Practical Resource Usage Prediction Method for Large Memory Jobs in HPC clusters

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Agenda

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Observations from real production job traces

Problem and design purpose

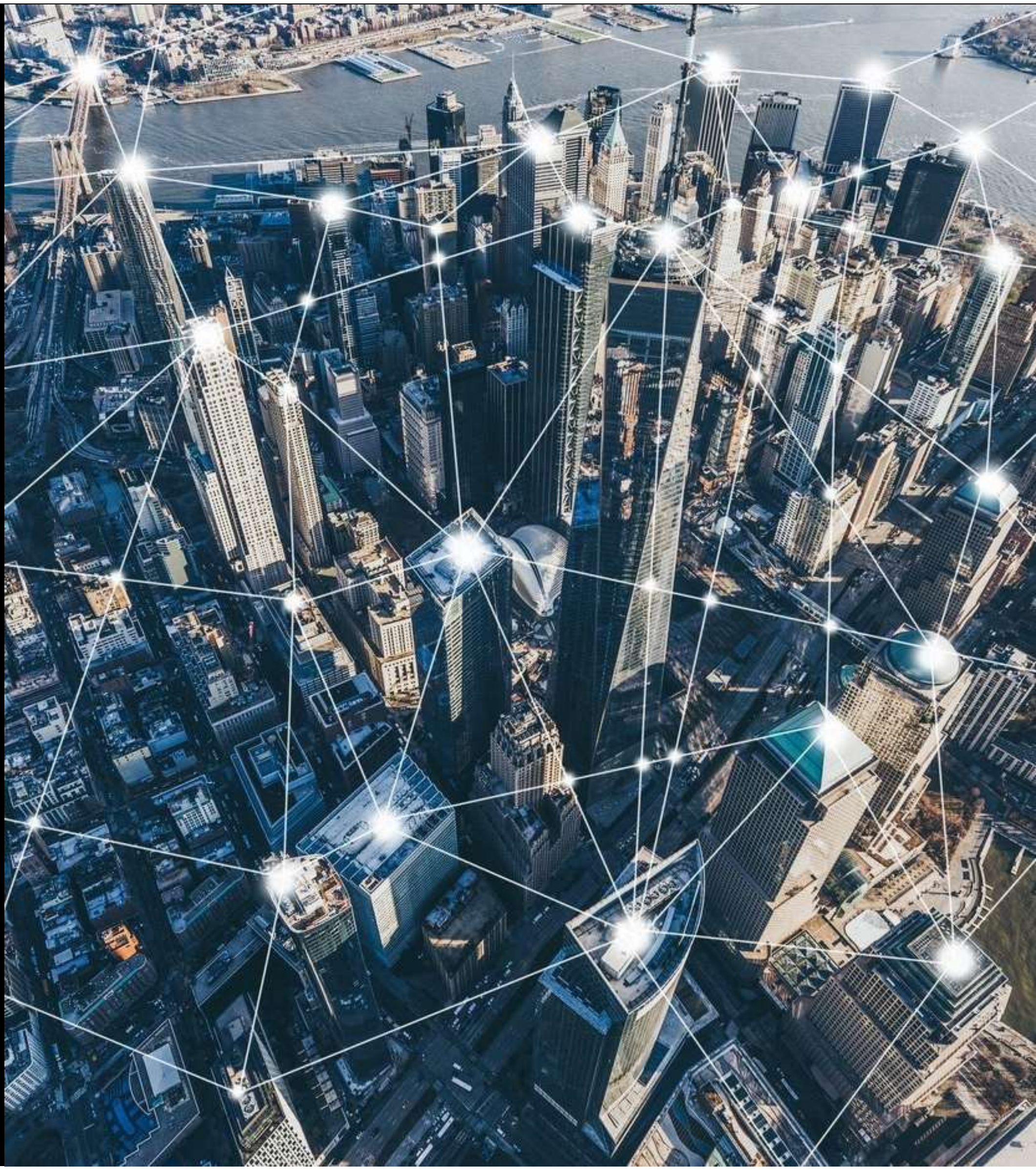
Two-stage large memory job prediction method

