

Master 1 MoSIG Research Project Report

Learning Job Runtimes in HPC Systems

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Abstract

In many HPC infrastructures, the descriptions of the tasks to be executed are subject to high uncertainty. We show that users are unreliable when estimating the run time of their jobs, and look into alternative solutions. Predictive techniques are investigated in order to infer the run time of jobs from their full description and system history. Two Machine Learning techniques, Random Forests and SVMs are applied and compared against the state of the art.

1 Introduction

High Performance Computing (HPC) systems are complex machinery at the frontier between research in scheduling and systems engineering. We outline two of the main difficulties that resource management software in this field have to face.

First, the ephemeral nature, and broad range of existing architectures of those systems make the development and application of theoretical results difficult. New schemes for distributing resources are more present than ever. Many recent systems have complex network and memory/hard drive sharing topologies. Moreover, the topology of HPC systems can now change on a hourly to monthly basis, since the hardware of distributed systems can be reconfigured or extended continually. Finding scheduling and resource management strategies which can deal with complex systems and adapt to their evolutions poses a challenge.

In addition, the data (i.e. the characteristics of the tasks to be executed) these systems have to work with presents many peculiarities. The nature of the information which users of the system provide is very often loose, by instance with only upper and/or lower bounds on numerical quantities provided. For instance, and this will be the focus of this paper, the run time of a given job on a specific system is seldom known in advance, but many cluster management software ask the users for an upper bound on this quantity.

As a consequence of these difficulties most free, open-source and commercial resource management software use

simple heuristics that can provide bounds on their performance and/or guarantee a few functional properties. An example of such a heuristic is the First Come First Serve (FCFS) policy to schedule parallel jobs on a homogeneous cluster of machines, which starts jobs as soon as possible, in the exact order they were submitted. Among other properties, such as robustness to lack of information about the amount of time jobs will run on the system, this strategy guarantees the avoidance of starvation.

1.1 Research Direction

The general direction we are headed in with this research project is to deal with the input data of the resource management systems. Accommodating for this data seems separable enough from the actual scheduling problems for work towards this objective to be rewarding. No innovative ways to query the data from the users will be studied, we will rely on existing logs from HPC systems. Instead, we seek to apply Machine Learning (ML) techniques in order to reduce uncertainty of, and extract information and/or structure from, the input data of the HPC systems. We will be working with the problem of presenting input data in the most valuable way possible to a scheduling algorithm. How to use this data to the fullest will not be discussed. When assessing the relevance of the specific information we choose to produce from the job characteristics, references from the scheduling literature and existing systems will provide ground to stand on.

1.2 Job runtimes

Most HPC resource management software (including the SLURM, OpenPBS, OpenLava and OAR software) do ask information about jobs to users, such as topological requests in terms of processing units and memory, the name of the executable, miscellaneous functional requirements and, last but not least, the expected run time of the job with respect to its hardware requirements. This user-provided estimate of the run time of a job on a specific system will be referred as **reqtime** in the rest of the paper. Most of these software use the **reqtime** of a job as an upper bound on its run time, and kill it should **reqtime** be violated. As a consequence, users overestimate this value, should they choose or be forced to provide it. The following section will present a statistical analysis pertaining to this relationship.

The true run time of a job with respect to a given affected

topology is of great interest, as the scheduling policies are highly dependent on this information to provide good solutions fefruc. We will refer to this quantity as the **runtime** of a job. It must be clear that in the context of topological heterogeneity, the **runtime** of a job is only defined with respect to a specific processing environment to which it might be affected. This can include, and is not limited to, the network topology of the processing units, the availability of shared memory, message passing costs, and the operating system supporting the computations.

1.3 Problem Statement

In this paper, the broad question of refining the data is reduced to a single variable, the **runtime**. The problem statement we are dealing with is the following.

Given a specific homogeneous HPC Cluster with negligible communication costs, how to best predict the value of the **runtime** of a job?

The choice of dealing with homogeneous distributed machines without communication costs in a first approach has the interesting property of separating the data treatment from the scheduling and interaction with the system. In this case, the **runtime** becomes an intrinsic attribute of a job. On the contrary to the input data which is always subject to peculiarities of the various systems and software, the **runtime** is always present as a simple field in workload logs of HPC systems, such as those available at the workload archive [?].

This problem statement implies a latent question: How to communicate the prediction to the rest of the system (e.g. single-value, probability density, confidence factor)? Alternatives will be discussed but ultimately, the focus will be on single-valued predictions. As mentioned previously, our ap-

proach is to use machine learning techniques. We will be inferring runtime from the job characteristics by learning from system logs, and since this is a value in $[0, +\infty]$, this is a supervised learning problem, namely regression.

