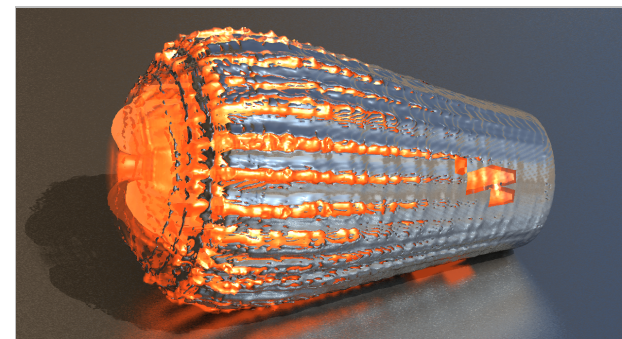


*Exceptional service in the national interest*



## Evaluation of Methods to Integrate Analysis into a Large-Scale Shock Physics Code

**Ron A. Oldfield, Ken Moreland, Nathan Fabian**  
Sandia National Laboratories

**David Rogers**  
Los Alamos National Laboratory

Approved for Public Release: SAND2014-XXXX



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# Extreme-Scale Computing

- Trends: More FLOPS with comparatively less storage, I/O bandwidth
  - Consequence: A smaller fraction of data can be captured on disk

## Oak Ridge National Laboratory

	System Peak	I/O BW
Jaguar (2008)	263 TFLOPS	44 GB/s
Jaguar PF (2009)	1.75 PFLOPS	240 GB/s
Titan (2012)	20 PFLOPS	240 GB/s
Factor Change	76×	5.5×

Bland, Kendall, Kothe, Rogers, and Shipman. "Jaguar: The World's Most Powerful Computer"  
[http://archive.hpcwire.com/hpcwire/2012-10-29/titan\\_sets\\_high-water\\_mark\\_for\\_gpu\\_supercomputing.html?featured=top](http://archive.hpcwire.com/hpcwire/2012-10-29/titan_sets_high-water_mark_for_gpu_supercomputing.html?featured=top)

## Argonne National Laboratory

	System Peak	I/O BW
Intrepid (2003)	560 TFLOPS	88 GB/s
Mira (2011)	10 PFLOPS	240 GB/s
Factor Change	17.8×	2.7×

<https://www.alcf.anl.gov/intrepid>  
<https://www.alcf.anl.gov/mira>

## Lawrence Livermore National Laboratory

	System Peak	I/O BW
ASC Purple (2005)	100 TFLOPS	106 GB/s
Sequoia (2012)	20 PFLOPS	1 TB/s
Factor Change	200×	9.4×

<http://www.sandia.gov/supercomp/sc2002/flyers/SC02ASCIPurplev4.pdf>  
<https://asc.llnl.gov/publications/Sequoia2012.pdf>

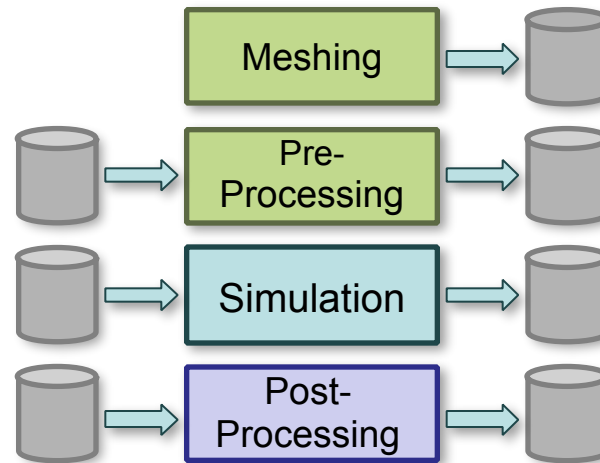
## Sandia National Laboratories

	System Peak	I/O BW
Red Storm (2003)	180 TFLOPS	100 GB/s
Cielo (2011)	1.4 PFLOPS	160 GB/s
Factor Change	7.8×	1.6×

<https://cfwebprod.sandia.gov/cfdocs/CCIM/docs/033768p.pdf>  
<http://www.llnl.gov/orgs/hpc/cielo/>

# Usage Models Conflict with Trends Sandia National Laboratories

Application Workflows historically use storage system for communication



- One way to relieve I/O pressure is to integrate simulation and analysis
  1. ***In-situ processing*** provides “tightly coupled” analysis through libraries linked directly with the simulation.
  2. ***In-transit processing*** provides “loosely coupled” analysis by performing analysis on separate processing resources.

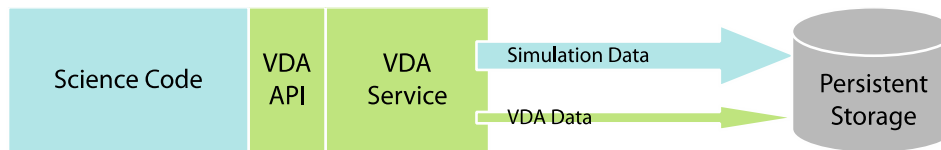
***This talk presents a detailed comparison of these approaches.***

# Pros/Cons for In Situ and In Transit

- In situ
  - + Most common approach for integrating analysis
  - + Straight forward to use (just function calls)
  - + If implemented right, could reuse application data structures
  - Synchronous (app must wait for viz to complete)
  - May add significant memory, computation, comm requirements
  - May cause concerns for stability, scalability, resilience.
- In transit
  - + Minimal client overhead (addresses resilience, scalability, ...)
  - + Asynchronous (overlap computation and analysis)
  - + Analysis can execute in different environment (e.g., linux vs lwk)
  - Requires additional compute resources
  - New use case: more complicated to schedule, load balance, ...

# Our *In situ* and *in transit* workflows

- Our *In situ* workflows uses *Catalyst*, an open source, VTK-based analysis library derived from ParaView.



- Our *In transit* workflows use the Network Scalable Service Interface (*Nessie*) to communicate with analysis services allocated on separate compute resources. *Nessie* is an open source data services library that is part of the Trilinos I/O Support package.



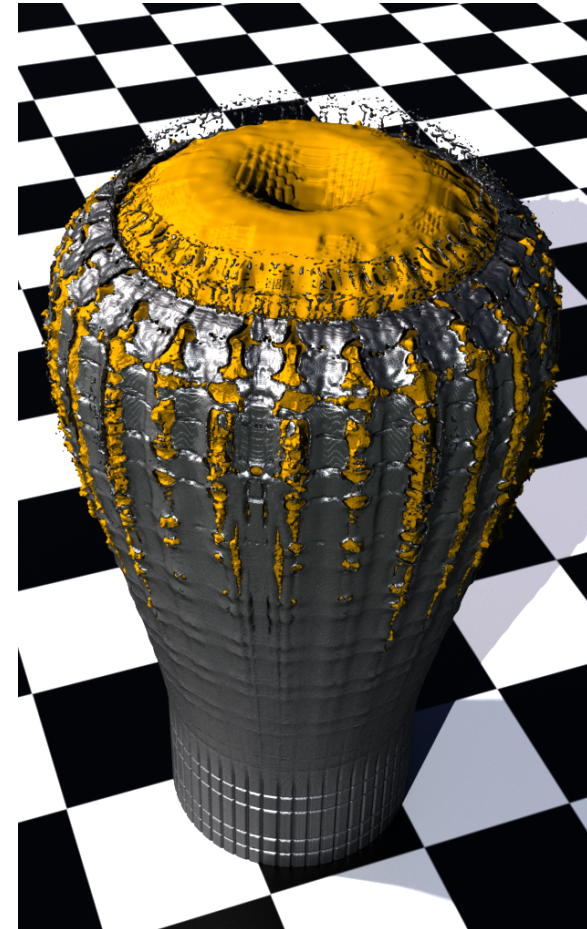
*The science code uses the same API for both approaches, making comparison between the two approaches trivial.*

# Customer Driven Use Case

## Characterize fragments in an explosion simulation

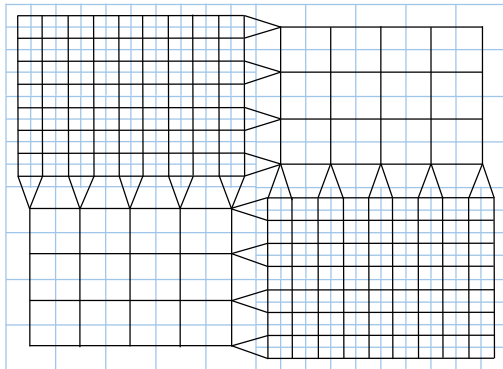
- An analysis step critical for understanding shock physics
- Partner: Jason Wilke – SNL Analyst
- Critical steps
  - Fragment detection (multiple operations required)
  - Characterize fragments (mass, velocity, etc.)
  - Extract useful information

*Our experiments focused on identifying the fragments.*  
This operation is a significantly complex part the analysis, so it serves as a useful way to characterize the operations in the driver use case.

