Spock: Fast Downward Stone Soup with Redundant Action Elimination

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Abstract

In this planner abstract, we introduce Spock, a submission to the sequential satisficing track of IPC 2023. Spock runs the Fast Downward Stone Soup 2018 portfolio and reduces each discovered plan by eliminating redundant actions. The action elimination process is based on a reformulation of the given planning task. Solving this novel planning task with an optimal planner identifies the most costly set of redundant actions within a plan, and removing it yields a cheaper plan and a lower upper bound for the next portfolio component. In numerous instances, the action elimination procedure can be executed in mere tenths of a second. As a result, Spock offers an affordable post-planning optimization step that enhances the performance of satisficing planners without significantly increasing computational demands.

Fast Downward Stone Soup

Fast Downward Stone Soup (FDSS) (Helmert, Röger, and Karpas 2011) is a portfolio planner based on the Fast Downward planning system (Helmert 2006). We use the version that competed in the sequential satisficing track of the IPC 2018, extending it with an action elimination module that removes redundant actions in the found plans (Salerno, Fuentetaja, and Seipp 2023). Since we do not make any changes to the portfolio, we only describe it briefly here, and refer to the original Stone Soup paper (Helmert, Röger, and Karpas 2011) and the 2018 planner abstract for further information (Seipp and Röger 2018).

Fast Downward Stone Soup receives the following inputs to build a portfolio: a set of planning algorithms, a set of training instances, and evaluations for each pair of algorithm and training instance (i.e., running time and plan cost). With this information, the Stone Soup algorithm chooses a subset of the input planning algorithms, and assigns each of them a time limit. The chosen algorithms are executed sequentially, and the cost of the best plan found at any step is used to perform pruning based on *g values* for subsequent planning algorithms.

What is a Spock?

In the Star Trek franchise, the character of Spock is known for his logical and analytical approach to problem-solving. He often identifies and eliminates redundant steps in complex procedures in order to streamline processes and make them more efficient. In this work, in a Spockian fashion, we take the Fast Downward Stone Soup planner (FDSS) and eliminate any existing redundancy in each new plan found.

For tasks without zero-cost actions, an optimal plan will not contain any redundant actions, but numerous works have shown that modern satisficing planning systems do generate plans with redundant actions (Chrpa, McCluskey, and Osborne 2012b,a; Balyo, Chrpa, and Kilani 2014; Med and Chrpa 2022). The process to identify and remove redundant actions is typically fast, compared to the time needed to find a plan. Doing this provides not only plans without redundancy, which intuitively is always desired, but also reduces the plan cost by removing unnecessary steps.

Redundant Actions and Plan Justification

Intuitively, redundant actions in plans are those actions that can be removed from a plan without affecting its validity. This notion is known as *plan justification* (Fink and Yang 1992). Fink and Yang define multiple types of plan/action justifications, but the strongest of the three is called *perfect justification*. Put simply, perfectly-justified plans are those for which no subsequence of actions can be removed from the plan without invalidating it. More formally, we say that a plan without any *plan reductions* is perfectly justified.

Definition 1 (Plan Reduction) *Let π be a plan for a planning task Π and ρ be a subsequence of π with $|\rho| < |\pi|$. ρ is a plan reduction of π if and only if ρ is also a plan for Π.*

Definition 2 (Perfectly-Justified Plan) *A plan π for the planning task Π is perfectly justified if and only if there is no plan reduction of π.*

Thus, if there is at least one plan reduction of a plan, the plan is not perfectly justified. The problem of finding the cheapest perfectly justfied plan reduction of a given plan π of a planning task Π is called Minimal Reduction (MR) (Nakhost and Müller 2010; Balyo, Chrpa, and Kilani 2014).

The main goal of action elimination is to find useful plans without redundant actions, but this process clearly reduces the plan cost as a side effect. We exploit this potential cost reduction and use a solver for the minimal reduction process as a post planning optimization step for each plan found by the portfolio. This process not only (potentially) finds

a cheaper plan without redundancy, but provides a better (lower) bound with which pruning based on g values can be performed on subsequent planner runs.

Minimal Reduction as Planning

We now introduce a compilation that encodes the MR problem as a planning task (Salerno, Fuentetaja, and Seipp 2023). Given a planning task and a plan, we define a new planning task that can eliminate subsequences of redundant actions from the plan. We encode the new task in a way that allows to either keep or skip each plan action. In the following, we consider the same action occurring at different positions in an action sequence as different actions. For this, we slightly abuse notation and let $a_i \in \pi$ represent that action a_i is at position i in π.