We will be careful to only learn our models on logs from homogeneous systems, or homogeneous subsets of systems which are sizeable enough to learn from. As for downplaying the impact of communication costs, we will further restrict our work to machines which do not possess overly complex topology or distribute computing nodes across more than a handful of routers. In essence, we are targeting large Beowulf clusters, supercomputers, GPU farms and mainframe clusters.

2 Motivation

2.1 Importance of runtime

Once again, we emphasise the role of the **runtime** in scheduling tasks. Virtually all results from scheduling theory use the ‘clairvoyant’ model [Dutot *et al.*, 2004], where **runtimes** of jobs with respect to all possible affectations on the system are known in advance. Intuitively, in order to use this extensive theoretical body, we would need to reduce uncertainty in this variable. It has been shown [Tsafrir *et al.*, 2007] that even in the classical approach (which is to use policies that are robust to this uncertainty), there is added value when this variable is refined. In all cases, reducing uncertainty in **runtime** is critical to the success of the approach used to schedule jobs.

As mentioned before, existing solutions use much simpler heuristics. We will now focus on a particular system in order to show why a simple scheduling heuristic is applied.

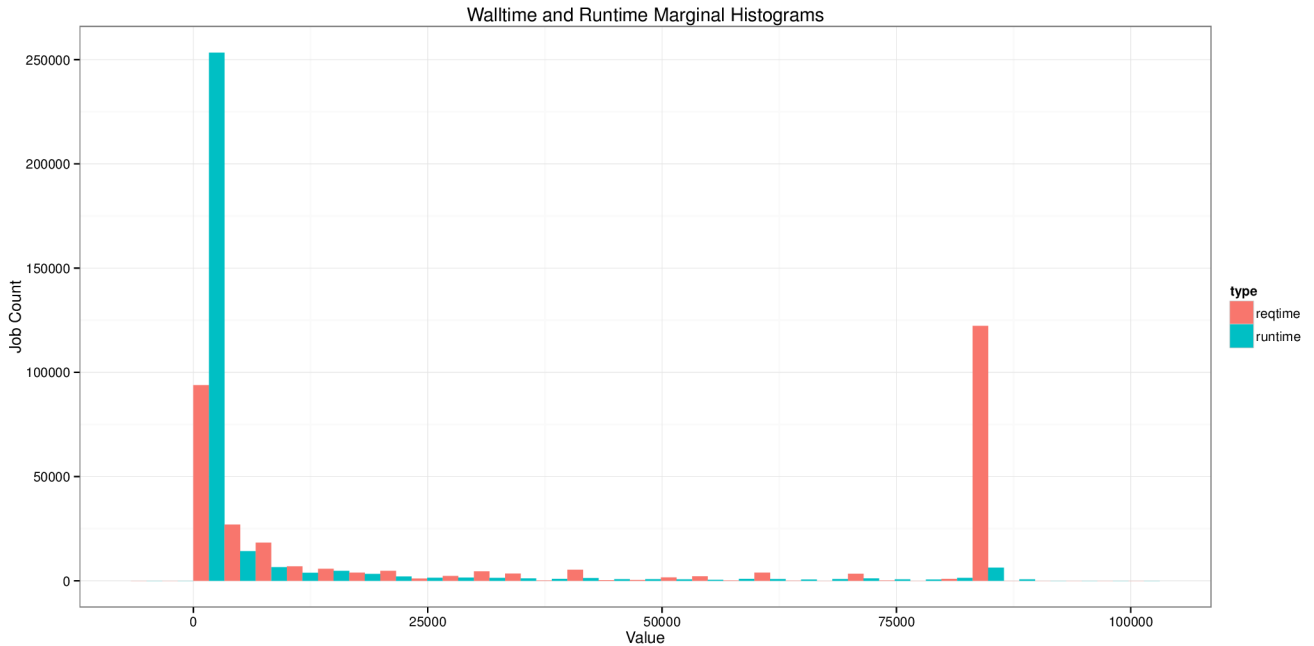


Figure 1: Marginal Histograms of the **reqtime** and **runtime** of all jobs from the CEA Curie log.

