Algorithm Configuration: Learning policies for the quick termination of poor performers

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Abstract. One way to speed up the algorithm configuration task is to use “fast” runs instead of “slow” runs as much as possible, but without discarding the configurations that eventually do well on the long runs. We consider the problem of selecting the top performing configurations of the Conditional Markov Chain Search (CMCS), a general algorithm schema that includes, for examples, VNS. We investigate how the structure of performance on fast tests links with those on slow tests, showing that significant differences arise between test domains. We propose a “performance envelope” method to exploit this; that learns when runs should be terminated, but that automatically adapts to the domain.

1 Introduction

Careful configuration of algorithms can lead to a significant improvement in performance [1, and many others]. This is usually done by searching in the space of configurations and evaluating each configuration on a set of target problems. However, such problems are often large and will require long runs, so direct and complete usage of such intended problems will be overly time-consuming. A natural desire is that, in a justified fashion, we should be able to reduce the run times by exploiting the results of “fast runs” in order to configure for “slow runs”: There is a need to learn how to extrapolate from “fast” to “slow”. This suggests that machine learning methods should be applied to collections of such “fast data”, to analyse patterns, and so produce predictions for the performance in the needed “slow” cases. This view suggests that for algorithm configuration at least 3 different ‘generic’ spaces are relevant:

- $C$ “Configuration space” – the direct parameters of the algorithms.
- $F$ “Fast space” the space of (detailed) results using fast runs.
- $S$ “Slow-space” results from slow runs.

A common procedure would be to do a (local) search in C-space, using fitnesses obtained from S-space. In this context, the usage of machine learning might be to develop a mapping (e.g. a decision tree or similar as in ParamILS [1]) from the C-space to the S-space. In this paper, we instead study the potential for learning the behaviours of mappings from F-space to S-space – aiming to exploit how short runs are able to predict longer term behaviours. The goal is to use such information to optimise the policies for when a trial of a particular configuration should be terminated – because there is high confidence it will not lead to a good final solution.
2 Experimental Setup

We used CMCS, a recent framework that defines the behaviour of a multi-component optimisation algorithm with a set of numeric parameters [2, 3]. We used three problem domains: the Simple Plant Location Problem (SPLP) [2], the Far From Most String Problem (FFMSP) (the details of our components, testbed, etc. are not yet published) and the Bipartite Boolean Quadratic Problem (BBQP) [3]. We generated all ‘meaningful’ 3-component configurations with deterministic control mechanism, thus ending up with a finite number of configurations. We do not include details of exactly what these mean (see [3, 2]), as for the purposes of this paper, these can simply be regarded as a categorical set of potential options, and defining the “C-space”. The goal of the work is to find configurations that are the best performers, with respect to the slow S-space, but exploiting their properties with respect to the F-space in order to reduce the overall time budget.

The full time budget for each ‘slow’ run was selected as 1024ms. Ten random instances were generated for each domain, with the size chosen to make them hard enough for this time budget. We then generated performance data\(^3\) for each domain, by solving each of the ten instances by each of the configurations, and recording the solution quality at 1ms, 2ms, 4ms, \ldots, 1024ms. Objective values were scaled to \([0, 1]\) for each instance, and then averaged over the data instances. Hence, quality 0 (resp. 1) means that, for each instance, the configuration yielded solution as good (resp. bad) as any other configuration within the full 1024ms time budget.