Let $\Pi = \langle \mathcal{V}, \mathcal{A}, \mathcal{I}, \mathcal{G} \rangle$ be a planning task and $\pi = \langle a_1, \ldots, a_n \rangle$ be a plan for Π. Let $F_\pi = \bigcup_{a_i \in \pi} \mathit{pre}(a_i) \cup \mathcal{G}$ be the set of facts that appear either in the precondition of an action in π or in $\mathcal{G}$. Now, we create a new planning task $\Pi^{skip} = \langle \mathcal{V}', \mathcal{A}', \mathcal{I}', \mathcal{G}' \rangle$, where:

- $\mathcal{V}' = \{v \in \mathcal{V} \mid |\mathcal{D}'(v)| > 1\} \cup \{pos\}$, where we keep variables v from the original task but with a redefined domain $\mathcal{D}'(v)$, only when $\mathcal{D}'(v)$ contains more than one value; and there is an additional variable pos with $\mathcal{D}(pos) = \{0, \ldots, n\}$ to track the last action from the original plan considered at any given state. For a variable v, $\mathcal{D}'(v)$ contains only the values of v that appear in F_π and an additional value θ, representing an *irrelevant value*. The value of a variable is irrelevant when it is set by either the initial state or the effect of some action in the plan, but the corresponding fact is not in F_π. Thus, $\mathcal{D}'(v) = \{d \in \mathcal{D}(v) \mid \langle v, d \rangle \in F_\pi\} \cup \Theta$, where $\Theta = \{\theta\}$ if $\langle v, d \rangle \notin F_\pi$ but $\langle v, d \rangle \in \mathcal{I}$ or there exists $a_i \in \pi$ with $\langle v, d \rangle \in \mathit{eff}(a_i)$, and $\Theta = \emptyset$ otherwise. The irrelevant value is used when the value of a variable is changed to a value which is not relevant to the plan. Just removing such effects is not enough because the variable does not maintain its previous value after the application of the action. This potentially reduces the size of $\mathcal{D}'(v)$ compared to $\mathcal{D}(v)$ since all facts in the effects of any action in π but not in F_π are represented by the single fact $\langle v, \theta \rangle$.
- $\mathcal{A}' = \{a'_i \mid 1 \leq i \leq n\} \cup \{skip_i \mid 1 \leq i \leq n\}$, where there is a new action a'_i for every action a_i in the plan and a skip action for every plan position. Actions a'_i are defined as: $\mathit{pre}(a'_i) = \mathit{pre}(a_i) \cup \{\langle pos, i-1 \rangle\}$ and $\mathit{eff}(a'_i) = \{\tau(f) \mid f \in \mathit{eff}(a_i)\} \cup \{\langle pos, i \rangle\}$, where the effects of the new action are the same as those of the original action, but changing the variable value to the irrelevant one for those facts not used in action preconditions or goals. Formally, $\tau(\langle v, d \rangle)$ is $\langle v, d \rangle$ if $\langle v, d \rangle \in F_\pi$ and $\langle v, \theta \rangle$ otherwise. The $skip_i$ actions just increase the value of pos from $i-1$ to i. They have zero cost, while the a'_i actions maintain the cost $c(a_i)$.
- $\mathcal{I}' = (\mathcal{I} \cap F_\pi) \cup \{\langle v, \theta \rangle \mid v \in \mathcal{V}', \langle v, d \rangle \in (\mathcal{I} \setminus F_\pi)\} \cup \{\langle pos, 0 \rangle\}$ contains the facts from the original initial state that are relevant for the plan, and relevant variables with an irrelevant initial value are set to the *irrelevant value*.The *pos* variable is initialized to zero.
- $\mathcal{G}' = \mathcal{G} \cup \{\langle pos, n \rangle\}$ contains the original goals and requires the *pos* variable to be at the end of the plan (this could be omitted but it can be useful for heuristics).

Plans for Π^{skip} only contain $skip$ actions (with a corresponding skipped action in the original plan) and actions from the original plan in the same order (if they appear in the plan at position i they are only applicable when *pos* is $i-1$). Therefore, there is a one-to-one correspondence between the actions in a plan π' for Π^{skip} and the actions in the plan π for Π, defined by the action positions. Consequently, it is straightforward to transform a plan for Π^{skip} into a plan for Π, i.e., by removing skip actions and replacing the remaining actions by their counterparts in Π.

