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Reducing Data Migration in the Context of Adaptive Partitioning for AMR

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Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

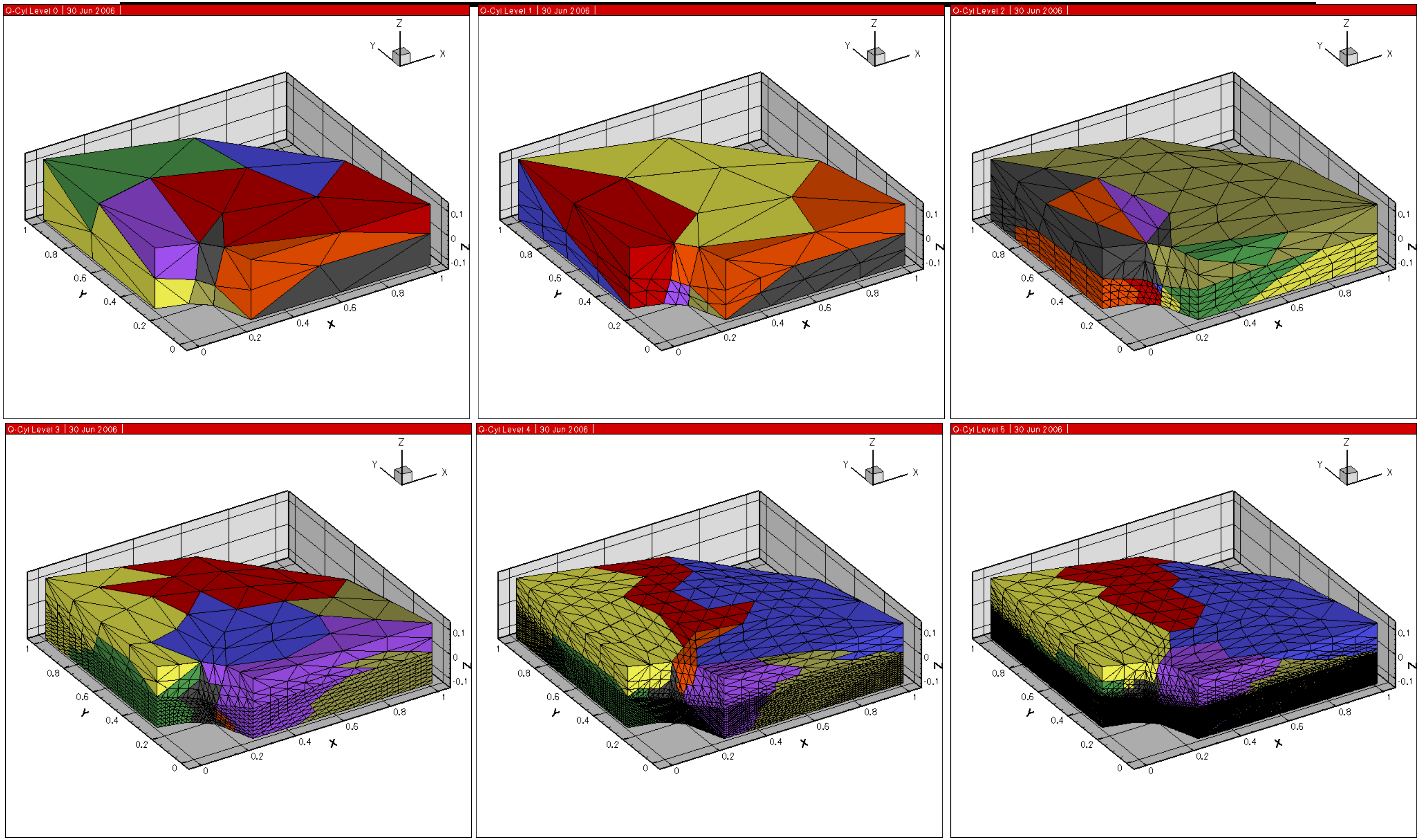
Credits

- John Peterson, CFDLab, University of Texas
- Karen Devine, Richard Drake, and James Overfelt, Sandia, NM
- Henrik Johansson, Uppsala University, Sweden
- Charles Norton, Jet Propulsion Lab, NASA, CA
- Jaideep Ray, Sandia, CA