2.2 Reqtme vs Runtime on a real system

The following study is conducted on a log[ref log] containing 20 months worth of data from the Curie[ref curie] supercomputer operated by the French government-funded research organization CEA (Commissariat à l'Énergie Atomique). It contains more than 300,000 jobs, submitted from February 2011 to October 2012 by 900 users in the 'cleaned' version from the workload archive [?]. The log has several homogeneous CPU partitions and CPU+GPU partitions, however in a each partition, all nodes are identical. Jobs are allocated to partitions using user preference. The system is managed using the SLURM (Simple Linux Utility for Resource Management) software. Figure 1 shows the marginal distributions of **reqtimes** and **runtimes** on this system. The marginal distributions are already revealing, we can see that many **reqtimes** are in the 24h bin. The reason for this is that 24h is both the maximal value and the default one: on this system, users may choose not to provide an estimate for their job's **runtimes**, in which case the maximum value is used by the scheduler. Further looking into the relationship between reqtime and runtime, Figure 3 shows how the ratio $\frac{\text{runtime}}{\text{reqtime}}$ is distributed. This histogram indicates that a majority of users either: have very little idea about the expected **runtime** of their jobs, or overestimate very strongly its value on purpose. Sophisticated scheduling methods are not applied: under such uncertainty in the **runtime**, their performance is equivalent to the simple heuristic which is applied, namely FCFS with Backfilling [Mu'alem and Feitelson, 2001].

3 State of the art in runtime prediction

As mentioned previously, the latent question when predicting the **runtime** is how to provide the information to the scheduling algorithm. This section presents a few alternatives and state of the art methods in each case.

3.1 Predicting a value

Predicting values has been first attempted [Gibbons, 1997] by binning jobs in a predefined partitioning of their feature space and averaging values in each bin to provide an estimate. In this method, the partitioning has to be provided by the Resource Management Software or the system administrator. This method assumes the data to be identically distributed and independent. It does not make use of dependency between successive jobs. Moreover, the binning has to be obtained through careful statistical analysis of the specific system and population.

A more simple approach [Tsafrir *et al.*, 2007] averages the two last available runtimes of the job's user. This method makes full use of the dependency between successive runtimes, but does not make use of the jobs's description. Its main selling point are it's simplicity and accuracy.

3.2 Predicting a distribution

An algorithms that uses a probability distribution of single job runtimes [Nissimov and Feitelson, 2008] have been proposed, with an accompanying distribution prediction tool [Nissimov, 2006]. This tool is similar to the previous method of averaging the two previous runtimes for the job's user, in the sense that it only relies on the runtime information. It treats successive runtimes of a given user as the observations of a Hidden

