NLM-CutPlan

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Abstract

NLM-CutPlan is a numeric planner based on heuristic search using the numeric LM-cut heuristic. For simple numeric planning, it has a specific configuration using an operator-counting heuristic with constraints extracted by LM-cut. In addition, it has configurations using symmetry breaking for optimal planning and greedy best-first search for satisficing and agile planning.

Introduction

Heuristic search is widely used in classical and numeric planning. In optimal planning, A* (Hart, Nilsson, and Raphael 1968) is typically used with admissible heuristics. In numeric planning, although past research developed heuristic search planners, they were limited to satisficing planning (Hoffmann 2003; Coles et al. 2013). However, recent research has proposed heuristics and pruning techniques for optimal numeric planning. Our planner, NLM-CutPlan, is a heuristic search planner for numeric planning based on this recent progress. While the main focus of NLM-CutPlan is optimal planning, it also has configurations for satisficing planning.

The LM-cut heuristic (Helmert and Domshlak 2009) is an admissible heuristic for classical planning. LM-cut has been generalized to simple numeric planning (SNP) (Kuroiwa et al. 2022) and linear numeric planning (LNP) (Kuroiwa, Shleyfman, and Beck 2022), showing state-of-the-art performance in optimal planning. In SNP, using LM-cut in the operator-counting (OC) framework (Pommerening et al. 2015) results in a significant performance gain (Kuroiwa et al. 2022). In OC, an admissible heuristic value is computed by solving a linear programming (LP) problem, where each decision variable is the number of applications of an action, and the objective is the total action cost. LM-cut can provide constraints over the decision variables in this problem. For LNP, recent work has proposed a method to extract the bounds of numeric variables, which is used to improve LM-cut (Kuroiwa, Shleyfman, and Beck 2023).

In addition to heuristics, symmetry breaking, which prunes symmetric states in search space, has also been imported to numeric planning from classical planning (Shleyfman, Kuroiwa, and Beck 2023). In particular, orbit space search (OSS) (Domshlak, Katz, and Shleyfman 2015), which performs A* transforming states to their canonical form to detect symmetry, achieves strong performance in optimal planning.

NLM-CutPlan uses LM-cut as the heuristic function. It has two configurations for optimal planning with different search algorithms: A* and OSS. For satisficing and agile planning, NLM-CutPlan uses LM-cut with lazy greedy-best first search (GBFS) (Helmert 2006). We implement NLM-CutPlan in Numeric Fast-Downward (Aldinger and Nebel 2017).[1]

Configurations

We describe seven configurations of NLM-CutPlan used in different tracks.

NLM-CutPlan

NLM-CutPlan is the basic configuration using A* with $h^{\text{LM-cut}}_{2b+}$ (Kuroiwa, Shleyfman, and Beck 2023). It is used in the optimal track.

NLM-CutPlan Orbit

NLM-CutPlan Orbit uses OSS with $h^{\text{LM-cut}}_{2b+}$ and is used in the optimal track. In OSS, a problem is represented by a numeric problem description graph (NPDG), and automorphism groups of the NPDG are used to detect symmetric states. We use blis 0.73 (Junttila and Kaski 2007) to detect automorphism groups of an NPDG.

NLM-CutPlan OC

NLM-CutPlan OC is specifically designed for SNP. It uses A* with an OC heuristic, $h^{\text{LC,S}}_{+,\text{LP}}$, which combines LM-cut with state equation constraints (Bonet 2013; Piacentini et al. 2018) and is only applicable to SNP (Kuroiwa et al. 2022). To compute a heuristic value of $h^{\text{LC,S}}_{+,\text{LP}}$, the LP problem is solved by IBM ILOG CPLEX 22.1.1. NLM-CutPlan OC is used for SNP in the optimal track.

NLM-CutPlan OC Orbit

NLM-CutPlan OC Orbit uses OSS with $h^{\text{LC,S}}_{+,\text{LP}}$ and is used for SNP in the optimal track.

[1]https://github.com/Kurororoorо/numeric-fast-downward

NLM-CutPlan Sat

NLM-CutPlan Sat uses lazy GBFS with $h^{\text{LM-cut}}_{2b+}$ and is used in the satisficing and agile tracks.

NLM-CutPlan OC Sat

NLM-CutPlan OC Sat uses lazy GBFS with $h^{\text{LC,S}}_{+,\text{LP}}$ and is used for SNP in the satisficing and agile tracks.

NLM-CutPlan Sat2

NLM-CutPlan Sat2 uses lazy GBFS with $h^{\text{LM-cut}}_{\text{cri},+}$ (Kuroiwa et al. 2022) and is used for SNP in the satisficing and agile tracks. Compared to $h^{\text{LC,S}}_{+,\text{LP}}$, which solves LP for each state, $h^{\text{LM-cut}}_{\text{cri},+}$ can be computed faster while its heuristic value tends to be less informative. Compared to $h^{\text{LM-cut}}_{2b+}$, $h^{\text{LM-cut}}_{\text{cri},+}$ is specific to SNP and does not need to extract bounds of numeric variables, so its initialization is slightly more efficient.

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