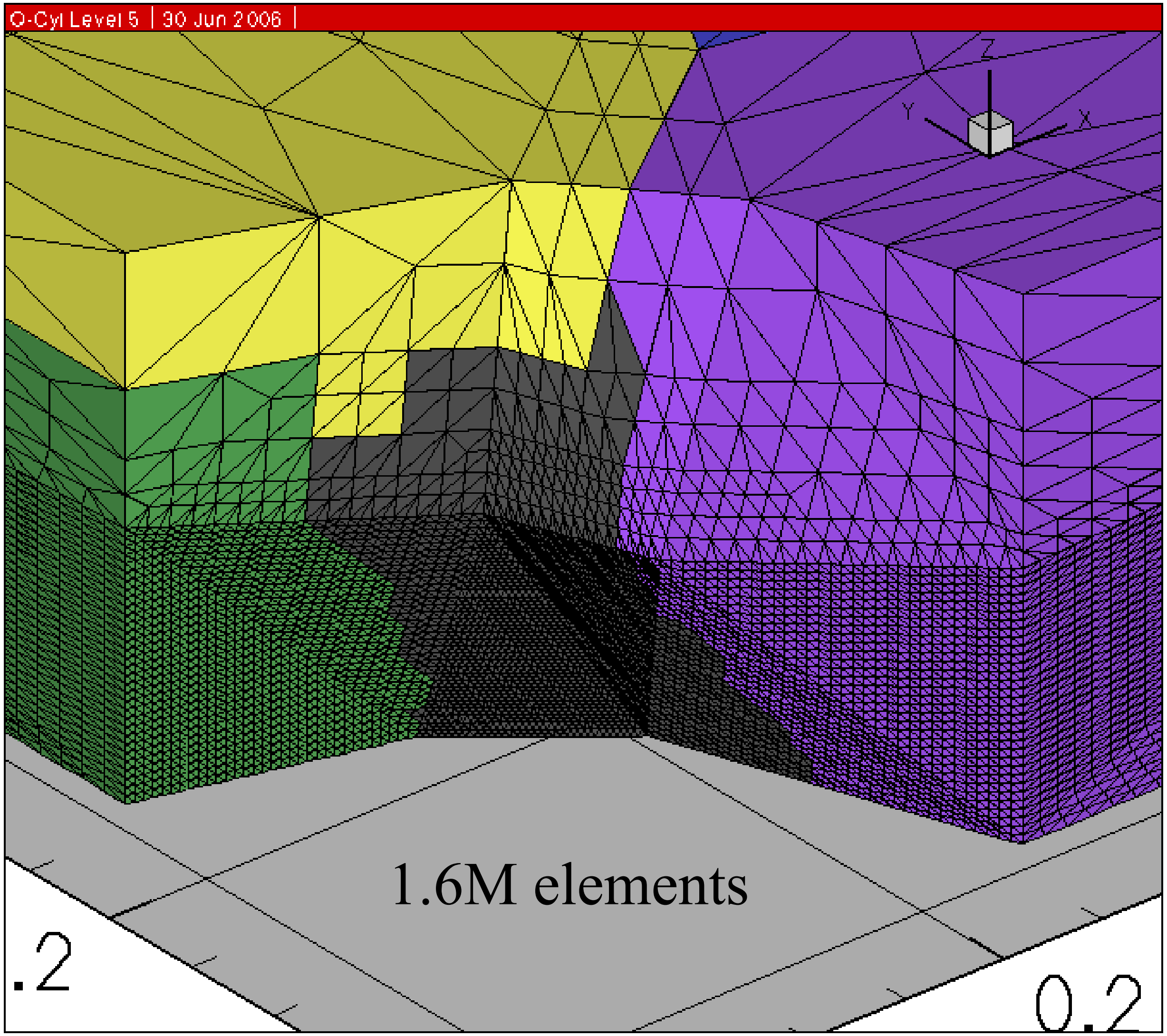
Outline

- Adaptive mesh refinement (AMR)
- Parallel AMR: Performance, scalability, and adaptive partitioning (AP)
- Reducing data migration at algorithm switching: uniform starting points (USP) and switching penalties (SP)
- Hypothesis: AP w/ USP/SP outperforms both static partitioning and “regular” AP
- Experimental setup: Applications, partitioners, the simulator, the cost function, and parameter space
- Results, conclusion and future work

AMR Case Study: Quake [Norton, Jet Propulsion Lab, NASA]