Evaluation results and analysis

Summary

Motivation

We aren’t that good at estimating

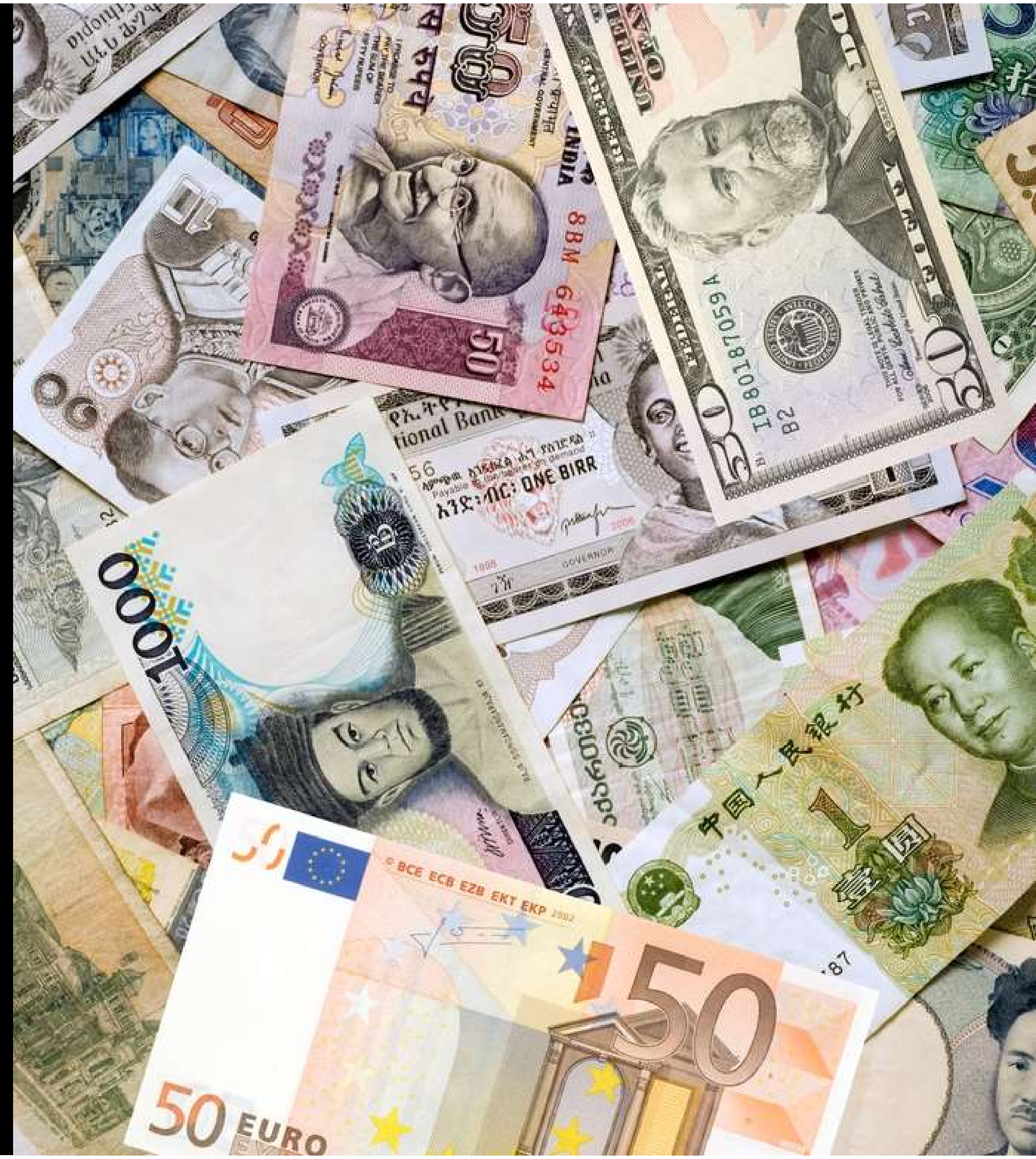


Impact

Lost Productivity

Impact

Increased Costs



The Need for Resource Prediction

Workload managers enforce scheduling policies based on job resource requirements (e.g. cores, memory size, job runtime limit, etc)

Typically, Users are not very good at estimating a jobs memory requirements or run time, and will often over estimate - e.g. asking for all the memory on a node, even if the job only really needs a small amount.

This leads to significant resource wastage, with increased turnaround times and costs (especially for single node/high throughput workloads).

Educating Users to provide better estimates is hard.

Job resource usage generally can be predicted as applications tend to be repeatedly executed in HPC clusters.

