Extending Temporal Causal Graphs For Diagnosis Problems

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Introduction

Abductive diagnosis (Brusoni et al. 1998) consists in finding explanations for given observations by using rules of inference based on the causal dependences of the system. Time is important for abductive diagnosis (Hamscher and Davis 1984), (Hamscher, Console, and Kleer 1992). There are few works in litterature handling temporal diagnosis (Kautz 1999). They differ in the expressiveness of the temporal knowledge.

We propose a new approach for Temporal Diagnosis Problems. This approach is an extension of Bouzid and Ligeza's method for temporal diagnosis problems. In this latter work, the authors define a Temporal Causal Graph (TCG) where time delays are expressed as temporal instants. We extend the TCG by including two quantitative relations in order to handle temporal intervals. We call ExTCG this new model. Solving a temporal diagnosis problem represented by the ExTCG consists of finding all possible explanations. It is performed using a backtrack search algorithm.

Extended Temporal Causal Graph

The language of temporal representation

We suppose that we are in a frame where time is linear and discrete. The ontology of time considers both the instant and the interval. First, we extend the TCG by introducing the notion of episode.

Definition 1. *An episode is defined by a pair (s, i) where s is a symptom. i is an interval or an instant. A symptom represents some phenomenon reflecting an occurence of partial characteristic of the system.*

We are interested in the truth value of s over time. An episode can have dates of beginning noted $start\_date$ or of end noted end_date. The diagnosis is based on the analysis of several observations spaced out in a unpredictable way in time.

Relations

We keep the causal relation and the logical relations ($\{AND, OR, NOT\}$) defined in (Bouzid and Ligeza 2000).

Temporal relations. $R_T = \{r_{ql}(\partial t) \mid r_{ql} \in R_{QL}\}$, where ∂t is a positif integer indicating the delay and R_{QL} the set of two temporal relations ($after\_end$, $after\_start$). $after\_end$ represents that the effect is after the end of the cause. $after\_start$ represents that the effect is after the beginning of the cause. These relations are transformed into equations and inequalities allowing to refer to an instant or to locate two episodes one to another. In a more precise way; we have e, c_1 and c_2 three episodes. If the relation is $after\_start$ with a delay d_1 between c_1 and e then $start\_time(c_1) = start\_time(e) - d_1$. If the relation is $after\_end$ with a delay d_2 between c_2 and e then $end\_time(c_2) = start\_time(e) - d_2$.

Let us note by R the set of relations proposed in our approach. $R = \{(r_t, r_c) \mid r_t \in R_T, r_c \in R_C\}$ where:
R_C defines all the causal relations and R_T defines all the temporal relations.

Extension of a TCG

An extended temporal causal graph noted ExTCG is a TCG where nodes are episodes, and edges are the relations defined above.

Definition 2. *An Extended Temporal Causal Graph (ExTCG) is a structure $G = (E, F, R)$, where:*

- *E : set of episodes.*
- *$F = \{(n, f, [n_1, \ldots, n_k])\}$ denotes the set of logical connections such that $f \in \{AND, OR, NOT\}$, $n_1, \ldots, n_k$ are the input nodes and n the output node.*
- *R : set of causal and temporal relations between episodes.*

Solving Method

A temporal diagnosis problem is defined by an ExTCG and a set of observations.

Definition 3. *A Temporal diagnostic problem P is defined by an ExTCG and a set of observations OBS as follows:*
$\{ExTCG, OBS = ((o_1, i_{o_1}), \ldots, (o_n, i_{o_n}))\}$,
where the ExTCG represents the theoretical domain and OBS the set of observations o_k at the instants i_{o_k}.

Solving a Temporal Diagnostic Problem consists of finding all the episodes explaining the given observations and placing them in time.

Definition 4. *Let us consider a temporal diagnostic problem* $P = \{ExTCG, OBS\}$. *A solution S to P is defined by a set of pairs of initial nodes:* $\{(e_1, i_{e_1}), \ldots, (e_n, i_{e_n})\}$, *where* i_{e_j} *can be an interval or an instant, such that:*

ExTCG $\cup S \models OBS$ *and S is consistent.*

To solve a temporal abductif diagnostic problem, we propose an algorithm of temporal propagation in the ExTCG, in order to find all possible explanations. We proceed in the following two steps.

Step 1 : Abduction and Propagation

For the sake of the presented approach abduction is considered as a backward search procedure.

It allows to generate all sets of explanations as well as the equations and inequalites corresponding to temporal information. A solution, noted sol is a couple $(explanation, \{equations/inequalities\})$. Let us note by Sol_{solve}, all the solutions sol generated in this step. Given an observation o, we visit the ExTCG using a depth-first strategy, moving backward from o to non abductibles episodes. In every step of abduction, we replace a node by its possible cause. Every temporal relation is converted into equation and inequality. In a more formal way :

- At abductive step k, o is an AND node, caused by $\{c_1, c_2, \ldots, c_n\}$ so : for each c_i, we convert r_t (r_t temporal relation between c_i and o) in equations and ineqalities, and o is replaced by $\{c_1, c_2, \ldots, c_n\}$.
- At abductive step k, o is an OR node, caused by $\{c_1, c_2, \ldots, c_n\}$ so : we select one by one the causes of o. For the number of causes, we duplicate the solution sol for every c_i, so we have one sol_{c_i} by node c_i. We replace o by every cause c_i and we do the same thing. Finally, we add every sol_{c_i} to Sol_{solve}.
- At abductive step k, o is a NOT node, caused by c. The steps are the same as for the link AND. Furthermore, it is necessary to modify the truth value of c; if the truth value of o is true (resp. false) then we set c to false (resp. true).

If in a step one node is not abductible, it is considered to be explaining o. It will be added to the explanation corresponding to sol. This step generates the set Sol_{solve}.

Step 2 : Resolution

This step consists in solving equations and inequalities generated in the first step. The intention is to locate the explanation temporally. We consider these equations and inequalities as numeric temporal constraints. For this reason we use Simple Temporal Problem (STP) (Planken, de Weerdt, and van der Krogt 2008). To see how an STP can be used to find the ansewer to our question, we first consider :

- the set of temporal variables $V = \{x_1, \ldots, x_{2n}\}$ representing the start and the end of n episodes ($x_i = start\_date$ or end_date),
- the domain : $\mathbb{N}^+$,
- and the set C of eqautions and inequalities.

Then we define the relation of precedence between two episodes E_1 and E_2 as :

- $start\_date(E_2) - start\_date(E_1) \in [d, +\infty[$ and,
- $start\_date(E_2) - end\_date(E_1) \in [d, +\infty[$,

where d is a positif integer indicating the delay. We use STP in order to verify the coherence of the given temporal information and to solve equations/inequalities.

To solve the formed STPs we use the P^3C algorihtm presented in (Planken, de Weerdt, and van der Krogt 2008).

Conclusion and Future Work

We have extended the TCG (Bouzid and Ligeza 2000) by including two qualitative relations in order to manipulate time intervals.

We have developed search algorithms for solving the ExTCG. These algorithms consist in a backward search by propagating temporal information. Temporal information is considered as constraints. Thus, we formalize a set of constraints associated to each possible explanation as an STP. To solve an STP we use the P^3C algorithm.

One possible improvement to this work is to integrate more powerfull models into the ExTCG in order to manipulate the causality as weights expressing preferences. These models can be qualitative such as CP-nets (Boutilier et al. 2004) or quantitative such as c-semiring (BISTARELLI, MONTANARI, and ROSSI 1997).

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