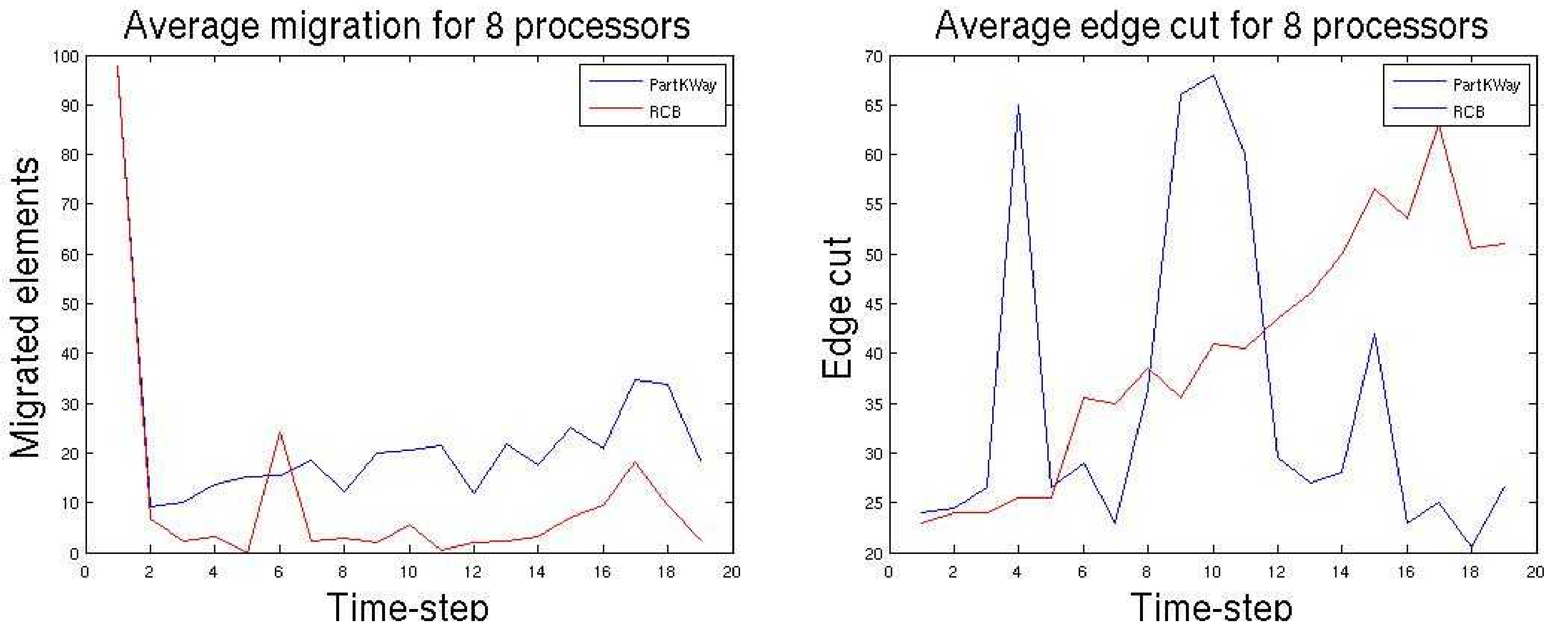
Quake: A Closeup



Data Partitioning and Scalability

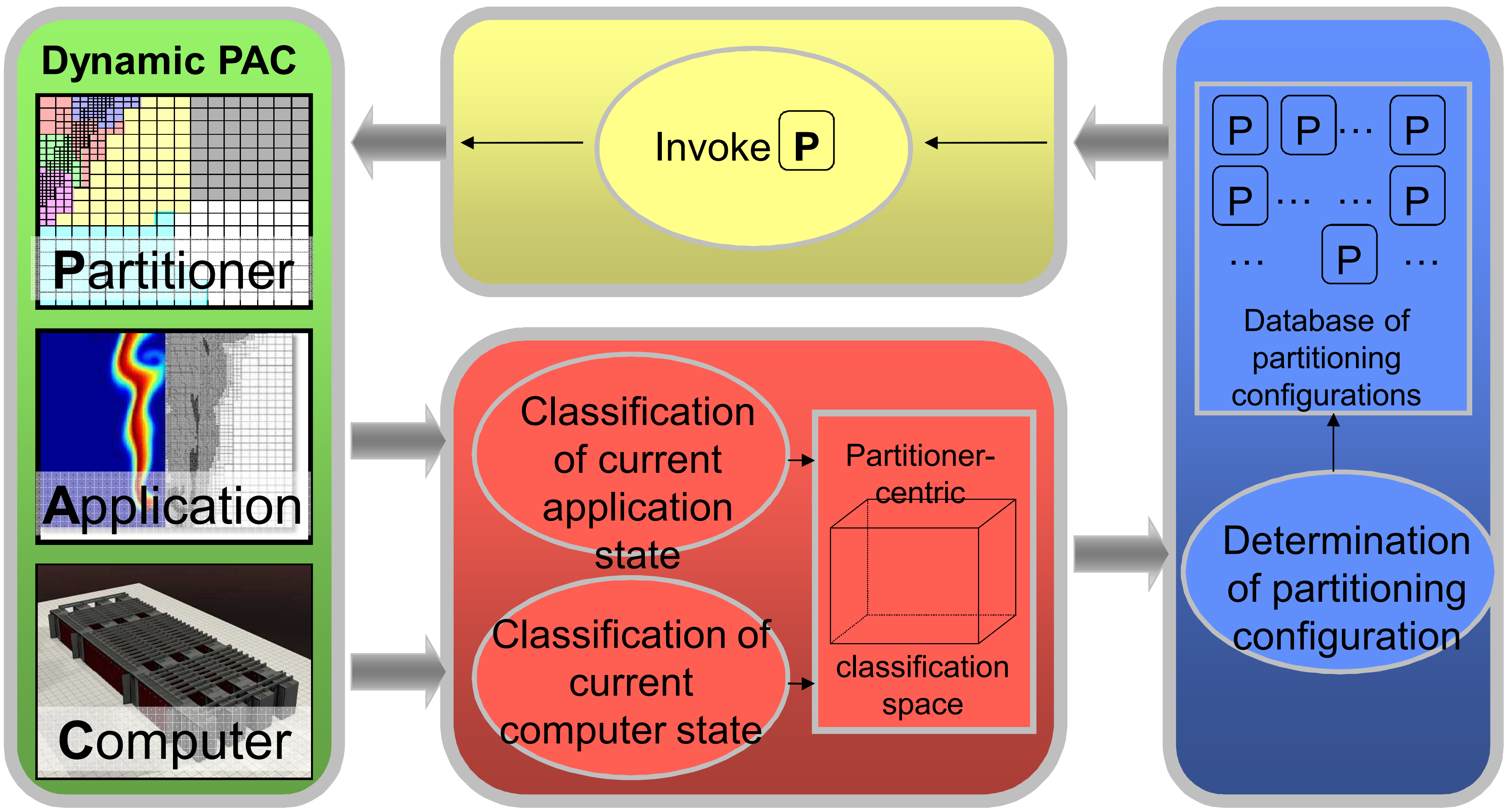
- Solution features drive the mesh dynamics
- As the mesh changes, the partitioning requirements change
- Consider the current run-time state for selecting, configuring, and invoking the most suitable partitioning algorithm →
- Dynamically adaptive partitioning
- Considerable amount of work for *structured* AMR
- How to make effective for *unstructured* AMR?

