SymBD: A Symbolic Bidirectional Search Baseline

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Abstract

We present SymBD, an entry to the optimal track of the International Planning Competition IPC'23. SymBD is a baseline running symbolic bidirectional blind search.

Introduction

Symbolic search (McMillan 1993) is a technique for state-space exploration that leverages the efficient representation of sets of states as Binary Decision Diagrams (Bryant 1986). This is a technique with a long history of success in optimal planning (Edelkamp and Helmert 2001; Jensen, Veloso, and Bryant 2008; Edelkamp and Kissmann 2011; Kissmann 2012; Edelkamp, Kissmann, and Torralba 2015; Torralba et al. 2017). The purpose of this planner is to represent this line of research in the IPC'23.

SymBD should not be taken as the state-of-the-art symbolic search planner, so the results of SymBD at the competition are not fully representative of the capabilities of these techniques. Rather, it should be taken as a baseline of what a relatively simple implementation of symbolic search with BDDs can accomplish. In fact, SymBD was already used in IPC'18 as a baseline. The current state of the art for classical planning using symbolic search with BDDs is, up to our knowledge, symbolic search with operator-potential heuristics (Fišer, Torralba, and Hoffmann 2022a,b), using a forward informed search with potential heuristics (Fišer, Horčík, and Komenda 2020) and backward blind search. For readers interested in planners capable of supporting advanced PDDL features and beyond, such as axioms/derived predicates (Thiébaux, Hoffmann, and Nebel 2005), state-dependent action costs (Speck et al. 2021), or top-K planning, Symk is the planner of choice (Speck et al. 2019; Speck, Mattmüller, and Nebel 2020; Speck 2022, 2023).

SymBD: Symbolic Bidirectional Blind Search

SymBD is a re-implementation of the SymBA* planner (Torralba et al. 2014), which won the optimal-track of IPC'14. The focus on the re-implementation was not on improving performance, but rather to simplify the code. SymBA* used symbolic bidirectional blind search until the search could not be continued, and then used abstraction heuristics to continue the search at an abstract level in order to identify which parts of the current frontier were most promising (Torralba, Linares López, and Borrajo 2016). Instead SymBD continues the symbolic bidirectional blind search until a timeout is reached, without trying additional searches at the abstract level. While this reduces the performance slightly, is a simpler approach and easier to extend in different ways.

SymBD is implemented on top of the Fast Downward Planning System (Helmert 2006), and uses the h^2 preprocessor to remove actions and simplify the planning task, and compute mutexes that are used to enhance symbolic backward search. We use the implementation of symbolic bidirectional search described by Torralba et al. (2017), using several enhancements such as optimized BDD variable ordering (Kissmann and Edelkamp 2011), disjunctive partitioning of the transition relation BDDs (Torralba, Edelkamp, and Kissmann 2013), and pruning using mutexes (Torralba and Alcázar 2013).

Conclusion

SymBD is an efficient implementation of symbolic bidirectional blind search, which leverages BDDs to perform search efficiently. The purpose of this planner is to represent what symbolic search planners are capable of even without using heuristics.

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