OAK RIDGE National Laboratory

Applying Machine Learning to Understand Write Performance of Large-scale Parallel Filesystems

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Applying Machine Learning to Understand Write Performance of Large-scale Parallel Filesystems

- Problem
  - Understand the write performance of HPC applications running on large-scale systems
- Contribution
  - Built accurate ML models for predicting the I/O write performance
  - Interpreted multi-stage write behaviors of large-scale I/O subsystems
- Impact
  - Demonstrated that ML can be applied to predict the write performance of large-scale I/O subsystems
  - Delivered a generic solution applicable to various large-scale I/O subsystems and technologies

Motivation: Reduce the Write Cost

- Configure write burst size/rate tradeoffs
- Guide I/O middleware (e.g., ROMIO) to adapt write patterns
- Inform system job schedulers to yield tighter/better estimates of I/O cost and application runtime

Related Works and Our Solution

- I/O performance studies
  - Profiling supercomputer I/O subsystems under production loads
  - Darshan toolkit
  - Statistical benchmarking
- I/O middleware systems
  - ROMIO, ADIOS
- ML in I/O performance prediction
  - Tune I/O parameters at application level
  - Learn I/O patterns from job logs and system monitoring data
- Our Solution
  - First ML work to predict write performance of large-scale parallel filesystems based on application write patterns, system architecture, and configurations

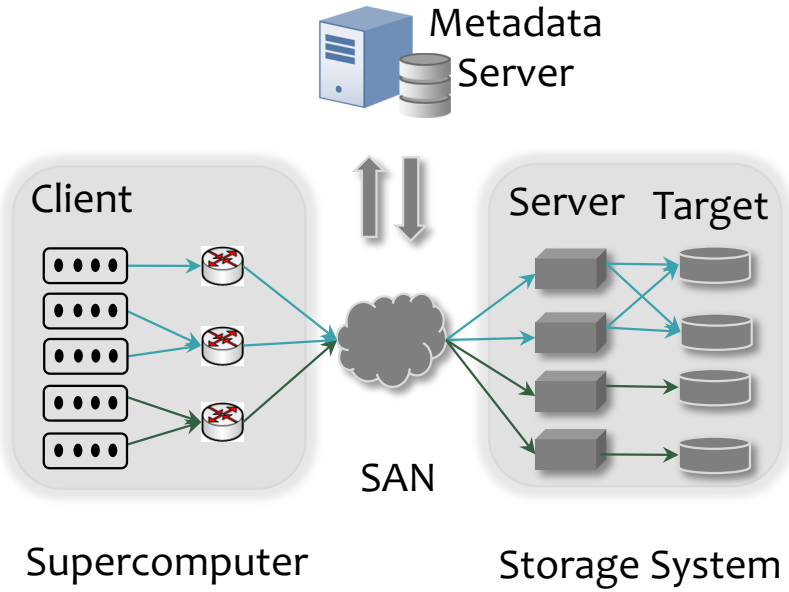
Typical Scientific Applications

- HPC codes compute for a long time at large scales
- Produce write bursts that stall application executions and impact application runtime

- A generic example: XGC
  - Evaluate **physical equations** iteratively over space: compute cost is predictable
  - **4 types of bursts** with different write frequencies and burst sizes:
    - state snapshots: 500MB to 1.2GB
    - diagnostic analysis bursts: 1MB – 400MB
    - Bursts are stored as independent files
  - **Write stalls** comprise 7-20% of run time

Target I/O systems

- Titan and Spider 2 at OLCF/ORNL
  - Cray XK7
  - Lustre filesystem
- Cetus and Mira-FS1at ALCF/ANL
  - IBM Blue Gene/Q
  - GPFS filesystem