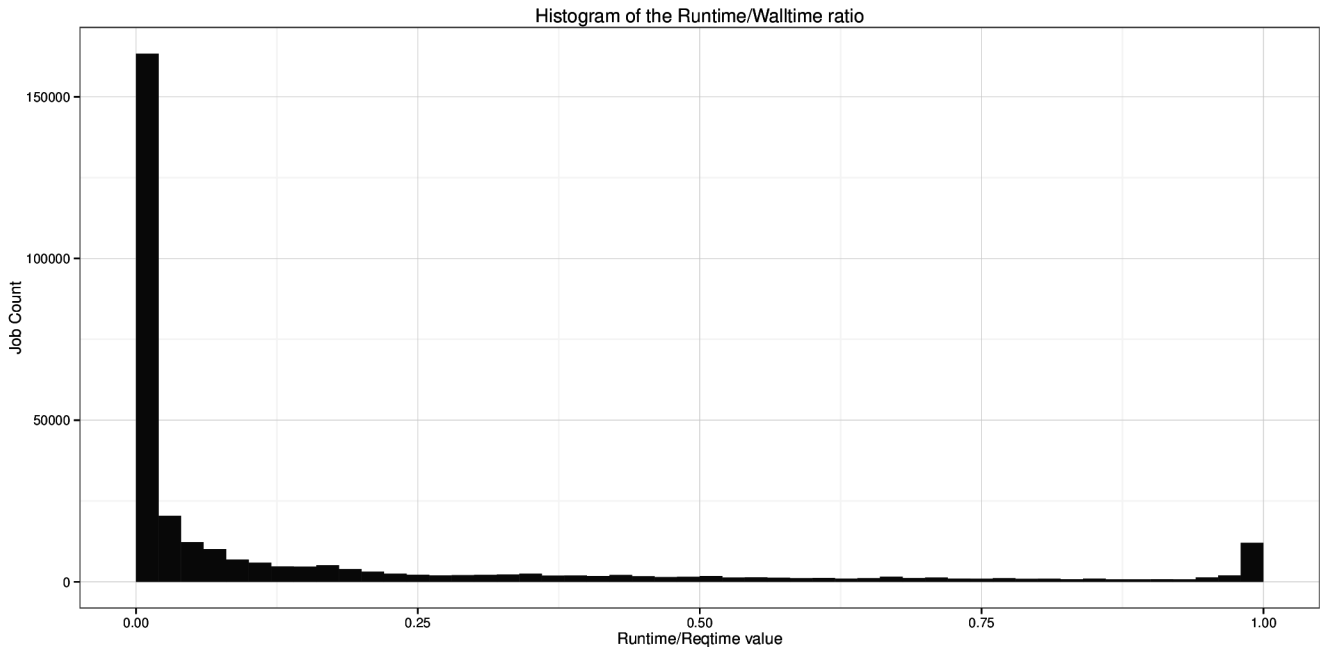


Figure 2: Histogram of the $\frac{\text{runtime}}{\text{reqtime}}$ ratio in the Curie log.

Markov Model [Rabiner, 1989]. It does not use the job description.

4 A Regression Approach

We make the observation that single job runtime prediction might be improved by using both the ‘runtime locality’ (i.e. the dependency between successive runtimes) and the job features. We will experiment with a method that will allow us to bridge this gap. The chosen method is to perform regression on vectors containing the following features:

- The continuous and discrete attributes from the job’s description, such as **reqtime**, number of cores required, or time of the day of the submission.
- The attributes of the last n jobs of this user, where n is to be chosen as to balance between the cost of fitting the model and its accuracy.
- Attributes from the user and the system, such as the amount of nodes the user is currently using on the system, or the mean runtimes of jobs of the user.
- Predicted values which come from other techniques, such as averaging the two previous runtime values.

This approach has the advantage of being rather adaptable to various formulations of the job description. No two HPC systems are identical, therefore this provides a clear added value, as it is now the algorithm’s responsibility deal with the particularities of the input data on each system. It is however difficult to provide validation of this aspect of the specific algorithm we will use, and this will not be in the scope of this paper.

4.1 Random Forests

The specific ML algorithm we use is called Random Forests, and in particular the CART [Breiman, 2001] method. This technique is an ensemble learning method based upon Decision Tree Learning [Breiman *et al.*, 1984]. Decision Trees partition the feature space: in a tree, the splitting is performed by using a threshold for continuous features and a all-way split on categorical features. Decision Trees are usually learned on a training set with a recursive top-down greedy algorithm which optimizes a function of the tree and the training set. Such a function can be for instance the Information Gain [Kullback and Leibler, 1951] of the tree on the training set. A criterion on the purity of leaves and/or amount of vectors which fall therein is used to stop the construction. Training set real output values are then averaged in each leaf to give predictions: When regressing a data point, it is sent trough the tree and the algorithm outputs the value of the corresponding leaf. The CART algorithm functions in the following manner:

- Training:
 - Randomly partition the training data.
 - Build decision trees on each partition.
- Predict a value by combining (e.g. average or linear combination) the results from all the trees.

4.2 Explainability

This approach has the advantage of producing an explainable model. Nodes which are, on average, higher up the decision trees are more important in the decision process. By ranking input vector attributes according to their average height in the

