A Temporal Extension to the Parsimonious Covering Theory

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Abstract

This paper presents a temporal extension to the parsimonious covering theory (PCT), so instead of associating to each disorder a set of manifestation as it is done in PCT, one associates to each disorder a temporal graph that contains information about duration and elapsed time between the beginning of the manifestations. The definitions of solutions for temporal diagnostic problems is presented as well as algorithms that compute this solution. We also include some limited form of probabilistic information into the model in order to study how categorical rejection, the elimination of explanations that contain a disease for which a necessary manifestation is not present, interacts with temporal information. An application in a medical domain is presented and discussed.

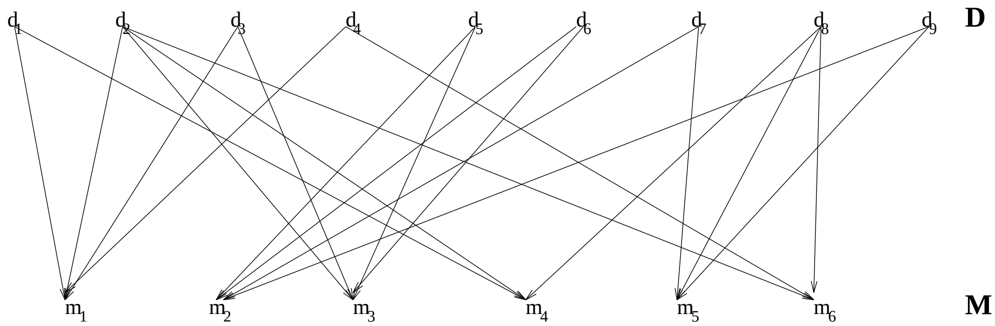
1 Introduction

Diagnostic reasoning is a complex cognitive process that involves the knowledge about a particular domain, general and domain specific heuristics about the diagnostic reasoning itself, and constrains imposed by cognitive limitations of the human diagnosticians. Parsimonious covering theory (PCT) [Pen90] is an attempt to formalize diagnostic reasoning. PCT has the advantage that it makes it explicit and self-contained the roles of the domain knowledge, domain heuristics, general diagnostic heuristics and provides some intuitions on how human cognitive limitations could impart on a diagnostic problem solving.

A limitation of PCT is that the domain specific knowledge is atemporal, that is, to each disease (cause) one associates a set of symptoms (effects), but it is not possible to specify how these symptoms evolve with time. Because of this atemporality, PCT can only be used to solve diagnostic problems in which all relevant symptoms are observable at the moment of diagnostic. But in many medical domain, and we expect in other diagnostic domains, that is not the case.

This paper extends the basic PCT so to each disease one can associate a temporal evolution of symptoms, or a history of symptoms. We call this extension **temporal PCT (t-PCT)**. In a second extension, we included some limited form of probabilistic information to the t-PCT in order to explore how categorical rejection, that is, the elimination of a disease due to the fact that one of its necessary manifestations is not present, would work in temporal domains. We call this second extension **categorical/temporal PCT (ct-PCT)**.

The next section describes the basic Parsimonious Covering Theory. Section 3 discusses the temporal PCT and section 4 discusses the categorical/temporal PCT. Section 5 reports on a diagnostic system for food borne diseases we implemented, and compare its efficiency



$$\begin{array}{ll} causes(m_1) = \{d_1, d_2, d_3, d_4\} & causes(m_2) = \{d_5, d_6, d_7, d_9\} \\ causes(m_3) = \{d_2, d_3, d_5, d_6\} & causes(m_4) = \{d_1, d_2, d_8\} \\ causes(m_5) = \{d_7, d_8, d_9\} & causes(m_6) = \{d_2, d_4, d_8\} \end{array}$$

Figure 1: Causal network of a diagnostic knowledge base $KB = \langle D, M, C \rangle$.

with a standard PCT implementation of the same diagnostic system. Finally section 6 discusses the limitations of the model proposed, and explore some future research topics.

2 Basics of Parsimonious Covering Theory

The basic version of PCT [Pen90] uses two finite sets to define the scope of diagnostic problems (see Figure 1). They are the set D, representing all possible **disorders** d_l that can occur, and the set M, representing all possible **manifestations** m_j that may occur when one or more disorders are present.

The relation C, from D to M, associates each individual disorder to its manifestations. An association $\langle d_l, m_j \rangle$ in C means that d_l may directly cause m_j; it does *not* mean that d_l *necessarily* causes m_j. The sets D, M, and C together are the knowledge base (KB) of a diagnostic problem.

To complete the problem formulation we need a particular diagnostic **case**. We use M^+, a subset of M, to denote the set of **observations**, that is, manifestations that are present in the case.

Definition 1 *A* **diagnostic problem** P *is a pair* $\langle KB, Ca \rangle$ *where:*

- $KB = \langle D, M, C \rangle$ *is the* **knowledge base**, *composed of*
  - $D = \{d_1, d_2, \ldots, d_n\}$ *is a finite, non-empty set of objects, called* disorders*;*
  - $M = \{m_1, m_2, \ldots, m_k\}$ *is a finite, non-empty set of objects, called* manifestations*;*
  - $C \subseteq D \times M$ *is a relation called* causation*; and*
- $Ca = \langle M^+ \rangle$ *is the* **case**, *and* $M^+ \subseteq M$ *is the set of* **observations**.

2.1 Solution for Diagnostic Problems

In order to formally characterize the solution of a diagnostic problem, PCT defines the notion of "cover", based on the causal relation C, the criterion for parsimony, and the concept of an explanation (explanatory hypothesis).

Definition 2 *For any $d_l \in D$ and $m_j \in M$ in a diagnostic problem P*

- $effects(d_l) = \{m_j | \langle d_l, m_j \rangle \in C\}$*, the set of manifestation directly caused by d_l;*
- $causes(m_j) = \{d_l | \langle d_l, m_j \rangle \in C\}$*, the set of disorders which can directly cause m_j.*

The set $effects(d_l)$ represents all manifestations that may be caused by disorder d_l, and $causes(m_j)$ represent all disorders that may cause manifestation m_j. These functions can be easily generalized to have sets as their arguments.