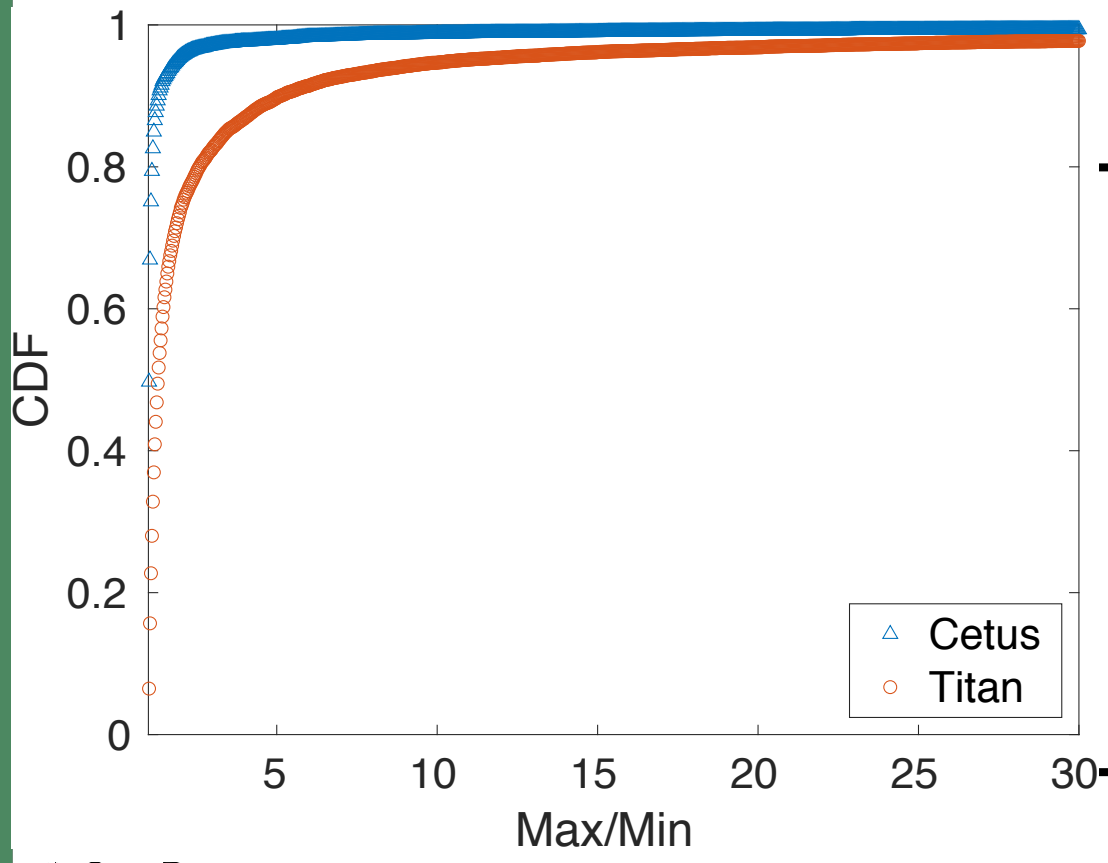


Challenges

- High performance variability
- Limited filesystem visibility for end-users

High Performance Variability

1. CDFs of write performance variations on Titan and Cetus.



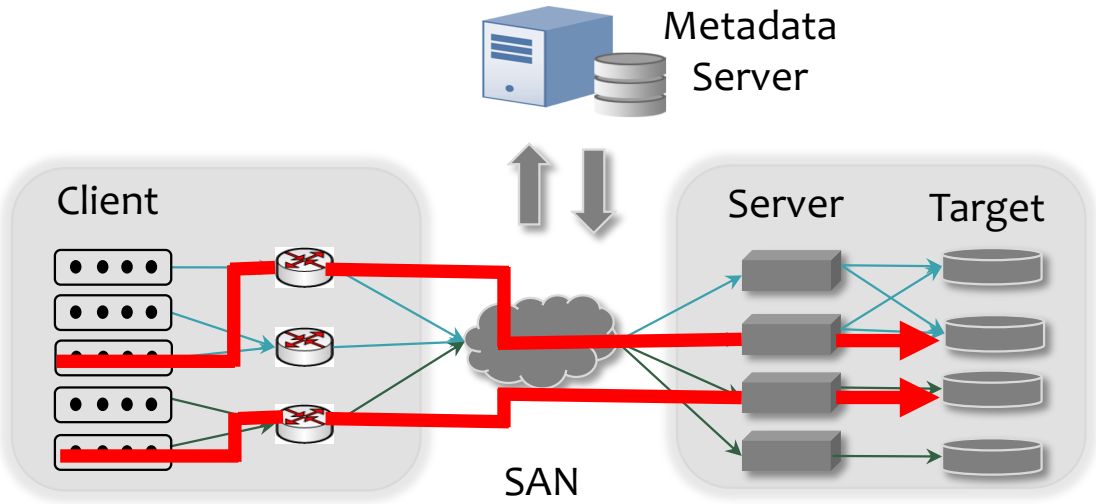
3. Write performance on Titan and Cetus is highly variable.

