



# Optimizing data staging based on autotuning, coordination, and locality exploitation on large scale supercomputers

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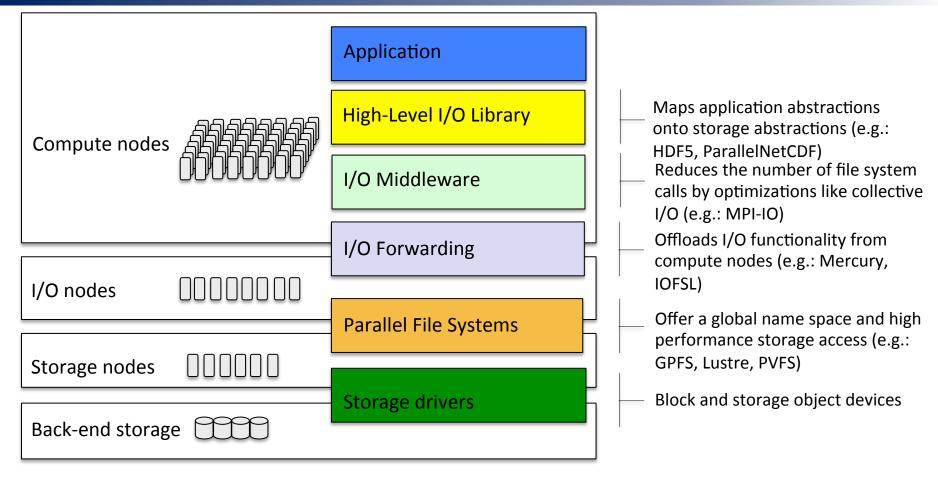






#### Current problems of storage I/O software stack





- Optimization: complex stack, deep distributed storage hierarchy
- Coordination: poor state of programmable control mechanisms are not available (e.g., for data staging, dynamic load balancing, resilience)
- Exploit data locality





Optimization: Model-based autotuning of collective I/O

Coordination: Data staging coordination

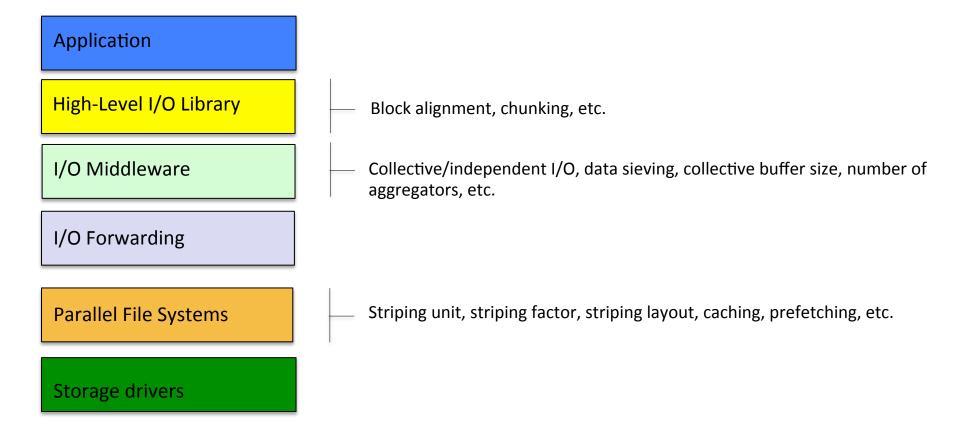
Exploit data locality: Improving the scalability and performance of the Swift workflow language by leveraging data locality through Hercules



#### Parallel I/O tuning



- Huge parameter space of the storage I/O software stack
- Domain knowledge is increasingly harder: software and hardware complexity





#### Parallel I/O autotuning approaches



#### Model based tuning

- Analytical: Extensive domain knowledge required: software stack, architectural characteristics
- Machine learning [Kumar2013, Yu2012]

#### Search-based tuning

- Genetic algorithms [Bezhad2013]
- Simulated annealing [Chen2000]
- Hybrid [Bezhad2014]

