Application of Naive Bayes classification to the resolution of recurrent combinatorial optimization problems

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1 Introduction

The objective of this work is to address the optimization of combinatorial problems that present some kind of recurrent structure. Stemming from the assumption that such recurrent problems are the realization of an unknown generative probabilistic model, data is collected from previous resolutions of such problems and then used to train a supervised learning model for classification. This model can then be exploited to operate a selection of the decision variables to obtain a reduced problem of significantly faster resolution time.

2 Problem Framework

As a practical example, in the context of energy production, the energy operator is faced with a unit-commitment problem whose model is the same every day: minimize the power generation cost under demand satisfaction and operational constraints (network capacity, technical and regulatory limitations, etc.). This problem is often cast as a Mixed Integer Linear Programming (MILP) problem. Each daily instance of such problems are random variations on the parameters of the model (surge in demand, unscheduled maintenance, etc.) that will require specific resolution.

When solving a MILP problem one is often faced with a non-negligible computational burden. For instances with many variables and/or constraints, resolutions based on standard Branch & Bound (BB) techniques may fail to deliver a solution within an acceptable time window, given the exponential complexity of such algorithms. Fixing the values of a subset of decision variables will reduce the dimension of the solution space and potentially speed up the process.

One can think of the decision variables as the targets of a classification problem whose outcome would be the choice of which variables to exclude from the resolution of the new instance of the model (their values being set heuristically). The *NaiBX* algorithm [2], an extension of Naive Bayes Classification [1] (NBC) into the domain of multi-label classification, was designed for such problems. The algorithm couples the agile complexity structure of NBCs with multi-label targets and the possibility of being trained online, offering computational gains.

As MILP problems are computationally very demanding *per se*, the choice of *NaiBX* as a supervised classifier guarantees a minimal fooprint on the optimization process.

3 Algorithmic Framework

When applying our hybrid paradigm, the classification and the optimization steps are carried out by independent pieces of software integrated together, thus allowing the user to take advantage of state-of-the-art solvers and the computational speed up granted by the classification step.

We experimented with this approach on a variety of MILP problems and drew conclusions on the computing time gains versus optimality losses. We also investigated the conditions that made such an approach profitable for optimization.

4 Conclusions and perspectives

We show that such a hybrid approach to optimization can deliver interesting and promising results. We plan to extend our work to Mixed Integer Nonlinear Programming (MINLP), where an effective variable selection can grant sizeable computational gains.

References

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