

Institute for Computer Science / GWDG



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A Workflow for Identifying Jobs with Similar I/O Behavior Utilizing Time Series Analysis



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Motivation

Data center staff are supporting users

- Optimization of programs
- Monitoring of (in)efficient usage

Assume you identified an interesting job

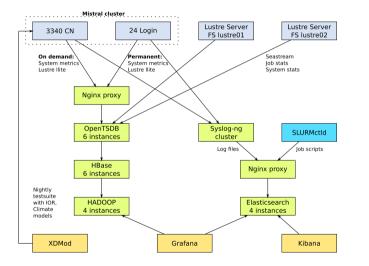
- Might be particularly inefficient or efficient
- e.g., via monitoring/tracing or user feedback
- Questions support staff may have
 - Will optimization pay off to other jobs?
 - Is the job a good blueprint for optimization?
- Problem: 100,000 of jobs are executed on a cluster
 - How can we find similar jobs?

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Approach

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DKRZ Monitoring System



Details

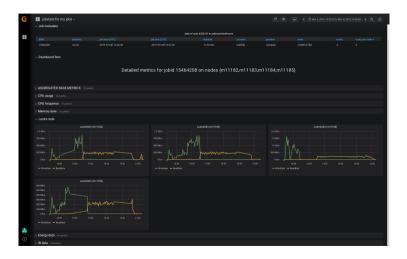
- Periodicity: 10s
- Record metrics
 - From /proc
 - 9 aggregated
- Jobs are linked to the data

Mistral Supercomputer

- 3,340 Nodes
- 2 Lustre file systems
- 52 PByte capacity
- 100+ OSTs per fs

Approach

Monitoring Data of a Job



Grafana visualization Read/write shown Metrics supported md file create md file delete md read (only) md_mod(ify) md other read bytes read_calls write bytes ▶ write calls

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Identifying Similar Jobs Using Time Series

- Previous work: utilized clustering algorithm(s)
- Today: workflow for supporting the investigation of jobs
- Derived meaningful distance measures
 - Must compare multiple metrics with different units/Range
 - Must handle variable number of nodes and runtime
- Conduct a study on 580,000 jobs (6 months of data from DKRZ)
 - Recorded using DKRZ monitoring system
 - Compute similarity of all jobs to three reference jobs
 - Quantitative analysis: behavioral comparison
 - Qualitative analysis: investigate top 100 similar jobs manually
 - Explored several algorithms

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Handle variable number of nodes and runtime

Variable number of nodes

- Calculate statistics across the number of nodes
- Obtain one time line per job metrics

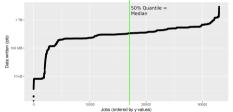
Segmentation across time dimension

- Segment: calculated average across 10 min time interval
- Result is time series of segments
- Earlier attempt: used additional statistics

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Compare Multiple Metrics with Different Units/Range

Convert raw data (X Bytes/s or Y opens/s) to categories



Categorization based on the quantiles of all jobs segments

Categories:

- ▶ 0 = non-IO (< 99% quantile)</p>
- \blacktriangleright 1 = HighIO (< 99.9% quantile)
- ▶ 4 = CriticalIO (>)
- Analysis of result shows that the categories are meaningful
 - e.g., 99% quantile is 1 op/s

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Algorithms

- Define the pre-processing and distance metrics
- Explored six algorithms that differ in:
 - Aggregation (Each metric indepenendly/together and which dimensions)
 - Coding (quantized/rounded to 17 states, binary)
 - Distance measure (Levensthein, Euclidean)
- Time series based algorithms
 - B-all: binary encode activity (Yes/No) of all metrics into one series
 - B-aggzero: remove subsequent segments of zero activity
 - Q-lev: quantized coding, Levensthein distance
 - Q-native: quantized, Euclidean distance, sliding window
 - ▶ Q-phases: extract phase information (metric \neq 0 and match)
 - Non time series algorithm: Kolmogorov-Smirnov
 - Concatenate individual node data (instead of averaging)

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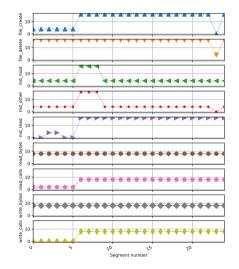
2 Approach

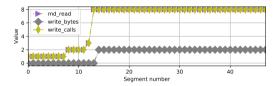
3 Evaluation

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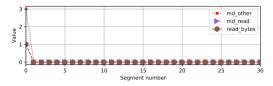
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The Three Reference Jobs (Average across all nodes)





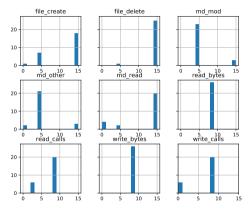
Job-M: 8 hours, 128 Nodes; other metrics == 0



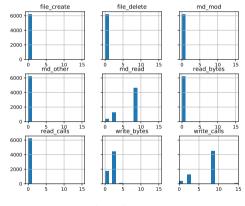
Job-L: 66 hours, 20 Nodes; other metrics == 0