# Input parameters Performance models Performance prediction Application Noise

#### This work

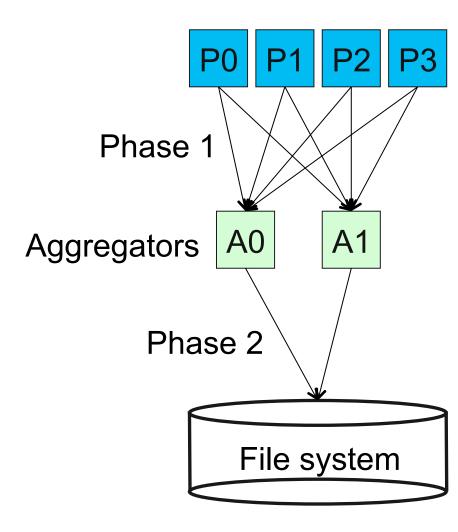
- Model-based tuning of two-phase-I/O, the most popular collective I/O implementation from ROMIO
- Combination of analytical and machine learning models
- IEEE Cluster 2015 paper



#### Collective I/O



- N processes collectively write or read to a file
- Two-phase I/O write
  - Computation and communication for mapping writes to the file domain
  - Communication for sending data to aggregators
  - Storage I/O for storing the data to the file system





#### Modeling framework



#### 4 parameters

n: number of nodes

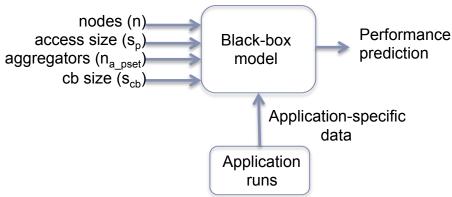
s: access size

n<sub>a</sub>: number of aggregators

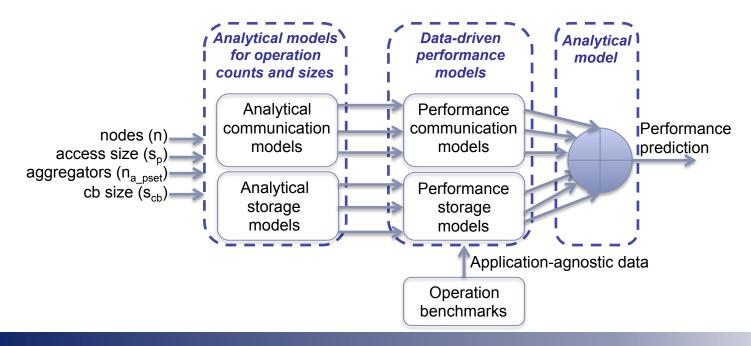
s<sub>cb</sub>: collective buffer size

Goal: tune n<sub>a</sub> and s<sub>ch</sub>

#### Black box model



#### Hybrid model





#### Experimental evaluation



- IOR benchmark: N processes concurrently write and non-overlapping region to the file system through MPI-IO
- ▶ MPICH 3.1
- Vesta Blue Gene/Q
  - ▶ 2048 compute nodes 1.6 GHz 16 cores 16GB RAM
  - ▶ 5D torus network interconnecting compute nodes
  - ▶ 1 I/O node per 32 compute nodes
  - Client (I/O node) cache: 4GB
  - ▶ GPFS 3.5: Block size: 8MB, 40 NSD SATA data drives (Max throughput: 250 MB/s)
- Benchmark for performance models: ALCF MPI benchmark



#### Machine learning model



#### Black box models and performance models

- linear regression, neural networks, support vector machines, random forests, and cubist
- Selected the model with best RMSE and R<sup>2</sup>

#### Data set:

- ▶ Black box model: 297 points
  - Processes: 2048 (128 nodes on 16 cores), 4196, and 8392
  - ▶ Transfer sizes/core (MB): 1, 2, 4, 8,16, 32, 64, 96, 128, 192, 256
  - ▶ Collective buffer size (MB): 8, 16 (default), 32
  - ▶ Number of aggregators per 128 nodes: 40, 136, 520 (default)

#### Performance models

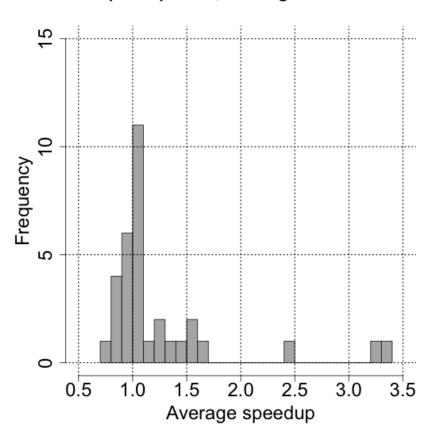
- ▶ Alltoall: : 51 points for 2,048, 4,096, and 8,192 ranks and for message sizes between 1 byte and 256KB.
- Alltoally: 1,044 points for distributing message sizes between 1 byte and 64 MB (in powers of 2) for subsets of 2,048, 4,096, and 8,192 ranks.
- Allreduce: 57 points for 2,048, 4,096, and 8,192 ranks and for message sizes between 4 bytes and 1 MB.
- ▶ POSIX: 567 points for various sizes and various subsets of 2,048, 4,096, and 8,192 ranks.