Large Memory in High Throughput Production LSF Clusters

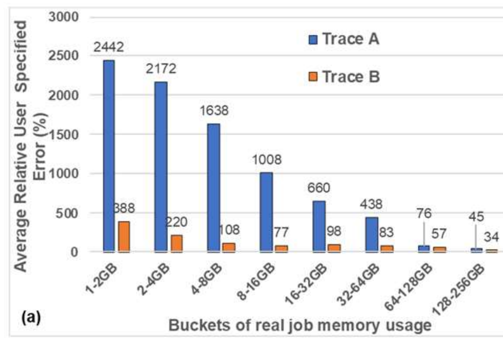
***Observation 1**: **Small** number of **large** memory jobs consume most of job memory*

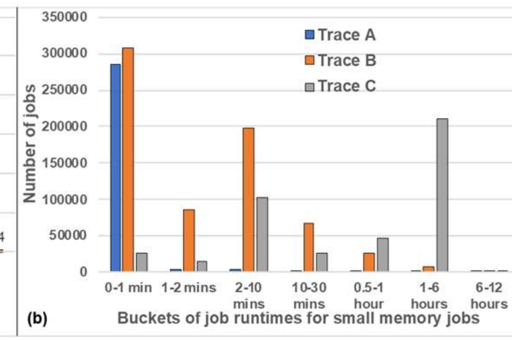
***Observation 2**: User specified memory sizes tend to be over-estimated with large errors*

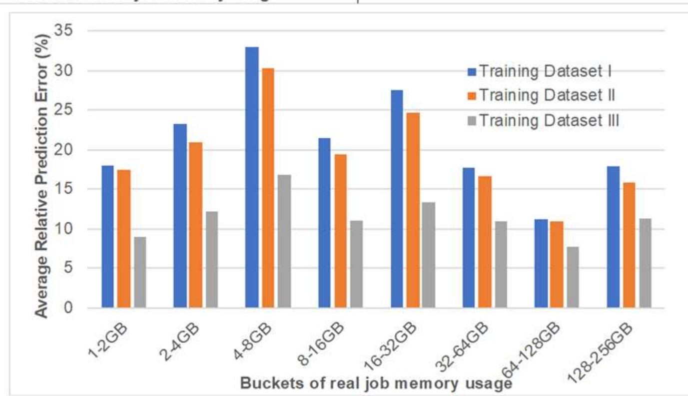
***Observation 3**: **Small** memory jobs tend to have **short** run time*

***Observation 4**: Prediction quality for **large** memory jobs reduces with more **small** memory jobs considered in training sets*

Traces	#Jobs	Small memory jobs (%)	Small memory usage (%)	Large memory jobs (%)	Large memory usage (%)
Trace A	587k	62.7	0.51	37.3	99.49
Trace B	907k	77	3.3	23	96.7
Trace C	1m	43.4	12.1	56.6	87.9







Problem Explored in This Study

Problem

- Improve job memory usage prediction for large memory jobs
- Administrators care more about the memory usage of large memory jobs
- Coarse grained memory requirements are acceptable for small memory jobs

