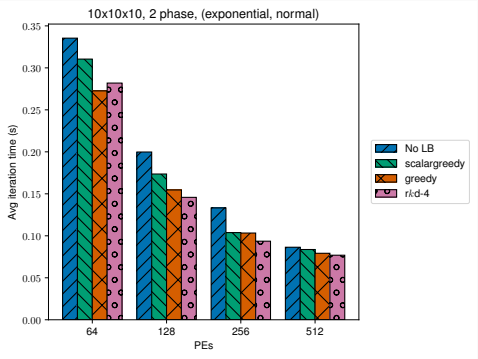


100 trials, Synthetic data: 3 phase (normal $\mu = 1_{(0.8)}, 5_{(0.2)}, \sigma = 0.1$, exp $\lambda = 0.15$, exp $\lambda = 0.15$)

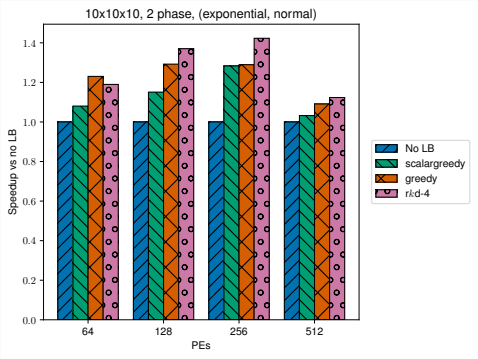
Charm++ 3D Stencil

- Phase-based mini-app with stencil structure
- Work in each phase is configurable
  - Accepts same configuration file as simulator
- 10x10x10 and 20x20x20 strong scaling studies on KNL partition of Stampede2

2 Phase Stencil - 10x10x10



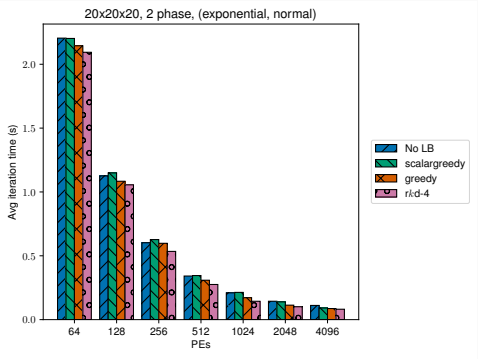
Runtime



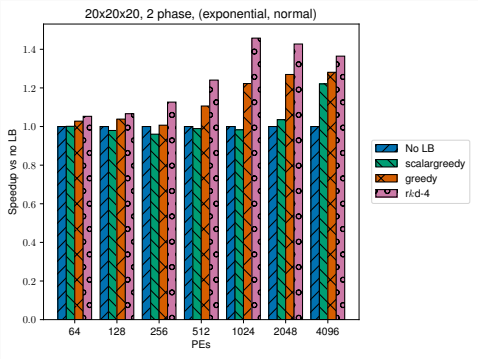
Speedup

KNL partition of Stampede2, 2 phase (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

2 Phase Stencil - 20x20x20



Runtime



Speedup

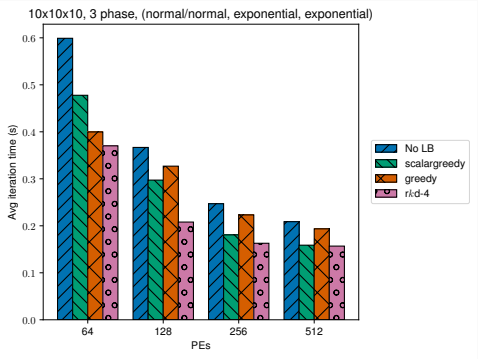
KNL partition of Stampede2, 2 phase (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

2 Phase Stencil Speedup

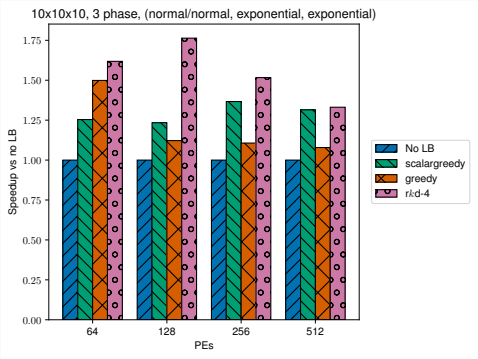
Size	Strategy	Speedup		
		Minimum	*Average*	*Maximum*
10x10x10	*Scalar Greedy*	1.03	1.14	1.28
	Greedy	1.09	1.23	1.29
	rk-d	**1.12**	**1.28**	**1.42**
20x20x20	*Scalar Greedy*	0.96	1.02	1.22
	Greedy	1.01	1.14	1.28
	rk-d	**1.05**	**1.25**	**1.46**

Speedup Over Baseline with Load Balancing for Two Phase (Exponentially, Normally) Distributed Problem

3 Phase Stencil - 10x10x10



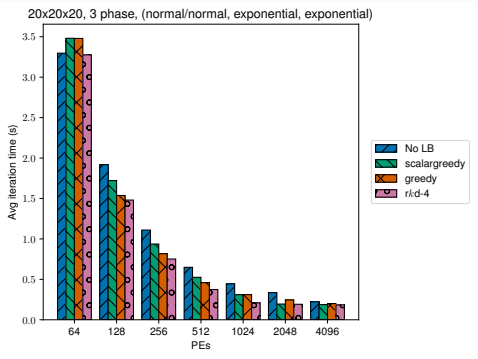
Runtime



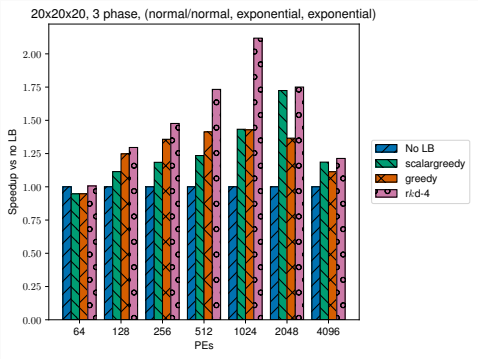
Speedup

KNL partition of Stampede2, 3 phase (normal $\mu = 1_{(0.8)}, 5_{(0.2)}, \sigma = 0.1$, exp $\lambda = 0.15$, exp $\lambda = 0.15$)

3 Phase Stencil - 20x20x20



Runtime



Speedup

KNL partition of Stampede2, 3 phase (normal $\mu = 1_{(0.8)}, 5_{(0.2)}, \sigma = 0.1$, exp $\lambda = 0.15$, exp $\lambda = 0.15$)

3 Phase Stencil Speedup

Size	Strategy	Speedup		
		Minimum	*Average*	*Maximum*
10x10x10	*Scalar Greedy*	1.23	1.29	1.37
	Greedy	1.08	1.20	1.50
	rk-d	**1.33**	**1.56**	**1.76**
20x20x20	*Scalar Greedy*	0.95	1.26	1.72
	Greedy	0.95	1.27	1.43
	rk-d	**1.01**	**1.51**	**2.12**

Speedup with Load Balancing for Three Phase (Normally/Normally, Exponentially, Exponentially) Distributed Problem

MPI Support

- Adaptive MPI is MPI on top of Charm++
  - Adds automatic load balancing to MPI programs
  - Measurement: RTS measures per-rank execution time
  - Overdecomposition: Use more ranks than PEs
  - Migratability: Ranks are ULTs that can migrate

MPI Support

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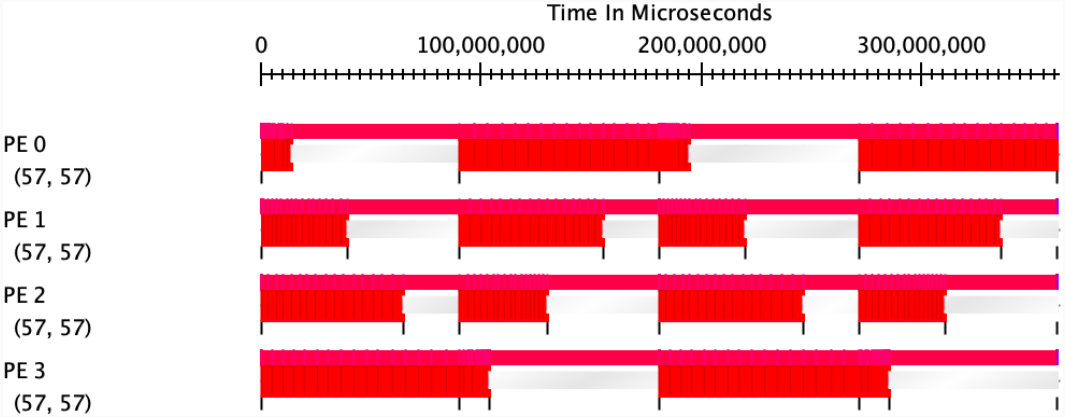
  - Measurement: RTS measures per-rank execution time
  - Overdecomposition: Use more ranks than PEs
  - Migratability: Ranks are ULTs that can migrate
- Added support for phase measurements
  - Call `void AMPI_Load_set_phase(int phase)` to mark boundary