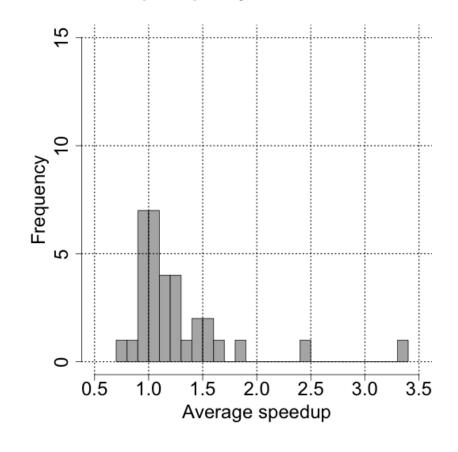
# Comparison between black-box and hybrid models



Speedup of ml; training set size=99



#### Speedup of hybrid over default

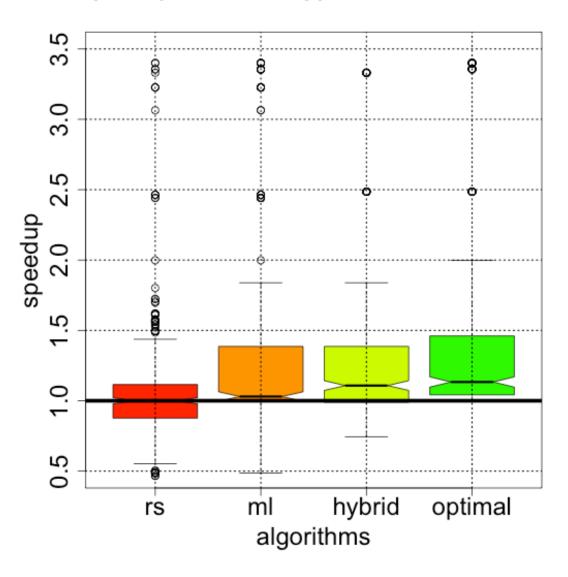




#### Comparison among various approaches



#### Speedup of various approaches over default

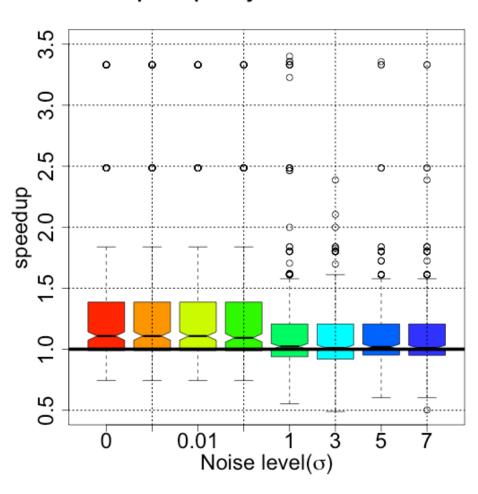




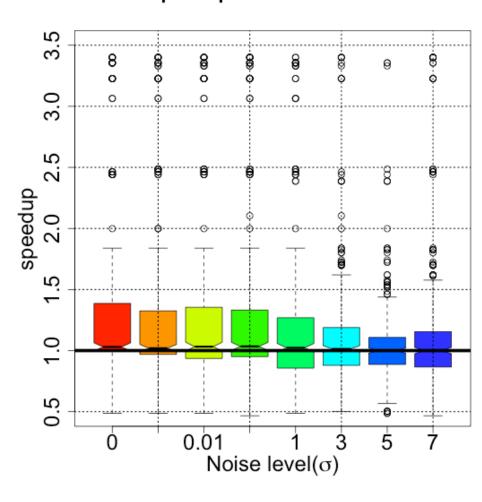
#### Impact of noise



#### Speedup of hybrid over default



#### Speedup of ml over default



#### Outline



Optimization: Model-based autotuning of collective I/O

Coordination: Data staging coordination

Exploit data locality: Improving the scalability and performance of the Swift workflow language by leveraging data locality through Hercules