Definition 3 *The set $D_L \subseteq D$ is a* **cover** *of $M_J \subseteq M$ if $M_J \subseteq effects(D_L)$.*

Definition 4 *A set $E \subseteq D$ is an* **explanation** *of M^+ for a diagnostic problem iff E covers M^+, and satisfies a given parsimony criterion.*

In the following definition we present the possible parsimony criteria:

Definition 5

- *A cover D_L of M_J is said to be* **minimum** *if its cardinality is the smallest among all covers of M_J.*
- *A cover D_L of M_J is said to be* **irredundant** *if none of its proper subsets is also a cover of M_J; it is* **redundant** *otherwise.*
- *A cover D_L of M_J is said to be* **relevant** *if it is a subset of $causes(M_J)$; it is* **irrelevant** *otherwise.*

In many diagnostic problems, one is generally interested in knowing all plausible explanations for a case rather than just a single explanation because they, as alternatives, can somehow affect the course of actions taken by the diagnostician. This leads to the following definition of the problem solution:

Definition 6 *The* **solution** *of a diagnostic problem $P = \langle KB, Ca \rangle$, designated $Sol(P)$, is the set of all explanations of M^+.*

In this paper we will use irredundancy as the parsimonious criterion, as suggested by [Pen90]. If one is interested in developing general algorithms for diagnostic problems, irredundancy seems to be the preferable choice since from the set of all irredundant explanations one can mechanically generate the set of all minimal explanations (by selecting the sets of minimal cardinality) and the set of all relevant explanations (by systematically adding new disorders to some of the irredundant explanations).

It is important to notice that minimality, which most likely one would choose as the parsimony criteria based on the Occam razor principle, is not a general heuristic, but a domain specific choice. For example in domains where disorders have different likehood or prior probabilities it may be more plausible say that two fairly common disorders are responsible for a set of observations, than to say that a single extremely rare disorder is the cause.

2.2 Limitations of PCT

The main problem with the basic version of PCT is that the solution of a problem tends to have many alternative explanations. Irredundancy as the parsimony criteria is too weak a criteria to significantly reduce the number of alternative explanations and thus, for most practical applications there is the need remove some of the explanations from the solution based on domain specific heuristics. Or, at least, provide a way of ranking the explanations in the solution set so that more "plausible" explanations are presented before less "plausible" ones.

A more elaborated version of PCT (called probabilistic causal model) is also presented in [Pen90] which incorporates probabilities to the links between a disorder and its manifestations, that is, the probability that the manifestation occurs provided that the disorder is present. This probabilistic information can be used to rank the explanations by the probability of it being the correct one.

Furthermore, this probabilistic information allows one to remove from the solution set those explanations that contain a disorder for which a necessary manifestation was not observed in the case. If a disorder d_i necessarily causes a manifestation m_j, that is, if the probability that m_j is present given d_i is 1, then if m_j is known not to be among the observations of the case, then one can remove the explanations that contain d_i. This is called **categorical rejection**. We will discuss categorical rejection, in particular in the presence of temporal information further below in this paper.

2.3 Algorithms for PCT

There are basically two approaches for developing algorithms for PCT based on how the set M^+ is presented. The set could be presented *a priori* to the algorithm, in which case we will say that the algorithm is non-interactive. This seems appropriate in situations when one can monitor all possible manifestations, so that the knowledge of which manifestations are present in the case is readily available. In the second alternative, the observations in M^+ are presented to the algorithm one at a time, possibly as the answer to a question posed by the diagnostic system. This approach seems more appropriate in situation where it may be costly to obtain all observations, which is the case for medical diagnostics.

Algorithms may also differ in the parsimonious criterium used to define an explanation: irredundancy or minimality. [Reg85] discusses two algorithms that uses minimality as the parsimonious criterium, `HT` an interactive algorithm, and `SOLVE` a non-interactive. [Pen90] presents the interactive algorithm `BIPARTITE` which uses irredundancy as the parsimonious criterium, which will be the base for the algorithms presented in this paper.

BIPARTITE makes use of generators, a compact representation of alternative explanations for a case. For the sake of completeness, we will very briefly describe some concepts and operations on generators since they are relevant for the algorithms we develop later in this paper. The interest reader should refer to [Pen90] for a more complete explanation.

If $g_1, g_2 \ldots g_m$ are pairwise disjoint subsets of D, then $G_I = \{g_1, g_2 \ldots g_m\}$ is a *generator*, and the class generated by G_I is $[G_I] = \{\{d_1, d_2, \ldots, d_m\} | d_i \in g_i\}$. $G = \{G_1, G_2, \ldots, G_N\}$ is a *generator-set* if G_I is a generator, and $[G_I] \cap [G_J] = \emptyset$.

We define the operations res, div and $augres$, where G and Q are generator-set, G_I and Q_J are generators, $H_I \subseteq D$, and $q_j \in Q_J$. Each operation has multiple definitions depending whether the arguments are generator-sets, generators or sets of disorders.

