

Temporal Preferences

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Abstract—While many frameworks for reasoning about time rely on the assumption that, as long as precedences are respected and there are no overlapping activities, any available time is just as good, all of us know that that is really not true! All of us would prefer avoiding heavy meetings right after lunch, waiting for connecting flights for endless hours or going on vacation at a selected destination during its rainy season. Among the many solutions to a temporal problem, being able select most preferred ones is a capability which is desirable in any intelligent system. On the other side, we may be often faced with over-constrained problems where relaxing hard constraints in a smart way can allow us to find a solution representing a better compromise.

This contribution takes an AI perspective and shows how an efficient and expressive way to reason about preferences can help to handle time in a more flexible and sophisticated way. Among the many frameworks for temporal reasoning, constraint-based ones (quantitative and qualitative) have provided the most suitable base for the introduction of preferences. We will discuss how temporal constraints have been extended to allow for the representation of preferences, how temporal preferences can coexist with uncertainty and how they can be made conditional. Moreover, we will show how preferences allow for a significant increase in terms of representational power often at a modest additional computational cost.

Keywords—Preferences; temporal constraints; uncertainty.

Constraints [?] are a very general and powerful reasoning paradigm that also lie at the core of many successful temporal frameworks, such as temporal problems based on Allen's algebra[?] and Temporal Constraint Satisfaction Problems (TCSPs) [?].

A constraint problem simply consists of a set of variables with domains containing the values they can be assigned, and a set of constraints. Each constraint involves a subset of the variables and consists of a subset of the Cartesian product of their domains. Only the tuples contained in such a subset satisfy the constraint.

In recent years constraints have been extended to allow to model “soft” information such as different degrees of preferences, rejection levels or costs [?]. The main idea behind such an extension is to equip constraint problems with an algebraic structure that provides preference values and operators to manipulate them. Such a structure is called a c-semiring and consists of a preference set, an idempotent additive operator for inducing the ordering over the prefer-

ences and an associative operator used to aggregate several preferences into a single one. Different c-semirings yield a different preference semantics. For example if the set of preferences is the interval between 0 and 1, the ordering is induced by *max* and preferences are aggregated via *min* we obtain fuzzy preferences. If instead preferences are positive integers, and they are aggregated by the arithmetic sum and ordered with *min* then we obtain a modeling of costs.

In the context of temporal reasoning the introduction of preferences has been called for by a plethora of real-life applications. Just to mention a few, temporal preferences have been used in the context of scheduling for several space missions such as the Mars Exploration Rovers [?] and fleets of Earth Observing Satellites (EOS) [?] and also in the temporal reasoning modules of assistive systems for elders [?].

The embedding of this general extension in the specific context of different constraint-based temporal reasoning frameworks has allowed to obtain interesting results and it has raised interesting technical issues. We will, thus, provide a brief overview of some, among the many, results belonging to this line of research.

We start by describing how STPs have been extended to STPs with fuzzy preferences[?]. In such problems variables represent the occurring time of instantaneous events and constraints, which are always binary, constrain the time difference between the occurrence of the two constrained variables to an interval. Intuitively, the interval of a constraint models the allowed durations or the allowed interleaving times of activities. STPs have been particularly successful due to their polynomial time complexity ($O(n^3)$ if n is a number of variables). They can either be solved using constraint propagation techniques, such as path consistency, or by a mapping into an all-pairs-shortest-path problem on a suitably defined weighted graph. The way preferences have been introduced is by augmenting constraints with preference functions mapping every value of the temporal interval into a preference. While adding preferences without any restriction can be shown to make the problem intractable, some natural assumption on the type of preferences used (e.g., fuzzy) and on the shape of the preference functions (e.g., semi-convex) allows to find an optimal solution in polynomial

time increasing the complexity of only a factor equal to the number of preferences used. This can be obtained either by performing the “soft” version of the propagation techniques or by decomposing the problem into the a set of STPs (without preferences) by exploiting the the fuzzy notion of α -cut.

Reasoning simultaneously with hard temporal constraints and preferences is crucial in many situations. However, in many temporal reasoning problems it is difficult or impossible to specify a local preference on durations. Moreover, in real world scheduling problems it is sometimes easier to see how much a solution is preferred, but it may be virtually impossible to say how specific ordering choices between pairs of events contribute to such global preference value. In [?] the difficulty in retrieving explicit temporal preferences is overcome by applying machine learning techniques to induce local preferences from global ones.

In rich application domains it is often necessary to simultaneously handle not only temporal constraints and preferences but also uncertainty. Some existing frameworks, such as Simple Temporal Problems with Uncertainty (STPUs) [?], [?], account for contingent events and have been extended to STPPUs in [?] to account also for fuzzy preferences. An STPPU is just like an STPP with the exception that some variables are uncontrollable, that is, their executing time is decided by an exogenous entity within a known time interval. When uncertainty is considered, consistency is replaced by controllability and, furthermore the presence of preferences makes it an optimization problem. There are several notions of controllability, usually called strong, weak, and dynamic, that basically differ on the level of robustness to uncertainty they require. However, all of them refer to the possibility of “controlling” the problem, that is, of assigning values to the controllable variables, in a way that is optimal w.r.t. what Nature has decided, or will decide, for the uncontrollable variables. When preferences are fuzzy and semi-convex, it is possible to show that for each of the above controllability notions, there are algorithms that check whether they hold, and that adding preferences does not make the complexity of testing such properties worse than in the case without preferences.

In real life scenarios there is often the need for modeling conditional plans where external events determine the actual execution sequence. Conditional Temporal Problems (CTPs) [?] have addressed such a need by extending the classical temporal constraint models [?] with conditions on the occurrence of some events. In CTPs, the usual notion of consistency is replaced by three notions (that is, weak, strong and dynamic consistency), which differ on the assumptions made on the knowledge available. Roughly speaking, a CTP is weakly consistent if in every situation there is a solution, it is strongly consistent if the same solution applies in all situations, and it is dynamically consistent if it is possible to build a solution online by relying only

on past observations. In [?], [?] CTPPs, that is, CTPs with fuzzy preferences, have been introduced by combining in a single formalism the expressive power of conditions and the flexibility of preferences. In order to do so, temporal constraints with preferences are allowed and the propositions and the activation rules associated with variables are fuzzified. CTPPs allow to generalize the conditions: external events are allowed to determine not only which variables are executed but also the preferences associated to their execution time.

It has been shown that preferences can be embedded also in inherently intractable problems such that those with disjunctions. For example in [?] disjunctive temporal problems have been extended with fuzzy preferences. Also other kinds of preferences have been considered. For example, in [?] STPs are generalized to incorporate utilitarian preferences, that is, preferences aggregated using the sum and where the highest preference is the best.

While we have focused only on preferences in the context of quantitative temporal constraints, much work has been done also on the side of qualitative constraints. For example, extensions of Allen-based temporal reasoning frameworks have been presented in [?], [?].

I. FUTURE DIRECTIONS

The handling of soft information, such as preferences and uncertainty, is unavoidable in the design of successful intelligent systems. So is time. The impressive development and success of intelligent systems we are witnessing at present will fuel this research line for long to come.

There are many aspects that have not been dealt with at all or in an insufficient way. Just to mention one, an exciting new perspective is the role of time and preferences and their interaction at a multi-agent level. In such a context temporal constraints and preferences come from different sources and need to be aggregated and satisfied in adequate ways that ensure the usual notions of consistency, controllability and optimality as well as new concepts such as fairness and strategy-proofness.