AMPI Vector LB

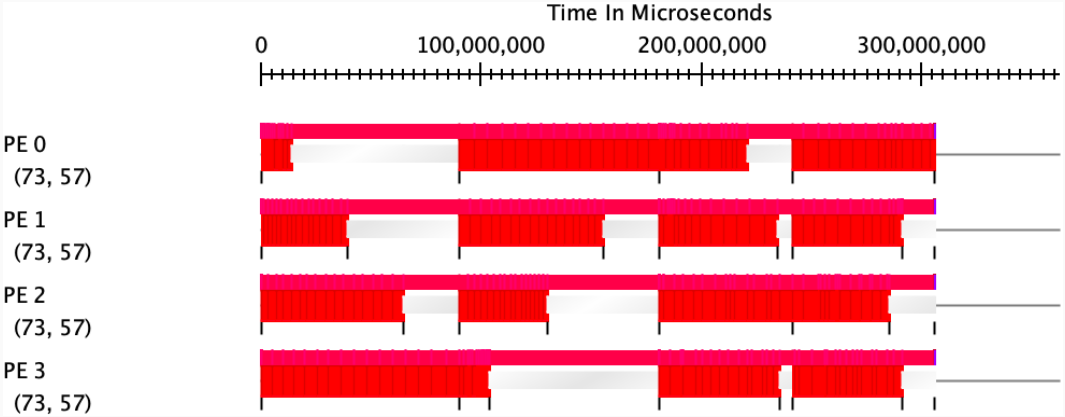
- Phase-based MPI mini-app
- Two phases:
  - First grows linearly with index
  - Second shrinks linearly with index
- Results from 4-core local test machine

AMPI No LB



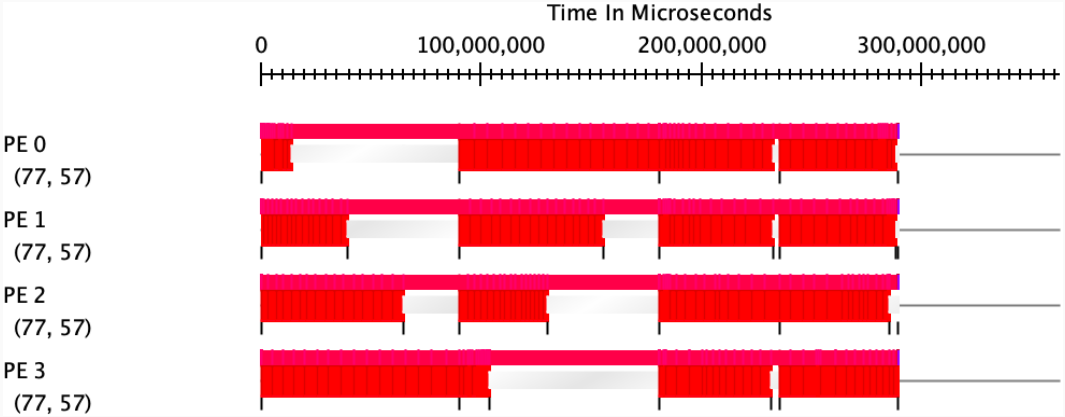
No Load Balancing

AMPI Scalar Greedy LB



Scalar Load Balancing

AMPI rk-d LB



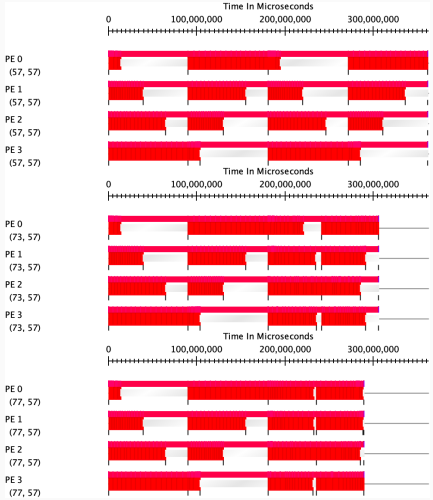
Vector Load Balancing

AMPI LB Performance

LB Off

Scalar Greedy LB
(1.44x speedup)

rk-d LB
(1.67x speedup, 1.16x over scalar)



VT (Virtual Transport)

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- Designed for modular use with MPI programs
- Supports phase-level load measurement, but no vector LBs

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- Designed for modular use with MPI programs
- Supports phase-level load measurement, but no vector LBs
- Wrote shim to use our vector LBs in VT

EMPIRE (ElectroMagnetic Plasma In Realistic Environments)

- Unstructured finite element PIC MPI code from Sandia
  - Used for electric field, magnetic field, high-energy plasma simulation
  - Details security controlled
- Partially ported to VT in attempt to deal with imbalance
- Complicated phase-based execution structure

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- Partially ported to VT in attempt to deal with imbalance
- Complicated phase-based execution structure
  - 14 dimensions
- rk-dLB gives 12% total VT runtime improvement over previous best LB strategy

32 PEs, Sandia cluster, 2.0 GHz ARM Cavium Thunder-X2, EDR Infiniband

EMPIRE - Previous Best LB

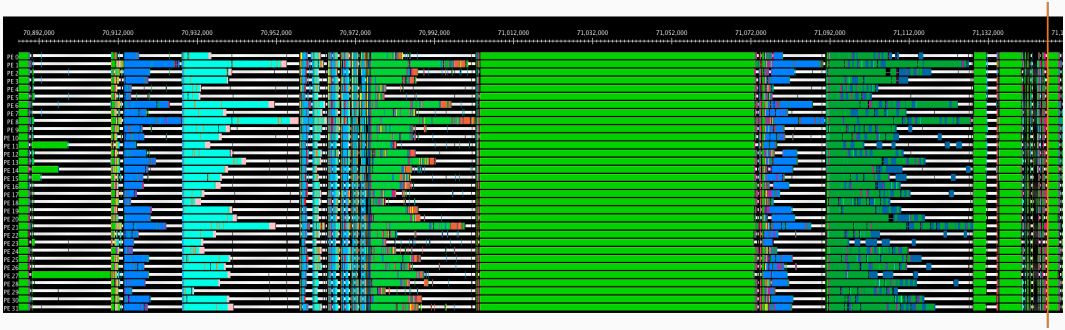


Figure 3: With previous best LB (263 ms/iteration)

32 PEs, Sandia cluster, 2.0 GHz ARM Cavium Thunder-X2, EDR Infiniband

EMPIRE - rk-d LB

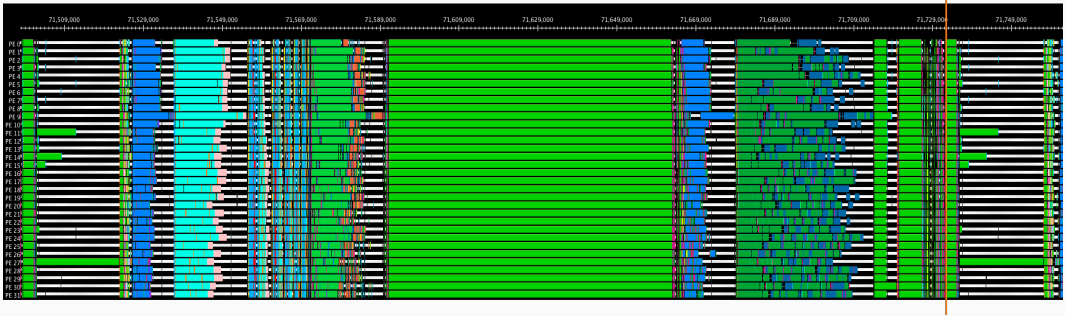


Figure 4: With rk-dLB (234 ms/iteration)

32 PEs, Sandia cluster, 2.0 GHz ARM Cavium Thunder-X2, EDR Infiniband

Phase-Based Summary

- Load vectors fixes fundamental load representation issue with scalar
- Demonstrated utility with multiple programming models: Charm++, MPI, VT
- Outperforms scalar LB across several tests, 12% on production application

Balancing Heterogeneous Applications

Heterogeneous Execution

- Two types of heterogeneous work:
  - *Retargetable* - Malleable tasks can execute on CPU or accelerator, intranode
  - *Non-Retargetable* - Tasks can execute on only one target architecture, but not all tasks have same target, intranode and/or internode
- We study these two cases separately

Balancing Heterogeneous Applications

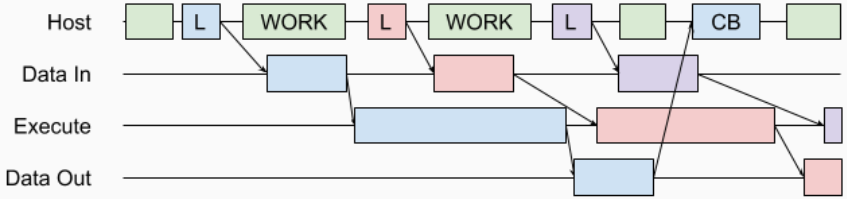
Retargetable Work

Intra-Node Balancing for Retargetable Work

- Use runtime information to manage execution of retargetable tasks
- Cede control of kernels, data, etc. to RTS
- Balance between resources to minimize idle time
- *Modifies* object's load vector
  - Load shifts from one dimension to another