$$
\begin{aligned}
res(G, Q) &= \begin{cases} G & \text{if } Q = \emptyset \\ res(res(G, Q_J), Q - \{Q_J\}) & \text{otherwise} \end{cases} \\
res(G, H_I) &= \bigcup_{G_I \in G} res(G_I, H_I) \\
res(G_I, Q_J) &= \begin{cases} \emptyset & \text{if } Q_J = \emptyset \\ res(G_I, q_j) \cup res(div(G_I, q_j), Q_J - \{q_j\} & \text{otherwise} \end{cases} \\
res(G_I, H_I) &= \begin{cases} \{\{g_1 - H_I, \ldots, g_n - H_I\}\} & \text{if } g_i - H_I \neq \emptyset \text{ for all } i, 1 \leq i \leq n \\ \emptyset & \text{otherwise} \end{cases}
\end{aligned}
$$

$$
\begin{aligned}
div(G, H_I) &= \bigcup_{G_I \in G} div(G_I, H_I) \\
div(G_I, H_I) &= \{Q_k | Q_k = \{q_{k1}, q_{k2}, \ldots q_{kn}\} \\
&\quad \text{and} \quad q_{kj} = \begin{cases} g_j - H_I & \text{if} j < k \\ g_j \cap H_I & \text{if} j = k \\ g_j & \text{if} j > k \end{cases}
\end{aligned}
$$

$$
\begin{aligned}
augres(G, H_I) &= \bigcup_{G_I \in G} augres(G_I, H_I) \\
augres(G_I, H_I) &= \begin{cases} \{\{g_1 - H_I, \ldots, g_n - H_I, A\}\} & \text{if } g_i - H_I \neq \emptyset, A \neq \emptyset \\ \emptyset & \text{otherwise} \end{cases} \\
&\quad \text{where } A = H_I - \textstyle\bigcup_{i=1}^{n} g_i
\end{aligned}
$$

2.4 Conclusions

PCT is a conceptually simple and powerful theory of diagnostic reasoning. It clearly separates the role of domain knowledge (sets M, D and principally the relation C), the role of general diagnostic reasoning (the parsimony criteria and the definition of cover), and domain heuristic (the choice of the parsimony criteria, the algorithms to further reduce or to rank the solution set, the algorithms for generating questions in an interactive algorithm). This separation allows one to gather and express the domain knowledge separately from domain heuristics, as opposed to rule base diagnostic systems [Sho76, Wei78], for example. For many domains of medical diagnsotics, PCT seems an appropriate model of diagnostics, because the form of the knowledge available in medical manuals and text boooks [Man90, Ber92] are in the form need by the PCT knowledge base: a description of what symptoms a particular disease cause (or may cause).

3 Temporal PCT

The aim of this research is to extend PCT so that instead of associating to each disorder a set of manifestation, one could associate an evolution of manifestations. Thus, the knowledge base could state that disorder d_1 causes first m_1 which will last between 2 and 5 days, followed in 2 to 3 days by m_2 which may last an undetermined amount of time, and will be followed at any moment by m_3. And so on. We accomplish this temporal representation using a graph, where vertices are manifestations and directed arcs between vertices represent temporal precedence. If there is quantitative information about the duration of the manifestation, it is associated with the corresponding node; if there is quantitative information about the elapsed time between the start of two manifestations, it is associated with the corresponding arc. Furthermore, quantitative information are not represented as a single number, but as an interval. Therefore one can state that a manifestation will follow another in 2 to 3 days. To each disorder one associates one such temporal graph.

Furthermore, one would also like to allow for some uncertainty in expressing the information about the observations. Describing the case, one should be able to say that a particular manifestation started anytime from 5 to 7 days ago, and lasted from 2 to 4 hours, that another manifestation is also present but one has no information when it started. This uncertainty about the temporal information about the observations in the case can be accomplished by using temporal graph to represent the case as well.

3.1 Temporal Representation

Time points will be the primitive objects to represent temporal information. **Intervals** are defined as non-empty convex sets of time points (points on the time line), represented by $I = [I^-, I^+]$ such that I^- and I^+ are the extreme points of interval I, respectively ($I^- \leq I^+$; $I^- > I^+$ indicates an empty interval I). We use the following notations of intervals operations:

- $I + J = [I^- + J^-, I^+ + J^+]$;
- $I \cap J = [max(I^-, J^-), min(I^+, J^+)]$;
- $I \leq p \Rightarrow I^+ \leq p$, where p is a time point.

A temporal graph is a *direct*, *acyclic*, *transitive*, and not necessarily connected graph where the nodes are manifestations. The existence of an arc from m_i and m_j in a temporal graph denotes the fact that the beginning of the occurrence of manifestation m_i must precede the beginning of the occurrence of m_j.

$DIST_8((m_4, m_5)) = [1, 3]$
$DIST_8((m_5, m_6)) = [2, 5]$
$DIST_8((m_4, m_6)) = [3, 8]$
$DUR_8(m_6) = [1, 2]$

$DIST_9((m_2, m_5)) = [2, 5]$
$DUR_9(m_2) = [10, 15]$
$DUR_9(m_5) = [7, 13]$

Figure 2: Temporal graphs of the disorders d_8 and d_9 with their temporal distance functions and duration functions.

Definition 7 *The* **temporal graph** *of a disorder $d_l \in D$, $G_l = (V_l, A_l)$, is a direct, transitive and acyclic graph defined as:*

- $V_l \subseteq M \equiv$ *set of manifestations directly caused by d_l, and*
- $A_l = \{(m_i, m_j) |$ *the beginning of m_i occurs* before *the beginning of m_j when the disorder d_l is said to be present$\}$.*

The impossibility to define cycles is a major restriction on the expressive power of the temporal representation formalism. In other words, it is not possible to represent recurring events. Nevertheless, this restriction is important since it reduces the complexity of the reasoning process [Con91].

The *temporal distance* between manifestations and the *duration* of a manifestation are represented by functions on the graph, denoted by $DIST$ and DUR, respectively. The temporal distance function $DIST$ associates an interval $R = [R^-, R^+]$ to each arc of a temporal graph G_l. $DIST(G_l, (m_i, m_j)) = R$ for $(m_i, m_j) \in A_l$, which we will abbreviate as $DIST_l((m_i, m_j)) = R$, states that the elapsed time between the beginning of m_j and the beginning of m_i in the temporal graph G_l of d_l must be within the interval R. The duration function DUR associates to each vertex m_i of a temporal graph G_l em G an interval J, that specifies that the duration of m_i must be within the interval J.

The transitivity of the temporal graph must be consistently carried over to the $DIST$ function: if $DIST_l(m_i, m_j) = R_1$ and $DIST_l(m_j, m_k) = R_2$ then $DIST_l(m_i, m_k) = R_1 + R_2$.