The plan obtained from solving Π^{skip} can contain redundant zero-cost actions. In terms of plan cost, these type of redundant actions do not have any negative effects, but if the goal is to find plans without redundant actions, costs from the original task must be adapted. We adapt the original costs of the input plan actions by setting the cost of all zero-cost actions to 1, and multiplying all other costs by the factor $f = \lceil \frac{m}{\mathit{mincost}} + \epsilon \rceil$, where m is the number of zero-cost actions in the input plan, *mincost* is the smallest positive action cost in the plan, and ϵ is an arbitrarily small positive real number. (If $\mathit{mincost} = 0$, f is undefined but also unneeded.) This factor satisfies $f \cdot m < \mathit{mincost}$, which guarantees that removing any action with a cost greater than zero will be more beneficial than removing any set of zero-cost actions. With this modification, an optimal plan for Π^{skip} is a MR for π.

Enhancing Π^{skip}

Identifying if *all* subsequences of actions in a plan are necessary is NP-hard (Fink and Yang 1992; Nakhost and Müller 2010). However, this does not mean that we cannot identify *some* actions as necessary in polynomial time. Med and Chrpa (2022) defined *plan action landmarks* as actions that must be part of any plan reduction of a given plan. For example, if only a single action a achieves a goal fact, removing a would render the plan invalid. Furthermore, if some preconditions of a are also achieved by only one action a', then a' is also necessary. We call this specific type of plan action landmarks *trivial plan action landmarks* (TPAL). To simplify the formal definition of trivial plan action landmarks, we extend a given plan with *virtual initial* and *goal* actions, defined as $a_0 = \langle \emptyset, \mathcal{I} \rangle$ and $a_{n+1} = \langle \mathcal{G}, \emptyset \rangle$, respectively.

Definition 3 (Trivial Plan Action Landmark, TPAL) *Let $\Pi = \langle \mathcal{V}, \mathcal{A}, \mathcal{I}, \mathcal{G} \rangle$ be a planning task and $\pi = \langle a_0, a_1, \ldots, a_n, a_{n+1} \rangle$ be a plan for Π extended with virtual initial and goal actions. Action a_i is a trivial plan action landmark iff: (1) $i = n+1$ (goal action) or (2) there is a trivial plan action landmark a_j, $i < j$, such that there is a fact $p \in \mathit{eff}(a_i) \cap \mathit{pre}(a_j)$, and there is no action a_k, $k < j$, $k \neq i$, such that $p \in \mathit{eff}(a_k)$.*

The set of facts in $\mathit{eff}(a_i)$ that comply with the condition specified in (2) are the reason why a_i is a TPAL. We will call this set the necessary effects, and will refer to it as $n\_\mathit{eff}(a_i)$.

The set of actions that can potentially be skipped is $A_s = \{a_i \in \pi \mid a_i \text{ is not a } \mathit{TPAL}\}$. With this, we create an en-

hanced task $\Pi^{skip}_{TPAL} = \langle \mathcal{V}', \mathcal{A}', \mathcal{I}', \mathcal{G} \rangle$, where $\mathcal{V}', \mathcal{I}', \mathcal{G}$ are defined exactly as for Π^{skip}, but the set of actions $\mathcal{A}' = \{a'_i \mid 1 \leq i \leq n\} \cup \{skip_i \mid a_i \in A_s\}$ only has $skip_i$ actions for actions a_i that are not TPAL.

We can further extend the definition by including the effects of known plan action landmarks when identifying new plan action landmarks. We define this type of plan action landmarks as *fix-point plan action landmarks* (FPAL). Put simply, an action is a *FPAL* if it is the only achiever of a fact that is needed after another FPAL overwrote that fact.