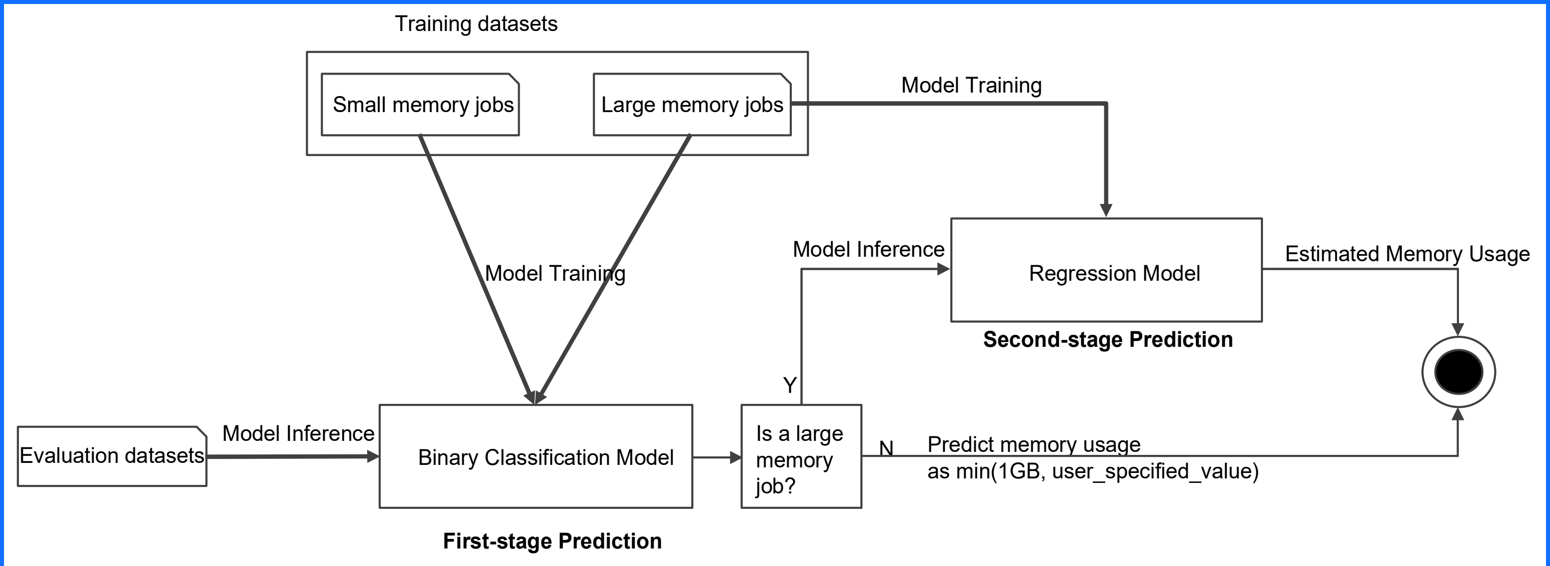
Design targets

- Improve prediction quality for large memory jobs with high coverage rates
- Reduce model training costs to enable frequent model updates
- Keep low model inference latency and reduce impacts on job submission

Two-stage memory usage prediction

Proposed method: combined two stage model to improve large memory job predictions

- A binary classification model to identify large memory jobs
- A regression model trained by only large memory jobs to predict large memory usage



Stage I: Memory Size Classification Efficiency

Binary classification model includes all jobs in training sets

– Good estimates should have large CR and small ICR

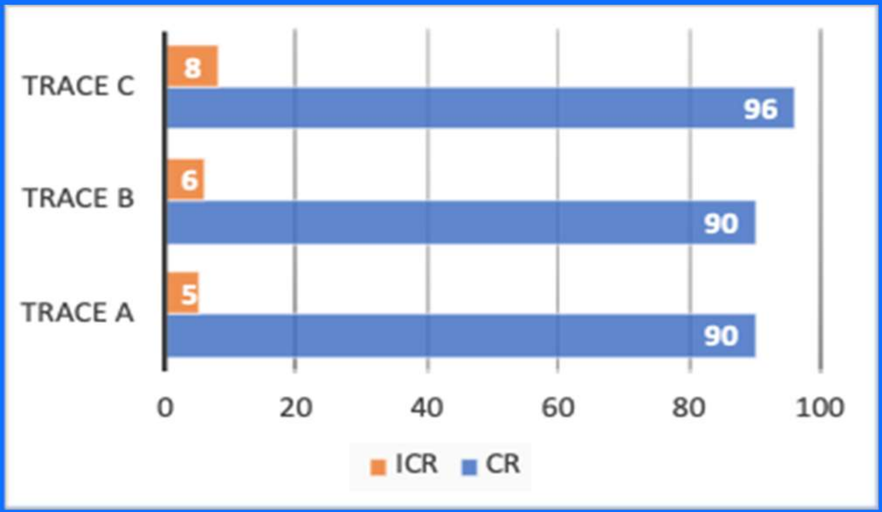
  CR=#Hit_LMEM_Jobs/#Total_LMEM_Jobs

  ICR=#Miss_SMEM_Jobs/#Total_SMEM_Jobs

– Without best hyper-parameter tuning, a binary classification model can have good estimates for testing traces

  • Binary classification complexity is lower than multi-class classification or regression

