Integrating Machine Learning with Constraint Solving: An Overview

Alexander Felfernig[1], Viet-Man Le[1], Mathias Uta[2], Seda Polat-Erdeniz[1], and Sebastian Lubos[1]

[1]Applied Software Engineering and AI, Graz University of Technology, Graz, Austria
[2]Siemens Energy AG, Erlangen, Germany
{alexander.felfernig, vietman.le, spolater, sebastian.lubos}@ist.tugraz.at, mathias.uta@siemens-energy.com

Abstract

Constraint solving is applied in scenarios such as the optimization of production schedules, the solving of resource balancing tasks, and the configuration of complex items. There exist various approaches that focus on the integration of machine learning techniques with constraint solving for the purpose of better guiding solution search. This presentation provides an overview of approaches to integrate constraint solving with machine learning. We compare the advantages and disadvantages of these approaches and also focus on related topics such as conflict detection and diagnosis.

1 Introduction

The increasing size and complexity of constraint problems triggers a need for intelligent approaches to support constraint solvers in efficiently identifying high-quality solutions (Epstein and Freuder 2001). Related evaluation criteria are a.o. *search efficiency* (time needed to find a solution), *prediction quality* (to which extent are the user preferences predicted correctly), and *minimality* (e.g., only relevant components are included in a configuration).

Machine learning (ML) can be applied to support constraint solvers (Popescu et al. 2022). Tasks that can be supported by ML in the context of constraint programming (CP) are manyfold (Popescu et al. 2022). For example, search heuristics can be learned to improve the quality (e.g., efficiency) of solution search (Nareyek 2004). Furthermore, ML can be used to increase the efficiency of solution search on the basis of predicting the satisfiability of complete or partial problems (Xu, Hoos, and Leyton-Brown 2012). Finally, individual solvers or solver parametrizations can be identified using case-based reasoning (O'Mahony et al. 2013).

2 Presentation

A major focus of this presentation is to provide an overview of existing algorithmic approaches based on bridge building between the research areas of constraint solving and ML. In this context, we discuss different application scenarios ranging from the learning of search heuristics to the automated prediction of problem satisfiability and solver parameters. Furthermore, we discuss ways to evaluate the quality/improvements of such integration approaches (Uta et al. 2021).

In our presentation, we take into account basic constraint solving scenarios but also include further topics such as conflict detection and diagnosis (Felfernig et al. 2009; Felfernig, Schubert, and Zehentner 2012), which play a major role in constraint-based applications (Felfernig et al. 2014). Finally, to stimulate further research supporting bridge-building between the communities of ML and CP, we discuss open research issues. Our presentation in parts follows the structure of our invited talk given at the CP'2021 *5th Workshop on Progress Towards the Holy Grail* (Popescu et al. 2022).

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