Definition 4 (Fix-point Plan Action Landmark, FPAL) *Let $\Pi = \langle \mathcal{V}, \mathcal{A}, \mathcal{I}, \mathcal{G} \rangle$ be a planning task and $\pi = \langle a_0, a_1, \ldots, a_n, a_{n+1} \rangle$ be a plan for Π extended with virtual initial and goal actions. The action a_i is a fix-point plan action landmark iff: (1) a_i is a trivial plan action landmark or (2) there is a fix-point plan action landmark a_j, $i < j$, such that there is a fact $\langle v, d \rangle \in \mathit{eff}(a_i) \cap pre(a_j)$, and there is another fix-point plan action landmark a_k, $k < i$, with an effect $\langle v, d' \rangle \in \mathit{eff}(a_k)$ where $d' \neq d$ and there is no other action a_l with $l \neq i$, $k < l < j$ such that $\langle v, d \rangle \in \mathit{eff}(a_l)$.*

We can now use FPALs to only define skip actions for actions that are not FPALs.

Finally, we propose one final enhancement: encapsulate consecutive sequences of FPALs in a single macro action (Fikes, Hart, and Nilsson 1972). For two consecutive FPALs a_i and a_j, we build the macro a_{ij} as follows: $pre(a_{ij}) = pre(a_i) \cup (pre(a_j) \setminus \mathit{eff}(a_i))$, and $\mathit{eff}(a_{ij}) = \mathit{eff}(a_j) \cup \mathit{eff}|_{a_j}(a_i)$, where $\mathit{eff}|_{a_j}(a_i)$ represents the effect of a_i restricted to those facts which variable does not appear in the effect of a_j: $\mathit{eff}|_{a_j}(a_i) = \{\langle v, d \rangle \mid \langle v, d \rangle \in \mathit{eff}(a_i) \wedge v \notin vars(\mathit{eff}(a_j))\}$. Longer sequences of macros result from iteratively applying this definition. Soundness for macros of FPALs is guaranteed since they contain consecutive actions of a valid plan.

Integrating Minimal Reduction into FDSS

The only thing left to do is to integrate the action elimination step into Fast Downward Stone Soup. We use Π^{skip} enhanced with FPALs and macro operators, and solve the resulting tasks using Fast Downward with A* and $h^{\max}$ (Bonet and Geffner 2001) as the heuristic function. The steps are straightforward: each time FDSS finds a new plan, we create and solve a Π^{skip} task. Then, we process the plan found for the Π^{skip} task to transform it into a plan for the original task. This transformation only consists of a few simple steps:

- Remove any *skip* actions that might be present.
- Break down macro actions of FPALs into individual actions.
- If cost scaling was done (i.e., if there were zero-cost operators in the input plan), compute the cost of the plan resulting from applying the last two steps using the costs of the original actions.

FDSS assigns a time limit to each planning algorithm, so we have to decide how much time to assign to the action elimination process. We went with the simplest approach and give the remaining time of the algorithm that found the plan to the action elimination procedure. We could have assigned a larger time limit to action elimination, but in most cases this process only needs less than a second to finish. For some particular domains where plans have thousands of actions and few to none actions are FPALs, the action elimination process might take a large amount of time to finish. We considered that reducing the time limit of subsequent planning algorithms in these cases was not worth the potential cost reduction that action elimination could achieve.

Conditional Effects

The base Π^{skip} compilation can be used without adaptation also in domains with conditional effects. However, the enhanced compilations with trivial and fix-point plan action landmarks need some modifications. In particular, we need to adapt how TPALs and FPALs are defined and identified.

Let $\pi = \langle a_1, \ldots, a_n \rangle$ be a plan that contains actions with conditional effects. For any action a, $cond(f)$ defines a potentially empty set of facts with the effect conditions for every $f \in \mathit{eff}(a)$. Without conditional effects, if $a_i \in \pi$ is a TPAL, then there must exist at least one effect $f = \langle v, d \rangle$ such that $f \in \mathit{eff}(a_i)$ and either $f \in \mathcal{G}$ or $f \in pre(a_j)$, for another TPAL a_j, $j > i$, with a_i being the only achiever of f either for $\mathcal{G}$ or for a_j. To extend this definition to account for conditional effects, if a_i was identified as a TPAL because of effect $f \in \mathit{eff}(a_i)$, then f is a *necessary effect* of a_i and thus every effect condition $\langle v_c, d_c \rangle \in cond(f)$ has to be taken as a regular precondition to identify new TPALs with Definition 3. Otherwise, the effect's conditions in $cond(f)$ are not considered when identifying other TPALs.

