

FD-Autotune: Domain-Specific Configuration using Fast Downward

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Abstract

The FD-Autotune learning planning system is based on the idea of domain-specific configuration of the latest, highly parametric version of the Fast Downward Planning Framework by means of a generic automated algorithm configuration procedure. We describe how the extremely large configuration space of Fast Downward was restricted to a subspace that, although still very large, can be managed by state-of-the-art automated configuration procedures. FD-Autotune uses the well-known ParamILS configurator and was realised using the recently developed HAL experimentation environment.

Introduction

Developers of state-of-the-art, high-performance algorithms for combinatorial problems, such as planning, are frequently faced with many interdependent design choices. These choices can include the heuristics to use during search, options controlling the behaviour of these heuristics, as well as which search techniques to use and in what combination.

Recent work in other combinatorial problem domains such as satisfiability (SAT) and mixed-integer programming (MIP) suggests that by exposing these design choices as parameters, developers can leverage generic tools for automated algorithm configuration to find performance-optimizing configurations of the resulting highly parameterised algorithm (Hutter et al. 2007; Hutter, Hoos, and Leyton-Brown 2010). In fact, the configurations resulting from this process often perform substantially better than those found manually through exploration by human experts.

These results suggest the following new approach to building a learning planner. Given a highly-parametric, general purpose planner P , a representative set I of planning instances from a specific domain, and a performance metric m to be optimised, we can obtain a configuration of the parameters of P optimised for performance on I with respect to m using a generic automated algorithm configuration tool.

For this submission, we apply the above approach using a new, highly-parameterised version of the Fast Downward planning system (Helmert 2006) and the state-of-the-art automated algorithm configuration tool ParamILS (Hutter, Hoos, and Stützle 2007; Hutter et al. 2009), creating domain-specific planning algorithms FD-Autotune.s (*speed*)

and FD-Autotune.q (*quality*). FD-Autotune.s refers to the specific configuration of Fast Downward resulting from using mean runtime to find an initial satisficing plan as the optimisation metric, and FD-Autotune.q is the configuration obtained when using mean plan cost after a fixed runtime as the optimisation metric. Due to the highly structured and potentially infinite configuration space in Fast Downward, we carefully limited the number of parameters in order to comply with the requirements of ParamILS and to retain as many potential planner configurations as possible. Our learning approach was implemented to take advantage of HAL, a recently released tool for automating the specification and execution of common empirical algorithm design and analysis tasks (Nell et al. 2011).

This work has been done in parallel, and sharing some team members, with IPC submissions applying the above approach to constructing domain-specific planners to LPG, another heavily parameterised planning system (Gerevini, Saetti, and Serina 2008).

The Fast Downward Planning Framework

In this section we describe the capabilities of the IPC-2011 version of the Fast Downward planning system. Since Fast Downward incorporates many different algorithms and approaches, which have each been published separately in peer-reviewed conferences and/or journals, we will simply list the available components with pointers to further information for the interested reader.

The Fast Downward planning system (Helmert 2006) is composed of three main parts: the translator, the preprocessor, and the search component, which are run sequentially in this order. The translator (Helmert 2009) is responsible for translating the given PDDL task into an equivalent one in SAS⁺ representation. This is done by finding groups of propositions which are mutually exclusive and combining them into a single SAS⁺ variable. The preprocessor performs a relevance analysis and precomputes some data structures that are used by the search and certain heuristics. The search component, whose capabilities we will describe in detail here, searches for a solution to the given SAS⁺ task.

Search

The search component features three main types of search algorithms:

- Eager Best-First Search — the classic best-first search. The same search code is used for greedy best-first search, A^* , and weighted A^* by plugging in different f functions. The multi-path-dependent $LM-A^*$ (Karpas and Domshlak 2009) is also implemented here.
- Lazy Best-First Search — this is best-first search with deferred evaluation (Richter and Helmert 2009). Here as well, the same search code is used for lazy greedy best-first search and lazy weighted A^* by using a different f function.
- Enforced Hill-Climbing (Hoffmann and Nebel 2001) — an incomplete local search technique. This has been slightly generalised from classic EHC to allow preferred operators from multiple heuristics, as well as enabling or disabling preferred operator pruning.