Example: RCB vs. PartKWay for Laser-Raster



→ To get the best possible parallel efficiency, we need adaptive partitioning

The Meta-Partitioner



Adaptive Partitioning: A Database Approach

Scientific application S with m timesteps: $S = \{s_1, s_2, s_3, \ldots, s_m\}$ sequence of meshes

A set of n partitioning algorithms operating on S:

$$P_1(S) = \{\partial_1^1, \partial_2^1, \partial_3^1, \ldots, \partial_m^1\}$$

$$P_2(S) = \{\partial_1^2, \partial_2^2, \partial_3^2, \ldots, \partial_m^2\}$$

$$\vdots$$

$$P_n(S) = \{\partial_1^n, \partial_2^n, \partial_3^n, \ldots, \partial_m^n\}$$

sequences of partitioned meshes

Quality METRICS

Cost function:

$$\text{Opt}\ (S,P) = \text{index} \min_{\substack{i=1:n \\ j=2:m}} \Pi(\partial_j^i, \partial_{j-1}^i) = \{P_{o_1}, P_{o_2}, P_{o_3}, \ldots, P_{o_m}\}$$

sequence of partitioners

Adaptive partitioning: $A = \{P_{o_1}(s_1), P_{o_2}(s_2), P_{o_3}(s_3), \ldots, P_{o_m}(s_m)\}$

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Suspicious Metrics (Data Migration)

Scientific application *S* with *m* timesteps: $S = \{s_1, s_2, s_3, \ldots, s_m\}$ sequence of meshes

A set of *n* partitioning algorithms operating on *S*:

$$P_1(S) = \{\partial_1^1, \partial_2^1, \partial_3^1, \ldots, \partial_m^1\}$$

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$$\vdots$$

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sequences of partitioned meshes

Quality METRICS

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sequence of partitioners

Adaptive partitioning: $A = \{P_{o_1}(s_1), P_{o_2}(s_2), P_{o_3}(s_3), \ldots, P_{o_m}(s_m)\}$

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Data Migration Problem for Adaptive Partitioning

- Partitioning algorithms fundamentally different→
- Their native mapping of data onto processors might be fundamentally different→
- At run-time, switching to a theoretically superior algorithm, might incur substantial data migration

Remedies

- Uniform starting point (USP)
- Switching penalties (SP)

Uniform Starting Point (USP)

Create more predictable sequence differences by

a) Selecting a scratch/remap technique P_k

b) Forcing $\partial_1^1 = \partial_1^2 = \partial_1^3 \ldots = \partial_1^n = \partial_1^k$

A set of *n* partitioning algorithms operating on *S*:

$$P_1(S) = \{\partial_1^k, \partial_2^1, \partial_3^1, \ldots, \partial_m^1\}$$

$$P_2(S) = \{\partial_1^k, \partial_2^2, \partial_3^2, \ldots, \partial_m^2\}$$

$$P_n(S) = \{\partial_1^k, \partial_2^n, \partial_3^n, \ldots, \partial_m^n\}$$

sequences of partitioned meshes

→ Greater probability for ∂_i^t and ∂_j^t being more similar

Switching Penalties (SP)

Original function for estimating the cost of invoking partitioner i at timestep t:

$$\Pi(\partial_i^t, \partial_j^{t-1}) = \mathrm{CCR} \times \mathrm{loadimb}(\partial_i^t) + \mathrm{ITR} \times \mathrm{edgec}(\partial_i^t) + \mathrm{migr}(\partial_i^t, \partial_j^{t-1})$$

P^I = Set of incremental algorithms

P^S = Set of scratch/remap algorithms

$$F(f) = \begin{cases} f \text{ for } P_i^I \rightarrow P^S \\ 1 \text{ otherwise} \end{cases}$$

New cost function:

$$\Pi(\partial_i^t, \partial_j^{t-1}) = \mathrm{CCR} \times \mathrm{loadimb}(\partial_i^t) + \mathrm{ITR} \times \mathrm{edgec}(\partial_i^t) + F(f) \times \mathrm{migr}(\partial_i^t, \partial_j^{t-1})$$

Uniform Starting Point + Switching Penalties

Scientific application S with m timesteps: $S = \{s_1, s_2, s_3, \ldots, s_m\}$ sequence of meshes

A set of n partitioning algorithms operating on S:

$$P_1(S) = \{\partial_1^k, \partial_2^1, \partial_3^1, \ldots, \partial_m^1\}$$

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sequences of partitioned meshes

Quality METRICS

Cost function:

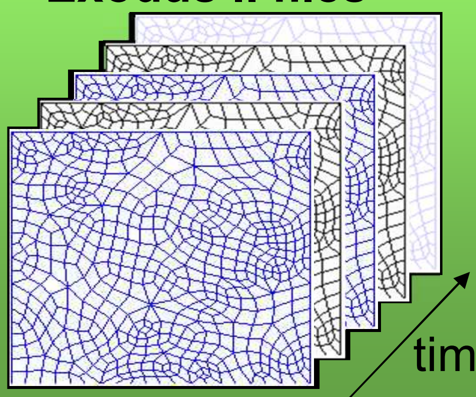
$$\text{Opt}\ (S,P) = \text{index} \min_{\substack{i=1:n \\ j=2:m}} \Pi(\partial_j^i, \partial_{j-1}^i) = \{P_{o_1}, P_{o_2}, P_{o_3}, \ldots, P_{o_m}\}$$

sequence of partitioners

Adaptive partitioning: $A = \{P_{o_1}(s_1), P_{o_2}(s_2), P_{o_3}(s_3), \ldots, P_{o_m}(s_m)\}$

The Parallel Mesh Application Simulator

Adaptive mesh as a sequence of *serial* Exodus II files



Exodus reader

First timestep?

Yes!

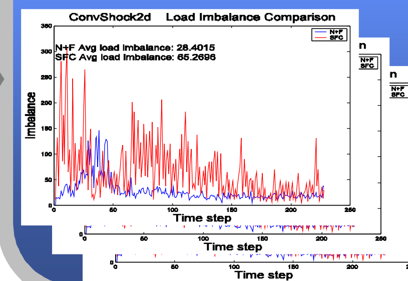
No!

