

TOWARDS MORE EFFICIENT JOB SCHEDULING IN ALICE:

PREDICTING JOB EXECUTION TIME USING MACHINE LEARNING Tomasz Lelek, Bartosz Baliś, , Michał Faciszewski, Sara Świętek, Mikołaj Zasada, Marcin Kurdziel AGH University of Krakow, Institute of Computer Science, Kraków, Poland email: balis@agh.edu.pl



MOTIVATION AND OBJECTIVES

Motivation:

- **Optimizing Resource Utilization**: The ALICE Grid processes a massive number of jobs daily. Efficient job scheduling is crucial to maximize the utilization across 60 computing centers.
- Improving Job Scheduling Efficiency: Current heuristicbased methods for predicting job execution times can lead to inefficiencies. More accurate predictions are needed to optimize scheduling.
- Supporting ALICE's Scientific Mission: Enhancing the efficiency of job scheduling in the ALICE Grid directly contributes to advancing particle physics research by improving the throughput and speed of computational

THE CURRENT ALICE SCHEDULING



- **Scheduling Challenge:** The scheduler must pick a job from the queue and assign a site and host without knowing the job's execution time beforehand.
- **Resource Allocation:** The Job Broker pressures the Job Agent to provide available resources, which are discovered when the Job Agent advertises them to central services.
- Job Selection: The Job Broker selects a • job from the queue that matches the available site and resources, prioritizing

analyses

Objective:

Develop a machine learning-based solution that accurately predicts job execution times in the ALICE Grid, capable of processing large batches of jobs in under 40 milliseconds, while ensuring the model remains robust and adapts to evolving data distributions over time.

INFERENCE WORKFLOW STEPS

1. Feature Extraction and Selection:

Identify and extract the most relevant features from the available data to improve the accuracy of the ML models.

2. Model Selection:

Determine the most effective ML models that can provide accurate and robust predictions for job execution times.

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jobs based on wait time, user quotas, and job priority.

EXPERIMENTS

- A model with predicted execution time features is more accurate than a model without such \bullet features.
- A model trained for a specific data cluster is more accurate than a model trained on all data (across all clusters).
- Limiting the features used in the model to the top N most important ones does not significantly reduce its accuracy (while increasing its training and prediction speed).
- Adding the sequence (history) of jobs executed on a given node increases prediction accuracy.
- Considering the features of the host where processing is performed makes the model significantly more accurate.
- Using pruning and sparsity techniques increases model efficiency without a significant loss in accuracy.
- Using quantization increases model efficiency without a significant loss in accuracy





3. Model Maintenance and Decay:

Develop strategies to maintain model accuracy over time, ensuring that the models adapt to new data and do not degrade in performance.

4. Near-Real-Time Processing:

Ensure that the models can make predictions for large batches of jobs in less than 40 milliseconds to support real-time scheduling decisions without compromising accuracy.

FUTURE WORK

Further research on optimizing inference in the end-to-end way in the ALICE environment.

| Model Type | RMSE | R2 | MAPE |
|--|------|------|------|
| The ideal model (Model 0) | 1.09 | 0.95 | 0.04 |
| The baseline model | 4.80 | 0.76 | 0.45 |
| Model 2 (two-stage method) with maxvirt prediction | 2.63 | 0.72 | 0.29 |
| Model 2 (two-stage method) with cputime and maxvirt prediction | 2.45 | 0.76 | 0.14 |
| | | | |

| Model Name | Predictor Name | Metric | Sklearn | TF |
|----------------|----------------|--------|---------|------|
| baseline model | lin_reg | R2 | 0.85 | 0.84 |
| | | RMSE | 1.96 | 2.03 |
| | | MAPE | 0.13 | 0.14 |

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|---------|-------------|--|
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| | MAPE | RMSE |
|----------|-------|------|
| DL model | ~0.50 | 1.9 |
| ML model | 1.99 | 2.7 |

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