

Hapori MIPlan

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Abstract

Hapori MIPlan¹ is a portfolio planner which participated in the optimal, satisficing, and agile tracks of the International Planning Competition (IPC) 2023. It uses the Mixed-Integer Programming approach by (Nuñez, Borrajo, and Linares López 2015) to compute a sequential static portfolio that achieves the best achievable performance with a linear combination of planners.

Definitions

Before we describe the greedy portfolio computation algorithm, we give some definitions concerning planning tasks, sequential portfolios and quality metrics.

Informally speaking, a classical planning task consists of an initial state, a goal description and a set of operators. In the setting of *satisficing planning*, solving a planning task entails finding any operator sequence that leads from the initial state to a goal state, with a preference for cheap solutions. On the other hand, in the setting of *agile planning*, the task is to find solutions as fast as possible, regardless of the solution cost. The third setting we consider in this planner abstract is *bounded-cost* planning, where plans must not be more expensive than a given bound.

We define $c(A, I, t)$ as the *cost* of the solution a planning algorithm A finds for planning task I within time t , or as ∞ if it does not find a solution in that time. Furthermore, we let $c^*(I)$ denote the *minimum known solution cost* for task I (approximated by a set of Fast Downward configurations). Following IPC evaluation criteria, we define the *solution quality* $q_{\text{sol}}(A, I, t) = \frac{c^*(I)}{c(A, I, t)}$ as the minimum known solution cost divided by the solution cost achieved by A in time t .

A *sequential planning portfolio* P is a sequence of pairs $\langle A, t \rangle$ where A is a planning algorithm and $t \in \mathbb{N}_{>0}$ is the time limit in seconds for A . We denote the portfolio resulting from appending a component $\langle A, t \rangle$ to a portfolio P by $P \oplus \langle A, t \rangle$.

We now define two quality scores $q(P, I)$ that evaluate the performance of a portfolio P on task I . In the satisficing and

bounded-cost settings we use the solution quality $q_{\text{sol}}(P, I)$. It is the maximum solution quality any of the components in P achieves for I , i.e.,

$$q_{\text{sol}}(P, I) = \max_{\langle A, t \rangle \in P} q_{\text{sol}}(A, I, t).$$

Following IPC 2018 evaluation criteria, for the agile planning setting we define *agile quality* as

$$q_{\text{agile}}(P, I) = \begin{cases} 0 & \text{if } t(P, I) > T \\ 1 & \text{if } t(P, I) \leq 1 \\ 1 - \frac{\log_{10} t(P, I)}{\log_{10}(T)} & \text{otherwise} \end{cases},$$

where $t(P, I)$ is the time that portfolio P needs to solve task I and T is the total portfolio runtime.

A portfolio's score on multiple tasks \mathcal{A} is defined as the sum of the individual scores, i.e., $q(P, \mathcal{I}) = \sum_{I \in \mathcal{I}} q(P, I)$, and the score of the empty portfolio is always 0.

Components and Training Data

As the pool of planners for our portfolios to choose from, we use all planners from the IPC 2018 and a selection of planners from IPC 2014. If an IPC 2018 planner is itself a portfolio, we use its component planners instead. We only consider each planner once. (Some IPC 2018 portfolios include planners that were also submitted separately and several portfolios included the same planners.)

Optimal Planners. For the optimal track, we exclude the planners MAPlan-1, MAPlan-2 and Meta-Search Planner because they use CPLEX, and Complementary1 because it may generate suboptimal solutions. Furthermore, the FDMS planners and Metis1 are covered by the Delfi portfolio already. This results in the following list of planners (or their components):

- Complementary2 (Franco, Lelis, and Barley 2018)
- components of DecStar (Gnad, Shleyfman, and Hoffmann 2018)
- components of Delfi (Delfi1 and Delfi2 have the same components; Katz et al., 2018b)

¹Hapori is the Maori word for community.