2. The x-axis represents the relative measures (max/min) of the write bandwidths of the experiment data (IOR benchmarks)

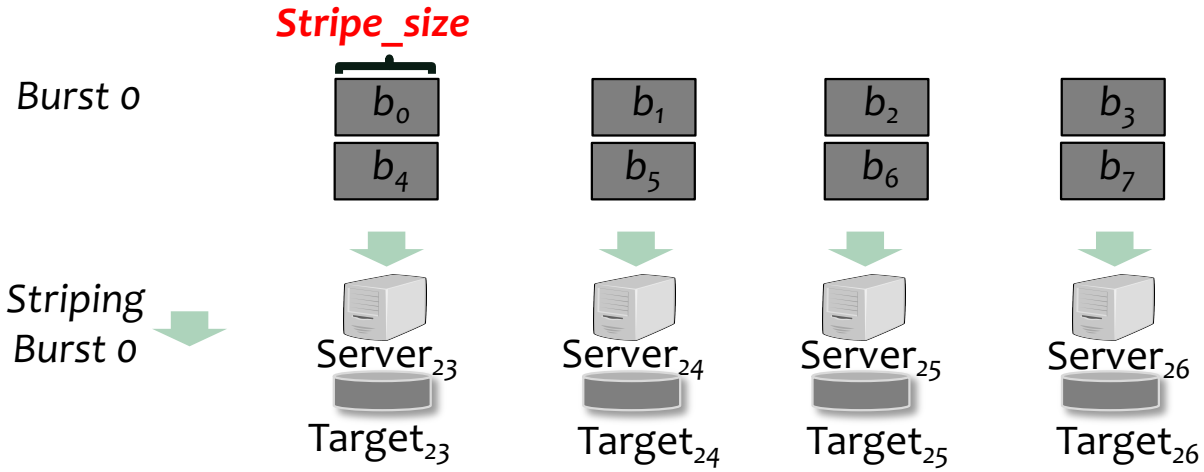
Our Approach

- Highly variable, but reverts to mean over time
  - **Model the mean performance**
  - **Effectively address the repeated I/O writes and aggregate impact**
- Limited visibility for end users
  - **Extract features from write patterns and system architecture and configurations**
- Interference
  - **Address noise as features**
- ML solution
  - **Convergence-guaranteed sampling method**
  - **Lasso models**
  - **Systematic ML methodology**

End-to-end I/O Write Path



Each Target is a RAID array.