Figure 1(a) shows the Performance Profile (PP); how the solution quality improves over time for SPLP. The solid line shows the PP of the top configuration, the configuration that demonstrated best solution quality after 1024ms. The dashed (resp. dotted) line, which we call cutoff line (1\%) (resp. (5\%)), shows the worst performance over the top 1\% (resp. 5\%) of all the configurations. (All three lines are monotonic, as CMCS records the best-so-far solutions.) As we hoped, there is a strong correlation between the fast and slow performance of the top configurations; specifically, the cutoff lines drop relatively quickly, suggesting that there is a potential for a significant speed up by terminating configurations that perform poorly in the ‘fast’ runs. To evaluate this, we plotted the ranks corresponding to the lines in Figure 1(b). The solid line is very low here; the top configuration was among the top performers throughout the run. The drop in the 1\% and 5\% cutoff lines indicates that the runs longer than 242ms are likely to be useful in early prediction of the ‘slow’ performance. E.g., at 242ms, the 1\% cutoff line potentially allows us to rule out 89\% of all the configurations. Evidently, the performance of a configuration in a short run does link with long-term performance and suggests that we should be able to use this to quickly terminate configurations that are not likely to have good long-term performance by observing short-term performance. However, Figures 1(c,d), showing the results for the FFMSP domain, demonstrate that in other domains one may need longer runs to predict ‘slow’ performance.

\(^3\) A URL will be provided
Fig. 1. Solution quality and configuration rank as they change throughout the run.

Finding the exact cutoff lines in advance is impractical, as it requires running all the configurations for the full time budget. We claim that some approximation, like the heuristic below, can be obtained quicker and still provide and exploit a reasonably-reliable cutoff line (1% in this case).

1. Randomly select 2% of all the configurations, run full-time tests for them and place them into the pool $P$. Generate the cutoff line as combined worst case PP for all the configurations in $P$.
2. First pass: for each previously unseen configuration, run it. At each of 1ms, 2ms, 4ms, ..., 1024ms, check the quality achieved by the configuration. If at any point it is above the cutoff line by more than 20% then terminate the run. Otherwise replace the worst performing (in the S-space) configuration in $P$ with this new configuration and update the cutoff line.
3. Second pass: repeat Step 2, scanning through all the configurations again, but starting with the cutoff line (and $P$) obtained in the first pass. Reuse previous results to determine configurations that had been pruned prematurely and rerun them. (This reduces excessive bias towards good initial performance.)
4. Return $P$ as an approximation of the top 1% of all the configurations.

Table 1 gives experimental results. The ‘Speed up’ column tells how much quicker the heuristic is compared to evaluating all the configurations in S-space.
Table 1. Accuracy of the cutoff approximation algorithm.

| Domain | #conf. | Speed up | Overlap (top conf.) | Overlap (1%) |
|--------|--------|----------|---------------------|--------------|
| SPLP   | 26,608 | 9.3      | 100%                | 99%          |
| FFBSP  | 8,064  | 2.3      | 100%                | 99%          |
| BBQP   | 9,860  | 5.4      | 100%                | 99%          |

The ‘Overlap (top conf.)’ tells how often the heuristic finds the best performing configuration (in 100 experiments), and the ‘Overlap (1%)’ column tells the average overlap between the true top 1% configurations and the ones found by our heuristic. Note the speed up factor significantly depends on the domain; the SPLP domain gave more than 9x speed up, though in FFBSP, the gain is much more modest. The third domain tested, BBQP, sits in between (we did not report the results for BBQP in Figure 1 due to the lack of space). In all the domains, our heuristic procedure successfully found the best performing configuration every time, and was 99% accurate in finding the top-1% of configurations.

3 Conclusions and Future Work

The PPs arising from CMCS were shown to have sufficient structure in their behaviours that a “performance envelope/cut-off” could be constructed to effectively determine when terminating a test run was safe, in that most of the good configurations would be found. Behaviours of the PPs differed between domains, suggesting that dynamic adaptive methods are needed. We gave a heuristic method for this, that automatically strengthens the cut-offs as more PPs are collected, and so reduces overall runtime.

The work here only used a PP of a simple linear aggregate over a set of different test instances. However, future extensions should consider “Performance Trajectories”: using the entire, time-dependent vector of the performances over the set of test instances. Initial explorations have taken such performance vectors at a given “fast time point” and then considered them as feature vectors with labels given by the ultimate aggregate quality with a slow runtime. For SPLP, standard classification methods did identify the regions in the F-vector space that lead to longer term good performance. This suggests that information in performance trajectories is also available that can be extracted by machine learning in order to classify (or cluster) behaviours and so potentially be used to optimise policies for when when tests on configurations can be terminated.

References

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