Figure 2 illustrates the temporal information about the disorders d_8 and d_9 of the diagnostic problem shown in Figure 1.

3.2 Temporal Diagnostic Problem Formulation

Definition 8 *The* **knowledge base** *of a temporal diagnostic problem is the tuple $KB = \langle D, M, G, DIST, DUR \rangle$ where D and M are defined as before, G is a set of temporal graphs, each one associated with one disorder of D, $DIST$ and DUR are the temporal information functions defined above.*

In order to represent the case, we will need the set of observations M^+, as before, and the temporal information about these observations. The function BEG^+ associates an interval to some of the observations in M^+. $BEG^+(m_j) = I$, $m_j \in M^+$, states that m_j started at any time within interval I. The origin of the time line for describing BEG^+ is arbitrary, provided the same origin is used in all temporal information for that case.

Similarly, the function DUR^+ associates to some of the observations in M^+ an interval, such that the duration of the observation was anything within that interval. It is important to notice that the model allows for incomplete knowledge about the observations. Both the beginning and the duration of a observation can be stated as an interval or they may not be stated at all.

Definition 9 *A* **temporal diagnostic problem** *P is a pair $\langle KB, Ca\rangle$ where KB is defined above, and $Ca = \langle M^+, BEG^+, DUR^+\rangle$ is the case.*

One can define the $effects$ and $causes$ functions in a similar way to definition 2. For example $causes(m_j) = \{d_l | m_j \in V_l$, for any temporal graph $G_l = (V_l, A_l) \in G\}$, represents the set of disorders that may cause m_j.

3.3 Solution for a Temporal Diagnostic Problem

In order to define a solution for a diagnostic problem, we need to define a set of concepts about temporal inconsistency. This will eventually allow us to remove the explanations that contain disorders in which the evolution of manifestations contradicts the evolution of the observations in the case. For example, if for a certain disorder m_1 precedes m_2 but in the case, the occurrence of m_1 started after the occurrence of m_2, then one can disregard all explanations that contain such disorder, since it contradicts the temporal information in the case.

Definition 10 *For a dynamic diagnostic problem P let $G_l = (V_l, A_l) \in G$, $(m_i, m_j) \in A_l$, such that $m_i, m_j \in M^+$. The* **arc (m_i, m_j) is temporally inconsistent with the case** *iff*

$$DIST_l((m_i, m_j)) \cap (BEG^+(m_j) - BEG^+(m_i)) = \emptyset.$$

$BEG^+(m_j) - BEG^+(m_i)$ is the possible range for the elapsed time between the beginning of m_i and m_j, given the uncertainty on the exact moments that the two observations occurred. $DIST_l((m_i, m_j))$ corresponds to the range that the disorder d_l allows for the elapsed time between the manifestations. If there is no intersection between these two intervals, then none of the possible distances between the beginning of the observations corresponds to what the disorder expects, and thus the arc (m_i, m_j) as specified by the disease d_l is temporally inconsistent with the case. The inconsistency criterion defined above is equivalent to one described in [Con93].

Definition 11 *For a dynamic diagnostic problem P let $G_l = (V_l, A_l) \in G$ the temporal graph of a disorder $d_l \in D$. The* **disorder d_l is temporally inconsistent with the case** *$Ca = \langle M^+, BEG^+, DUR^+\rangle$ iff*

- *exist at least one arc $(m_i, m_j) \in A_l$ temporally inconsistent with respect to the case , or*

- *exist at least a vertex $m_j \in V_l$, such that, $m_j \in M^+$ and $DUR_l(m_j) \cap DUR^+(m_j) = \emptyset$.*

Thus a disorder is temporally inconsistent with the case, if it has a temporally inconsistent arc, or if the range for the duration of one of its manifestations does not agree with the range for the duration of the corresponding observation.

Finally, based on the above definitions, we formalize the notions of temporally consistent explanation and temporally consistent solution.

Definition 12 *A set $E \subseteq D$ is said to be a* **temporally consistent explanation of the case** *for a dynamic diagnostic problem P iff*

1. *E covers M^+, and*
2. *E satisfies a given parsimony criterion, and*
3. *for any $d_l \in E$, d_l is* **not** *temporally inconsistent with the case.*

Definition 13 *The* **temporally consistent solution** *of a dynamic diagnostic problem $P = \langle Kb, Ca \rangle$ designated by $Sol(P)$, is the set of all temporally consistent explanations of the case.*

3.4 Algorithm

We present here an interactive algorithm that computes all explanations to a temporal diagnostic problem. The algorithm is a modification of the BIPARTITE algorithm in [Pen90]. The important aspect of the algorithm is that temporal consistency is not implemented as a filter, that is, it is not applied after the original BIPARTITE algorithm has generated the solution, but it is incorporated very early into the process of merging the causes on the "new" observation into the set of current explanations. Thus the algorithm has to deal with smaller sets of explanations.

The auxiliary function CTC (check temporal consistency) is used when the beginning of a new observation m_j is given, and returns the set of disorders evoked by m_j that are temporally inconsistent with $BEG^+(m_j)$.

function CTC($D_L, G, DIST, BEG^+, m_j$)
  variables
    D_I: **set-of-disorders**; (* temporally inconsistent disorders *)
    neighbors: **set-of-arcs**; (* *)
    inconsistent: **boolean**; (* flag *)
  begin
    $D_I = \emptyset$;
    while $D_L \neq \emptyset$ **do**
      $d_l \in D_L$;
      $G_l = (V_l, A_l) \in G$;
      $neighbors = \{(m_i, m_j) | (m_i, m_j) \in A_l$, and $BEG^+(m_j)$ is defined $\} \cup$
        $\{(m_j, m_k) | (m_j, m_k) \in A_l$, and $BEG^+(m_k)$ is defined $\}$;
      $inconsistent$ = **false**;
      while $neighbors \neq \emptyset$ **and not** $inconsistent$ **do**