GPU Manager

- Kernels registered with Charm++
- Runtime manages dataflow, execution, callbacks when kernels complete
- Asynchrously overlaps data movement and execution



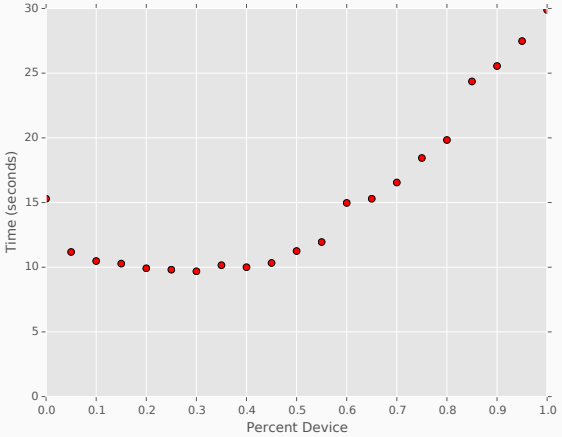
Accel Framework

- Generates code for specially written and tagged functions
  - Host CPU and CUDA variants
  - Code written with `splitIndex`, `numSplits`, analogous to `threadIdx`, `blockDim` in CUDA
  - Annotations for data flow direction, lifetime
  - Can batch kernel launches, other optimizations
- Execution platform decided at runtime
  - Various scheduling strategies available

Benchmark Description

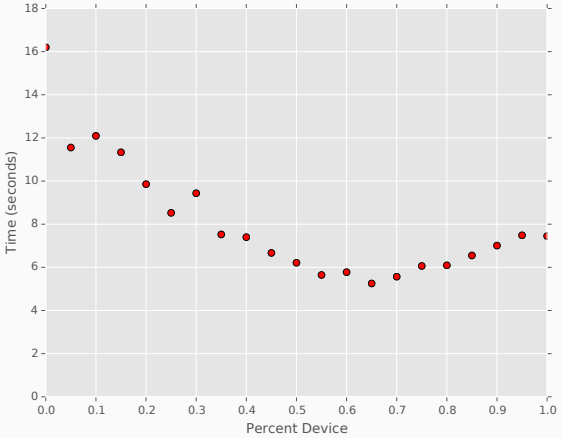
- 2D Stencil
  - 5-point stencil
  - 6144x6096 grid
- Molecular Dynamics
  - 5x5x5 grid
  - 32k molecules
- Messaging goes through CPU, so requires copy back
  - MD has higher FLOP/byte ratio, better for GPU
- One GPU node of Stampede (2x Intel Xeon E5-2680, NVIDIA K20)

2D Stencil Results



Timing for `stencil2d`

Molecular Dynamics Results



Timing for `md`

Intranode Results

	Best Split	Host Only	Device Only
`stencil2d`	30% device	1.58x	3.09x
`md`	65% device	3.02x	1.46x

Speedup of Best Configuration Relative to Host/Device Only

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Speedup of Best Configuration Relative to Host/Device Only

Intranode balancing of retargetable work helps performance

Balancing Heterogeneous Applications

Non-Retargetable Work

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- Have some GPU-only tasks, some CPU-only tasks
  - Both sets executing simultaneously

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- Each hardware resource gets own dimension in vector
- Performance determined by which resource finishes last
  - Use maximum-based objective function

Why Non-Retargetable?

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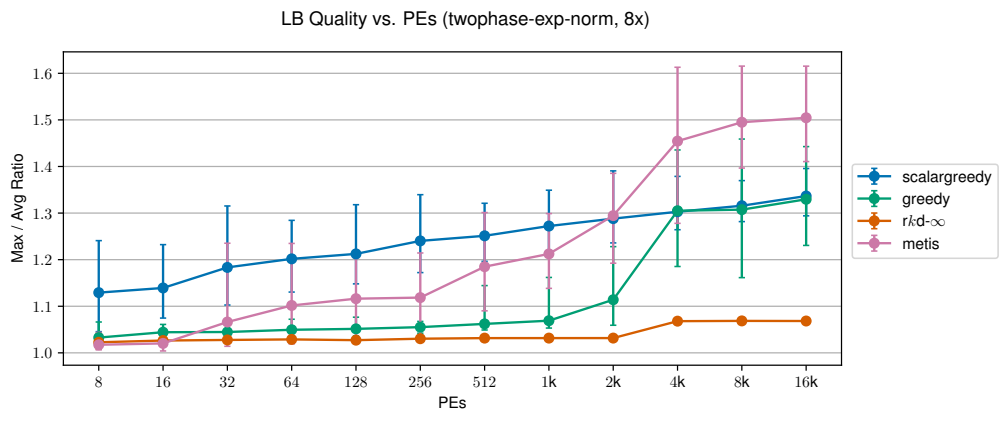
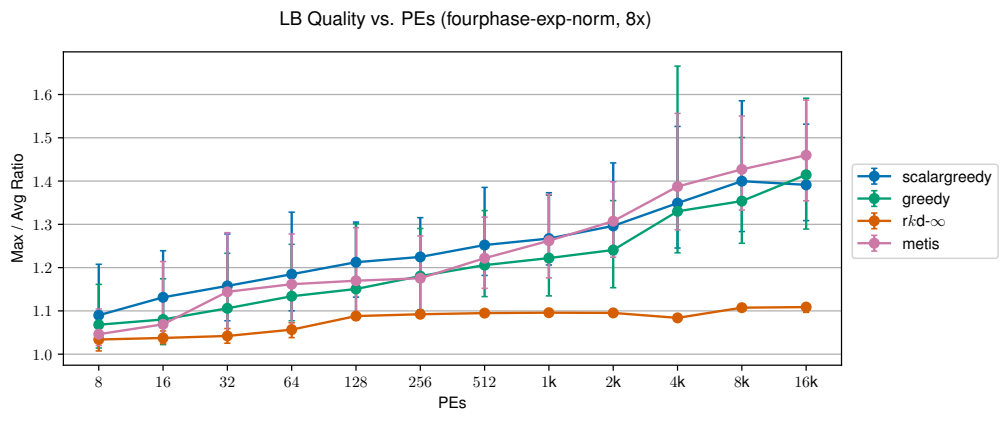
- Low-level primitives, proprietary features
- Easier to integrate into existing applications
- Used by NAMD, ChaNGa, etc.

Overlap LB Quality - 2D



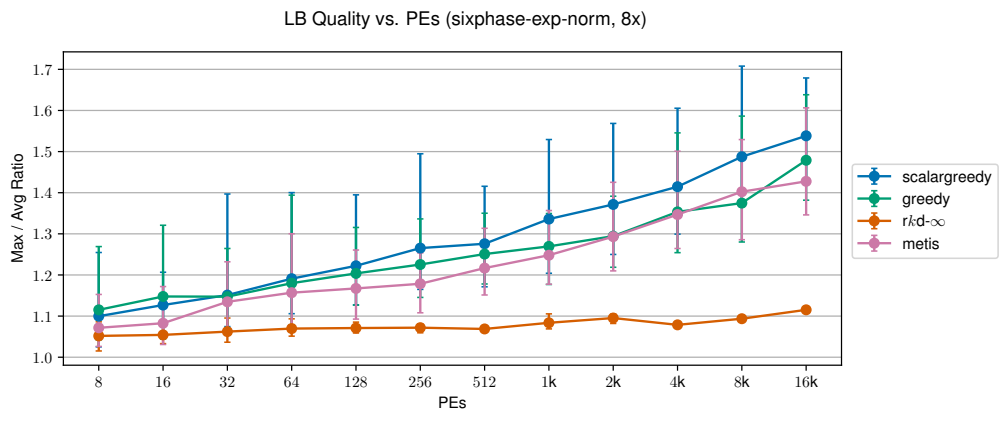
100 trials, Synthetic data: 2 phase (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Overlap LB Quality - 4D



100 trials, Synthetic data: 4 phase (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Overlap LB Quality - 6D



100 trials, Synthetic data: 6 phase (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Heterogeneous LB Summary

- Runtime intranode task retargeting improves balance and performance
- Vector allows for accurate representation of heterogeneous load
- Vector LB can balance tasks targeted to different hardware

Balancing With Constraints

Constraint LB Motivation

- System constraints may restrict load balancing remappings
  - Moving objects with large memory footprints may exceed node's capacity
  - Router buffer sizes may constrain number of messages sent from node

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  - Router buffer sizes may constrain number of messages sent from node
- Constraints likely different units, different scale compared to load timings
- Can add constraints to vector, but need specialized balancer

rk-d Constraint LB

- New variant of rk-d based LB
- Accepts list of constraints corresponding to dimensions of load vector