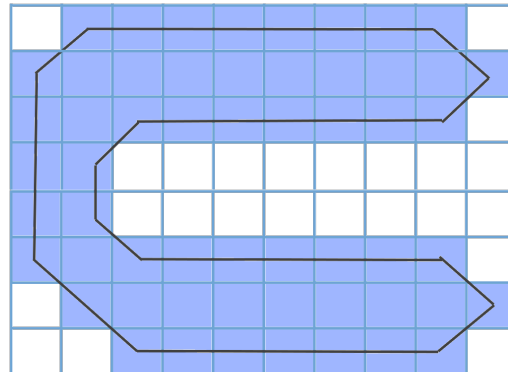


# Fragment detection

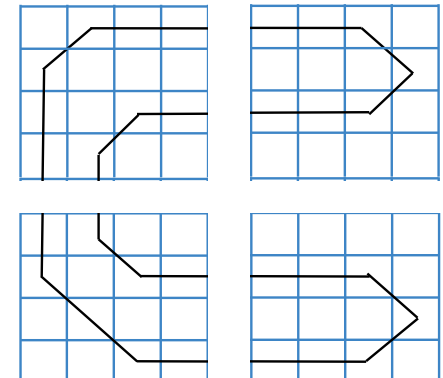
- Operations required for fragment detection (requires a watertight surface)
  1. Find block neighbors
  2. Build a conforming mesh over AMR boundaries
  3. Identify boundaries of fragments
  4. Find fragment components that are connected (*not in these experiments* — **Now Complete!**)



Step 2



Step 3

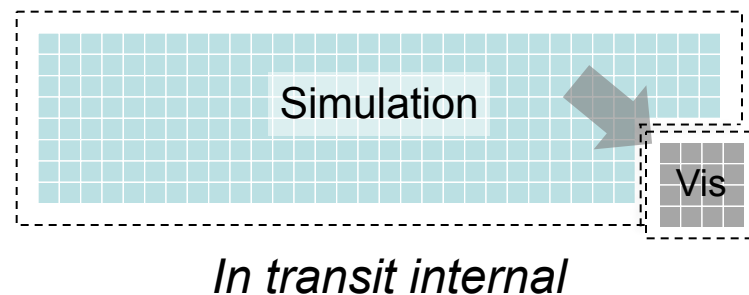
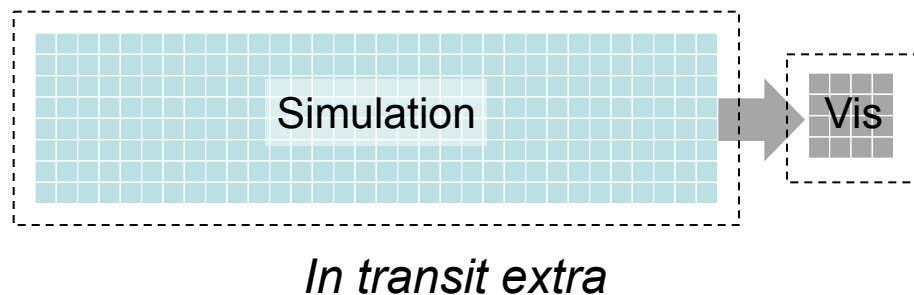


Step 4



# Application Workflows

1. *In situ baseline*: Global comm to find AMR block neighbors
2. *In situ refined*: Gets AMR block neighbors from CTH.
3. *In transit extra*: Extra nodes used for analysis
4. *In transit internal*: Carve out nodes for analysis (less cores for CTH)
5. *Disk-based post processing*: Traditional approach



***In transit and post-processing workflows use baseline algorithm.***



# Experimental Setup

- System: Cielo supercomputer at LANL
  - 8,944 node Cray XE6 (1.37 Petaflops peak)
  - Node: 2 AMD Opteron 6136 (Magny-Cours) 8-way processor chips
  - 32 GB memory/node
- Application: CTH (AMR) + Catalyst
  - 500 time steps of CTH
  - 51 analysis steps (approximately once every 10 time steps)
  - Five application workflows from previous slide
- Experiments
  - Strong scaling for three datasets: 33k blocks, 218k blocks, 1.5m blocks
  - Five runs for variance data
  - Data captured from instrumented code and HPCToolkit
  - Over 10m node hours for development, debugging, experiments.


# Choosing the Number of Service Nodes


## Memory Requirements for In Transit Service

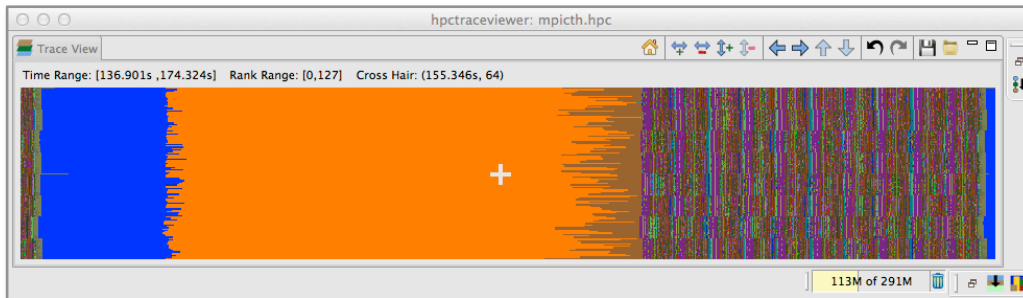
- Constraints given 32 GiB/node
  - Based on “trial and error” we found that one node can manage/process ~16K AMR blocks from CTH.
- Number of service nodes required for In Transit
  - 33k blocks: 2 nodes
  - 129k blocks: 16 nodes
  - 1.5m blocks: 100 nodes