Each of these search algorithms can take several parameters and use one or more heuristics (heuristic combination methods will be discussed next). In addition, these searches can be run in an iterated fashion. This can be used, for example, to produce RWA^* (Richter, Thayer, and Ruml 2010), the search algorithm used in LAMA (Richter and Westphal 2010).

Heuristic Combination

As mentioned previously, the search algorithms described above can work with multiple heuristic evaluators. There are several heuristic combination methods available in the Fast Downward planning system, which are implemented as different kinds of *open lists*.

Some of these combination methods amount to simple arithmetic combinations of heuristic values and can use a standard (“regular”) open list implementation, while others treat the different heuristic estimates $\langle h_1(s), \dots, h_n(s) \rangle$ as a vector that is not reduced to a single scalar value (Röger and Helmert 2010).¹ As a result, some of these latter methods do not necessarily induce a total order on the set of open states. The following combination methods are available in Fast Downward, in addition to performing a regular search using a single heuristic:

- Max — taking the maximum of several heuristic estimates: $\max\{h_1(s), \dots, h_n(s)\}$.
- Sum — taking the sum or weighted sum of several heuristic estimates: $w_1 h_1(s) + \dots + w_n h_n(s)$.
- Selective Max (Domshlak, Karpas, and Markovitch 2010) — a learning-based method which chooses one heuristic to evaluate at each state: $h_i(s)$ where i is chosen on a per-state basis using a naive Bayes classifier trained on-line.
- Tie-breaking — considering the heuristics in fixed order: first consider $h_1(s)$; if ties need to be broken, consider $h_2(s)$; and so on.

¹To simplify discussion, this description assumes that search algorithm behaviour only depends on heuristic values, but all these algorithms can also take into account path costs as in A^* or weighted A^* .

- Pareto-optimal — all states whose heuristic value vector is not Pareto-dominated by another heuristic value vector are candidates for expansion, with selection between multiple candidates performed randomly.
- Alternation (Dual Queue) — heuristics are used in round-robin fashion: the first expansion uses $h_1(s)$, the second uses $h_2(s)$, and so on until $h_n(s)$ and then continuing again with $h_1(s)$. Alternation can also be enhanced by *boosting* (Richter and Helmert 2009).

Each combination method can take several parameters. One important parameter is whether the open list contains only states which have been reached via preferred operators, or all states.

Moreover, wherever this makes sense, instead of using different *heuristics* as their components, these combination methods can also combine the results of different *open lists* which can themselves employ combination methods, and this nesting can even be performed recursively. For example, it is possible to use alternation over one regular heuristic, one Pareto-based open list, and one open list that uses tie-breaking over various weighted sums.

Such combinations allow us to build the “classic” boosted dual queue of Fast Downward: use an alternation approach, which combines two standard open lists, one of which holds all states, and the other only preferred states, both of which are based on a single heuristic estimate. To use two heuristic estimates as in Fast Diagonally Downward (Helmert 2006) or LAMA (Richter and Westphal 2010), alternation over four open lists would be used (for each heuristic, one holding all states and one holding only preferred states).

Heuristics

So far, we have discussed the search algorithms and heuristic combination methods available in the Fast Downward planning system. We now turn our attention to the heuristics available in Fast Downward. Due to the number of heuristics, we simply list the available heuristics, with pointers to relevant literature.

Admissible Heuristics

- Blind — 0 for goal states, 1 (or cheapest action cost for non-unit-cost tasks) for non-goal states
- h^{\max} (Bonet, Loerincs, and Geffner 1997; Bonet and Geffner 1999) — the relaxation-based maximum heuristic
- h^m (Haslum and Geffner 2000) — a very slow implementation of the h^m heuristic family
- $h^{M\&S}$ (Helmert, Haslum, and Hoffmann 2007; 2008) — the merge-and-shrink heuristic
- h^{LA} (Karpas and Domshlak 2009; Keyder, Richter, and Helmert 2010) — the admissible landmark heuristic
- h^{LM-cut} (Helmert and Domshlak 2009) — the landmark-cut heuristic