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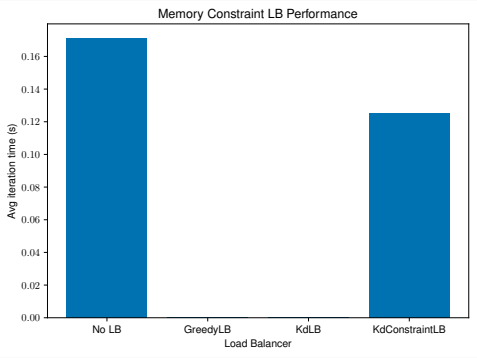
- Culls search space to non-constraint violating hypervolume
  - Minimizes as normal for other dimensions within this
- Supports arbitrary # of dimensions/constraints, norm selection

Memory Constrained Experiment

- Modify 3D stencil mini-app to have two types of objects:
  - Compute heavy/memory light
  - Compute light/memory heavy
- Too many memory heavy objects on a node will run out of memory
- 2D load vector: (cpu load, memory footprint)
- Tested on KNL partition of Stampede2

Memory Constrained Results



Avg. Iteration Time for Memory Constrained Scenario

- No LB case runs, but slow
- Greedy and regular rk-d exceed memory and crash
- rk-d-constraint runs and gives 1.37x speedup

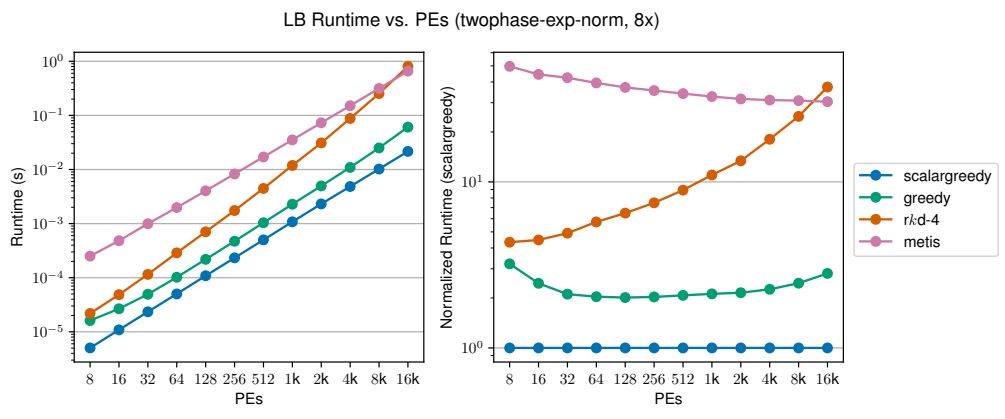
4 nodes on KNL partition of Stampede2, 2D vector (CPU load, memory footprint)

Scaling Vector Load Balancing

Vector LB Performance Overview

- Vector LB improves quality, but runtime can be long
  - Lack of total order $\rightarrow$ inefficient data structures
  - Curse of dimensionality
- At scale, large PE counts and even more objects can make performance problematic
  - Can be multiple orders of magnitude slower than scalar

Vector LB - Baseline 2D



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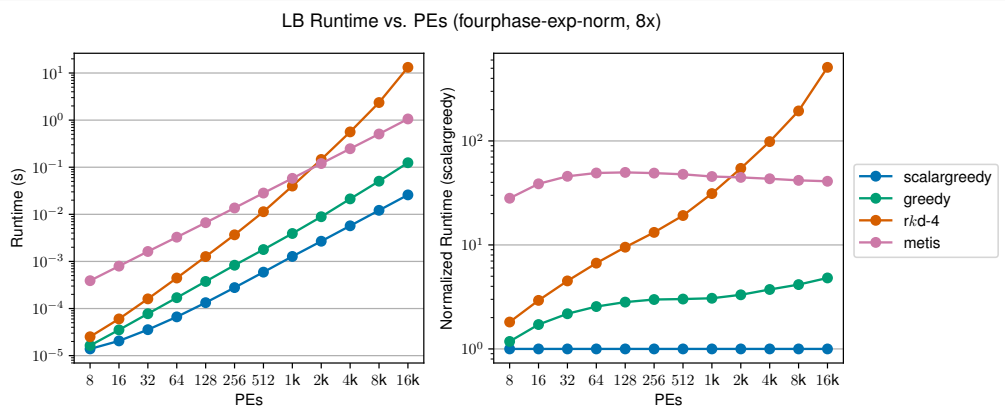
Vector LB - Baseline 4D



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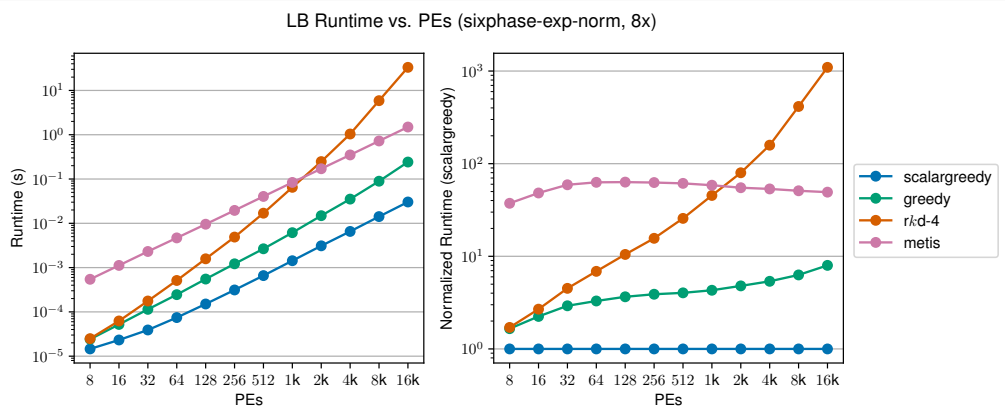
Vector LB - Baseline 6D



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Vector LB Performance Problems

- Previously, we saw robust quality offered by k-d strategy
- However, for 6D case, k-d over 1000x slower than scalar greedy, over 10x slower than METIS

Vector LB Performance Problems

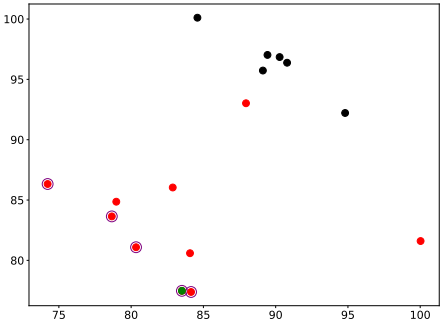
- Previously, we saw robust quality offered by k-d strategy
- However, for 6D case, k-d over 1000x slower than scalar greedy, over 10x slower than METIS
- Study three optimizations:
  - Pareto search
  - Early exit
  - Hierarchical execution

Scaling Vector Load Balancing

Pareto Search

Pareto Search

- Norm-minimizing PEs will always be in Pareto frontier of PEs
- Reduce search space by restricting to Pareto frontier
  - No change in results



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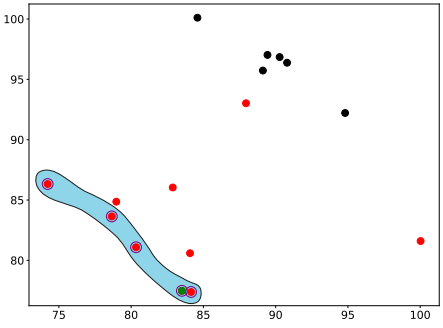

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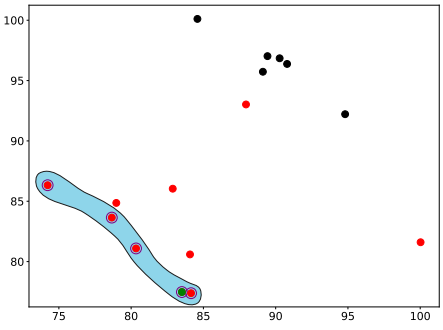


Iteration of rk-d Search

Reduce from 10 to $\leq$5 PEs searched

Pareto Search

Algorithm 1: rk-d Pareto Algorithm

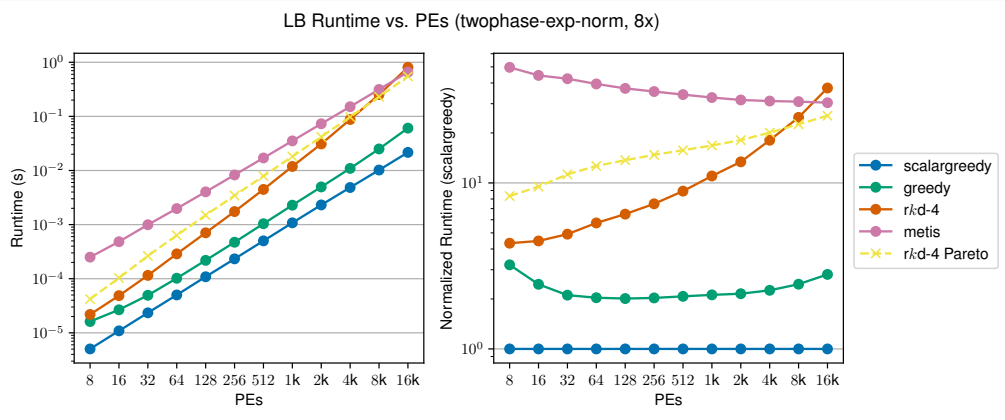
Input: Set of objects O, set of PEs P
Output: New mapping in sol