Pre-partition with respect to current partitioning

Repartition with the settings of choice

Derive metrics:
- Data migration
- Edge cut
- Load imbalance
- Border elements
- Partitioning time

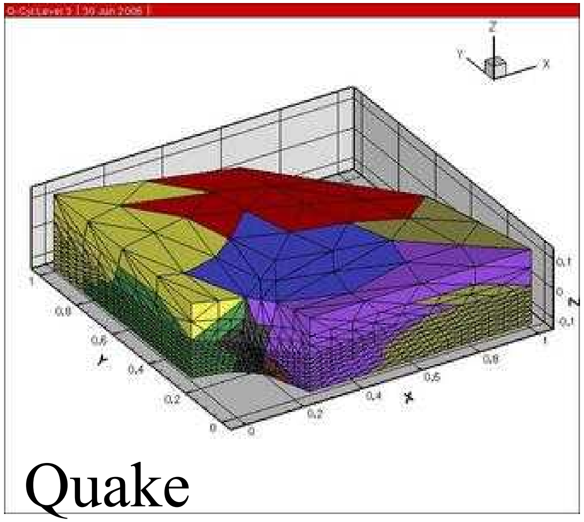
Statistics data files and plots

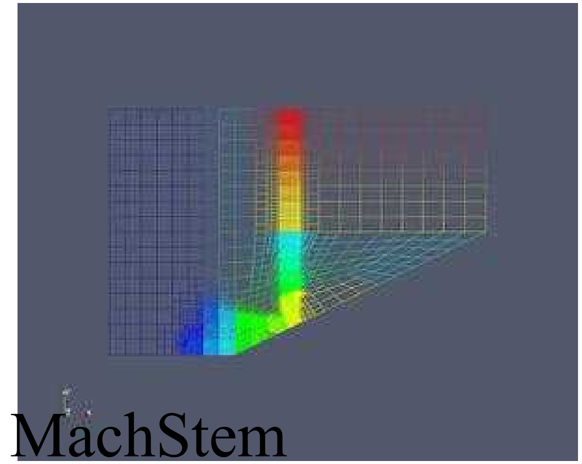


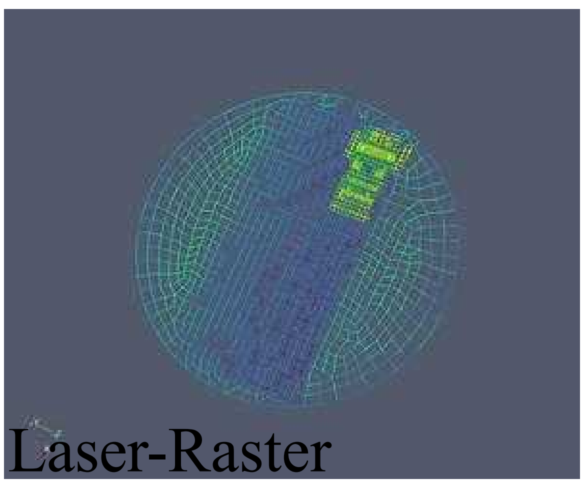
Zoltan:
- ParMetis (…)
- RCB
- RIB
- HSFC

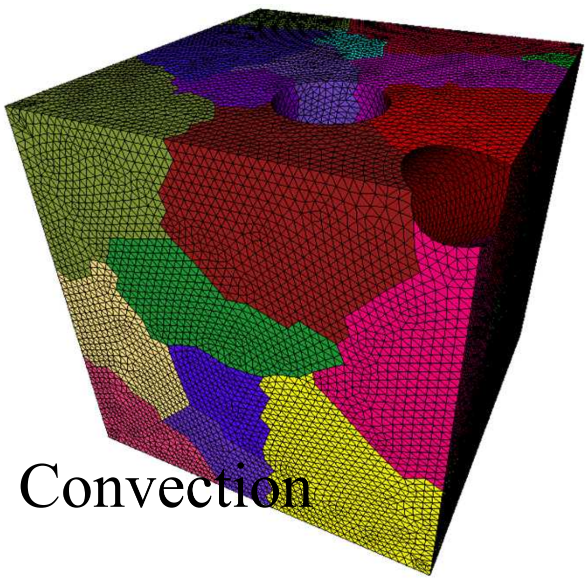
Partitioning parameters

Real-World AMR Applications









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Application Specifics

Applic.	Elmnt	Dim	Steps	Avg *E*	Max *E*
Quake	Tetra	3	6	308K	1.6M
Mach-Stem	Quad	2	109	8.2K	13K
Laser-Raster	Cube	3	65	4.4K	10K
Conv.	Tetra	3	73	87K	94K