Definition 5 (Extended PAL Precondition) *Let $\Pi = \langle \mathcal{V}, \mathcal{A}, \mathcal{I}, \mathcal{G} \rangle$ be a planning task with conditional effects and $\pi = \langle a_0, a_1, \ldots, a_n, a_{n+1} \rangle$ be a plan for Π extended with virtual initial and goal actions. Given a PAL a_i, the extended PAL precondition of action a_i is $e\_pre(a) = pre(a_i) \cup \bigcup_{c \in n\_\mathit{eff}(a_i)} cond(c)$, where $n\_\mathit{eff}(a_i)$ is the set of necessary effects of a_i.*

When the input task has conditional effects, TPALs are identified using $e\_pre(a_j)$ instead of $pre(a_j)$ in Condition 2 of Definition 3.

FPALs take into account the effects of other FPALs when identifying new FPALs. In similar fashion as what was explained for TPALs, Definition 4 can be modified in a way that, when identifying FPALs (Condition 2 in Definition 4), an effect $f \in \mathit{eff}(a_k)$ is only considered if $cond(f) = \emptyset$ or if f was the reason a_k was identified as an FPAL (i.e., it is a necessary effect).

Macro actions

In the presence of conditional effects, macro actions of consecutive FPALs constructed as described previously are no longer guaranteed to be sound. This is the case because a sequence of FPALs might have been applicable in the original plan, but removing actions might change what conditional effects are applied when executing the actions composing the macro. To remedy this, we simply only create macros of consecutive FPALs that do not have conditional effects.

Limitations

Our action elimination module has two limitations: disjunctive preconditions and derived predicates. We cannot handle disjunctive preconditions for two reasons. The first is due to a technical detail in our implementation. When disjunctive preconditions are present, Fast Downward's translator module generates multiple actions with the same name but different preconditions. In our implementation of the action elimination module, we use the actions' names as a unique identifier, which causes inconsistent behavior when there are multiple actions with the same name in the input task. If we changed this implementation detail, we could utilize the base Π^{skip} compilation to solve MR for tasks with disjunctive preconditions and derived predicates. However, even with this implementation detail changed, we would still need to adapt the definition and implementation of trivial and fixpoint plan action landmarks to tasks with disjunctive preconditions and derived predicates.

Since we were unable to make the necessary changes before the IPC submission deadline and since our experiments demonstrated that the use of plan action landmarks is crucial for solving Π^{skip} tasks efficiently (Salerno, Fuentetaja, and Seipp 2023), we decided not to run action elimination for tasks with disjunctive preconditions or derived predicates.

Results

To analyze the performance of Spock in the competition, we compare the cost of plans found by FDSS 2018 with the cost of plans found by Spock. Note that, since Spock only performs a post-planning optimization step after plans are found, there should be no difference in coverage.

Table 1 contains the results of the experiment. For each domain, we show the number of task solved out of the total number of tasks (in parentheses), and the sum of the cost of the best plans found by each configuration. Spock and FDSS solve the same number of tasks, as expected. In all domains except for Rubik's cube and Quantum layout, both approaches yield the same minimum plan cost for all tasks. For the Quantum layout domain, Spock manages to remove redundant actions from the last plan found by FDSS, finding a better plan for a single instance in that domain. However, in the Rubik's cube domain, the time needed to run the action elimination step in Spock is counterproductive: in three instances Spock finds worse plans than FDSS. In this particular domain, only one plan found by FDSS over all instances had redundant actions. This could explain why Spock performed worse in the Rubik's cube domain, since the overhead of identifying redundant actions does not benefit the process, and only results in time loss. We also noted that, in general, only the plans found early in the process by FDSS contain redundant actions. This means that running the action elimination step after the planner has found a few plans is not beneficial in most cases for the IPC 2023 tasks.

With these observations, two easy changes could be implemented to improve Spock's performance: (1) Reduce the time allocated for the action elimination step and (2) only run the action elimination step for a fixed number of plans found early in the process. These variations, as well as testing Spock with different planners, remain as future work.

Domain	Coverage	FDSS 2018	Spock
Folding	7 (20)	**64**	**64**
Labyrinth	0 (20)	–	–
Quantum Layout	20 (20)	1032	**1030**
Recharging Robots	14 (20)	**211**	**211**
Ricochet Robots	6 (20)	**208**	**208**
Rubik's Cube	20 (20)	**732**	778
Slitherlink	0 (20)	–	–

Table 1: For each domain, we show the number of solved tasks and the sum of the lowest plan cost found by FDSS 2018 and Spock for each task.

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