1 $T \leftarrow MakeTree(P)$;
2 $F \leftarrow MakeFrontier(T)$;
3 **forall** $o \in sorted(O)$ **do**
4 $\quad p_{min} \leftarrow FindMinNormPE(F, o)$; `/* Search only through frontier F */`
5 $\quad T \leftarrow Remove(T, p_{min})$;
6 $\quad F \leftarrow Remove(F, p_{min})$;
7 $\quad nn \leftarrow NearestNeighbor(F, p_{min})$;
8 $\quad sol.Assign(o, p_{min})$;
9 $\quad T \leftarrow Add(T, p_{min})$;
10 $\quad F \leftarrow UpdateFrontier(T, nn)$;
11 **end**

Experimental Configuration

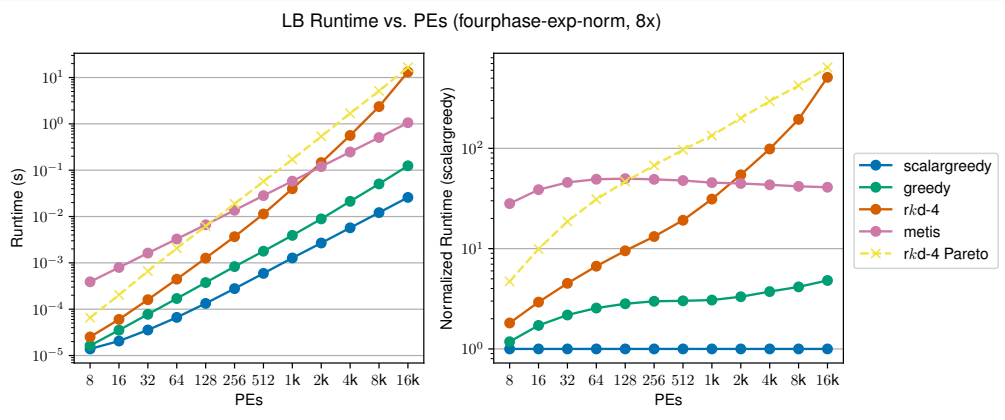
- All tests conducted on dedicated 4-core node with ARM Ampere A1 at 3 GHz
- Compiled with `gcc 11.3.0` with `-O3` and the `-ffast-math`
  - Floating-point precision loss is acceptable
- Quality evaluations use the sum-based objective function (used for phase-based LB)
- Ignores statistics collection and migration time

Pareto Search Runtime - 2D



100 trials, Synthetic data: 2D (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Pareto Search Runtime - 4D



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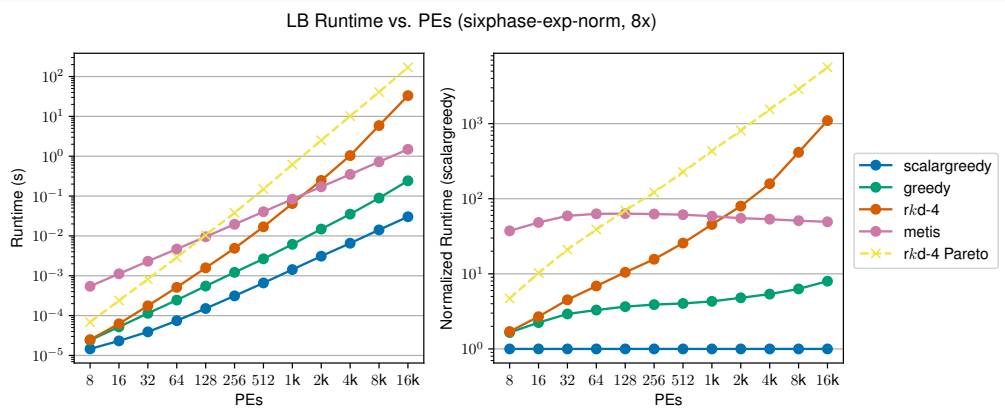
Pareto Search Runtime - 6D



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Pareto Search Performance

- Only beneficial at large scale and low dimensionality (e.g. 2D at 16k PEs)
- Progressively slower with increasing dimensionality
- Improves as scaling continues, but absolute time still large

Strategy	Runtime (s)		
	2D	*4D*	*6D*
rk-d	0.81	13.19	33.22
rk-d Pareto	0.55	16.60	170.14

rk-d/Pareto Runtime, 16k PEs, (Exp., Norm.) Load Vectors

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rk-d/Pareto Runtime, 16k PEs, (Exp., Norm.) Load Vectors

Search time reduces, but cost of maintaining frontier too high

Scaling Vector Load Balancing

Early Exit

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- In regular k-d strategy, we search whole space to find norm-minimizing PE
  - Prune where possible, but still have to search many PEs
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- Quality determined not by any one PE, but maximum load vector across all
- If we find a PE that does not increase the maximum load vector, stop searching and return!

Early Exit Design

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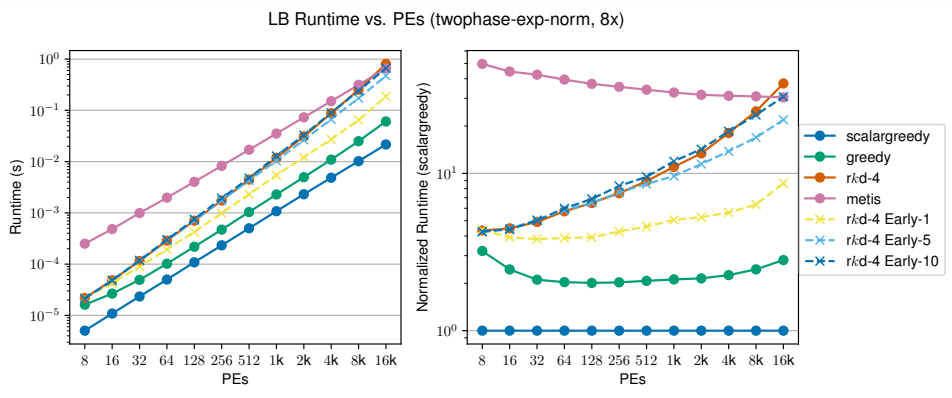
- Test with $limit = 1, 5, 10$

Early Exit Algorithm

Algorithm 2: rk-d Early Exit Algorithm

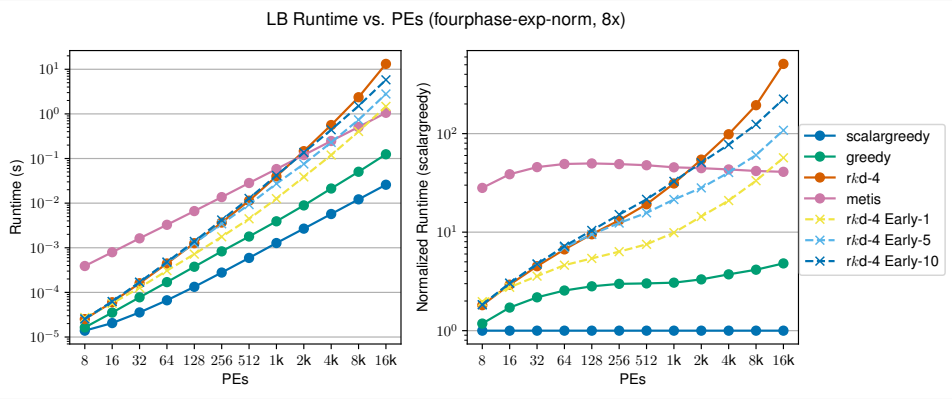
```
1  Function FindMinNormPEEarly(tree, o, limit, bounds = ⟨0, ..., 0⟩):
2      if tree.left ≠ NULL then
3          p_best, limit ← FindMinNormPEEarly(tree.left, o, limit, bounds);
4      end
5      if limit > 0 ∧ ||tree.data + o|| < norm_best then
6          norm_best ← ||tree.data + o||;
7          p_best ← tree.data;
8          if (tree.data + o)[i] ≤ load_max[i] ∀i ∈ 1, ..., d then
9              limit ← limit − 1;                    /* Candidate found, so reduce limit */
10         end
11     end
12     if limit > 0 ∧ tree.right ≠ NULL then
13         oldBound ← bounds[tree.dim];
14         bounds[tree.dim] ← tree.data[tree.dim];
15         if ||bounds + o|| < norm_best then
16             p_best, limit ← FindMinNormPEEarly(tree.right, o, limit, bounds);
17         end
18         bounds[tree.dim] ← oldBound;
19     end
20     return p_best, limit
```

Early Exit Runtime - 2D



100 trials, Synthetic data: 2D (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Early Exit Runtime - 4D