# Choosing the Number of Service Nodes

## Computing Requirements for In Transit Service

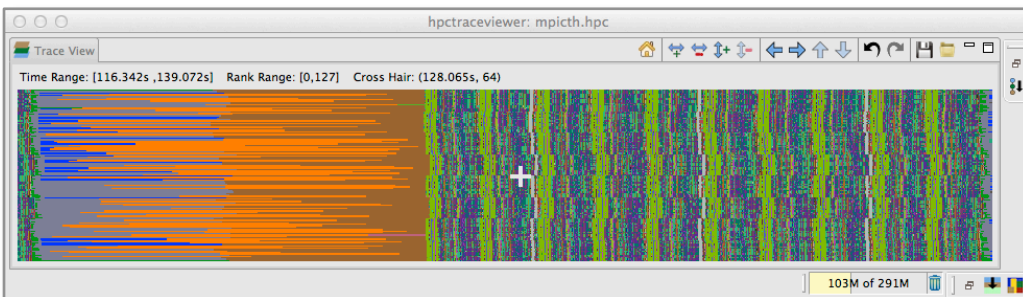
 Wait for Server

 Transfer Data



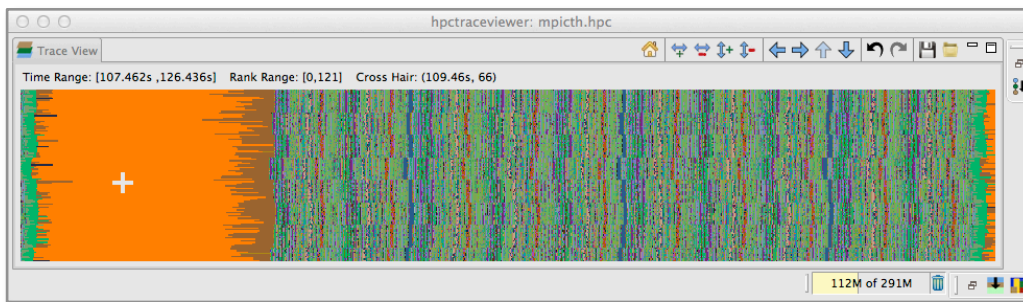
2 server cores: 64:1

- 10 cycles in 37 secs
- Client idle waiting for servers (also affects xfers)



4 server cores: 32:1

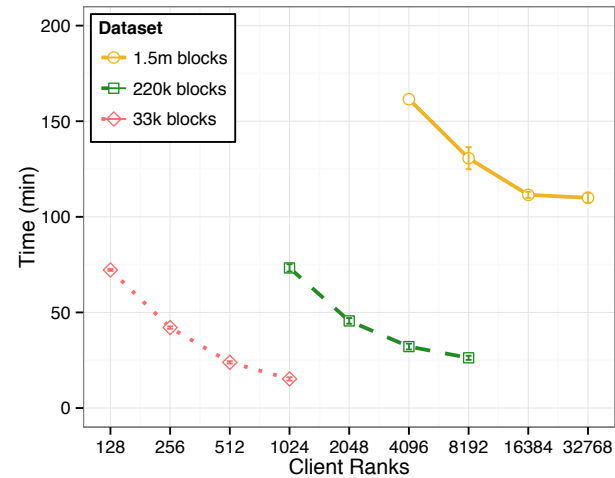
- 10 cycles in 23 secs



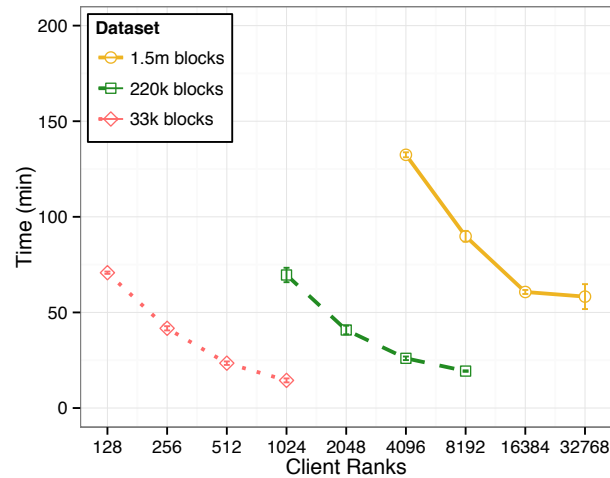
8 server cores: 16:1

- 10 cycles in 19 secs
- Less than 1% time waiting

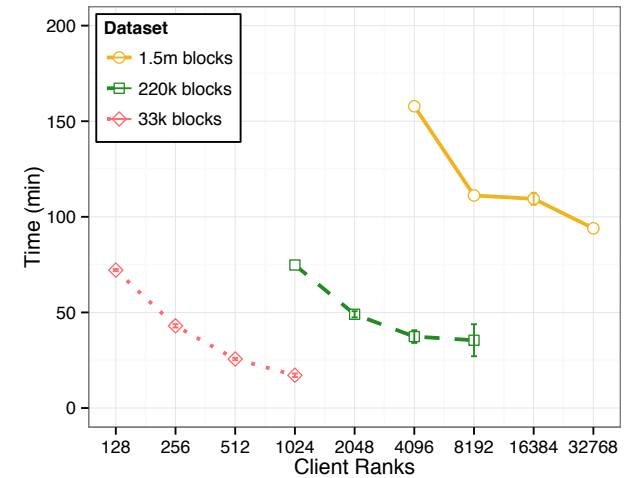
# Total Runtime for All Experiments Sandia National Laboratories