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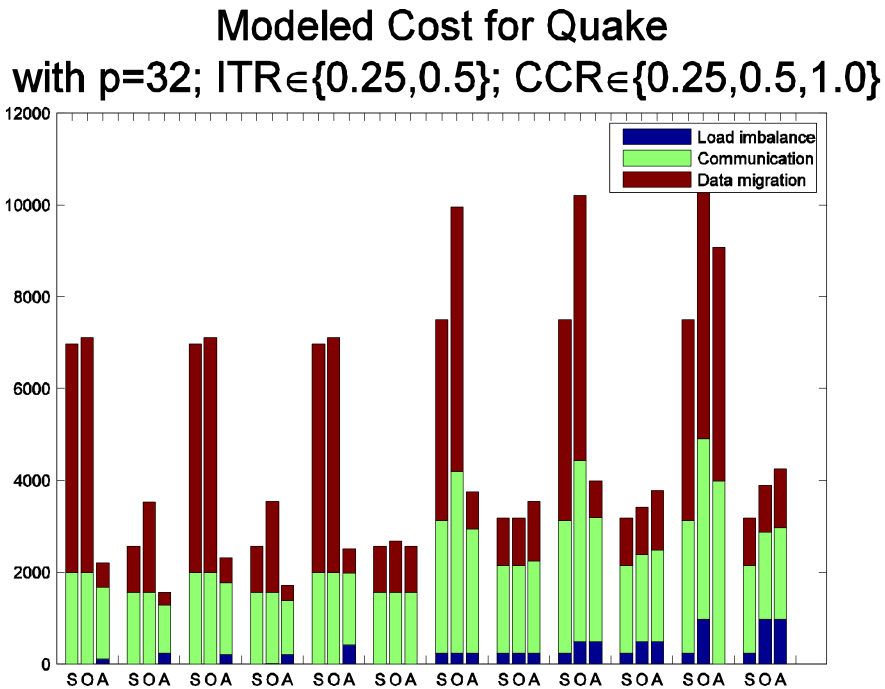
The Partitioners

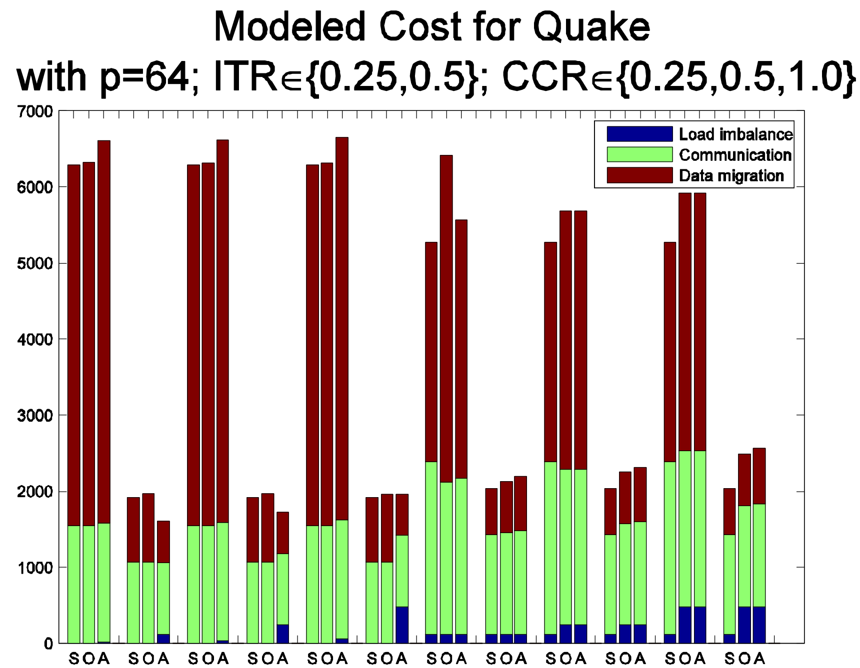
- Need partitioners from different classes with fundamentally different properties:
- RCB: Zoltan native; geometric
- RCB+Remap: Zoltan native; geometric; scratch/remap
- AdaptiveRepart: ParMetis; graph-based; incremental or scratch/remap (adaptive)

Experimentation

- **Hypothesis: Adaptive partitioning with USP/SP is beneficial within our experimental parameters**
- **Measure partitioner impact with cost function**
- **Chose parameters for "equal contribution" →**
- ***f*=1; 2; 4; ITR=0.25; 0.5; CCR=0.25; 0.5; 1.0;**
- **Two sets of data; two sets of #*p***
- **Static: RCB, RCB+Remap, AdaptiveRepart →**
- **Opt(*f*) (min cost for each timestep for *f*) →**
- **Adaptive(*f*) (true adaptive for *f*, determined by Opt)**