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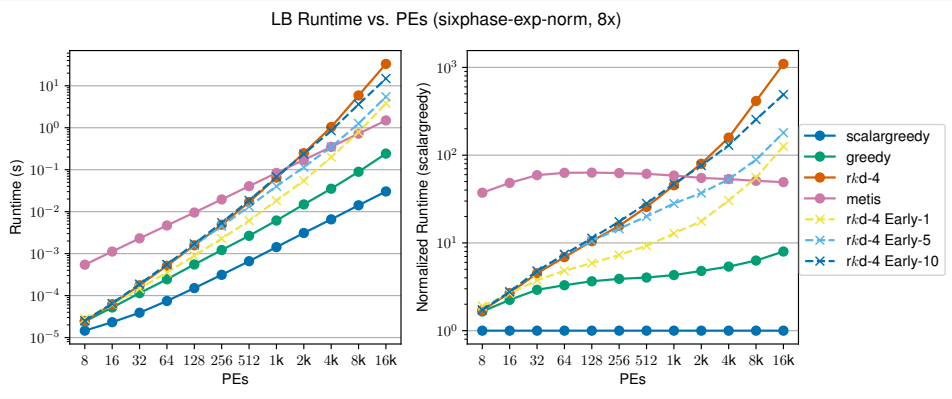
Early Exit Runtime - 6D

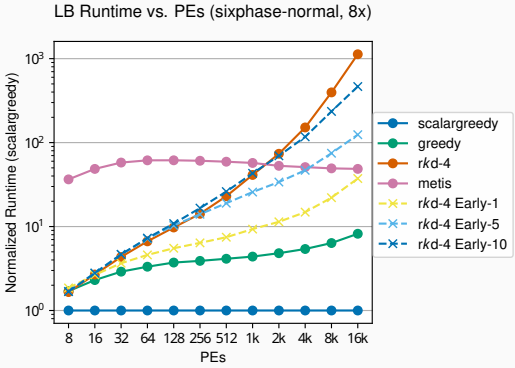


100 trials, Synthetic data: 6D (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

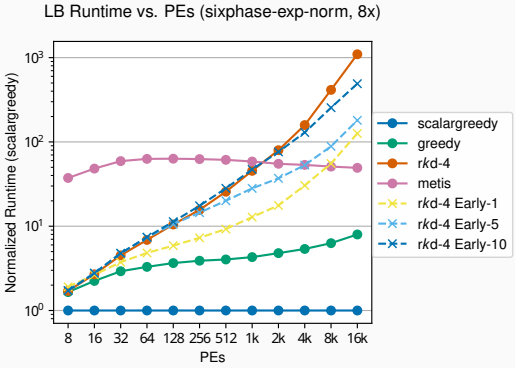
Early Exit Performance

- Improves runtime significantly
  - Benefit increases as dimension increases
  - Almost order of magnitude faster for 6D
- Performance improvement depends on load distribution

Early Exit Runtime - Load Dependence

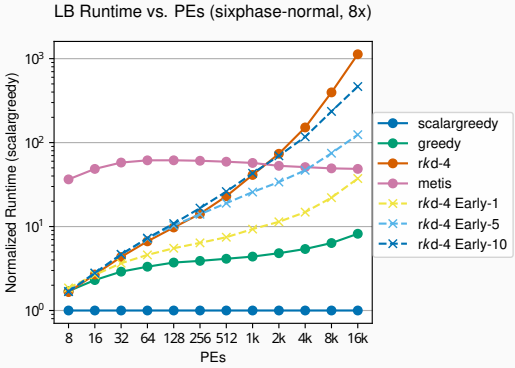


6D (Normally) Distributed



6D (Exponentially, Normally) Distributed

Early Exit Runtime - Load Dependence



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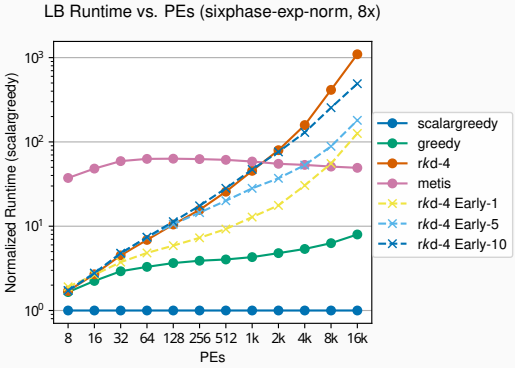
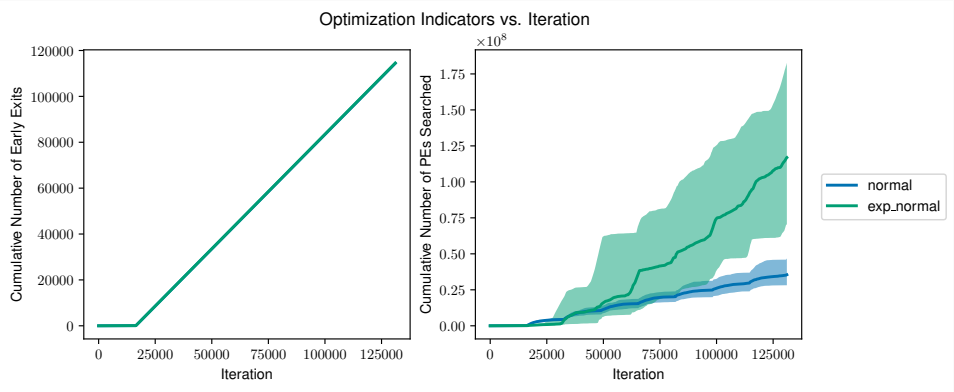


6D (Exponentially, Normally) Distributed

At 16k PEs, Early-1 beats METIS for (normal) case, loses for (exponential, normal)

Early Exit Performance Indicators

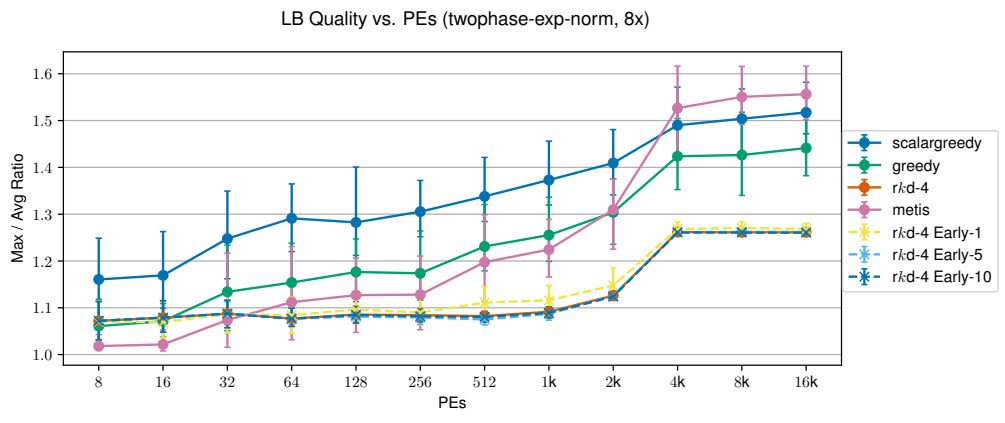


Comparison of Cumulative Early Exit Performance Indicators for 6-Normally and 6-(Exponentially, Normally) Distributed Vectors, 16k PEs

Early Exit Quality

- Early exit may not pick norm-minimizing PE at each iteration
- Can affect quality
  - Early exit iterations do not alter max load vector
  - But may force non-early exit iterations to make worse choices

Early Exit Quality - 2D



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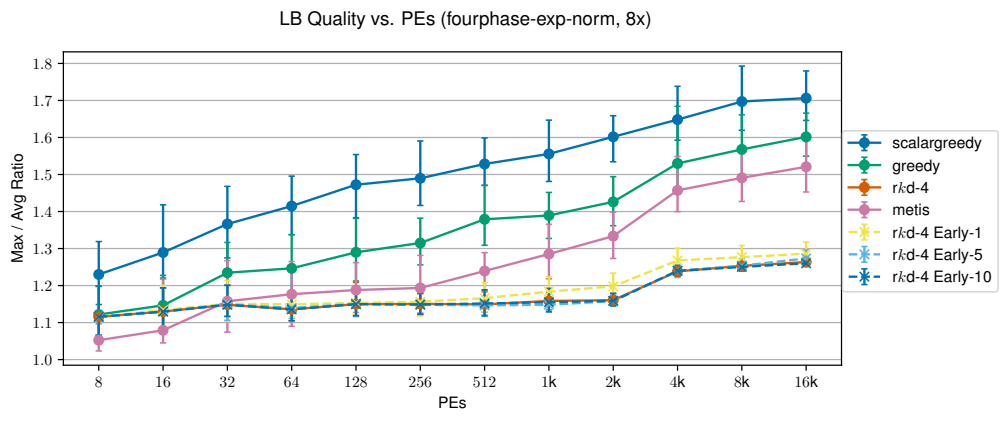
Early Exit Quality - 4D



