Hapori Stone Soup

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Abstract

Hapori Stone Soup[1] is a portfolio planner which participated in the optimal and satisficing tracks of the International Planning Competition (IPC) 2023. It uses the Stone Soup algorithm (Helmert, Röger, and Karpas 2011) to compute a sequential static portfolio over IPC 2018 planners in an offline preprocessing phase.

Building the Portfolios

The Stone Soup algorithm requires the following information as input:

- A set of *planning algorithms* $\mathcal{A}$. We use a different set of Fast Downward configurations depending on the track, which we describe below.
- A set of *training instances* $\mathcal{I}$, for which portfolio performance is optimized. We use a set of 7330 instances, described below.
- Complete *evaluation results* that include, for each algorithm $A \in \mathcal{A}$ and training instance $I \in \mathcal{I}$,
  - the *runtime* $t(A, I)$ of the given algorithm on the given training instance on our evaluation machines, in seconds (we did not consider anytime planners), and
  - the *plan cost* $c(A, I)$ of the plan that was found.

  To generate this data, we limit memory to 8 GiB and use time limits of 30 minutes for optimal planners and 5 minutes for satisficing planners. If algorithm A fails to solve instance I within these bounds, we set $t(A, I) = c(A, I) = \infty$.

The procedure computes a portfolio as a mapping $P : \mathcal{A} \to \mathbb{N}_0$ which assigns a time limit (possibly 0 if the algorithm is not used) to each component algorithm. It is a simple hill-climbing search in the space of portfolios, shown in Figure 1.

In addition to the algorithms and the evaluation results, the algorithm takes two parameters, *granularity* and *timeout*, both measured in seconds. The timeout is an upper bound on the total time for the generated portfolio, which is the sum of all component time limits. The granularity specifies the step size with which we add time slices to the current portfolio.

build-portfolio(*algorithms*, *results*, *granularity*, *timeout*):
  portfolio $:= \{A \mapsto 0 \mid A \in$ *algorithms*$\}$
  repeat $\lfloor$*timeout*$/$*granularity*$\rfloor$ **times**:
    candidates $:=$ successors(*portfolio*, *granularity*)
    portfolio $:= \arg\max_{C \in \textit{candidates}}$ score$(C,$ *results*$)$
  portfolio $:=$ reduce(*portfolio*, *results*)
  return *portfolio*

Figure 1: Stone Soup algorithm for building a portfolio.

The search starts from a portfolio that assigns a time limit of 0 seconds to all algorithms. In each hill-climbing step, it generates all possible *successors* of the current portfolio. There is one successor per algorithm A, where the only difference between the current portfolio and the successor is that the time limit of A is increased by the given granularity.

We evaluate the quality of a portfolio P by computing its *portfolio score* $s(P)$. The portfolio score is the sum of *instance scores* $s(P, I)$ over all instances $I \in \mathcal{I}$. The function $s(P, I)$ is similar to the scoring function used for the International Planning Competitions since 2008. The only difference is that we use the best solution quality among our algorithms as reference quality (instead of taking solutions from other planners into account): if no algorithm in a portfolio P solves an instance I within its allotted runtime, we set $s(P, I) = 0$. Otherwise, $s(P, I) = c^*_I / c^P_I$, where c^*_I is the lowest solution cost for I of any input algorithm $A \in \mathcal{A}$ and c^P_I denotes the best solution cost among all algorithms $A \in \mathcal{A}$ that solve the instance within their allotted runtime $P(A)$.

In each hill-climbing step the search chooses the successor with the highest portfolio score. Ties are broken in favor of successors that increase the timeout of the component algorithm that occurs earliest in some arbitrary total order.

The hill-climbing phase ends when all successors would exceed the given time bound. A post-processing step reduces the time assigned to each algorithm by the portfolio. It considers the algorithms in the same arbitrary order used for breaking ties in the hill-climbing phase and sets their time

[1] Hapori is the Maori word for community.

limit to the lowest value that would still lead to the same portfolio score. Finally, Stone Soup orders the algorithms with non-zero time slices by the number of tasks they solve, in decreasing order.

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)
- 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.

Resulting Portfolios

We ran the Stone Soup algorithm with *timeout* set to 1800 seconds and with 35 different *granularity* values between 10 and 900 seconds. For the optimal track, the highest coverage (1645 tasks) was achieved with *granularity*=300s, while for the satisficing track, the highest quality score (2131.69 points) was achieved with *granularity*=40s. The two resulting portfolios are shown in Tables 1 and 2.

Planner	Time	Marginal Tasks
Scorpion	883	326
SymBA*1	297	184
Metis2	287	75
DecStar: blind search	209	119

Table 1: Portfolio learned for the Optimal Track. For each planner $\mathcal{A}$ in the portfolio, we list its time slice and its marginal contribution, i.e., the number of tasks solved by $\mathcal{A}$, that no other of the three planners solves within their time slice.

[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

Planner	Time	Tasks	Score
ipc2018-saarplan	298	74	73.29
ipc2014-jasper	274	60	59.37
ipc2018-dual-bfws	36	4	7.47
ipc2018-olcff	80	1	11.78
ipc2018-bfws-pref	238	47	63.95
ipc2018-fdss-2018:22	80	7	11.39
ipc2018-fdss-2018:46	40	1	4.82
ipc2018-fdss-2018:44	38	1	4.92
ipc2018-fdss-2018:10	37	3	5.20
ipc2018-fdss-2018:17	39	1	5.27
ipc2018-fdss-2018:59	36	2	5.23
ipc2018-fdss-2018:53	40	2	4.27
ipc2018-fdss-2018:05	24	0	2.63
ipc2018-fdss-2018:23	119	9	14.69
ipc2018-fdss-2018:50	79	6	11.16
ipc2018-mercury2014	39	7	11.32
ipc2014-probe	32	0	5.41
ipc2014-mpc	79	14	18.12
ipc2018-dfs+	80	1	10.73
ipc2018-freelunch-madagascar	38	7	10.75

Table 2: Portfolio learned for the Satisficing Track. For each planner $\mathcal{A}$ in the portfolio, we list its time slice and its marginal contributions with respect to coverage and quality score, i.e., the decrease in coverage and quality score that would occur if we took $\mathcal{A}$ out of the portfolio.

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.

Post-Competition 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.

In the optimal track, there were 22 competing planners. The objective was to optimally solve the tasks. The best planner solved 77 tasks, the blind baseline 50, the LM-cut baseline 34, and our Hapori Stone Soup portfolio 62 tasks, ranking 6th. Unfortunately, our Hapori submissions had many technical problems, such as writing to inaccessible temporary directories, making their results hard to analyze. We aim to fix these problems and do a thorough comparison of the Hapori portfolios in a journal article.

In the satisficing track, there were 22 competing planners. The objective was to find plans of high quality. The best planner achieved a summed score of 71.86, only closely beating the baseline LAMA with a score of 68.76, and our Hapori Stone Soup portfolio scored 54.52 points, ranking 14th. Here, too, our planner had some bugs that lead to selecting a planner by the wrong name or choosing a planner which did not support some PDDL features.

In the agile track, there were 22 competing planners. The objective was to find plans as quickly as possible. The best planner achieved a score of 40.25, closely below the baseline LAMA-first with a score of 40.28, and our Hapori Stone Soup portfolio, identical to the one used in the satisficing track, scored 28.49 points, ranking 10th.

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