$(m_i, m_k) \in neighbors$;
if $(BEG^+(m_i) + DIST_l((m_i, m_k))) \cap BEG^+(m_k) = \emptyset$
then
inconsistent =**true**;
$D_I = D_I \cup \{d_l\}$;
endif
$neighbors = neighbors - \{(m_i, m_k)\}$;
endwhile
$D_L = D_L - \{d_l\}$;
endwhile
return D_I;
end

function `t-BIPARTITE`(KB)
variables
m_j: **manifestation**; (* new observation *)
hypothesis: **generator-set**; (* all explanations *)
D_C, (* consistent disorders *)
D_I, (* all inconsistent disorders *)
H, (* disorders evoked by m_j *)
H_I, (* inconsistent disorders due to BEG *)
H'_I: **set-of-disorders**; (* inconsistent disorders due to DUR *)
M^+: **set-of-manifestations**;
BEG^+,
DUR^+: **function**;
begin
$hypothesis = \{\emptyset\}$;
$D_C = \emptyset$;
$D_I = \emptyset$;
$M^+ = \emptyset$;
while `MoreObservations` **do**
$H_I = \emptyset$;
$H'_I = \emptyset$;
m_j = `NextObservation`; (* obtain next observation *)
$H = causes(m_j)$;
$H = H - D_I$;
if $DUR^+(m_j)$ is defined
then
$H'_I = \{d_l | d_l \in H$, and $DUR_l(m_j) \cap DUR^+(m_j) = \emptyset\}$;
endif
if $BEG^+(m_j)$ is defined
then
$H_I =$ `CTC`$((H - H'_I) \cap D_C, G, DIST, BEG^+, m_j)$;
endif
$hypothesis = res(hypothesis, H_I \cup H'_I)$;
(*seleciona as hipóteses correntes não inconsistentes*)
$D_I = D_I \cup H_I \cup H'_I$;
$D_C = (D_C \cup H) - (H_I \cup H'_I)$;
if $(H - D_I) = \emptyset$ **or** $(hypothesis = \emptyset$ **and** $M^+ \neq \emptyset)$

```
25            then
26               return nil (* there is no consistent explanation *)
27            else
28               hypothesis = revise(hypothesis, H − D_I);
29         endif
30         M+ = M+ ∪ {m_j};
31      endwhile
32      return hypothesis
33   end.
```

The function *revise* in line 28 is define as

$$revise(G, H_I) \quad = \quad F \cap res(Q, F)$$
$$\text{where } F = div(G, H_I) \text{ and } Q = augres(G, H_I)$$

The functions `MoreObservations` and `NextObservation` are entry-points for the module that interacts with the patient, asking questions about the presence of manifestations. In order to ask effective questions this module must have access to current set of explanations, the knowledge base and very likely will use domain specific heuristics to select the question to ask.

At the beginning of a new cycle, after a new observation has been entered (line 9), the disorders evoked by the new observation are checked for temporal consistency with the case information so far (line 11). Then explanations that contain the temporally inconsistent disorders are eliminated from the set of current hypotheses (line 20) and the new temporally consistent evoked disorders are used to update the set of hypothesis (line 28).

The example below illustrates the basic ideas of the algorithm. For example in Figure 1, we have that $S_1 = \{\{d_1\}, \{d_2\}, \{d_3, d_8\}, \{d_4, d_8\}\}$ is the set of all explanations (irredundant covers) of $M^+ = \{m_1, m_4\}$ which are temporally consistent with $BEG^+(m_4) = [10, 10]$ and $DUR^+ = \emptyset$. Note that all irredundant covers for M^+ are consistent given BEG^+ and DUR^+. Each time a new observation is discovered and the beginning or duration are available, we verify the temporal consistency of the hypotheses in S_1, and update the hypotheses in the correct way. Thus, consider m_5 new observation of M^+, and $BEG^+(m_5) = [16, 18]$ and $DUR^+(m_5) = [2, 3]$. First, we obtain the disorders evoked by m_5 (i.e. $causes(m_5) = \{d_7, d_8, d_9\}$) that are temporally inconsistent with $BEG^+(m_5)$ and $DUR^+(m_5)$. As an illustration, consider d_8 and d_9 the disorders in Figure 2. Disorder d_8 is temporally inconsistent because the arc (m_4, m_5) with label $[1, 3]$ is inconsistent with $BEG^+(m_4)$ and $BEG^+(m_5)$ by Definition 10 (making the correct substitutions we have $([10, 10] + [1, 3]) \cap [16, 18] = \emptyset$). On the other hand, disorder d_9 is temporally inconsistent because the duration of m_5 in d_9 is inconsistent with $DUR^+(m_5)$, by Definition 11 (making the correct substitutions we have $[7, 13] \cap [2, 3] = \emptyset$).

In the next step, we remove all explanations in S_1 that contain these temporally inconsistent disorders. Thus, $S_2 = \{\{d_1\}, \{d_2\}\}$ is the set of all explanations that are not inconsistent. It is worth noting that once a disorder is considered temporally inconsistent it can not be part of any hypothesis. Finally, the consistent disorders (only d_7 in this case) are used to update the current explanations. $S_3 = \{\{d_1, d_7\}, \{d_2, d_7\}\}$ is thus the set of all explanations temporally consistent with the case (with m_5 added). If no other manifestation is present than S_3 represents the temporally consistent solution.

3.5 Discussion

This section presented our first extension to PCT, which includes temporal representation of manifestations and observations in the original PCT. As we discussed, this temporal representation allows for many kinds of uncertainty. Time information may be expressed as intervals or may not be expressed at all, both for the knowledge base and for the case. In fact, the t-PCT is a true extension of the original PCT, since by not providing any temporal information one has both a PCT knowledge base and a PCT case, and in this case the definition of a solution for a temporal diagnostic problem will coincide with the PCT's definition of solution for a diagnostic problem.