Results: Quake





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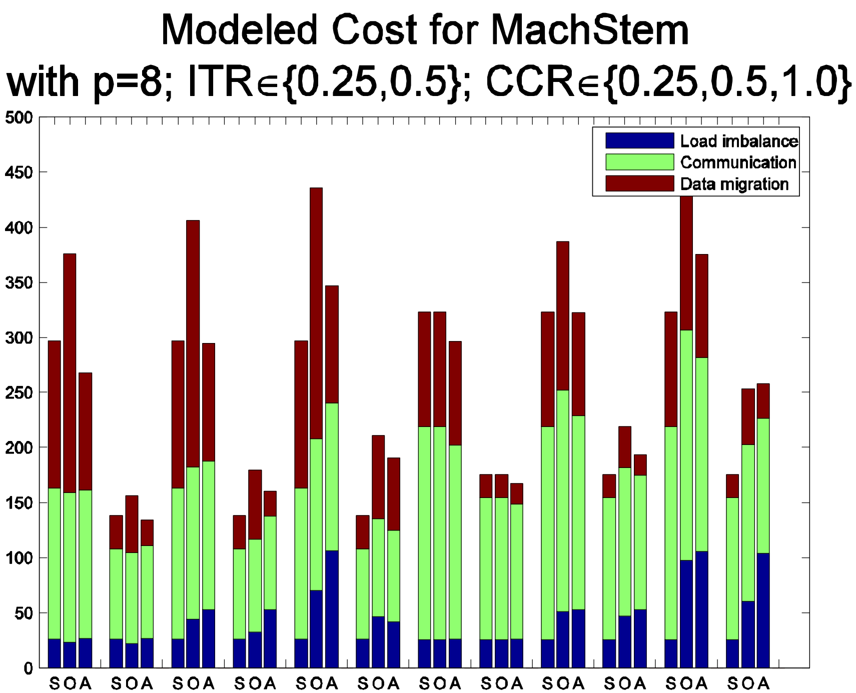
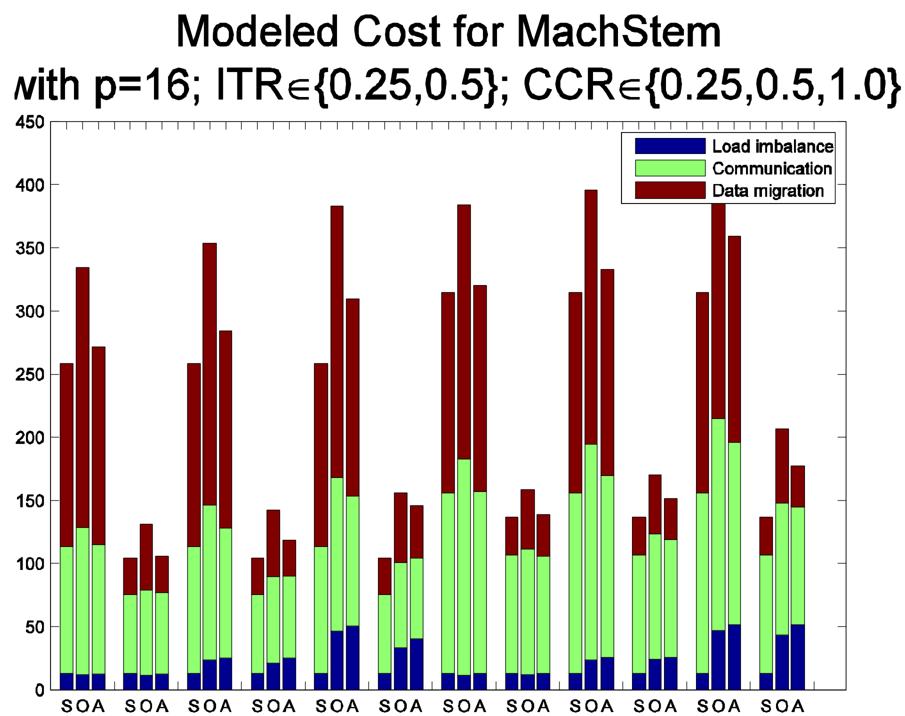
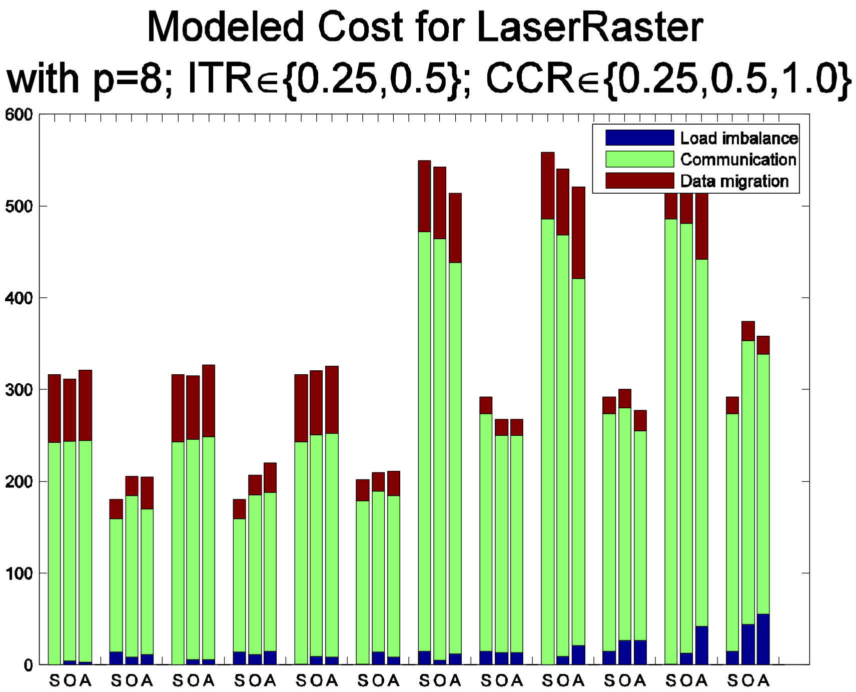
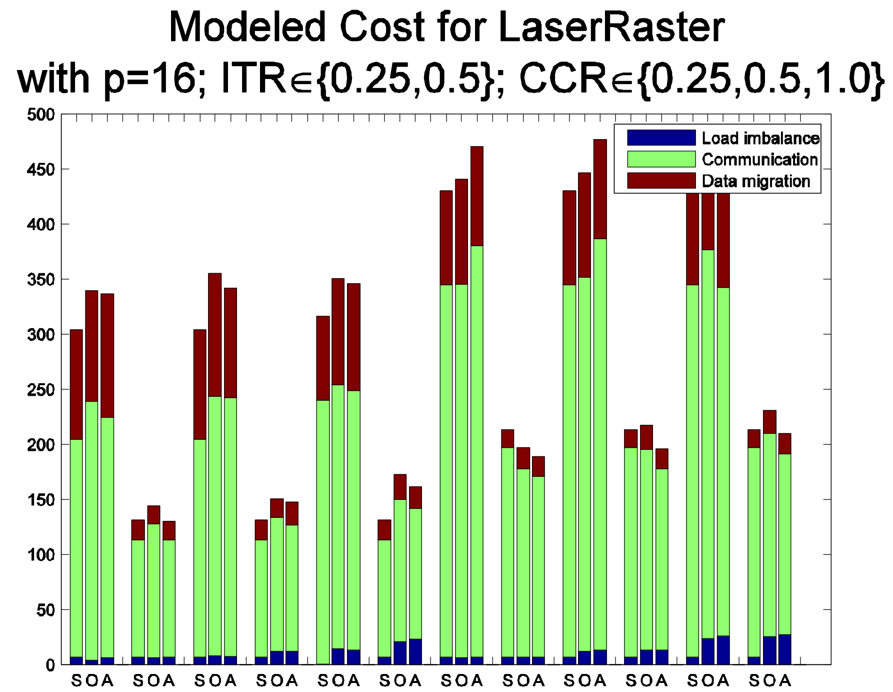
Results: MachStem