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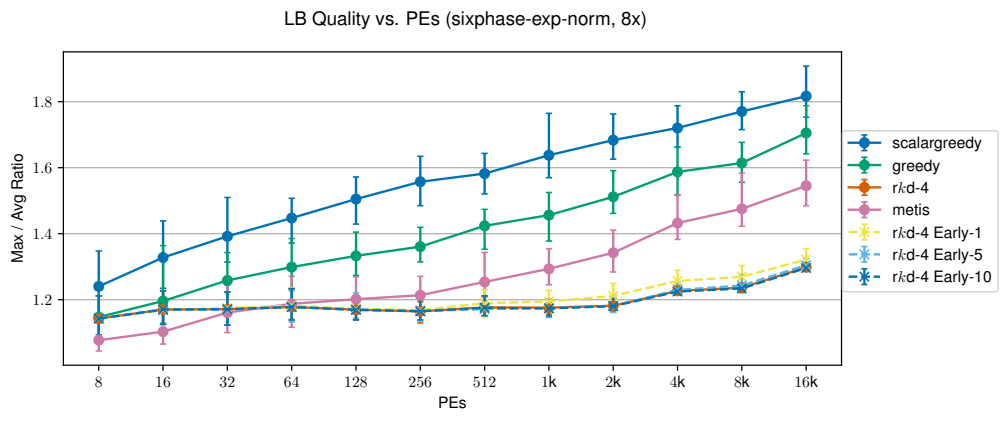
Early Exit Quality - 6D



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Early Exit Quality Table

Strategy		PEs											
		8	*16*	*32*	*64*	*128*	*256*	*512*	*1K*	*2K*	*4K*	*8K*	*16K*
rk-d	*Min*	0.94	0.93	0.94	0.96	0.97	0.97	0.98	0.98	0.98	0.98	0.98	0.98
	Median	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Max	1.10	1.08	1.06	1.07	1.06	1.04	1.04	1.03	1.05	1.05	1.05	1.03
Early-1	*Min*	0.94	0.92	0.91	0.97	0.98	0.96	0.98	0.98	0.97	0.99	0.99	0.99
	Median	1.00	1.00	1.01	1.01	1.01	1.01	**1.02**	**1.02**	**1.02**	**1.02**	1.01	**1.02**
	Max	1.09	1.09	1.11	1.13	1.13	1.13	1.14	**1.15**	1.10	1.12	1.10	1.08
Early-5	*Min*	0.94	0.93	0.93	0.96	0.97	0.96	0.98	0.98	0.98	0.98	0.98	0.98
	Median	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Max	1.10	1.08	1.05	1.06	1.06	1.06	1.07	1.07	1.07	1.06	1.06	1.07
Early-10	*Min*	0.94	0.93	0.94	0.95	0.97	0.97	0.98	0.97	0.98	0.98	0.98	0.98
	Median	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Max	1.10	1.08	1.06	1.07	1.06	1.04	1.04	1.04	1.05	1.04	1.05	1.04

Quality of Early Exit with Varying $limit$ Normalized to Median of rk-d (All Tests)

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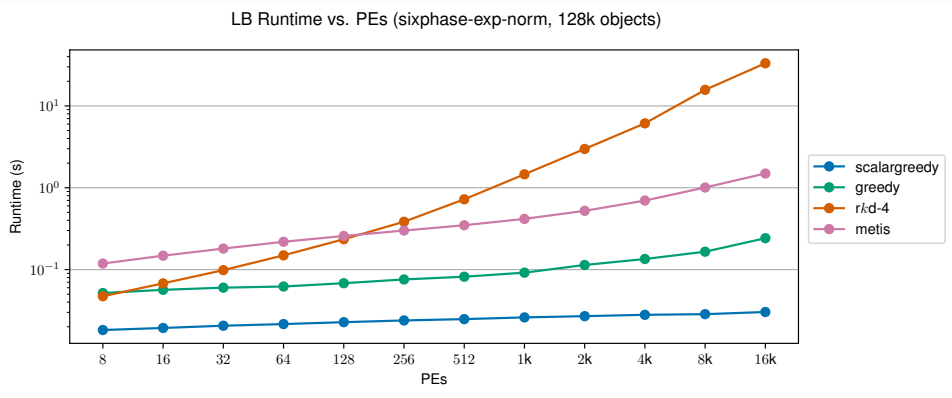
- $limit = 1$ best choice for performance

Scaling Vector Load Balancing

Hierarchical Execution

Hierarchical Motivation - Fixed # Objects



Runtime with 6D (Exponentially, Normally) Distributed Vectors, 128k Objects

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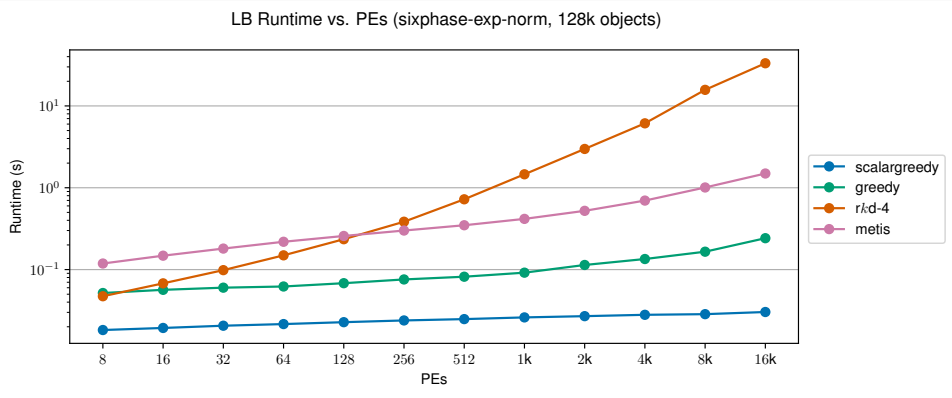
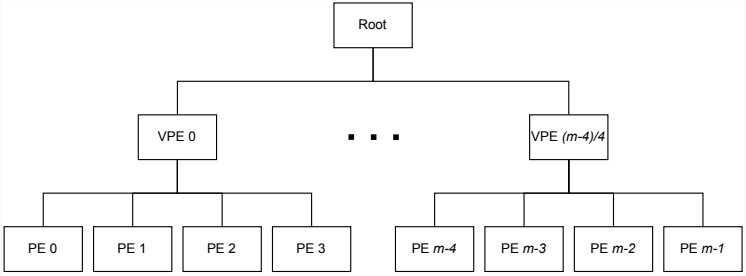


Runtime with 6D (Exponentially, Normally) Distributed Vectors, 128k Objects

Vector LBs most affected by change in PE count (especially rk-d)

Hierarchical Load Balancing

- Decompose problem hierarchically, run LB at each level
- Coarsen PEs on upward pass, uncoarsen coming down
- Root assigns to small number of coarsened "virtual" PEs, intermediate nodes remap to actual PEs in subtree



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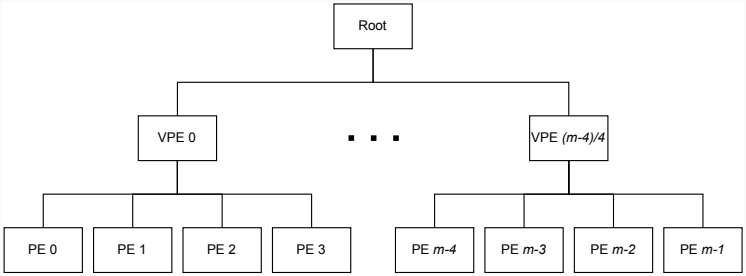
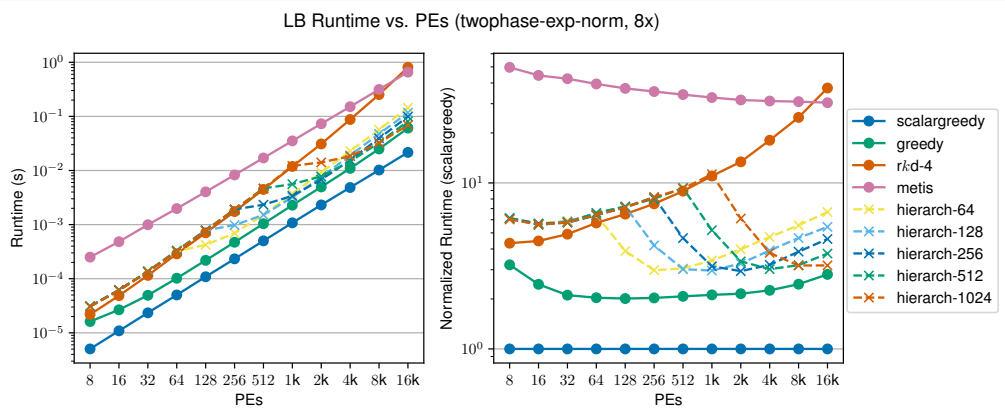
  - Intermediate LBs can run in parallel