#### Data staging challenges



- Concurrent parallel data flows
  - Lack of data staging coordination
    - Among applications
    - Between applications and the system
- Increasing storage hierarchy
- Lack of standards for dynamic monitoring of large scale infrastructures (e.g. load, faults)
- Coupled control and data mechanisms
- Goal: offer novel mechanisms for data staging coordination to improve
  - Load balance
  - Resilience
  - Parallel I/O scheduling



#### Coordination approach : CLARISSE library



- Decouple the data and control paths
- Data-path: abstractions used to implement data access operations
  - Collective I/O
    - ▶ 2 implementation: view based I/O, list-IO (can be used as both server-based I/O and client-based I/O)
- Control path: Based on a publish/subscribe substrate (e.g. Beacon)
  - Processes can subscribe to events having certain properties
    - Associate call-back
    - Wait for an event
    - Check for the arrival of an event
- Hierarchical control
  - Global controller
  - Application controller
  - Node controller
  - All nodes participate in control



#### CLARISSE hierarchical control infrastructure





**Node Controller** 



**Application Controller** 

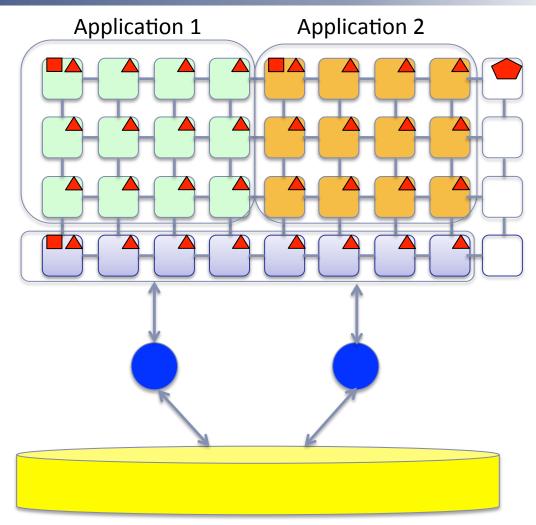


**Global Controller** 

Shared servers

I/O nodes

File system





