SymK – A Versatile Symbolic Search Planner

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Abstract

SymK is a planner that performs symbolic search using Binary Decision Diagrams to find a single optimal or the best k plans. It is designed to be a versatile planner by supporting several expressive extensions to the classical planning formalism. Our planner, SymK, therefore natively supports features relevant for compact modeling of planning tasks, such as conditional effects and derived predicates with axioms.

Introduction

Symbolic search is a state-space exploration technique that originated in model checking (McMillan 1993). Symbolic search algorithms are similar to their explicit counterparts. However, they expand and generate entire sets of states rather than individual states. Over the years, symbolic search has proven to be a highly competitive approach to optimal planning, yielding impressive results at previous International Planning Competitions (Edelkamp and Helmert 2001; Torralba et al. 2014; Kissmann, Edelkamp, and Hoffmann 2014; Edelkamp, Kissmann, and Torralba 2015; Torralba et al. 2017; Speck, Geißer, and Mattmüller 2018b; Franco et al. 2018).

One strength of symbolic search is that it does not require strong heuristics to be competitive, since symbolic bidirectional blind search is among the strongest search strategies (Torralba et al. 2017; Speck, Geißer, and Mattmüller 2020; Fišer, Torralba, and Hoffmann 2022). For this reason, symbolic search does not necessarily suffer from the restriction of strong state-of-the-art heuristics to the planning formalism. With this in mind, the SymK planner was developed with the goal of being a versatile symbolic search planner that supports several expressive extensions of traditional classical planning while retaining the core of the formalism (Speck 2022). Among other things, SymK can find multiple optimal solutions or even all solutions for a given planning task (Speck, Mattmüller, and Nebel 2020; von Tschammer, Mattmüller, and Speck 2022), and supports conditional effects, oversubscribed goal descriptions (Speck and Katz 2021), state-dependent action costs (Speck, Geißer, and Mattmüller 2018a), and complex state descriptions with derived predicates and axioms (Speck et al. 2019). Despite the broad feature support, SymK also implements a symbolic search that is tailored to efficiently search for a single optimal solution for a given classical planning task.

The following describes the details of the SymK configuration submitted to the *optimal track* of the 2023 International Planning Competition to find a single optimal solution, and which and how SymK supports the PDDL language features of the competition.

Implementation

SymK is based on Fast Downward 22.06 (Helmert 2006) and SymBA* (Torralba et al. 2014). For preprocessing, we use the h^2 preprocessor for invariant computation and spurious action pruning (Alcázar and Torralba 2015). For the competition, we chose to perform a bidirectional symbolic blind search, which is known to be one of the dominant search strategies for symbolic search (Torralba et al. 2017; Speck, Geißer, and Mattmüller 2020). At each search iteration, either a forward or a backward search step is performed. To decide which direction is more promising, the runtime of the last forward step is compared to the runtime of the last backward step. To represent formulas, sets of states, and transition relations, we use Binary Decision Diagrams (BDDs) (Bryant 1986) of the CUDD library (Somenzi 2015). We also use a fixed variable ordering based on an analysis of the causal graph known as the Gamer variable ordering described in Kissmann and Hoffmann (2013, 2014). Finally, we combine as many actions as possible into a transition relation until the BDD representation exceeds 100k nodes, perform state set partitioning based on the resulting transition relations, and use mutexes to prune spurious states during search (Torralba and Alcázar 2013; Torralba, Edelkamp, and Kissmann 2013; Torralba 2015; Torralba et al. 2017).

Language Support

SymK supports *PDDL 2.2 Level 1* (Fox and Long 2003) plus the *action cost requirement* from PDDL 3.1 and *all ADL features* such as quantified and conditional effects and negation, disjunction, and quantification in conditions. In particular, SymK natively supports conditional effects and derived predicates with axioms, which are rarely supported by optimal planners. SymK supports *conditional effects* by encoding them directly in the transition relations as described in Kissmann, Edelkamp, and Hoffmann (2014). *Derived predicates and axioms* are supported by SymK using the symbolic translation approach of Speck et al. (2019), where all occurrences of derived predicates in the planning task are replaced by their corresponding primary representation using BDDs as the underlying data structure. Finally, beyond the IPC requirements, SymK implements top-k planning to generate *many* or even *all plans* with increasing costs as an output stream and supports *oversubscribed goals* and *state-dependent action costs*.

Conclusions

SymK is a planner based on symbolic search. It focuses on optimal planning while supporting extensions to the classical planning formalism. It is a new planner in the sense that SymK has never participated in a previous International Planning Competition, although SymBA* and Fast Downward, on which SymK is based, have. For the competition, we chose to use symbolic bidirectional blind search, for which several optimizations have been published over the years, which we have summarized in this planner abstract. The latest version of SymK is available online:

`https://github.com/speckdavid/symk`

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