  • Classification accuracy can be further tuned with hyper-parameter settings

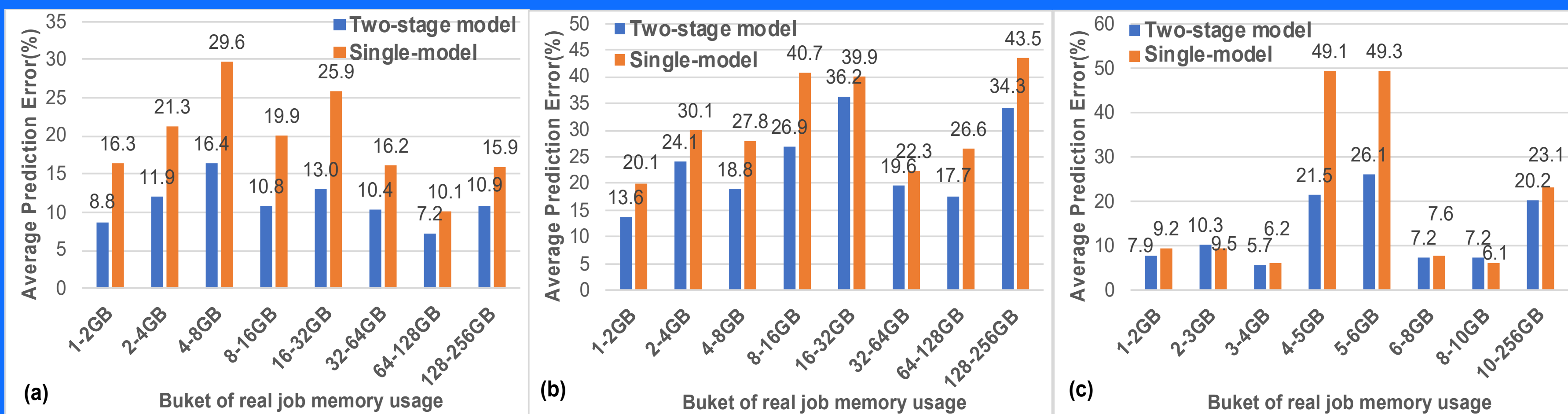


Prediction results with three production traces:
- Random forest model is used
- Hyper-parameters: n_estimators=50, n_jobs=10, max_depth=auto

Stage II: Regression Quality for Large Memory Jobs

The second stage adopts regression model which trained with only large memory jobs

- Average prediction errors can be reduced by 40.7, 24.3 and 14.5 percent compared with the single model approach
- Remove noise of small memory jobs achieve better prediction accuracy

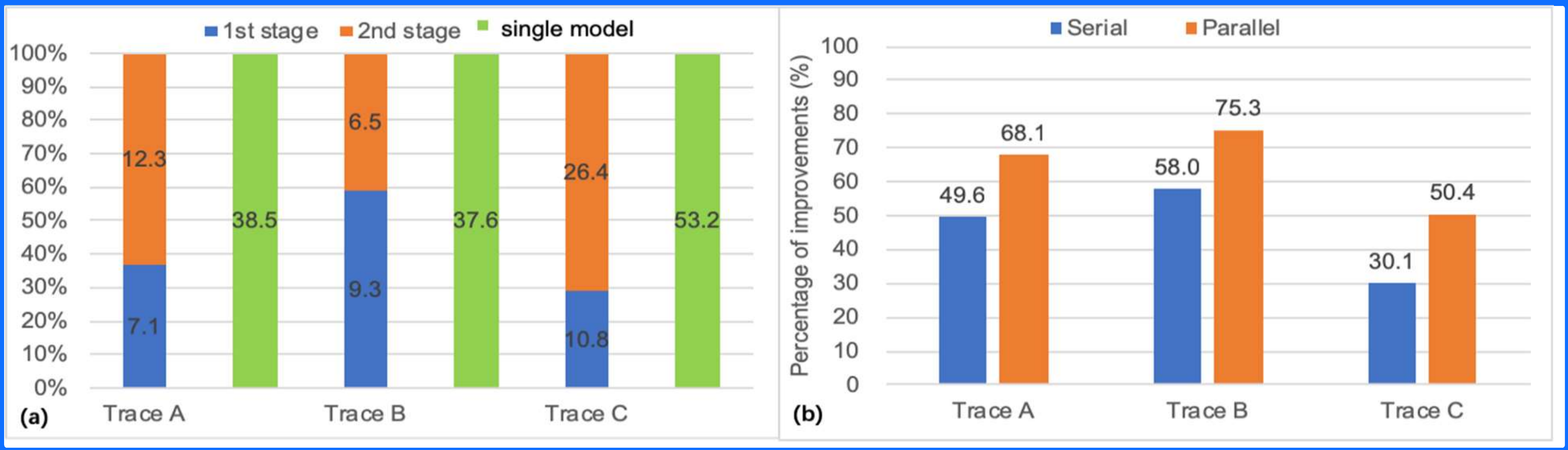


Comparisons of prediction errors for three production traces:
Random forest regression model with n_estimators=100 and n_jobs=10 is used for the tests