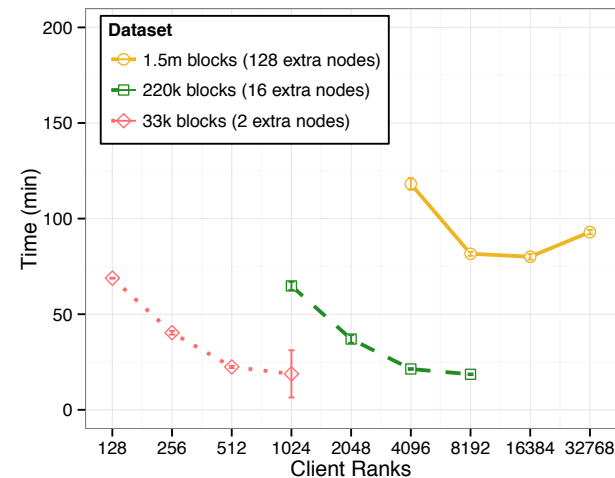
*In situ* baseline



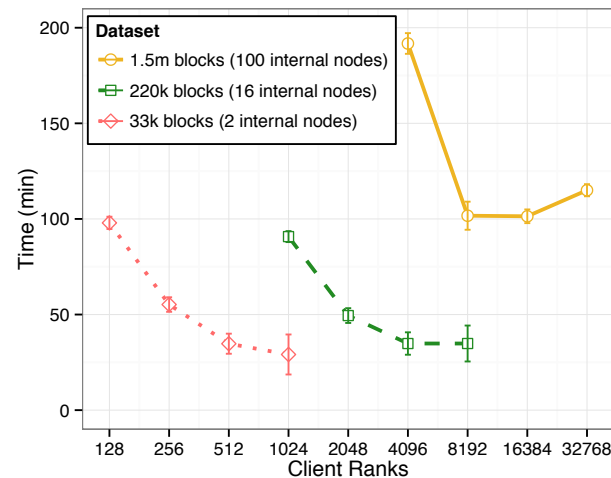
*In situ* refined



Disk-based post processing



*In transit* extra nodes



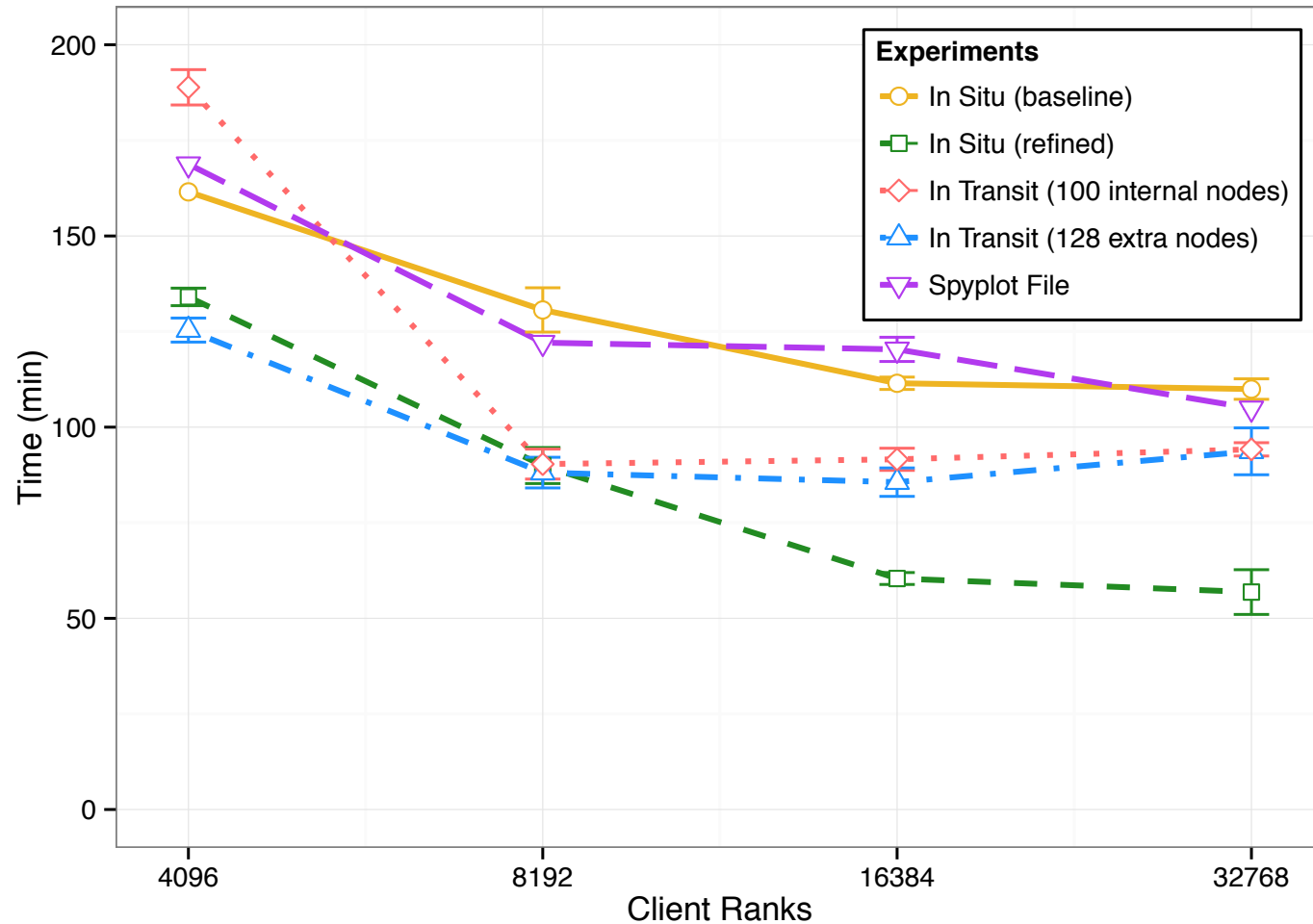
*In transit* internal nodes

5 applications  
3 datasets

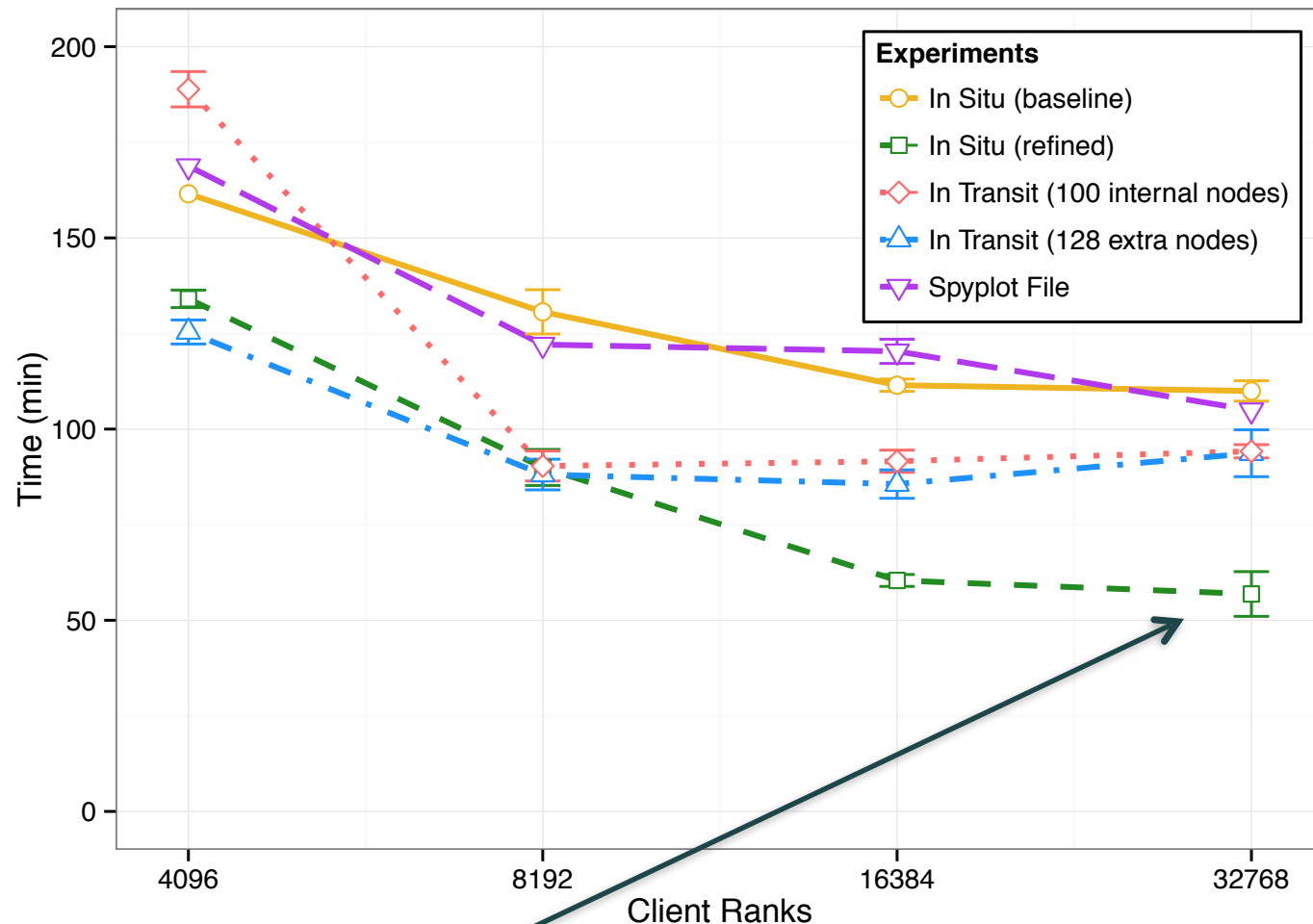
Strong scaling for each dataset

Error bars show variance

# Summary Timing (1.5m blocks)

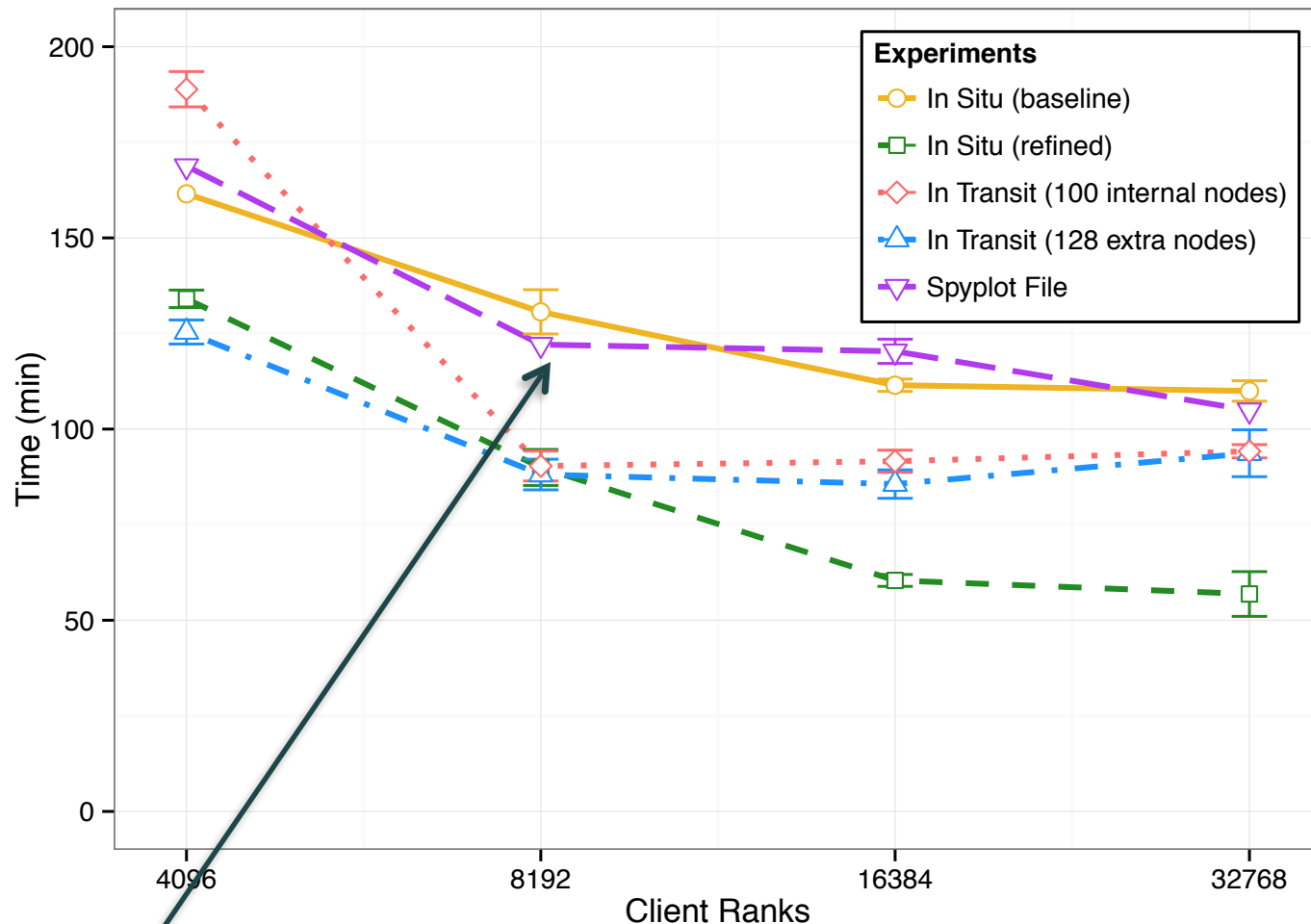


