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Empirical decision model learning. (English) Zbl 1404.68113

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Summary: One of the biggest challenges in the design of real-world decision support systems is coming up with a good combinatorial optimization model. Often enough, accurate predictive models (e.g. simulators) can be devised, but they are too complex or too slow to be employed in combinatorial optimization.

In this paper, we propose a methodology called Empirical Model Learning (EML) that relies on Machine Learning for obtaining *components* of a prescriptive model, using data either extracted from a predictive model or harvested from a real system. In a way, *EML can be considered as a technique to merge predictive and prescriptive analytics.*

All models introduce some form of approximation. Citing [*G. E. P. Box* and *N. R. Draper*, Empirical model-building and response surfaces. John Wiley & Sons, Hoboken, NJ (1987; Zbl 0614.62104)] "Essentially, all models are wrong, but some of them are useful". In EML, models are useful if they provide adequate accuracy, and if they can be *effectively exploited by solvers for finding high-quality solutions.*

We show how to ground EML on a case study of thermal-aware workload dispatching. We use two learning methods, namely Artificial Neural Networks and Decision Trees and we show how to encapsulate the learned model in a number of optimization techniques, namely Local Search, Constraint Programming, Mixed Integer Non-Linear Programming and SAT Modulo Theories. We demonstrate the effectiveness of the EML approach by comparing our results with those obtained using expert-designed models.

MSC:

68T05 Learning and adaptive systems in artificial intelligence
68T20 Problem solving in the context of artificial intelligence (heuristics, search strategies, etc.)
90C27 Combinatorial optimization

Keywords:

combinatorial optimization; machine learning; complex systems; local search; constraint programming; mixed integer nonlinear programming; SAT modulo theories; artificial neural networks; decision trees

Software:

BARON; C4.5; EGO; LocalSolver; MINLP; WEKA; z3

Full Text: DOI

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