- Metis2 (Sievers and Katz 2018)
- Planning-PDBs (Moraru et al. 2018)
- Scorpion (Seipp 2018b)
- SymBA*1 (IPC 2014; Torralba et al., 2014)
- Symple-1 and Symple-2 (Speck, Geißer, and Mattmüller 2018)

Satisficing Planners. All planners participating in the IPC 2018 satisficing track also participated in the agile track (except for Fast Downward Stone Soup 2018), with an identical code base but possibly with different configurations. We thus only have one set of planners but multiple configurations for these two tracks. We exclude the Alien planner because we could not get it to run, and Freelunch-Doubly-Relaxed, FS-blind and FS-sim because they have a large number of dependencies which results in planner images too large to be included in our planner pool. Furthermore, IBaCoP-2018 and IBaCoP2-2018 use a large number of planners or portfolios of which newer and stronger versions participated in IPC 2018 as standalone planners, or which we failed to get to run, so we only cover the component planners Jasper, Madagascar, Mercury, and Probe. This results in the following list of planners (or their components):

- Cerberus and Cerberus-gl (Katz 2018)
- components of DecStar (Gnad, Shleyfman, and Hoffmann 2018)
- components of Fast Downward Remix (Seipp 2018a)
- components of Fast Downward Stone Soup 2018 (Seipp and Röger 2018)
- Jasper (IPC 2014; Xie, Müller, and Holte, 2014)
- Dual-BFWS, BFWS-preference, BFWS-polynomial and DFS⁺ (Francès et al. 2018)
- Madagascar (IPC 2014; Rintanen, 2014)
- Mercury2014 (Katz and Hoffmann 2014)
- MERWIN (Katz et al. 2018a)
- OLCFF (Fickert and Hoffmann 2018)
- Probe (IPC 2014; Lipovetzky et al., 2014)
- Grey Planning configuration of Saarplan (Fickert et al., 2018; rest covered by DecStar)
- Symple-1 and Symple-2 (Speck, Geißer, and Mattmüller 2018)

Benchmarks and Runtimes. For training the portfolios, we use all tasks and domains from previous IPCs, from the Delfi training set (Katz et al. 2018b), and from the Autoscale 21.11 collection Torralba, Seipp, and Sievers (2021), leading to a set of 92 domains with 7330 tasks. We use Downward Lab (Seipp et al. 2017) to run all planners across all benchmarks on AMD EPYC 7742 2.25GHz processors, imposing a memory limit of 8 GiB and a time limit of 30 minutes for optimal planners and 5 minutes for satisficing and agile planners. For each run, we store its outcome (plan found, out of memory, out of time, task not supported by planner, unexpected error), the execution time, the maximum resident memory, and if the run found a plan, the plan

length and plan cost. This data set is available online.² As training data for our optimal (respectively satisficing/agile) portfolios, we select from each domain the 30 tasks which are solved by the fewest optimal (or satisficing/agile) planners, which results in 1926 (optimal) and 2377 (satisficing/agile) tasks.

MIPLAN

MIPLAN portfolios have been generated using Mixed-Integer Programming (MIP), which computes the portfolio with the best achievable performance with respect to a selection of training planning tasks (Núñez, Borrajo, and Linares López 2015). The resulting portfolio is a linear combination of candidate planners defined as a sorted set of pairs $\langle \text{planner}, \text{time} \rangle$. Our MIP model considers an *objective function* that maximizes a weighted sum of different parameters including overall running time and quality.

Since we consider two different criteria (time and quality), it could be viewed and solved as a multi-objective maximization problem. Instead, we solve two MIP tasks in sequence while preserving the cost of the objective function from the solution of the first MIP. Specifically, we first run the MIP task to optimize only *quality*, i.e., q_{sol} or q_{agile} depending on the track. If a solution exists, then a second execution of the MIP model is performed to find the combination of candidate planners that achieves the same quality (denoted as Q) while minimizing the overall running time. To enforce a solution with the same quality an additional constraint is added: $\sum_{i=0}^n \text{quality}_i \geq Q - \epsilon$, where ϵ is just any small real value used to avoid floating-point errors. Clearly, a solution is guaranteed to exist here, since a first solution was already found in the previous step. Pseudocode 1 shows the steps followed to generate all the submitted portfolios where quality was maximized first, and then running time was minimized among the combinations that achieved the optimal quality. In our experiments, $\epsilon = 0.001$.

Algorithm 1 Build a portfolio optimizing quality and time

- 1: set weights to optimize only quality
 - 2: $\text{portfolio}_1 :=$ solve the MIP task
 - 3: $Q :=$ the resulting value of the objective function
 - 4: **if** a solution exists **then**
 - 5: add constraint $\sum_{i=0}^n \text{quality}_i \geq Q - 0.001$
 - 6: set weights to optimize only overall running time
 - 7: $\text{portfolio}_2 :=$ solve the MIP task **return** portfolio_2
 - 8: **else**
 - 9: exit with no solution
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The MIP task used in this work does not result in any particular order to execute the planners. It only assigns an execution time to each planner, which is either zero or a positive amount of time.