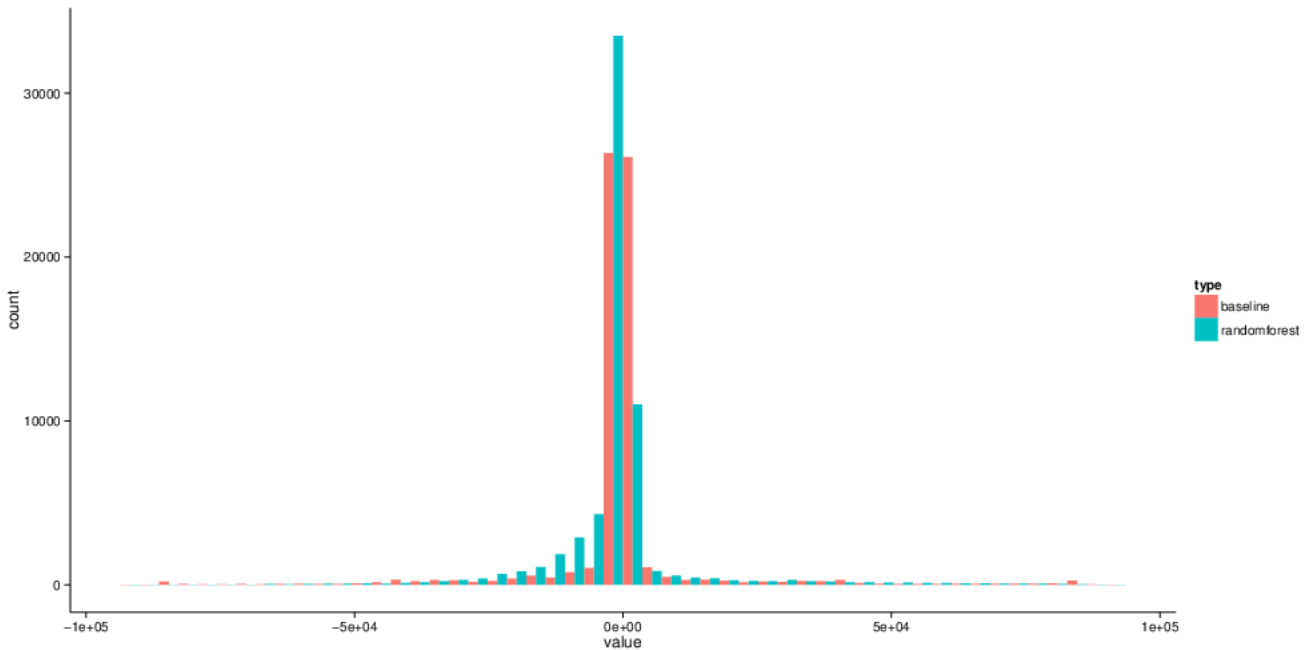


Figure 3: Histogram of the error made in predicting for both the baseline(averaging the two last known runtimes of the user) and random forest methods.

trees, we will be able to gain insight about which feature is the most crucial to predicting the runtime.

5 Preliminary Results

We run the CART algorithm on a data set built from the Curie dataset which was analyzed in 2.2. In a first approach, we choose to validate our approach by training the algorithm with the first 80% of the job/runtime associations and predicting the last 20% of the runtimes. We then compare our results with an existing popular baseline, namely averaging the two last available runtime values from the job user [Tsafrir *et al.*, 2007], in order to validate our method.

5.1 Feature List

We build data vectors with the following features:

Features
Processor Request
Reqtme
Average of two last Runtimes of job user
Last known runtime of user
Second to Last known runtime of job's user
Thinktime preceding this job
Maximum length of already running job of job's user
Sum of already running jobs of job's user
Amount of jobs of this user running
Average runtime by curr. running jobs of user
Total cores currently used by user
User ID
Group ID
Day of Week
Day of Month
Last known job exiting status of user
Second to Last known job exiting status of user

Features ... and ... are extracted by replaying the log with the simpy [Muller and Vignaux, 2003] discrete event simulation package.

The experiments are run using the scikit-learn [Pedregosa *et al.*, 2011] package. Features *UserID*, *GroupID*, *DayofWeek*, *LastStatus*, *SecondtoLaststatus* are encoded in a one-hot fashion, as the package we use only builds binary decision trees on continuous attributes. We intend to run the experiments again with systematic full splitting on categorical attributes.

5.2 Comparison with the baseline

TODO: We compare the results from our method with the baseline ... Figure 3 Sum of squares for tsafrir: $1.24186e+13$
Sum of squares for randomforest: $9.897605e+12$

5.3 Feature importances

TODO: We discuss feature importances Figure 4

6 Conclusions and Extensions

7 Acknowledgements

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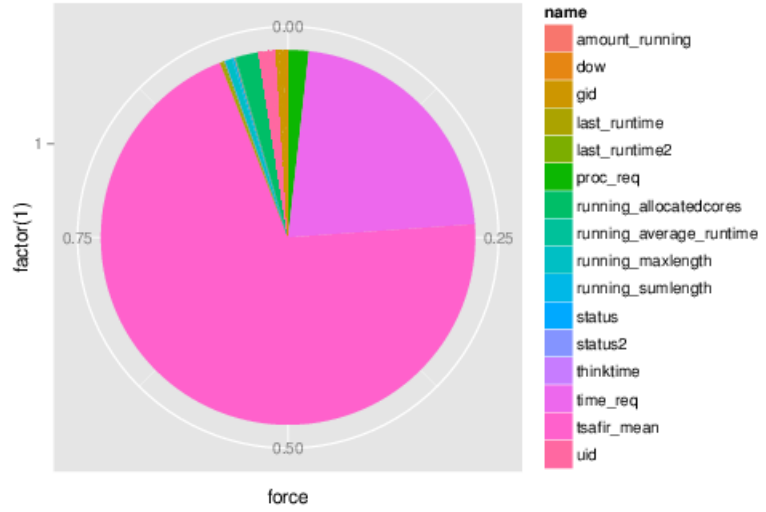


Figure 4: Relative importance of features in the Random Forests algorithm.

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