Results: Laser-Raster





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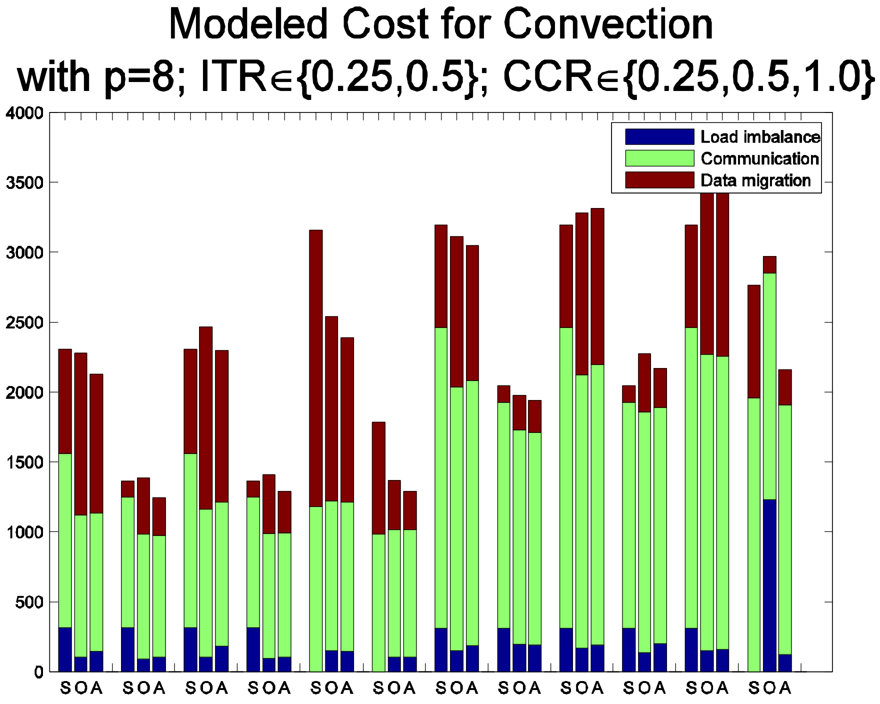
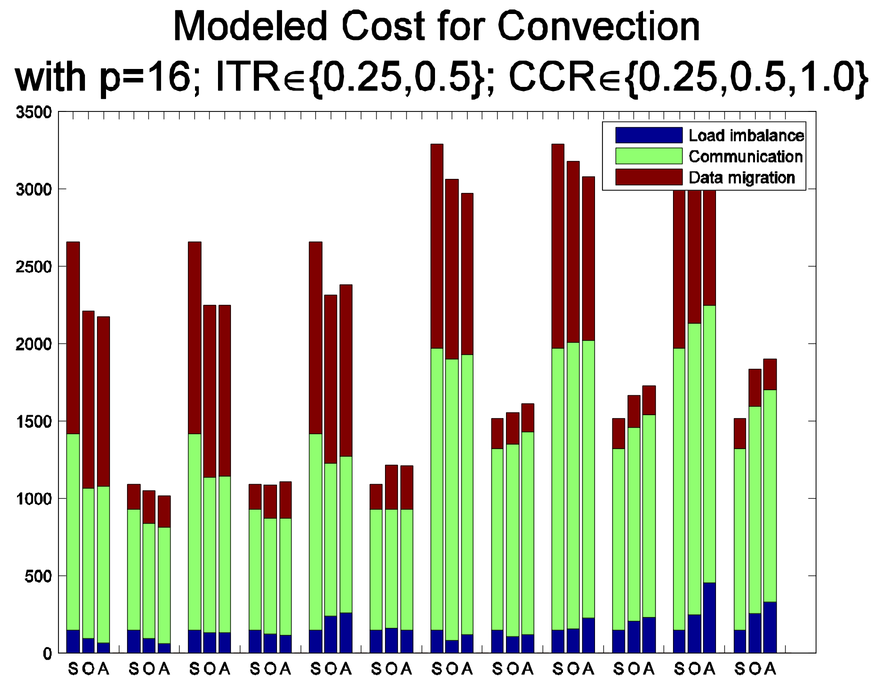
Results: Convection





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Results: Summary

- Adaptive partitioning with USP/SP outperformed the best static algorithm in about 40% of the experiments
- AP with USP/SP generally improved on “regular” AP (about 75% of the experiments).
- Adaptive partitioning performs slightly better for 8 (32) processors than for 16 (64).
- No clear correlation between CCR, ITR, and *f* compared to the effectiveness of the AP.

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Conclusions and Future Work

- AP seems applicable in a variety of (hard to define) AMR conditions
- Future work includes (a) finding better ways to estimate data migration due to different native data mappings, and (b) gaining a better understanding of conditions beneficial for AP
- New hypothesis: Smarter migration estimation & leveraging better understanding of conditions → AP beneficial for vast gamut of application-computer combinations

Questions?

- Read more on http://hpcn.sandia.gov/~jsteens