Benefits of Two Mode Training Costs

Binary classification cost is small due to its low training complexity

- The cost of the 2-stage regression model is significantly reduced due to removing large amounts of small memory jobs (noise)
- Running two models can be run in parallel due to no data dependency between two stage models



Comparisons of a) training cost in seconds and b) model training savings by training two-stage models sequentially or in parallel

Impacts on Model Inference Costs

The proposed two stage model prediction will add one more inference steps for each job:

- Results show that inference overhead is very small, and in most cases could be ignored when compared to normal job submission latency (especially when submission filters are used)
- Model inference delay can be further hidden by running two models in parallel with additional computing resources

Trace Name	Avg. model inference latency (microseconds)		
	1st stage	2nd stage	Single model
Trace A	2.38	7.28	4.88
Trace B	1.57	7.31	2.87
Trace C	1.76	4.49	3.04

Per-job average model inference latency

Trace Name	Total time of model inference (milliseconds)			Inference delay (per-cent)
	1st stage	2nd stage	Single model	
Trace A	279.6	318.2	597.8	4.38
Trace B	325.3	343.7	595.9	12.3
Trace C	442.8	618.2	765.7	38.6

Total cost of model inference and overhead compared with single model approach

Summary

Conclusions

- A small number of large memory jobs dominate the memory usage in these clusters
- The two-stage model approach can remove the noise of small memory jobs to get better prediction quality for large memory jobs
- The model achieves high prediction accuracy with little inference overhead.
- The model training costs can also be substantially reduced to enable possibility of frequent model updates

Future directions

- Further model tuning to minimize miss prediction for classifying large memory jobs
- Explore the application for predicting other job resource metrics. e.g. long running jobs

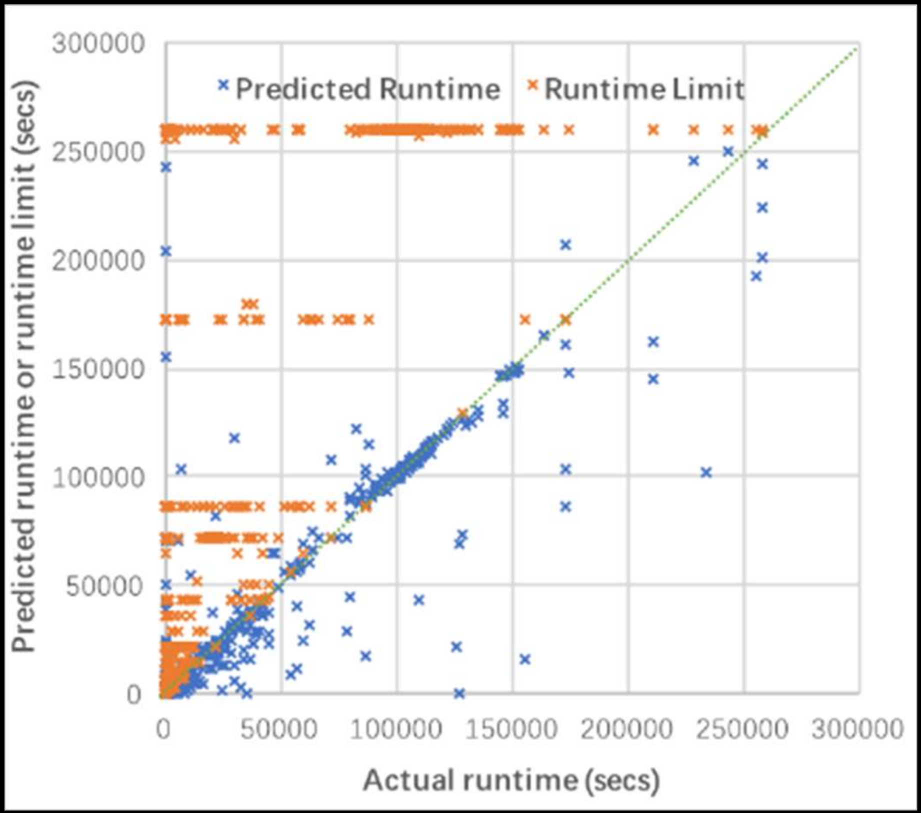
Runtime Prediction

Under-specifying runtime leads to:

- Jobs being killed - loss of productivity.
- Delayed execution for other users.
- Many organisations do not specify run limits as killing production workloads is unacceptable.

Over-specifying runtime leads to:

- Lower utilization - loss in productivity
- Poor backfill scheduling.
- Poor multi-cluster and hybrid cloud forwarding decisions



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