Forward Backward Novelty Search

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Abstract

It has been shown recently that width-based search algorithms can be employed to search over the regression space (backward search). While many benchmarks are challenging for the width-based backward search, it performs significantly better than the forward counterparts in certain domains. This *orthogonal* behavior of forward and backward width-based search is quite suitable for an integrated approach. Indeed, it has been shown that a simple forward-backward integration that runs forward best-first width search (BFWS) with novelty pruning followed by the backward counterpart results in better coverage than both. Similarly, pairing forward-backward *pruned* BFWS algorithm with the state-of-the-art *Dual-BFWS* improves the overall coverage over the IPC *satisficing* benchmark. In this paper, we present an integration of approximate novelty search with the forward-backward BFWS.

Backward Best-First Width Search

Lei and Lipovetzky (2021) showed that BFWS and k-BFWS (Lipovetzky and Geffner 2017a,b) can be adapted to solve the regression state model directly. The definition of novelty is the same in both directions, as it only depends on the syntax of the states, i.e. the state variables. The critical paths heuristic h^2 (Haslum and Geffner 2000; Alcázar and Torralba 2015) is generated from s_0, the initial state of the forward model, to extract the set of forward mutex fluent pairs (Blum and Furst 1997). Mutexes are used to prune partial states in the regression unreachable from s_0, and hence a generated state s is pruned if it contains a mutex pair $h^2(p, q) = \infty$, $p, q \in s$. The goal counter instead of keeping track of the number of unrealized forward goals $g \in G$ in progression, $\#g(s) = |s \cap I| + |s \setminus I|$ keeps track of the number of initial state fluents I achieved, as well as the number of fluents that still have to be removed from s to reach one of the regression goal states. The goal counter is further strengthened by creating an *I-ordering* $p < q$ of fluents $p, q \in I$ when all actions requiring p *edelete* q. In regression, an action a *edeletes* a fluent q if $q \in add(a)$ or $\exists_{p \in pre(a) \cup del(a)} h^2(p, q) = \infty$. This I-ordering graph refines the goal counter $\#g(s)$ by counting as achieved fluents $p \in s, p \in I$ whose precedences are satisfied in s.

Width-Based Forward Backward Search

The experiment results introduced by (Lei and Lipovetzky 2021) show that forward and backward search can be orthogonal. One of the prominent combinations of forward search and backward search is *FB* where F stands for forward k-BFWS(f_5) (Lipovetzky and Geffner 2017b), B for the backward counterpart, and $k = 2$. *FB* is a simple integration where F is run first and then B runs only if F stops with no solution. *FB* solves the most instances, 794 over 1095 test instances from 42 domains introduced in the satisficing tracks of IPCs 1998–2018, 60 problems more than F over 10 different domains. This is witnessed further by the results over *Dual-BFWS*, runner-up on the last satisficing track at the IPC-2018 (Francès et al. 2018). *Dual-BFWS* runs first a forward F with $k = 1$, and a second complete BFWS (Lipovetzky and Geffner 2017a) if no solution is found. The results show that running *FB* with $k = 1$ first instead improves the state-of-the-art (*Dual-FB*). *FB* with $k = 1$ can be thought of as a quick preprocessing step that could be integrated into every state-of-the-art planner as it either solves a problem or fails fast.

Forward Backward Sequential BFWS(f_5) planner

In Forward Backward Sequential BFWS(f_5), we iteratively call forward and backward variants of BFWS(f_5) until we find a solution or run out of time. The algorithm *approximates* the *state novelty* and uses an *adaptive policy* to control the open-list (Singh et al. 2021) which allows the planner to give space and time guarantees on the function that computes the novelty measure. The planner makes recursively calls to forward and backward k-BFWS(f_5), increasing k by 1 at each iteration, i.e. it begins by calling forward k-BFWS(f_5), $k = 1$, in which nodes of novelty greater than 1 are pruned. If the search fails to find a solution, it calls the backward counterpart. If it fails again, it repeats the steps with $k = 2$, and so on. As an optimization step, based on *empirical* reasoning, we stopped the backward runs for $k \geq 2$ in the planner we submitted into the IPC. Also, we modified the *satisficing* track submission, allowing it to optimize the plans with weighted A* used in LAMA (Richter and Westphal 2010) until timeout.

	Folding	Labyrinth	Quantum L.	Recharging R.	Ricochet R.	Rubik's C.	Slitherlink
NoveltyFB (*agl*)	0.14	0.00*	18.88	0.83*	1.18	4.00	0.48
NoveltyFB (*sat*)	1.00	0.00*	18.31	8.00*	13.80	5.00	4.00

Table 1: The *scores* of Forward Backward Sequential BFWS(f_5) (NoveltyFB) in Agile and Satisficing tracks. The scores impacted by the preprocessing error[1] are marked with a '*'.

Empirical Analysis

We had many challenging domains in the International Planning Competition 2023. Unfortunately, our Forward Backward Sequential BFWS(f_5) planner (NoveltyFB) performed poorly on these domains compared to its forward-only counterpart (Singh et al. 2023). From Table 1, we see that the NoveltyFB planner scored well on Quantum Layout and Ricochet Robot. However, upon closer investigation of the logs, we observed that all instances in these two domains were solved by forward search. We could not find evidence suggesting that backward k-BFWS(f_5) helped lower the runtimes. This leads us to believe that the domains in this year's IPC did not have the structure that the backward k-BFWS(f_5) could exploit, which existed in the domains like *Floortile and Childsnack* in the previous IPCs (Lei and Lipovetzky 2021).

Conclusion

The results make us believe that the IPC 2023 problems lacked the combinatorial structure that could benefit from the novelty search in the backward direction. Hence, even though the forward and backward novelty search were previously shown to have orthogonal behavior (Lei and Lipovetzky 2021), our Forward Backward Sequential BFWS(f_5) search underperformed compared to the forward-only counterpart.

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[1]Our integration with FAST-DOWNWARD Grounder failed in Labyrinth and Recharging-robots instances with *single-goal atoms*, resulting in the planner terminating unexpectedly at the step when the search engine's data structures are initialized. The IPC 2023 results presented in Table 1 were impacted by this error.