This true extension property is mainly a positive trait since many diagnostic domains (including some medical domains) are atemporal in the sense described above, and t-PCT could be the appropriate diagnostic theory for them as well. But the true extension property places at least some limits in the range of uncertainty allow to describe the case: it is not possible to state that a observation has already occurred, but it is not present anymore. Or in other words, it is not possible to state constraint on both the beginning time and duration of manifestations (for example that the beginning time plus the duration is less then the current time) without stating them.

The time representation used here is similar to the ones used by other researchers both in medical domains [Ham87, Con91, Con93] and robotics [Dou93]. But to our knowledge, this is the first time such representation is used in conjunction with the Parsimonious Covering Theory.

4 Categorical Temporal Diagnostics

As we mentioned, the basic PCT can be extended so that probabilities can be associated to each manifestation in a disorder. This information, together with the prior probabilities of the disorders themselves allow one to rank the explanations based on the posterior probability that the disorders are really present given the observations.

But besides ranking the explanations, probabilities can be used to categorically reject some explanations from the solution. If a disorder d_j necessarily causes the manifestation m_i and m_i is not among the observations of the case, then one can reject all explanations that contain d_j. When the manifestations are not atemporal but occur in time, one has to be sure that there has been enough time for the manifestation m_i above to occur, before categorically rejecting all explanations that contain d_j.

4.1 Problem Formulation and its Solutions

In this paper we are not interested in a general probabilistic (numeric) information relating manifestations and disorders, but just some information whether the disorder necessarily causes the manifestation, or whether the causation is only possible. Thus, in the knowledge base KB we add a function $POSS$ that attributes to each vertex of each temporal graph either the label N, for necessary, or the label P, for possible. Thus, $POSS(G_l, m_j) = N$, abbreviated as $POSS_l(m_j) = N$, states that disorder d_l necessarily causes the manifestation m_j.

For categorical diagnostic problems, one is interested in manifestations known to be absent in the case, called **negative observations**. Thus we add, M^-, the set of negative observations, and I_{now}, the time point that represents the moment of diagnosis, to M^+, BEG^+, DUR^+ as the components of the case Ca.

We can now define when a disorder is categorically inconsistent with the case.

Definition 14 *Let P=$\langle KB, Ca\rangle$ be a categorical diagnostic problem and $G_l = (V_l, A_l) \in G$. The* **disorder d_l is categorically inconsistent with the case** *iff*

- *exist an arc (m_j, m_k) in A_l, such that, $POSS_l(m_j) = N$, $m_j \in M^-$ e $m_k \in M^+$, or*
- *exist an arc (m_i, m_j) in A_l, such that, $POSS_l(m_j) = N$, $m_j \in M^-$, $m_i \in M^+$ and $BEG^+(m_i) + DIST(m_i, m_j) \leq I_{now}$.*

The definition above has two conditions. For both of them, the disorder d_l is categorically inconsistent due to the combination of two factors: a necessary manifestation is not present ($POSS_l(m_j) = N$ and $m_j \in M^-$) and there has been enough time for it to happen. In the first condition, the second factor is warranted because a later manifestation has already occurred ((m_j, m_k) in A_l and $m_k \in M^+$). In the second one, this factor is warranted because all values of a set of valid values (time points) for the beginning m_j are lower or equal than the actual instant ($BEG^+(m_i) + DIST_l(m_i, m_j) \leq I_{now}$).

Finally, we define an explanation of a categorical dynamic diagnostic problem.

Definition 15 *A set $E \subseteq D$ is said to be a* **consistent explanation** *of the case for an open dynamic diagnostic problem $P = \langle KB, Ca\rangle$ iff*

- *E covers M^+, and*
- *E satisfies a given parsimony criterion, and*
- *for any $d_l \in E$, d_l is* not *temporally inconsistent, and*
- *for any $d_l \in E$, d_l is* not *categorically inconsistent.*

4.2 Algorithm

We present below an algorithm that interactively solves a categorical/temporal diagnsotic problem.

function `ct-BIPARTITE`(KB)
    variables
        m_j: **manifestation**; (* new observation *)
        hypothesis: **generator-set**; (* all explanations *)
        D_C, (* consistent disorders (temp. and categ.) *)

D_I, (* inconsistent disorders (temp. and categ.)*)
H, (* disorders evoked by m_j *)
H_I, H'_I, H_{CI}, H_1: **set-of-disorders**;
L_{CIC1}, L_{CIC2}, L_1, L_2, L_3, L_4:**sets**;
M^+: **set-of-manifestations**; (* observations *)
BEG^+, DUR^+: **function**;
I_{now}: **time point**; (* now *)
begin
$hypothesis = \{\emptyset\}$;
$D_C = \emptyset$;
$D_I = \emptyset$;
$L_{CIC1} = \emptyset$;
$L_{CIC2} = \emptyset$;
$M^+ = \emptyset$;
I_{now}=`now`;
while `MoreObservations` **do**
m_j= `NextObservation`;
$H = causes(m_j)$;
$H = H - D_I$;
if `NextObservation.status` = present (* $m_j \in M^+$ *)
then
$H_I = \emptyset$;
$H'_I = \emptyset$;
$H_{CI} = \{d_l | \{d_l, M_L\} \in L_{CIC1}$, and $m_j \in M_L\}$;
$\cup \{d_l | \{d_l, A\} \in L_{CIC2}$, and there exists an arc $(m_j, m_k) \in A$, such that
$BEG^+(m_j) + DIST_l((m_j, m_k)) \leq I_{now}\}$;
$L_{CIC1} = \{\{d_l, M_L\} | \{d_l, M_L\} \in L_{CIC1}$, and $d_l \notin H_{CI}\}$;
$L_{CIC2} = \{\{d_l, A\} | \{d_l, A\} \in L_{CIC2}$, and $d_l \notin H_{CI}\}$;
if $DUR^+(m_j)$ is defined
then
$H'_I = \{d_l | d_l \in H - H_{CI}$, and $DUR_l(m_j) \cap DUR^+(m_j) = \emptyset\}$;
endif
if $BEG^+(m_j)$ is defined
then
$H_I = \texttt{CTC}((H - (H_{CI} \cup H'_I)) \cap D_C, G, DIST, BEG^+, m_j)$;
endif
$hypothesis = res(hypothesis, H_{CI} \cup H_I \cup H'_I)$;
$D_I = D_I \cup H_{CI} \cup H_I \cup H'_I$;
$D_C = (D_C \cup H) - (H_{CI} \cup H_I \cup H'_I)$;
if $(H - D_I) = \emptyset$ **or** ($hypothesis = \emptyset$ **and** $M^+ \neq \emptyset$)
then
return nil (* there is no consistent explanation *)
else
$hypothesis = revise(hypothesis, H - D_I)$;
endif
$M^+ = M^+ \cup \{m_j\}$
else (*$m_j \in M^-$*)
$H_1 = \{d_l | d_l \in H$, and $POSS_l(m_j) = N\}$;
$L_1 = \{\{d_l, M_L\} | d_l \in H_1$, and $M_L = \{m_k | (m_j, m_k) \in A_l\}\}$;