Hierarchical Configuration

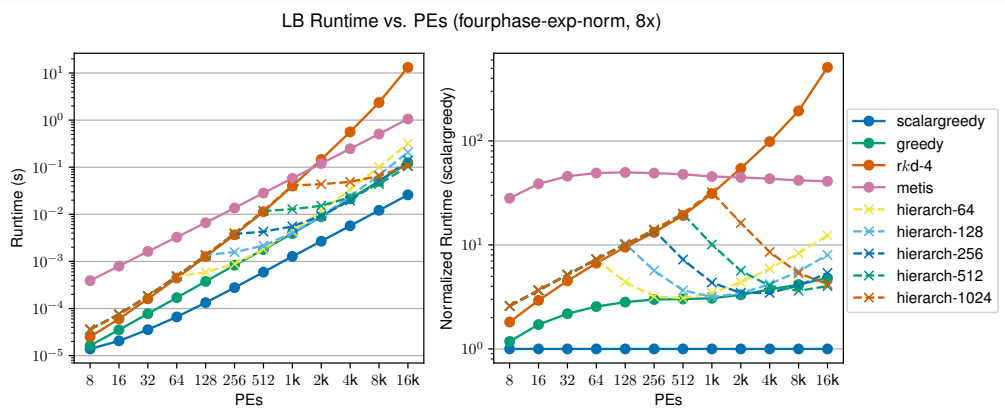
- Three level tree
- rk-d-4 at root and intermediate levels of tree
- Branching factor varies from 64-1024

Hierarchical LB Runtime - 2D



100 trials, Synthetic data: 2D (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Hierarchical LB Runtime - 4D



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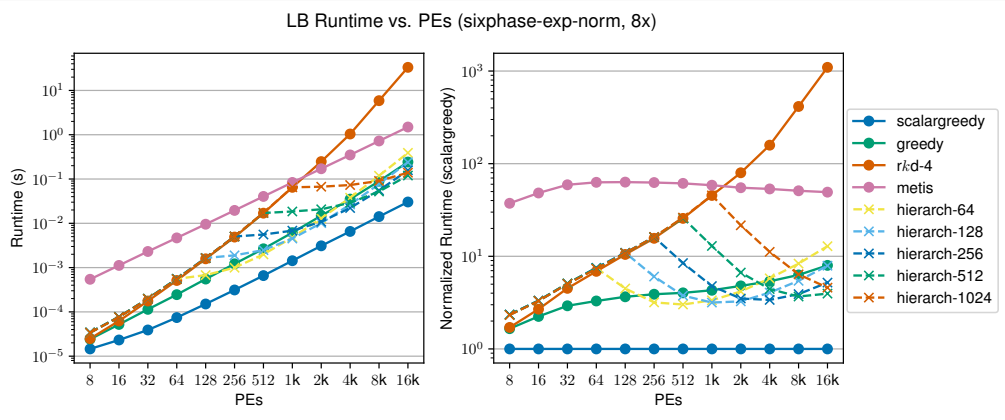
Hierarchical LB Runtime - 6D



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Hierarchical Performance Summary

- Fastest of all tested optimizations by far
  - Within roughly one order of magnitude of scalar greedy
  - Benefit increases with dimensionality
- Branching factor “sweet spot” depends on PE count

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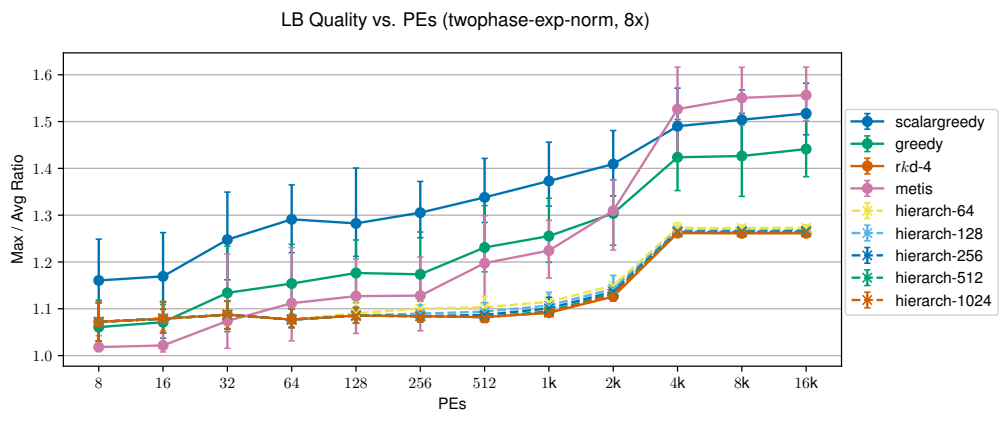
- Fastest of all tested optimizations by far
  - Within roughly one order of magnitude of scalar greedy
  - Benefit increases with dimensionality
- Branching factor "sweet spot" depends on PE count
- Impacts quality, since less "global" information is available for each instance of LB
  - Root sees coarsened data
  - Intermediate only sees subtree

Hierarchical Quality - 2D



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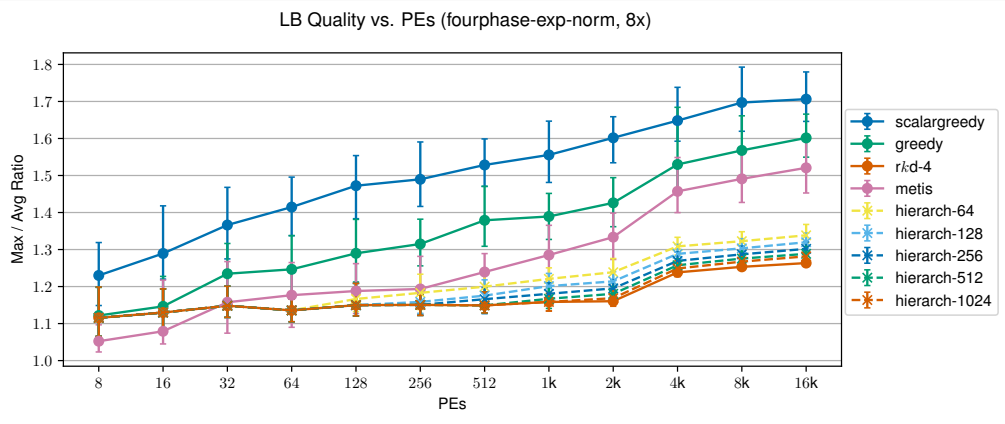
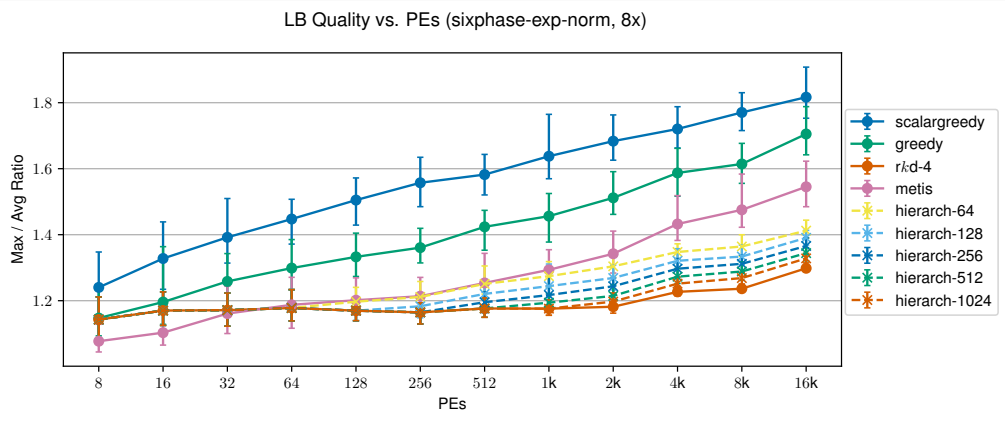
Hierarchical Quality - 4D



100 trials, Synthetic data: 4D (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Hierarchical Quality - 6D



100 trials, Synthetic data: 6D (exp $\lambda = 0.15$, normal $\mu = 10, \sigma = 3$)

Hierarchical Quality Summary

- Larger branching factors provide better quality
  - Better information for final assignments to PEs at intermediate nodes
- Degradation in quality increases with both dimensionality and scale
  - Can be tuned via branching factor
- In all cases, still better quality than next best LB

Scaling Vector LB Summary

- Varied degree of success with optimizations
  - Pareto too limited to be useful, often worse than original
  - Early Exit gave good benefits without much quality degradation
  - Hierarchical fastest of all, can degrade quality, but degree is tunable via parameters
- Significant performance improvement makes vector LB tenable at large scale
- Optimizations are mutually compatible, can compose in future if needed

Future Directions & Conclusions

Future Directions

- Add vector support to more types of balancers
  - Migration-aware, communication-aware, geometrical, distributed
- Preprocessing load vectors for dimensionality reduction
- ML to select relevant metrics for inclusion in vector
- Support heterogeneous execution within phases
- Package for wider public use

Contributions

- Characterized the objectives and applications of vector LB
- Designed and implemented new vector LBs
- Demonstrated improvements over existing LBs for phase-based, heterogeneous, constrained scenarios
- Proposed and analyzed performance optimizations for scaling vector LB
- Showed usability from multiple programming models: Charm++, {A}MPI, VT

Conclusions

- Load characteristics of complex, modern applications cannot be captured in a single scalar, but vector suffices
- New strategies can utilize the additional detail provided by a load vector for different objectives and constraints
- Vector LB improves over scalar LB across several classes of synthetic and production applications
- Runtime can be slow, but optimizations are effective

Questions?

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