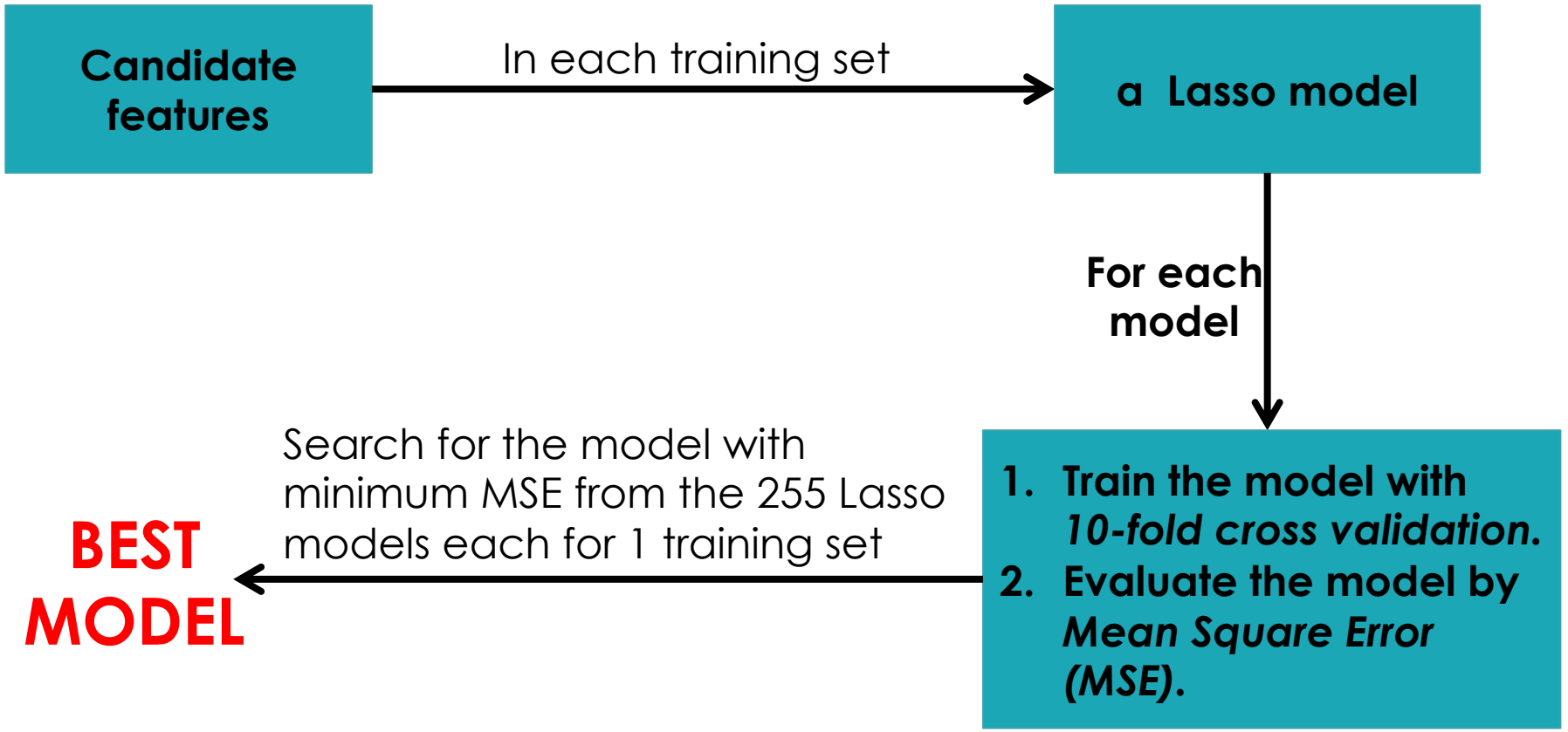


Example:
***Stripe_Count*=4**
***Starting_OST*=23**

Extract Features

- Insight: infer end-to-end burst absorption time based on performance-related parameters (**write load**, **load skew**, **resources in use**) at each stage
- Collectable performance-related parameters on Titan and Cetus
- Predictable performance-related parameters on Spider 2 and Mira-FS1
- Positive and inverse forms of performance-related parameters on separate stages, adjacent stages, and noise
- Titan/Spider 2: 41 features; Cetus/Mira-FS1: 30 features

Systematic Machine Learning Approach



Experiments

- Train models on a small scale data set
  - 3,465 (Titan) and 4,715 (Cetus) converged samples collected with multiple IOR benchmarks on the scale of 1-128 compute nodes
- Evaluate models on medium scale
  - 668 (Titan) and 874 (Cetus) converged samples produced by 200 -512 compute nodes
- Evaluation criteria
  - Accuracy of the best model
  - Effectiveness of features

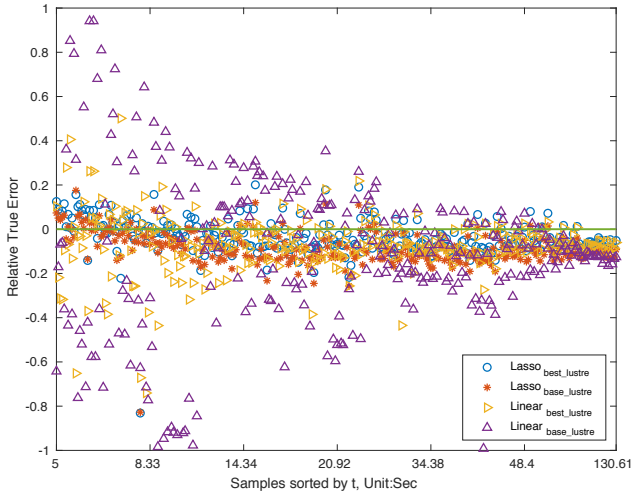
Reported 4 models

- $Lasso_{best}$
  - *With minimum Mean Square Error* from 255 Lasso models across the training set candidates
- $Lasso_{base}$
  - The Lasso model trained on the write scales of 1-128 compute nodes
- $Linear_{best}$
  - *With minimum Mean Square Error* from 255 Linear models across the training set candidates
- $Linear_{base}$
  - The Linear model trained on the write scales of 1-128 compute nodes