#### CLARISSE hierarchical control infrastructure





**Node Controller** 



**Application Controller** 

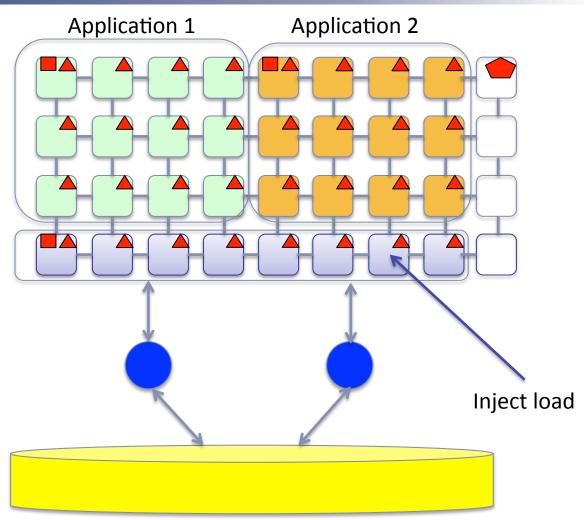


**Global Controller** 

Shared servers

I/O nodes

File system

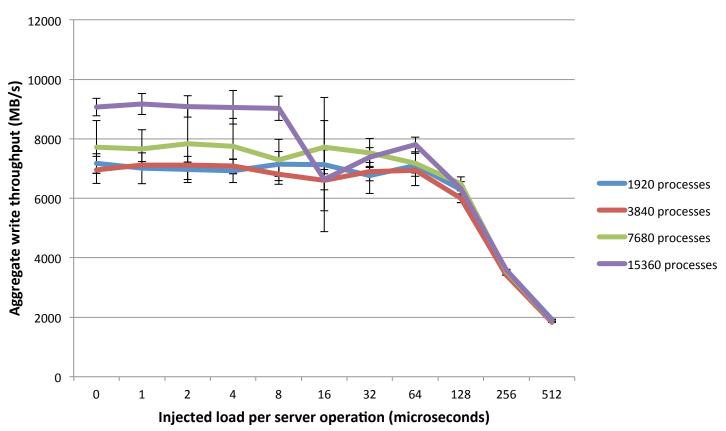




#### Load injection at 1 server (1 application)



# Aggregate write throughput for injecting load on one server (one operation of 30 Gbytes)

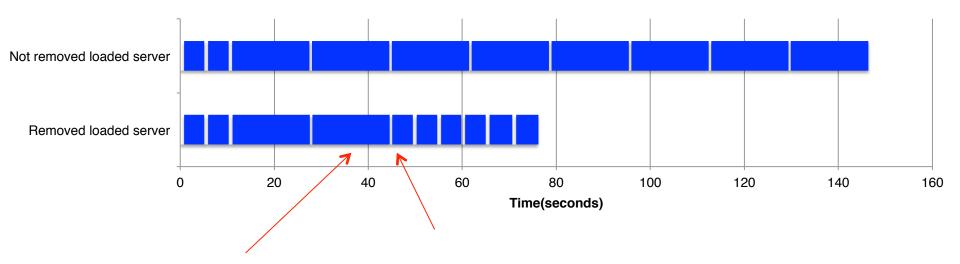




#### Dynamically scaling-down



#### Write time (10 operations, 3840 processes, 256/255 servers)



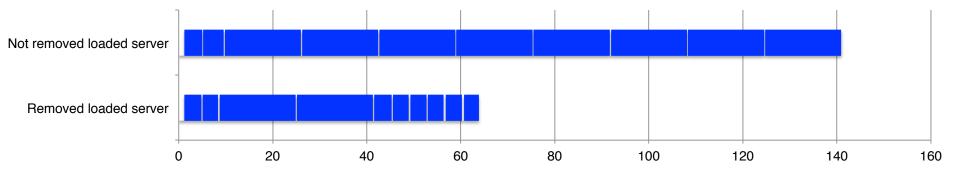
Detect loaded server Reconstruct server map New epoch with fewer servers



#### Dynamically scaling-down



#### Write time (10 operations, 15360 processes, 1024/1023 servers)





#### Parallel I/O scheduling



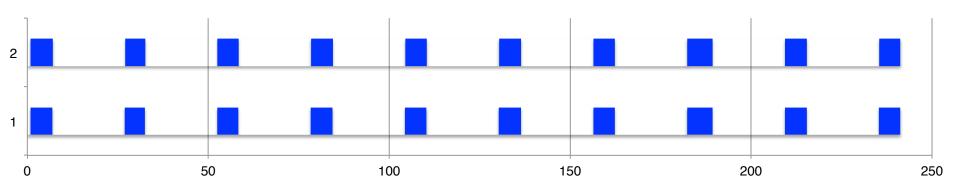
- Several applications share
- The application controller notifies the global controller
- The global controller schedules the next application to be run
- Several policies possible
  - FCFS evaluation



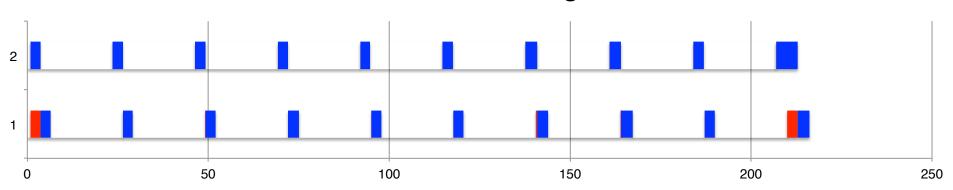
#### FCFS scheduling versus no scheduling



# Write timeline for two parallel clients with 3840 processes each - No scheduling



# Write timeline for two parallel clients with 3840 processes each - FCFS scheduling



#### Outline



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Swift/T: Language and runtime for dataflow applications