# Summary Timing (1.5m blocks)



No significant improvement at 32K cores. Probably insufficient work for analysis (only 45 blocks per process).

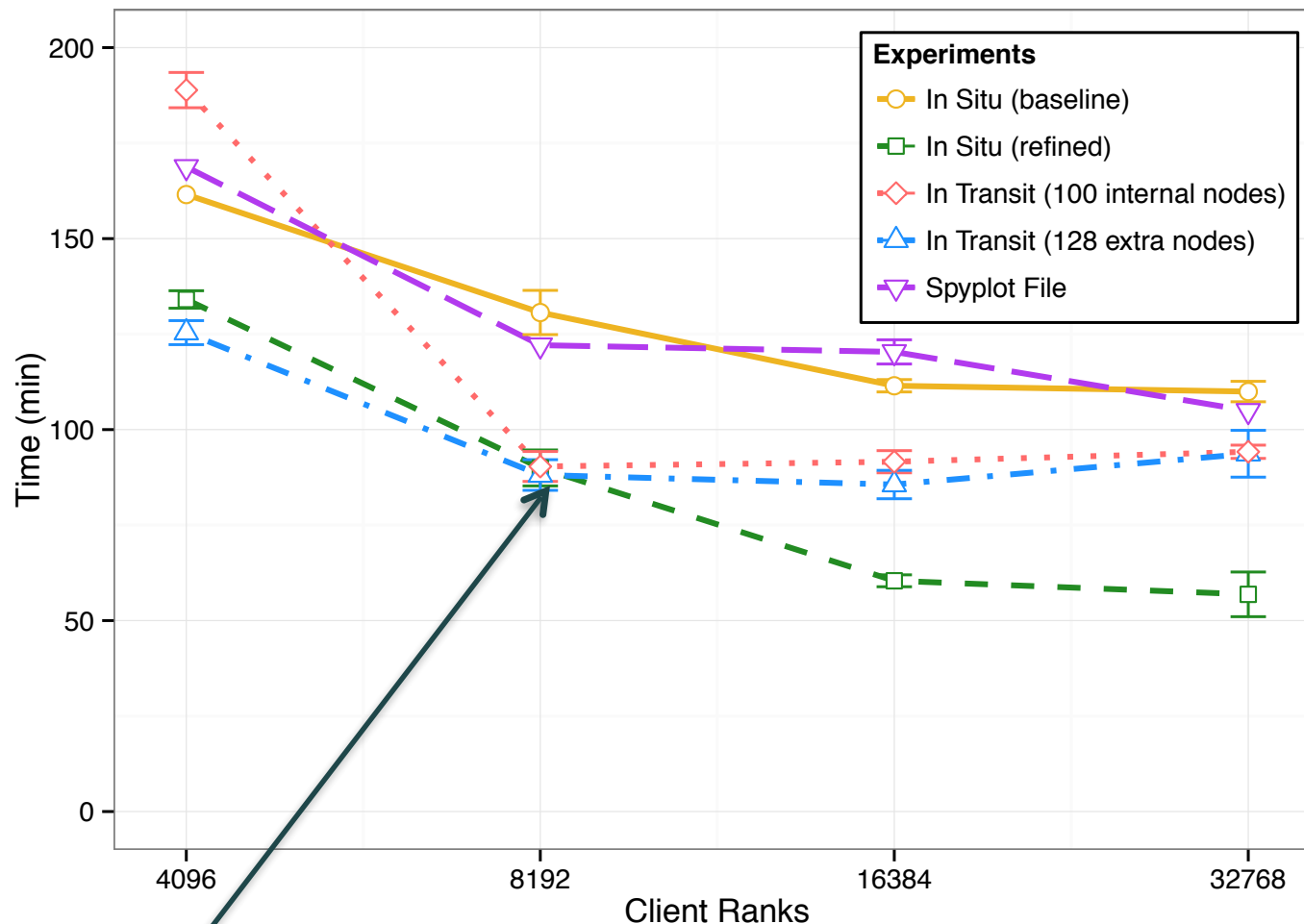
# Summary Timing (1.5m blocks)



Writing files surprisingly fast. Although slower than most alternatives, still a viable option.

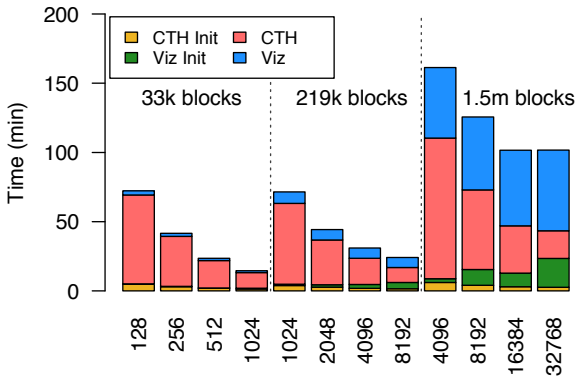


# Summary Timing (1.5m blocks)

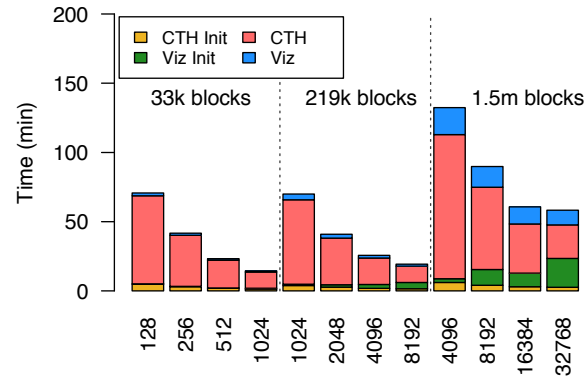


“Sweet spot” at 8K cores: *in transit* with unrefined algorithm equal to *in situ* with refined algorithm.