Inadmissible Heuristics

- Goal Count — number of unachieved goals
- h^{add} (Bonet, Loerincs, and Geffner 1997; Bonet and Geffner 1999) — the relaxation-based additive heuristic

- h^{FF} (Hoffmann and Nebel 2001) — the relaxed plan heuristic
- h^{cg} (Helmert 2004) — the causal graph heuristic
- h^{cea} (Helmert and Geffner 2008) — the context-enhanced additive heuristic (a generalisation of h^{add} and h^{cg})
- h^{LM} (Richter, Helmert, and Westphal 2008; Richter and Westphal 2010) — the landmark heuristic

Apart from Goal Count, all heuristics listed above are cost-based versions (that is, they support non-unit cost actions). This also allows another option for these heuristics: action-cost adjustment. It is possible to tell the heuristics (as well as the search code) to treat all actions as unit-cost (regardless of their true cost) or to add 1 to all action costs. This has been found to be helpful in tasks with 0-cost actions (Richter and Westphal 2010).

Configuration Space

Algorithm	Categorical	Numeric	Total	Configurations
FD-Autotune.s	40	5	45	2.99×10^{13}
FD-Autotune.q	64	13	77	1.935×10^{26}

Table 1: The number of categorical and numeric parameters in the reduced configuration space for both FD-Autotune.s and FD-Autotune.q, as well as the total number of distinct configurations for each.

The configuration space of Fast Downward poses a challenge in formulating the parameter space to be explored by a parameter-tuning algorithm: structured parameters. For example, it is possible to configure an alternation open list which alternates between two internal alternation open lists, each of which alternates between their own internal alternation open lists, and so on. Since ParamILS (Hutter et al. 2007) does not handle structured parameters, we had to limit the configuration space somewhat.

The configuration space used for the competition contains a boolean parameter for each heuristic (all heuristics for satisficing planning, only admissible heuristics for optimal planning), indicating whether that heuristic is in use or not. The other parameters of the heuristic (if any) are conditional on the heuristic being used.

For optimal planning, the search algorithm is predetermined (A^*), and so our only other choice is, when more than one heuristic is used, how the heuristics are combined (the relevant options are max or selective max). This is controlled by another parameter, which is conditional on more than one heuristic being chosen.

For satisficing planning, the setting that applies to the planning and learning competition, the theoretical configuration space is much more complex, since combination methods such as alternation and weighted sums introduce an infinite set of possibilities.

To keep the configuration space manageable, we only allow one layer of alternation, and its components must be standard open lists (sorted by scalar ranking values), one for each heuristic that was selected, and possibly more if

preferred operators are used. In addition, we can combine search algorithms using iterated search as in RWA^* . Here, we limit the number of searches to a maximum of 5, in order to avoid an infinitely large structured configuration space. As shown in Table 1, FD-Autotune.s and FD-Autotune.q have many parameters, with 2.99×10^{13} and 1.935×10^{26} distinct configurations, respectively. (The difference is due to the fact that iterated search is not very useful for the “speed” setting, and hence is not enabled there.) The configuration space of FD-Autotune.q is one of the largest ever experimented with using automated algorithm configuration tools.

Domain-specific Configuration

While our approach could in principle utilise any sufficiently powerful automatic configuration procedure, we have chosen the FocusedILS variant of ParamILS (Hutter, Hoos, and Stützle 2007; Hutter et al. 2009). At the core of the ParamILS framework lies Iterated Local Search (ILS), a well-known and versatile stochastic local search method that iteratively performs phases of a simple local search, such as iterative improvement, interspersed with so-called perturbation phases that are used to escape from local optima. The FocusedILS variant of ParamILS uses this ILS procedure to search for high-performance configurations of a given algorithm by evaluating promising configurations, using an increasing number of runs in order to avoid wasting CPU time on poorly-performing configurations. ParamILS also adaptively limits the amount of runtime allocated to each algorithm run using knowledge of the best-performing configuration found so far.