²<https://github.com/ipc2023-classical/planner19/tree/latest/experiments/data/01-opt-planners-eval> and <https://github.com/ipc2023-classical/planner19/tree/latest/experiments/data/02-sat-planners-eval>

Executing Sequential Portfolios

In the previous sections, we assumed that a portfolio simply assigns a runtime to each algorithm, leaving their sequential order unspecified. With the simplifying assumption that all planners use the full assigned time and do not communicate with each other, the order is indeed irrelevant. In reality the situation is more complex since we do not know upfront how long a selected planner will really run. Therefore, we treat per-algorithm time limits defined by the portfolio as relative, rather than absolute values: whenever we start an algorithm, we compute the total allotted time of this and all following algorithms and scale it to the actually remaining computation time. We then assign the respective scaled time to the run. As a result, the last algorithm is allowed to use all of the remaining time.

In the satisficing setting we would like to use the cost of a plan found by one algorithm to prune the search of subsequent planner runs (in the agile setting we stop after finding the first valid plan). However, since we use the planners as black boxes, this is impossible in our setting.

We use the driver component of Fast Downward (Helmert 2006) which implements the above described mechanism for running portfolios.

Resulting Portfolios

Optimal Track

We pass the quality score q_{sol} and execution time obtained by the optimal planners in the benchmarks described above to Algorithm 1, together with a time limit of 1800 seconds. The resulting portfolio for the optimal track consists of 8 component algorithms. The minimum and maximum time limit are 14 and 861 seconds, allocated to a Delfi configuration and Scorpion, respectively. As we mentioned before, the MIP task does not specify the execution sequence of the generated portfolios. However, we have sorted the execution sequence of the portfolio in decreasing order of the allotted time.

Satisficing Track

We pass the quality score q_{sol} and execution time obtained by the optimal and satisficing planners in the benchmarks described above to Algorithm 1, together with a time limit of 1800 seconds. The resulting portfolio for the satisficing track consists of 82 component algorithms. The minimum and maximum time limit are 1 and 261 seconds, allocated to two different Fast Downward components. We have sorted the execution sequence of the portfolio in decreasing order of the allotted time.

Agile Track

In this case, we pass the agile score q_{agile} and execution time obtained by the satisficing planners in the benchmarks described above to Algorithm 1, together with a time limit of 300 seconds. The resulting portfolio for the agile track consists of 37 component algorithms. The minimum and maximum time limit are 1 and 41 seconds, allocated to a Fast Downward Component and LAPKT-BFWS-Preference, respectively. Unlike the other tracks, execution order plays a

role in the Agile track. We defined the execution sequence by randomly ordering the planners with non-zero execution time assigned.

Post-IPC Analysis

The IPC 2023 used 7 domains with 20 tasks each, resulting in a benchmark set of 140 planning tasks, for all three tracks. Each planner was limited to 30 minutes of CPU time and 8 GiB of memory. Hapori MIPlan ranked average in the three IPC 2023 tracks, being the second best performer among the Hapori portfolios participating in these tracks.

Hapori MIPlan got the 8th place (out of 22 participants) in the optimal track with 60 problems solved, compared to the 77 problems solved by Ragnarok, the winner planner which was also a portfolio of base solvers. In the satisficing track, Hapori MIPlan got the 12th place (out of 22 participants) with a score of 60.74, compared to the 71.86 obtained by Maidu-sat, the winner planner. Finally, in the agile track, Hapori MIPlan got the 12th place (out of 22 participants) with a score of 27.82, compared to the 40.28 obtained by LAMA-first, which was used as a baseline and turned out to beat all competitors of the track.

Overall Hapori MIPlan behaved as expected: the schedules returned by the MIP are guaranteed to be optimal for the training set, and perform reasonably well as long as the test distribution remains somewhat similar. There were some engineering errors common to all the Hapori portfolios that prevented Hapori MIPlan from achieving slightly better results. These errors are related to exceptions not handled correctly, and the scheduler calling base solvers with the wrong name. We are actively working on fixing these bugs, and aim to do a thorough comparison of the Hapori portfolios in a subsequent journal article.

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