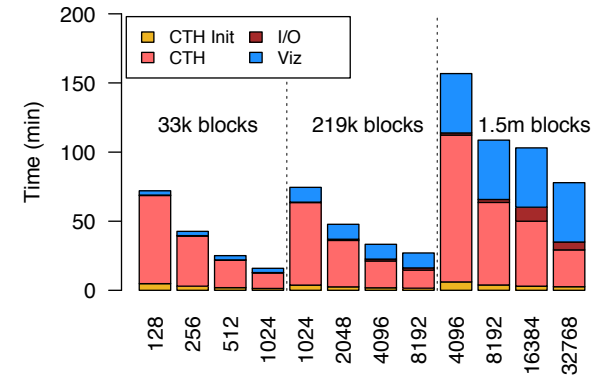
# Timing Per Task



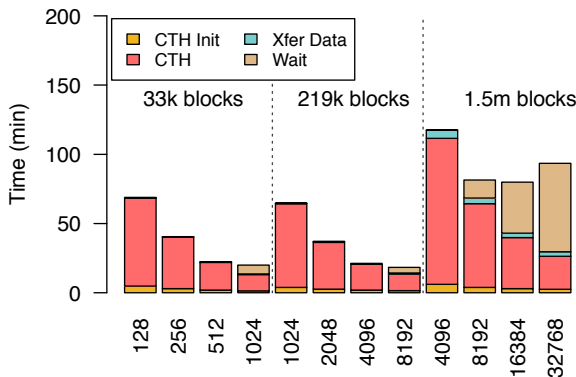
*In situ baseline*



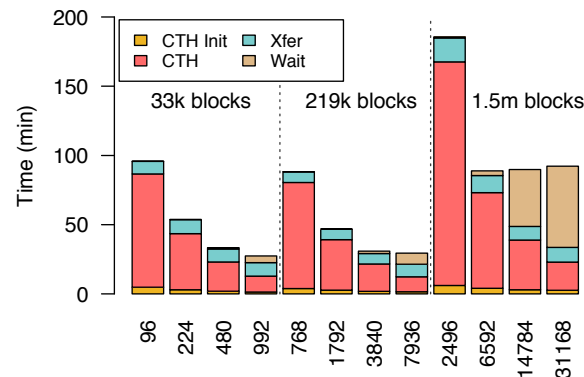
*In situ refined*



Disk-based post processing



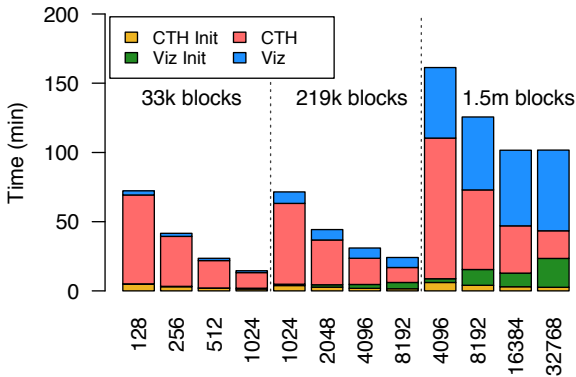
*In transit extra nodes*



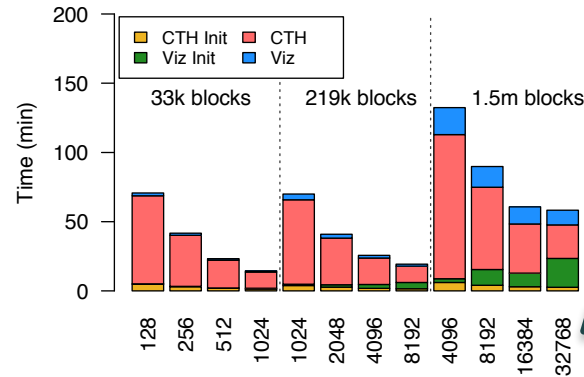
*In transit internal nodes*

- CTH scales well.
- Baseline algorithm does not scale
- Spyplot I/O not bad

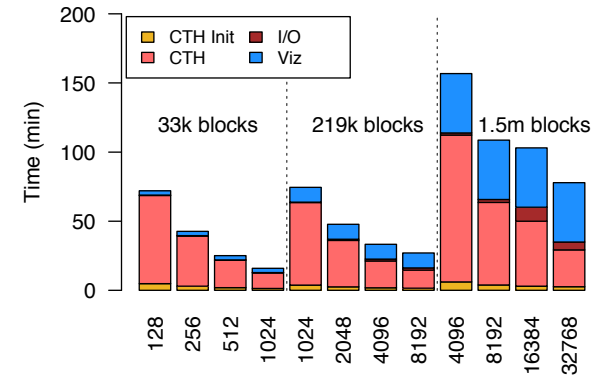
# Timing Per Task



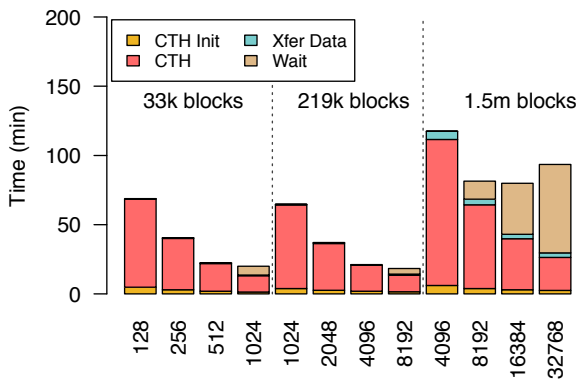
*In situ* baseline



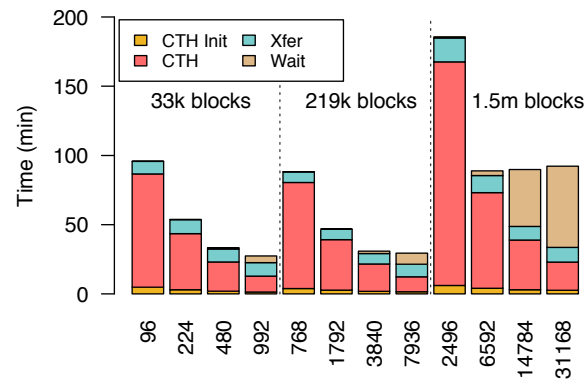
*In situ* refined



Disk-based post processing



*In transit* extra nodes

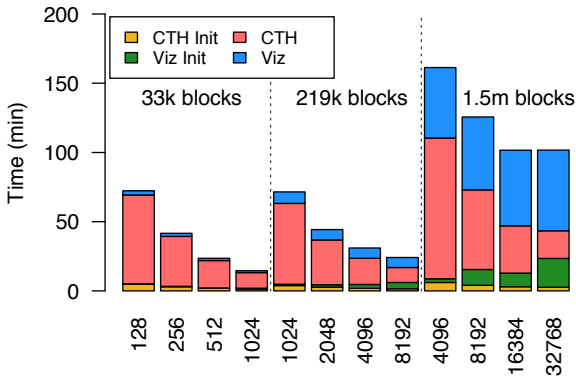


*In transit* internal nodes

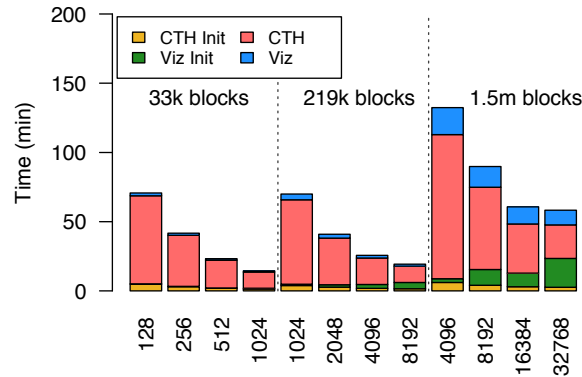
Refined analysis has lower overhead, but initialization cost is problematic.