ParamILS has previously been applied to configure state-of-the-art solvers for SAT (Hutter et al. 2007) and mixed integer programming (MIP) (Hutter, Hoos, and Leyton-Brown 2010), along with solvers in several other combinatorial problem domains. This work resulted in a version of the SAT solver SPEAR that won the first prize in one category of the 2007 Satisfiability Modulo Theories Competition (Hutter et al. 2007); it further contributed to the SATzilla solvers that won prizes in 5 categories of the 2009 SAT Competition and led to large improvements in the performance of CPLEX on several types of MIP problems (Hutter, Hoos, and Leyton-Brown 2010). Differently from SAT and MIP, in planning, explicit domain specifications are available through a planning language, which creates more opportunities for planners to take problem structure into account in parameterised components (e.g., specific search heuristics). This can lead to more complex systems, with greater opportunities for automatic parameter configuration, but also greater challenges (bigger, richer design spaces can be expected to give rise to trickier configuration problems).

Implementation using HAL

Empirical algorithm analysis and design techniques are often used in an ad-hoc fashion, relying upon informal experimentation. Furthermore, the techniques used in practice are often rather simplistic (or incorrect), as many researchers and practitioners do not have sufficient knowledge

of, or easy access to, more sophisticated techniques. Even when the best available techniques are used, the implementations of these techniques are often difficult to use, if publicly available at all.

HAL (the High-performance Algorithm Laboratory) was developed to address this need for easy access to powerful empirical techniques (Nell et al. 2011). HAL was created to support both the computer-aided design and the empirical analysis of high-performance algorithms, by means of ready-to-use, state-of-the-art procedures. It should be noted that HAL is designed to support these procedures for a wide range of problem domains, and is not designed for or limited to planning in any way.

In this work, we use several meta-algorithmic procedures provided by HAL, primarily the algorithm configuration tool ParamILS and the plug-in providing support for empirical analysis of a single algorithm. We also leverage the robust support in HAL for data management and run distribution on compute clusters.

For each given planning domain, our submission uses HAL to run ten independent runs of ParamILS on a provided set of training instances, using a maximum runtime cutoff of 900 CPU seconds for each run of Fast Downward and a total configuration time limit of five CPU days. In the case of FD-Autotune.s, we can leverage support in ParamILS for adaptive runtime capping to drastically reduce the runtime required for each run of Fast Downward.

After all ten configuration runs have completed, we run Fast Downward with a runtime cutoff of 900 CPU seconds on each instance in the training set in order to evaluate the so-called training score for each of the ten incumbent configurations. For FD-Autotune.s, this score is the mean runtime required to find a satisficing solution, and for FD-Autotune.q it represents the mean plan cost, with timeouts assigned a plan cost of $2^{31} - 1$. The incumbent configuration with the best training score is returned as the learned knowledge for the given domain.

Conclusions and Future Work

We believe that the generic approach underlying our work on FD-Autotune represents a promising direction for the future development of efficient planning systems. In particular, we suggest that it is worth including many different variants and a wide range of settings for the various components of a planning system, instead of committing at design time to particular choices and settings, and to use automated procedures for finding configurations of the resulting highly parameterised planning systems that perform well on the problems arising in a specific application domain under consideration. We plan to further investigate modeling the highly structured and potentially infinite space of Fast Downward within tools for automated algorithm configuration such as ParamILS.

We note that our approach naturally benefits from future improvements in planning systems (and in particular, from new heuristic ideas that can be integrated, in the form of parameterised components, into existing, flexible planning systems or frameworks) as well as from progress in automated algorithm configuration procedures. In principle,

planning systems developed in this way can also be used in combination with techniques for automated algorithm selection, giving even greater performance than any single configuration alone (Xu et al. 2008; 2009; Xu, Hoos, and Leyton-Brown 2010). We also see much potential in testing new heuristics and algorithm components, based on measuring the performance improvements obtained by adding them to an existing highly-parameterised planner followed by automatic configuration for specific domains. The results may not only reveal to which extent new design elements are useful, but also under which circumstances they are most effective – something that would be very difficult to determine manually.

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