Konrad-Zuse-Zentrum
für Informationstechnik Berlin

Takustraße 7
D-14195 Berlin-Dahlem
Germany

TIMO BERTHOLD[1,⋆]
THIBAUT FEYDY[2]
PETER J. STUCKEY[2]

Rapid Learning for Binary Programs

[1] Zuse Institute Berlin, Takustr. 7, 14195 Berlin, Germany, berthold@zib.de
[2] National ICT Australia** and the University of Melbourne, 111 Barry St, Carlton 3053, Victoria, Australia,{tfeydy,pjs}@csse.unimelb.edu.au
⋆ Supported by the DFG Research Center MATHEON *Mathematics for key technologies* in Berlin.
** NICTA is funded by the Australian Government as represented by the Department of Broadband, Communications and the Digital Economy and the Australian Research Council.

ZIB-Report 10-04 (March 2010)

Rapid Learning for Binary Programs

Timo Berthold*[1] and Thibaut Feydy[2] and Peter J. Stuckey[2]

[1] Zuse Institute Berlin, Takustr. 7, 14195 Berlin, Germany
berthold@zib.de
[2] National ICT Australia** and the University of Melbourne, Victoria, Australia
tfeydy,pjs@csse.unimelb.edu.au

Abstract. Learning during search allows solvers for discrete optimization problems to remember parts of the search that they have already performed and avoid revisiting redundant parts. Learning approaches pioneered by the SAT and CP communities have been successfully incorporated into the SCIP constraint integer programming platform.
In this paper we show that performing a heuristic constraint programming search during root node processing of a binary program can rapidly learn useful nogoods, bound changes, primal solutions, and branching statistics that improve the remaining IP search.

1 Introduction

Constraint programming (CP) and integer programming (IP) are two complementary ways of tackling discrete optimization problems. Hybrid combinations of the two approaches have been used for more than a decade. Recently both technologies have incorporated new *nogood learning* capabilities that derive additional valid constraints from the analysis of infeasible subproblems extending methods developed by the SAT community.

The idea of *nogood learning*, deriving additional valid *conflict constraints* from the analysis of infeasible subproblems, has had a long history in the CP community (see e.g. [1], chapter 6) although until recently it has had limited applicability. More recently adding carefully engineered nogood learning to SAT solving [2] has lead to a massive increase in the size of problems SAT solvers can deal with. The most successful SAT learning approaches use so called *first unique implication point (1UIP)* learning which in some sense capture the nogood closest to the failure that can infer new information.

Constraint programming systems have adapted the SAT style of nogood learning [3,4], using 1UIP learning and efficient SAT representation for nogoods, leading to massive improvements for certain highly combinatorial problems.

Nogood learning has been largely ignored in the IP community until very recently (although see [5]). Achterberg [6] describes a fast heuristic to derive

* This research was partially funded by the DFG Research Center Matheon in Berlin
** NICTA is funded by the Australian Government as represented by the Department of Broadband, Communications and the Digital Economy and the Australian Research Council.