Embarrassingly Greedy Inconsistency Resolution of Qualitative Constraint Networks*

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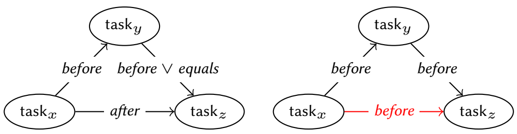
Qualitative Spatio-Temporal Reasoning (QSTR) is a rich symbolic AI framework that deals with representing and reasoning about abstract, qualitative, spatio-temporal information via human-like natural language descriptions [2]; as an example, consider a relation of the form x {*is north of* ∨ *is east of*} y, which abstracts from numerical information and yet is very intuitive. Such QSTR descriptions or relations, and disjunctions thereof, can be modeled as a qualitative constraint network (QCN), a simplified example of which is provided in Figure 1a. The QSTR literature has been deeply invested in point/interval-based calculi, with Allen's Interval Algebra being the most representative example [3], as intervals can be used to represent and reason about anything from durative actions in planning or tasks in robotics [4] to temporal abstractions in multivariate time series classification [5], among other applications; see also [6].



(a) An inconsistent plan as a simplified QCN.

(b) An *optimal* scenario of the simplified QCN.

Figure 1: The qualitative constraint network (QCN) in Figure 1a is inconsistent, and one solution of the MAX-QCN problem [7], viz., an *optimal* scenario, is shown in Figure 1b, with one unsatisfied constraint.

Context & Motivation: In [1], we focus on the problem of maximizing satisfiability in a qualitative constraint network, formally called the MAX-QCN problem [7]. Specifically, given a QCN $\mathcal{N}$, the MAX-QCN problem is the problem of obtaining a spatial or temporal configuration that maximizes the number of satisfied constraints in $\mathcal{N}$; see also Figure 1 for an example. The motivation behind studying this problem lies in the fact that representing spatial or temporal information may inevitably lead to inconsistencies, due to e.g. human error and/or inaccurate classifiers. As illustration, timetabling is an instance of scheduling where inconsistencies can naturally form due to the lack of resources for certain tasks, among other reasons. In the context of a hospital, for example, an inconsistency can occur when two surgeons are allocated the same operating room in overlapping temporal intervals; the inconsistency must then be repaired by considering available temporal intervals and preferences alike, and minimizing changes so as to perturb the structure of the timetable as little as possible. In the broader context of neuro-symbolic AI architectures [8], classifiers may construct inconsistent spatio-temporal KBs due to inaccurate predictions, and minimizing inconsistency (i.e., maximizing satisfiability) is an essential step of logical reasoning in the neuro-symbolic cycle, see, e.g., Figure 1 in [9].

State of the Art & Contribution: The state of the art in solving the MAX-QCN problem with respect to *constraints* and *SAT encodings* consists of the works in [7] and in [10], respectively. Specifically, both of these approaches try to obtain a refinement of the input QCN that maximizes the number of satisfied constraints in the QCN. In doing so, they are trying to solve two problems of different nature at the same time: extracting a scenario of the QCN, whilst ensuring that the extracted scenario is optimal. This is particularly crippling for the performance of the constraint-based approach in [7], as, should the constraint not be part of an optimal scenario in the end, taking a refinement of it in the beginning might create a huge branch in the search tree that is useless to explore. The clause learning of the SAT-based approach in [10] circumvents this issue, but, on the other hand, [10] does not exploit tractability properties for QCNs, viz., *Horn theories* and/or *maximal tractable subsets* of relations [11]; nevertheless, it significantly outperforms [7]. In [1], with respect to the previous discussion, we provide a greedy constraint-based approach for tackling the MAX-QCN problem that treats the constraints of the input QCN in whole and, hence, may avoid—to a relatively greater extent—redundant exploration of search space. Specifically, the greedy technique consists in adding the original constraints of a QCN to a new, initially empty, network, one by one, all the while filtering out the ones that fail the satisfiability check. What makes or breaks this technique is the ordering in which the constraints will be processed to saturate the empty QCN, and for that purpose we use many different strategies to form a portfolio-style implementation. Then, we experimentally compare this approach against one of the most compact to date Partial MaxSAT encodings for the MAX-QCN problem, which builds upon [12, 13], and comment on the trade-off between optimality and efficiency, making our source code freely available.

ENIGMA-23, September 03–04, 2023, Rhodes, Greece

* This is an extended abstract of the homonymous TIME 2023 paper [1]. The work was partially funded by the Agence Nationale de la Recherche (ANR) for the "Hybrid AI" project that is tied to the chair of Dr. Sioutis, and the I-SITE program of excellence of Université de Montpellier that complements the ANR funding.

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