Refined algorithm requires additional data to be passed. Not done for *in transit* experiments.

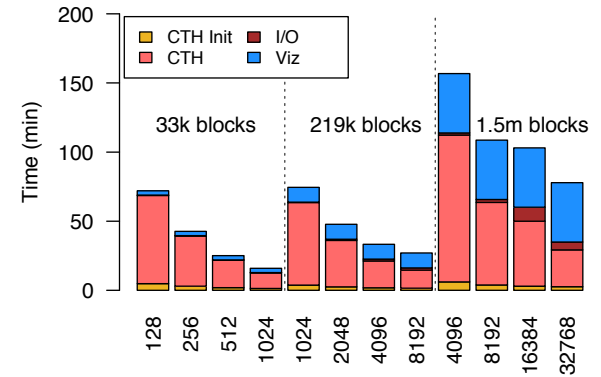
# Timing Per Task



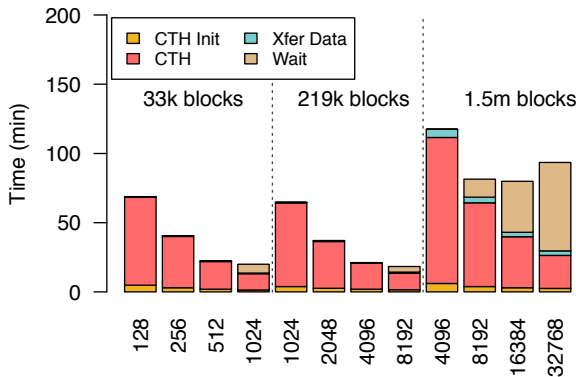
*In situ baseline*



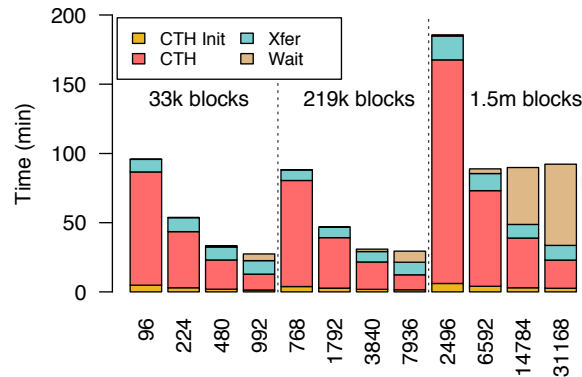
*In situ refined*



Disk-based post processing



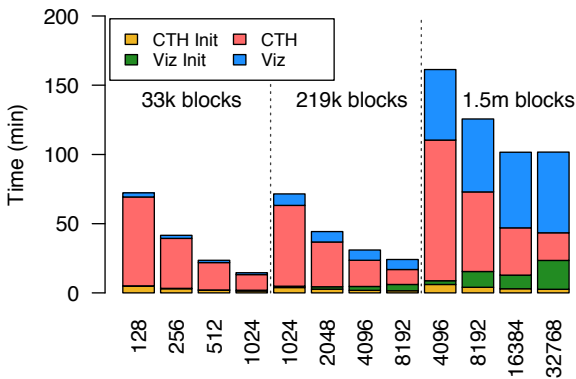
*In transit extra nodes*



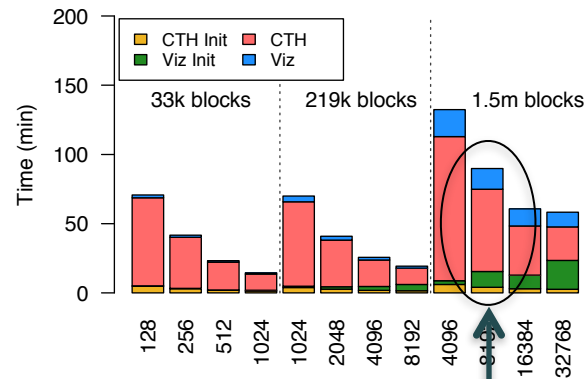
*In transit internal nodes*

Service is a fixed size (100 nodes), the wait time should be independent of the number of cores on the client.

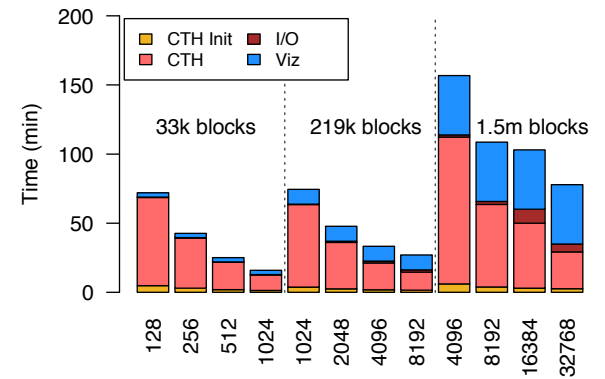
# Timing Per Task



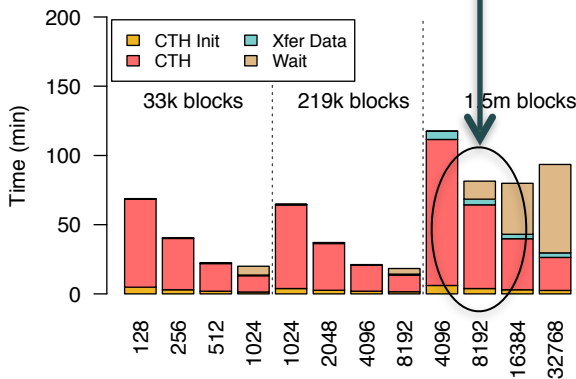
*In situ baseline*



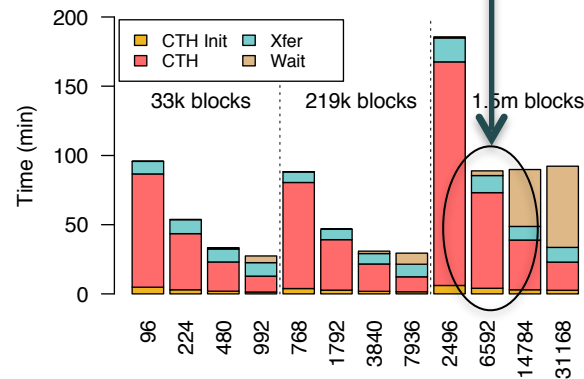
*In situ refined*



Disk-based post processing



*In transit extra nodes*



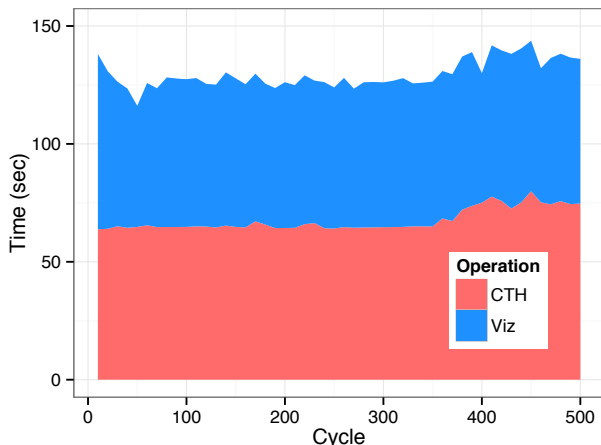
*In transit internal nodes*

“sweet spot”