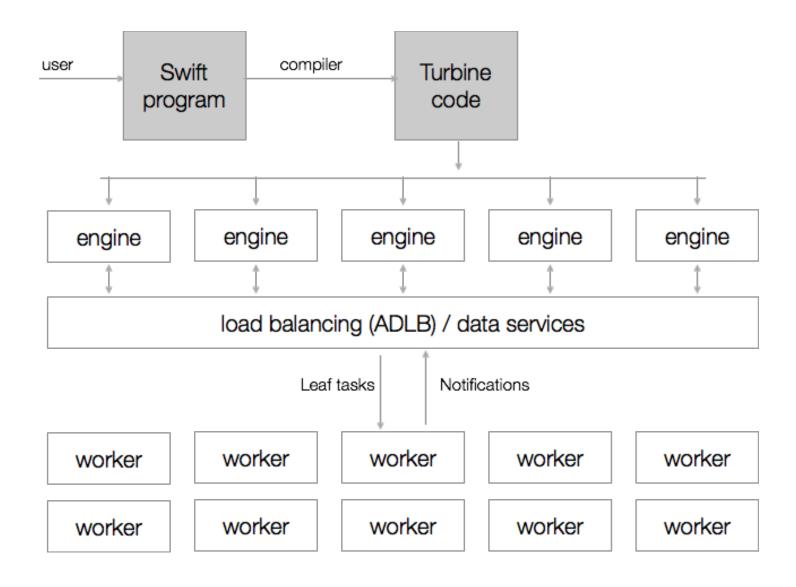
```
(int r) myproc (int i, int j)
{
   int f = F(i);
   int g = G(j);
   r = f + g;
}
```

- F() and G() implemented in native code or external programs
- F() and G() run concurrently in different processes
- r is computed when they are both done



#### Swift/T architecture







#### Problem description



- Load balancer is not locality-aware
- Tasks communicate through the parallel file system (bottleneck)
- Objectives:
  - Improve the performance of inter-task communication
    - Data locality
  - Investigate the tradeoffs between data locality and load-balance in workflow execution
    - Ideal load balance, but poor locality
    - Ideal data locality, but poor load balance (not all nodes used)



#### Approach



#### Hercules

- persistent key value store based on Memcached
- On-demand deployment of servers on application nodes

#### Data placement over the servers

- Consistent hashing (original Memcached)
- Locality-aware (implemented)
- Load-aware (under implementation)
- Capacity aware

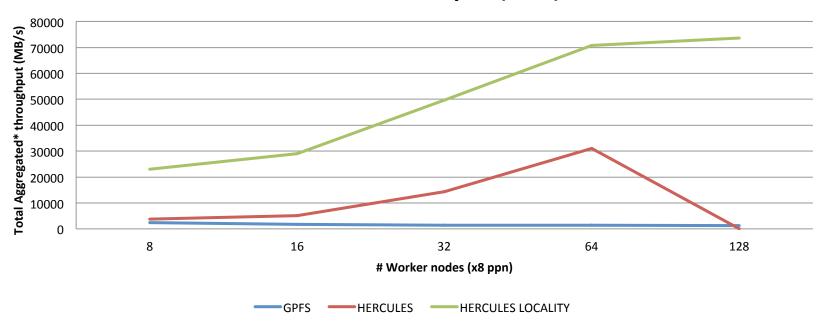
#### New Swift language constructs

- Soft location: best effort task placement
- Hard location: enforce data locality





# File-copy Strong Scalability - Aggregated Throughput\* 1024 files x 256 MBytes (R+W)



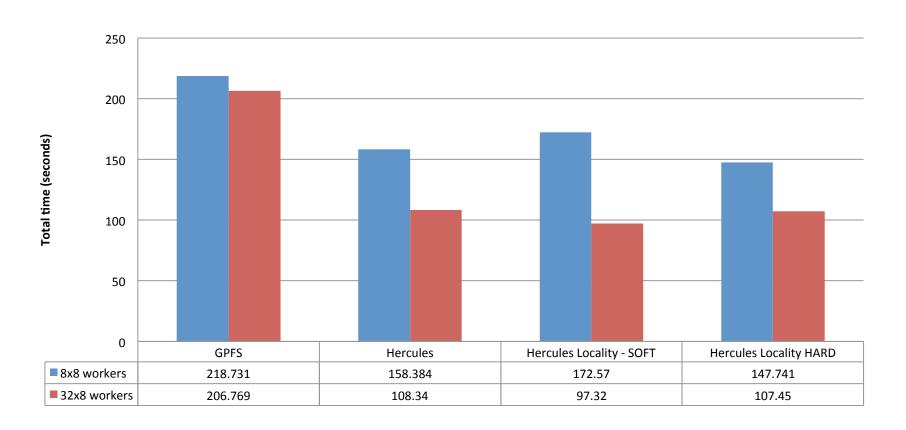
#### **Fusion Linux cluster**

- 320 nodes, 2 x quad core, 36 GB RAM
- Infiniband QDR (4 GB/s) and gigabit ethernet
- GPFS: up to 2500 MB/s