43 $L_2 = \{\{d_l, M_L\} | \{d_l, M_L\} \in L_1, M_L \cap M^+ \neq \emptyset\}$;
44 $H_{CI} = \{d_l | \{d_l, M_L\} \in L_2\}$;
45 $H_1 = H_1 - H_{CI}$;
46 $L_3 = \{\{d_l, A\} | d_l \in H_1$, and $A = \{(m_i, m_j) | (m_i, m_i) \in A_l\}\}$;
47 $L_4 = \{\{d_l, A\} | \{d_l, A\} \in L_3$, and there exists an arc $(m_i, m_j) \in A$, such that
48 $BEG^+(m_i) + DIST_l((m_i, m_j)) \leq I_{now}\}$;
49 $H_{CI} = H_{CI} \cup \{d_l | \{d_l, A\} \in L_4\}$
50 $hypothesis = res(hypothesis, H_{CI})$;
51 $D_I = D_I \cup H_{CI}$;
52 $D_C = D_C - D_I$;
53 $L_{CIC1} =$ `UPDATE`$(L_{CIC1}, L_1 - L_2)$;
54 $L_{CIC2} =$ `UPDATE`$(L_{CIC2}, L_3 - L_4)$;
55 **if** $hypothesis = \emptyset$ **and** $M^+ \neq \emptyset$
56 **return nil**
57 **endif**
58 **endif**
58 **endwhile**
60 **return** $hypothesis$
61 **end.**

The algorithm works by keeping track of two lists of disorders that are candidates for categorical rejection. A disorder is a **candidate for categorical rejection** if one of its necessary manifestations is not present in the case, but for which one does not have yet enough information on whether that necessary manifestation should have already occurred or not (the second factor in the two conditions in definition 14).The list L_{cic1} is defined as $L_{cic1} = \{\{d_l, \{m_{l1}, \ldots, m_{lk}\}\}, \ldots\}$ such that d_l is a candidate for categorical rejection and $\{m_{l1}, \ldots, m_{lk}\}$ is the set of manifestations that happens after the necessary manifestation of d_l that is not present in the case. If one of the m_{li} is entered in a later cycle as an observation then, d_l can be surely declared as a categorical inconsistent, and placed in the list D_I. Similarly, the list L_{cic2} is defined as $L_{cic2} = \{\{d_l, \{(m_i, m_j) \in A_l, \ldots\}, \ldots\}$ where d_l is a candidate for categorical rejection and m_j is the necessary manifestation that is not present in the case.

In its main loop, the algorithm is divided into two segments: lines 14 to 37 treat a new observation ($m_j \in M^+$), while lines 39 to 58 treat a negative observation ($m_j \notin M^+$). If the manifestation is present then line 17 determines all disorders in L_{cic1} and L_{cic2} that indeed became categorically inconsistent by the presence of m_j. Lines 20 and 21 update the lists, and lines 22 to 39 basically repeat the correspondent segment of code in algorithm `t-BIPARTITE`, taking also into consideration the categorically inconsistent disorders.

In case the manifestation m_j is not present, the algorithm has to determine which disorders became categorically inconsistent and add them to D_I (line 51), which disorders are candidates for categorical rejection, and update the lists L_{cic1} and L_{cic2} accordingly. This is performed by the function `UPDATE` below which guarantees that there is only one entry in each list for each disorder,

function `UPDATE`(L_{CIC}, L)
variables
L_1, L_2, L_3: **sets**;

begin

$L_1 = \{\{d_l, C_1 \cup C_2\} | \{d_l, C_1\} \in L_{CIC}$ and $\{d_l, C_2\} \in L\}$;

$L_2 = \{\{d_l, C_1\} | \{d_l, C_1\} \in L_{CIC}$, such that $\nexists \{d_l, C_2\} \in L\}$;

$L_3 = \{\{d_l, C_1\} | \{d_l, C_1\} \in L$, such that $\nexists \{d_l, C_2\} \in L_{CIC}\}$;

return $L_1 \cup L_2 \cup L_3$;

end

5 Implementation

We developed a small example of a medical diagnostic system as a test for the theory developed herein. This diagnostic system deals with food-borne diseases which is a domain of application where temporal information is very important. The domain included all 28 diseases presented in [Man90, chap. 86], which amounted to around 60 different symptoms.

The whole knowledge base was developed in four days, based mainly on that medical manual. A specialist was consulted once during the development phase, mainly to provide the categorical information on the manifestations of each disease, since such information was not always available (or was unclear) in the manual. The specialist also verified the temporal graphs for some of the diseases. The total time of consultation with the specialist was arround two hours.

A version of the knowledge base without the categorical or temporal information was also developed. The intention was to compare the efficiency and accuracy of the diagnostic algorithm for both the ct-PCT and the original PCT, which would use this restricted knowledge base.

When developing the knowledge base we faced two main problems. The first was that categorical information was not readily available in the medical manuals [Man90, Ber92]. We had to consult the specialist for that information, and in some cases where the manual would provide categorical information, the specialist's opinion would disagree with that.