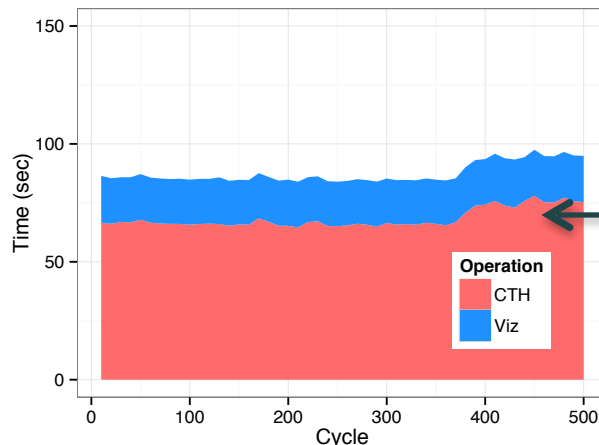
In transit internal shows  
balanced simulation and  
analysis

# Time-Series Analysis (8k cores)

10-cycle increments



*In situ baseline*



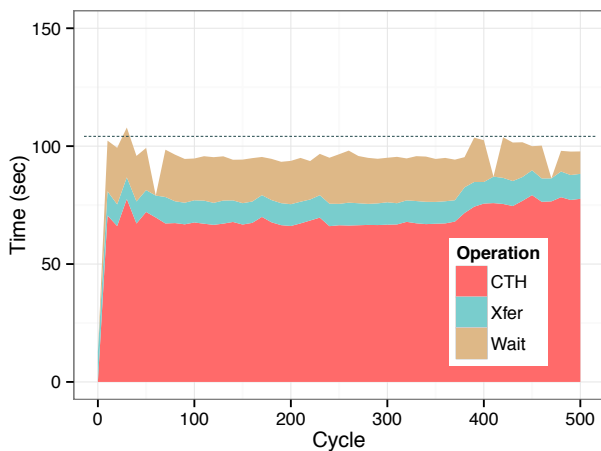
*In situ refined*

Although number of blocks changes very little, CTH runtime gets longer as simulation progresses.

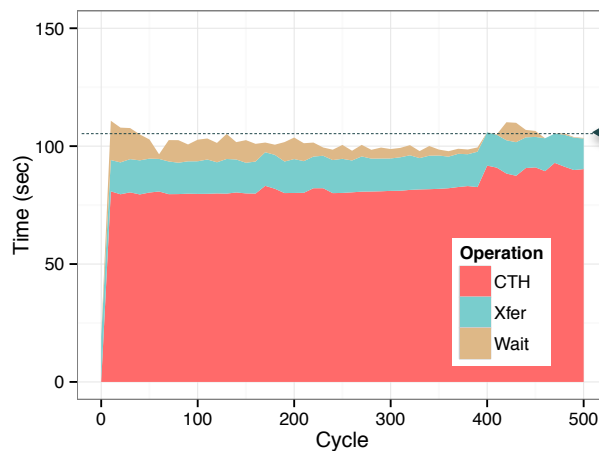
Vis time is roughly constant.

*In transit* “wins” when xfer + wait is less than viz.

*In transit* can flatten the runtime as long as extra simulation time consumes only wait time.



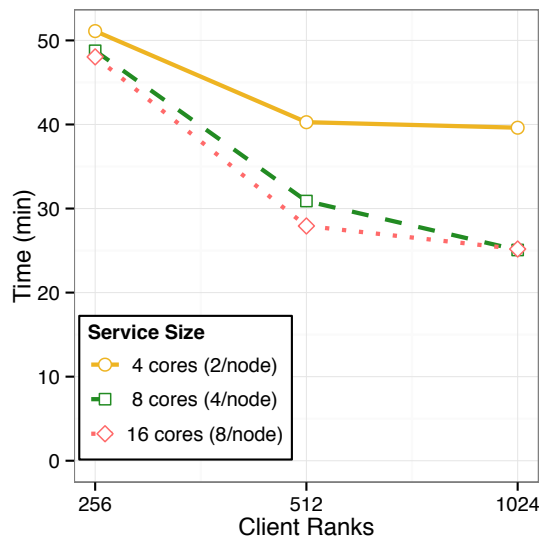
*In transit extra nodes*



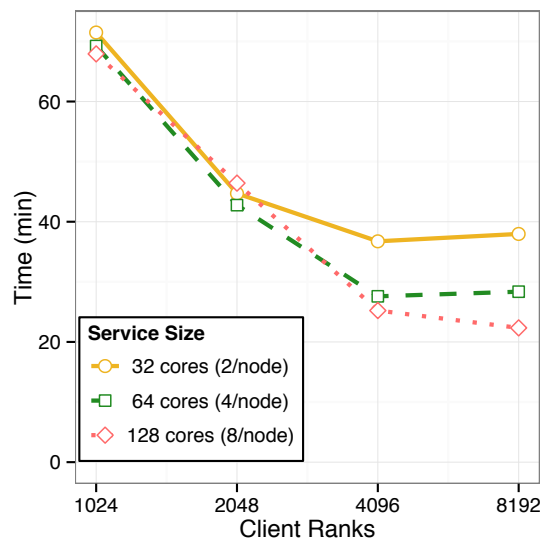
*In transit internal nodes*

# In Transit Service-Node Core Scaling

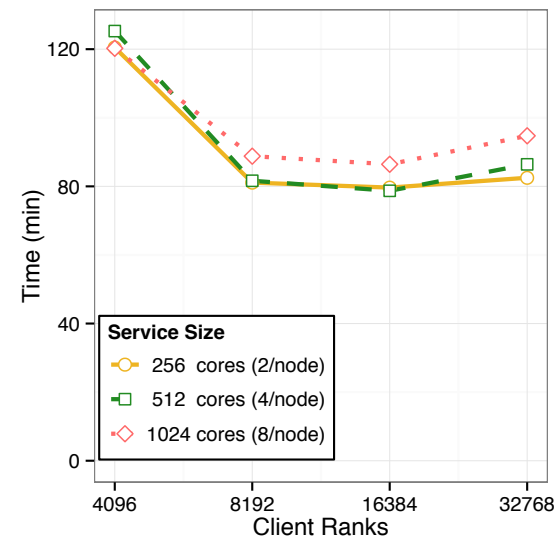
33k blocks



218k blocks



1.5m blocks



For small datasets, there is clear benefit to using 4 and 8 cores/node (agreement from preliminary tests)

For the 1.5m blocks dataset (at large scale), the opposite appears to be true. Needs further study.



# Conclusions

- In situ is extremely effective when analysis algorithm scales with the simulation code.
- In transit is beneficial for complex cases, where data-transfer (and wait) costs less than analysis.
- Balance is the key. Efficient use of resources requires careful consideration of memory, compute, and network requirements of both simulation and analysis codes.
- Traditional disk-based post-processing approaches are not dead... yet.
- Better system support is needed for in-transit approaches. Scheduling is a challenge and node sharing is not possible.

# Summary and Future Work

- Trends in hardware, data volumes, power, and desire for high-resolution analysis are motivating the integration of workflows
- Tightly coupled and loosely coupled approaches will co-exist
- Gaps remain before these approaches become “productive”
  - System software is inadequate (being addressed in Hobbes)
    - Scheduling, load balancing, node and data placement
    - Runtime requirements may differ for coupled components
  - Need portable, memory efficient mechanisms for sharing data
    - Data structure mismatches
    - Multi-resolution/Multi-scale issues
  - Need new definitions for “persistence” of transient data
    - E.g., time windows, data set versioning, ...