#### MapReduce-like WC application 256 files x 256 MB - 64 GB Total execution time





#### Ongoing and future work



#### Model-based autotuning I/O

- Performance predictability
- Improve individual models
- Noise
  - Load and noise modeling for load detection in data staging (multiple servers)

#### Data staging coordination

- Topology-aware server/aggregator placement JL Colaboration with E. Jeannot, F. Tessier (INRIA), V. Vishnavath (ANL)
- ▶ Multiple stage coordination (aggregation burst buffer file system)
- ▶ Load prediction based on Omnisc'lO (Mathieu Dorrier ANL)
- Adaptive buffering in parallel applications workflows (Decaf project)
- Adopt Global Information Bus from Argo and Hobbes (Beacon, Exposé)
- Need for sub-second monitoring and notification

#### Exploit locality in workflows

- Load-aware placement
- Tradeoff locality load balance
- New applications? New architectures? New coordination scenarios?





# Thank you



#### Conclusions - autotuning



#### Automatic parameter configuration

- Machine learning and hybrid models approaches outperform the default values in most cases
- Hybrid models higher robustness to noise than pure machine learning
- Hybrid model do not require application reruns

#### Factors that limit efficiency of the I/O stack optimization

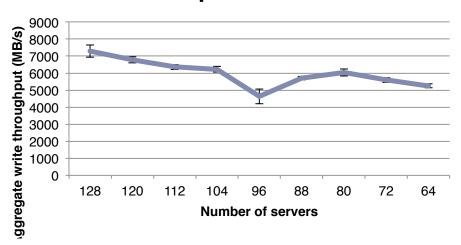
- POSIX consistency semantics: File locking
- File system noise
- The lack of information about the state of storage hierarchy (e.g. cached versus non-cached)
- Performance predictability needs to improve



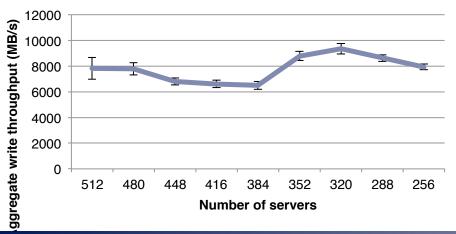
# Scale-down number of servers (1 application)



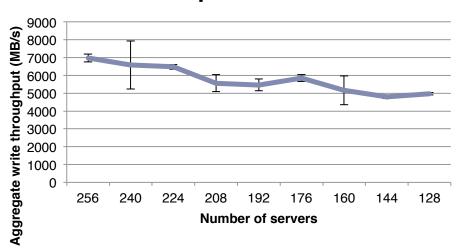
# Aggregate write throughput for 1920 processes



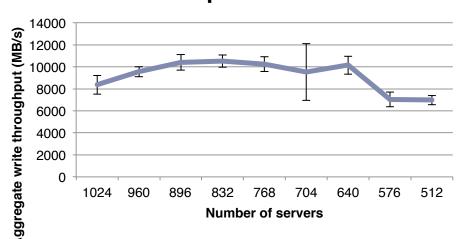
# Aggregate write throughput for 7980 processes



# Aggregate write throughput for 3840 processes



### Aggregate write throughput for 15360 processes





#### Dynamic removal of loaded server



- Assumes the availability of a load detection mechanism
- One application process detects a loaded server
- Notifies the application controller
- Application controller informs all node controllers and ask them to prepare to start a new epoch with less servers
- Node controller
  - Decides the last operations to be executed from the current epoch
  - Suspends all operation from the future epoch
  - Updates the server map
  - Notifies the application controller
  - Application controller ask all nodes to start a new epoch
- Each node controller resumes the suspended operations if any



#### Conclusions - coordination



- Data staging coordination
- Separation of data and control
- Hierarchical controlling
- Significant benefits
  - Load/Fault aware sever-scale down
  - Parallel I/O scheduling
- Scalable load and fault monitoring is required



#### Conclusions – data locality



- Integration Swift/T Hercules
- Substantially improves the throughput over shared file systems
- ▶ I/O performance scales up with the number of application nodes
- Exploit data locality in workflows
- Less sensitive to file system noise and contention



#### Vesta Blue Gene/Q system at ANL