The second problem, which was already identified in [Pen90], is that PCT does not deal with the fact that diseases and specially manifestations are organized into hierarchies: particular manifestation m_a may be a specialization of another manifestation m_b. PCT does not define what should be done if the disease expect m_b but we have information that the more specific m_a did occur, or the reverse, if the disease expects m_a but the only available information is that the more general m_b occurred. We had this problem in the case of two diseases: *Chinese restaurant syndrome* which has as one of its manifestations paresthesias, and *paralytic shelfish poisoning (PSP)* which has paresthesias of the lips, tongue and throat as manifestations [Man90]. We decided to treat paresthesias and paresthesias of the lips, tongue and throat as four different manifestations.

We tested the system with some artificial (non-clinical) cases and the solution was verified by the specialist. For a particular case, the `ct-BIPARTITE` (with the temporal/categorical knowledge base and with some temporal information about the case) performed 70% faster than the `BIPARTITE` algorithm (with the atemporal knowledge base and atemporal case). For this case, the `ct-BIPARTITE` found only one explanation with one cause, against 6 explanations with one cause for the `BIPARTITE`. The number of explanations with two causes in the solution was 2 for the `ct-BIPARTITE` against 73 for the

BIPARTITE.

The ct-BIPARTITE algorithm and the original BIPARTITE algorithm used for comparison were implemented in Arity Prolog on a PC-286 computer. Although it is an information of limited utility, the ct-BIPARTITE program would compute the solution for problems in this domain in two seconds, on the average.

6 Conclusions

This work has presented two extensions of the original Parsimonious Covering Theory. The first extension allows one to associate to each disorder an evolution of manifestations, and the second allows one to add categorical information about the necessity or possibility of a manifestation occurring in a disease. We believe that the two extensions can be treated independently, that is one is about time, and the other a weakening of the probabilistic causal model [Pen90], in which only the information whether a manifestation is necessary or possible is used.

The temporal/categorical extension to PCT has some limitations. First, it does not allow for cycles in the temporal graphs. This poses some limits on the adequacy of the representation to model some phenomena. For example, in medical diagnostics, few but important diseases have recurrent events. Malaria is one of them [Ber92]: one distinguishes different forms of malaria by the period between the re-occurrence of the fever episodes.

Second, it does not allow to state that a observation has already happened and is no longer present without stating explicitly the time and duration for the observation. We believe that this limitation is a severe one, specially for medical domains, and we are currently working to solve it.

Another important limitation refers to multiple simultaneous disorders. PCT assumes that multiple disorders that cause the same manifestation do not interfere with each other. That is, if both d_i and d_j cause m_k then they can both be part of an explanation for the observation m_k. Unfortunately, in the presence of temporal information it is very unlikely that two disorders will not interfere with each other. As an example, let us suppose that d_i causes m_k with duration I and d_j causes m_k with duration J. Then certainly the presence of both disorders simultaneously will cause some change on the duration of m_k (the same can be true for the temporal relation of m_k with other manifestations in both d_i and d_j). This has been documented in other areas of medical diagnostics [Pat81]. PCT, and therefore our extension to it, cannot represent and deal with this interference. In the example above, if either I and J are mutually inconsistent ($I \cap J = \emptyset$) or either one of them is inconsistent with the duration of the observation m_k ($DUR^+(m_k) \cap I \cap J = \emptyset$) then the hypothesis that contains both d_i and d_j will be discarded as temporally inconsistent with the case. How to represent interference among disorders and how to incorporate it to the PCT and its extensions are important research topics that still need to be investigated.

This PCT extension presented in this paper suggested a few lines of further research, some of them derived from the limitations of PCT itself, and others derived specifically from the temporal aspects of this theory. As PCT related issues we can mention:

- development of domain specific heuristics to rank explanations. The explanations in a solution set should be ranked so that more "relevant" explanations are presented before "less relevant" ones. A possible domain independent heuristics would be to include probabilistic information in the knowledge base and rank the explanations according to their posterior probabilities. But there are a set of domain specific heuristics which must be explored. In the medical domain, for example one can rank the explanations based on the severity of future developments of the diseases (an explanation that contains a mortal disease should gain "relevance"), urgency of the treatment (an explanation that contains a disease that must be treated as soon as possible should also gain "relevance").

- development of algorithms and heuristics for question asking. Asking questions about the presence or absence of a manifestation involves both algorithmic and heuristics aspects. On the algorithmic side one would want to reduce the number of explanations in the solution set. If the knowledge base contains categorical information, then asking for manifestations that are necessary for the diseases that belong to the current explanations may reduce the number of these explanations if they were not present. If the knowledge base only contains temporal information, then one should ask for the manifestations that have not been checked that belong to the diseases in the explanation, in the hope that if present, the temporal information will make some of the diseases inconsistent. The algorithm would have to evaluate which question would be most effective in reducing the solution set.

  On the heuristic side, one has to take into consideration that in medicine, investigating the presence of a manifestation may involve tests, which may be costly, life-threatening, take a very long time to yield the results, and so on. The heuristics has to balance the impact of the information gained by performing the test against the many costs of performing it.

- extending the PCT theory to deal with interference among disorders, as discussed above.

On the specific temporal aspects of the theory, a research issue were brought up by the physicians questions on the idea of temporal inconsistency. Some of the specialists where uncomfortable by the fact that a disease would be disconsidered from the explanations based on the fact that it was temporally inconsistent with the case. We believe that this uneasiness derives from a conceptual difference between how intervals are used by the physician in a diagnostic and by this model. In this model, the interval denotes the *maximum possible* range for a time measure (distance or duration), whereas for the physician it represents the *typical* range for that measure. Thus the fact that a measure does falls within the typical interval should not be enough to characterize the measure as inconsistent with the interval.

This suggests that temporal consistency should not be a boolean attribute, but a fuzzy one: if a measure falls within the typical interval, it is fully consistent, and its consistency would decrease the further away from the is from the typical interval. The idea of fuzziness must then be carried over to all concepts in the model.

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