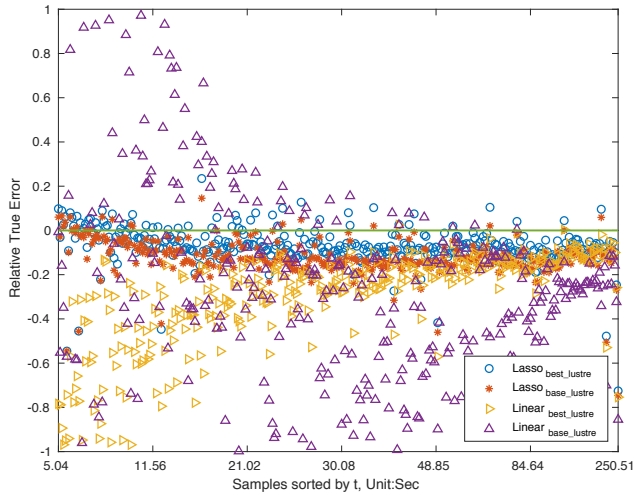
Results on Titan and Cetus

Titan/Spider 2

test set with 200, 256 nodes

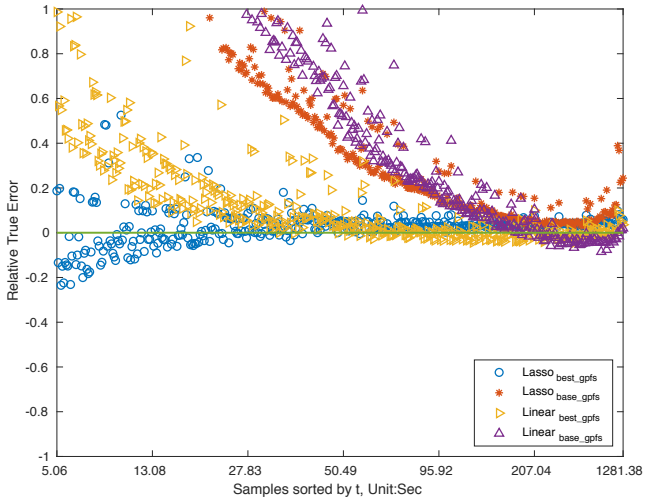


test set with 400, 512 nodes

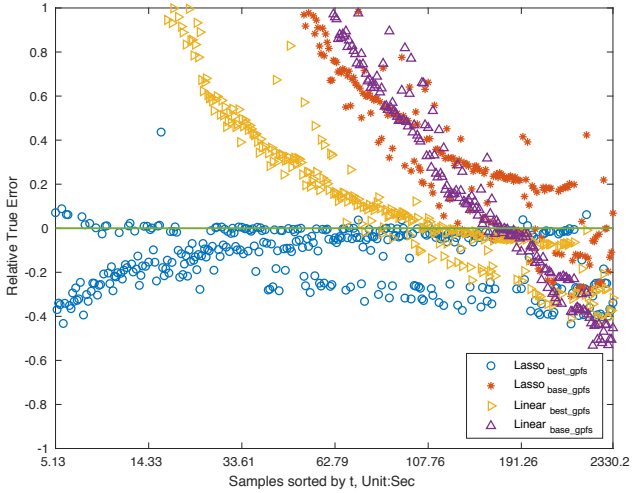


Cetus/Mira-FS1

test set with 200, 256



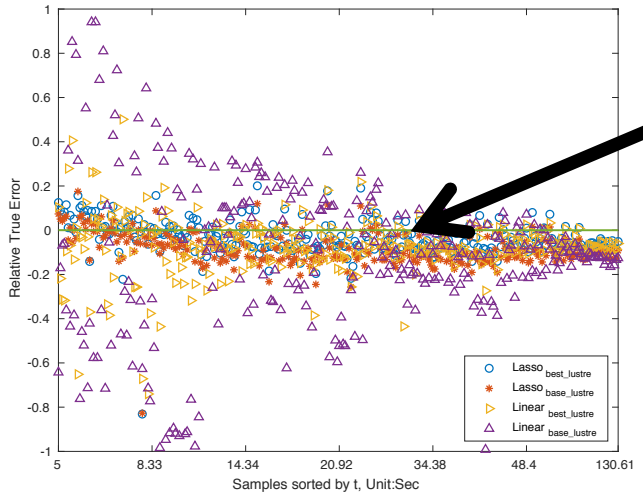
test set with 400, 512

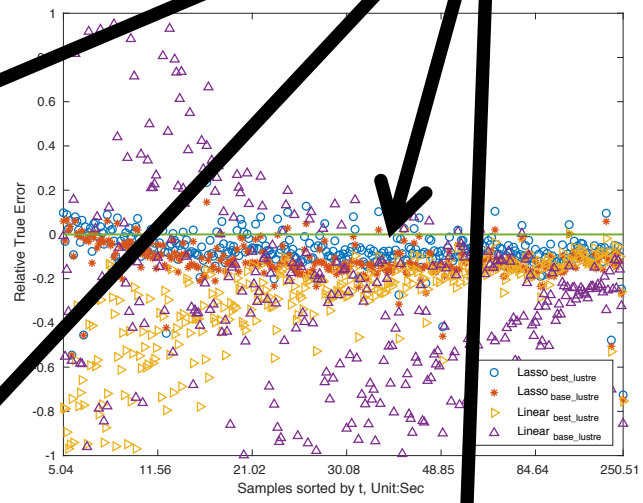


Results on Titan and Cetus

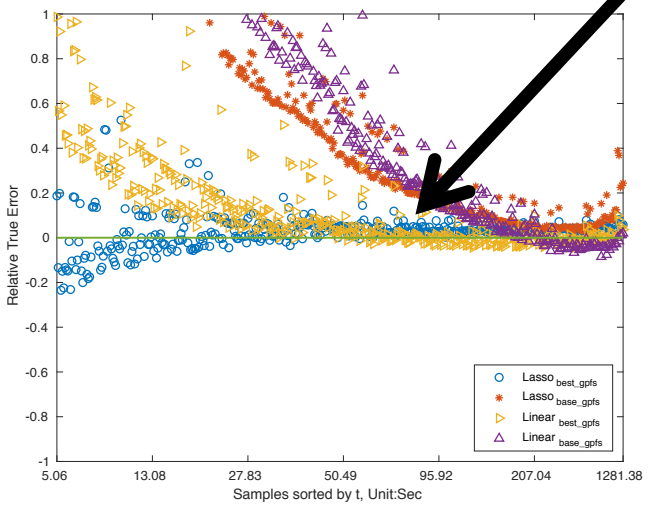
***Lasso_best* is highly accurate and the best model**

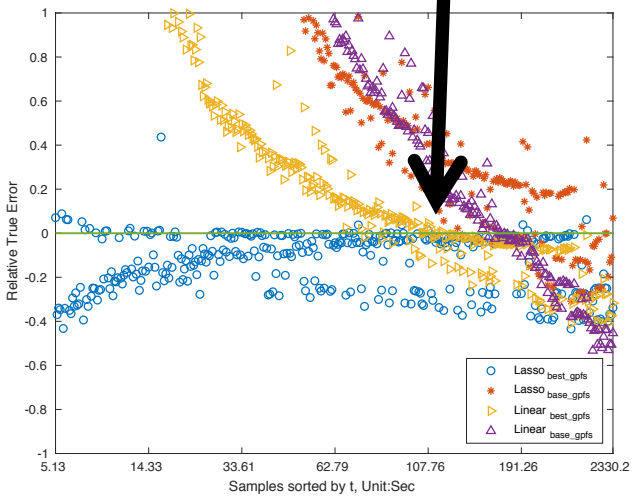
Titan/Spider 2





Cetus/Mira-FS1





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Conclusions

- Problem
  - Understand the I/O write performance of large-scale supercomputers
- Our Solution
  - Systematic ML approach with Lasso
  - Modeling the mean performance, extracting features from application write patterns, system architecture and configurations, convergence-guaranteed sampling
- Findings
  - $Lasso_{best}$ is the most accurate model for both Titan and Cetus
  - Most effective features are load skew in supercomputers and resources in use on the system side
- Applicability
  - Lasso models, features: Lustre, GPFS deployment
  - Systematic modeling method: generic supercomputer I/O subsystems

Acknowledgement