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Histogram of Jobs in Quantized coding



Job-S Histogram



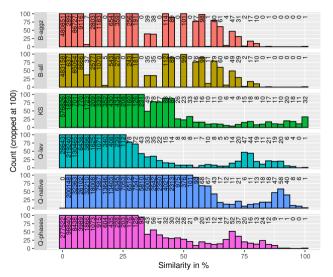
Job-M Histogram

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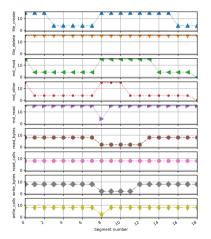
Similarity to Job-S



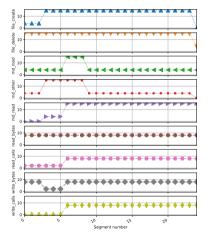
- 100% sim is the reference job
 - Job-S is CMORization control
- Names in the job pool
 - 22,580 have somewhat "cmor"
 - 367 have somewhat "control"
- Observations
 - Most jobs have a low similarity
 - Clusters are visible
 - 30-40 of most similiar jobs have control in the name
 - All algorithms work somewhat
- User may explore from most similar job to least
 - A cluster is reasonable cut-off

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Inspecting Selected Jobs: B_aggzeros



Non-cmor job: Rank 76, SIM=69%



Non-control job: Rank 4, SIM=81%

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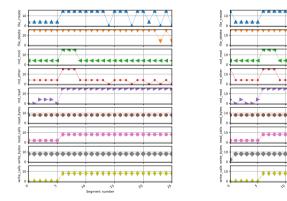
Approach

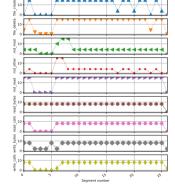
Evaluation

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Inspecting Selected Jobs: Q_Lev





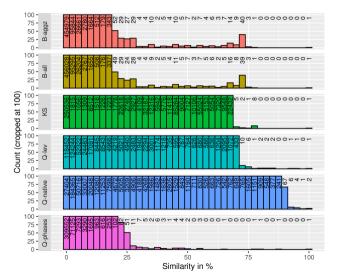
Rank 2, SIM=96% Rank 15, SIM=90% That looks rather similar, even better than B_aggzeros

Rank 100, SIM=79%

Segment number

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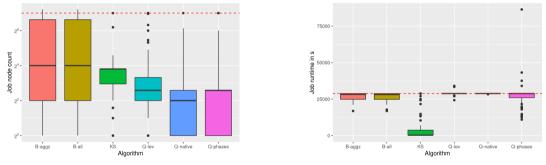
Similarity to Job-M



- Different behavior than for Job-S
- Much smaller similarity
- Q-native has highest similarity

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Inclusivity and Specificity for Job-M 100 Similar Jobs



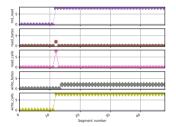
Distribution of node counts (job=128)

Distribution of Runtime (*job* = 28, 828*s*)

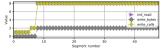
The algorithms identify a wide range of job runtime, node counts and different users

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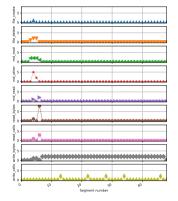
Inspecting Selected Jobs: Q-native



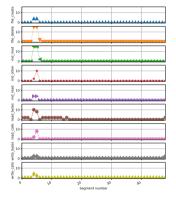
Rank 2, SIM=99%



Rank 3, SIM=97%



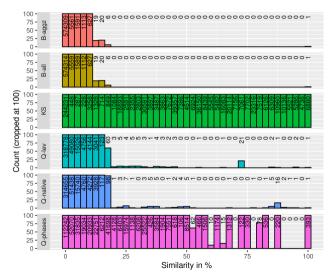
Rank 15, SIM=91%



Rank 100, SIM=88%

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Similarity to Job-L



- There are not many such long jobs
- The Q-phases and KS algorithms finds many jobs
 - There is only one IO phase
 - Many jobs have indeed similar profiles
- What to include?
 - It depends on the definition of similarity

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Conclusions

- Distance measures allow to find similar jobs
- Utilizing time series of system statistics seems suitable
 - All algorithms worked rather well on Job-S
 - ▶ For Job-M and Job-S, we prefer Q-native and Q-lev
 - Runtime (not shown here) is also feasible (near realtime)
- It all depends on our expectation of "similarity"
 - > What does a user need? Find similar phases in jobs? Do we require the same job length?
 - The community should define "similarity"

Article will apear in JHPS: Julian Kunkel and Eugen Betke A Workflow for Identifying Jobs with Similar I/O Behavior Utilizing Time Series Analysis The Journal of High-Performance Storage, https://jhps.vi4io.org/issue/2

Check the previous paper for this work:

Eugen Betke and Julian Kunkel Classifying Temporal Characteristics of Job I/O Using Machine Learning Techniques The Journal of High-Performance Storage, https://jhps.vi4io.org/issue/1