

Generation and revision of Delayed Biological Regulatory Systems

Emna Ben Abdallah¹, Tony Ribeiro^{1,2}, Morgan Magnin^{1,3}, Olivier Roux¹, and Katsumi Inoue³

¹ LUNAM Université, École Centrale de Nantes, IRCCyN UMR CNRS 6597 (Institut de Recherche en Communications et Cybernétique de Nantes), 1 rue de la Noë, 44321 Nantes, France.

² The Graduate University for Advanced Studies (Sokendai), 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8430, Japan

³ National Institute of Informatics, 2-1-2, Hitotsubashi, Chiyoda-ku, Tokyo 101-8430, Japan.

Abstract. The modeling of biologicals systems relies on background knowledge, deriving either from literature and/or the analysis of biological observations. But with the development of high-throughput data, there is a growing need for methods that are able to automatically generate (resp. revise) the existing models with regard to new (resp. additional) observations obtained by biologists. Our research aims at providing a logical approach to generate (resp. to revise) biological regulatory networks thanks to time series data, *i.e.*, gene expression data depending on time. In this paper, we propose new methodology for models expressed through a timed extension of the Process Hitting framework (which is a restriction, well suited for biological systems, of networks of synchronizing timed automata). The revision methods we introduce aim to make the minimum amount of modifications (addition/deletion of actions between biological components) to a given input model so that the resulting model is the most consistent as possible with the observed data. We illustrate the merits of our method in a two fold way: (1) we exhibit the benefits of such automatic approach on qualitative model proposed through Dream challenge 4; (2) we lead computational experiments on this benchmark to show the performances of our algorithm.

Keywords: network construction, network revision, dynamic modelisation, biological regulatory networks, time-varying genetic networks, Process Hitting

1 Introduction

With both the spread of numerical tools in every part of daily life and the development of NGS methods (New Generation Sequencing methods), like DNA microarrays in biology, a large amount of time series data is now produced every day, every minute, every second [16]. This means that the number of experiments - and corresponding data - led on a biological system grows drastically. The

newly produced data - as long as the associated noise does not raise an issue with regard to the precision and relevance of the corresponding information - can give us some new insights on the behavior of a system. This justifies the urge to design efficient revision methods that are able to update previous knowledge on a model with regard to additional information. In other words, there is a strong need for automatic methods that update a given model so that the dynamics of the model is consistent with given observations and a set of criteria (for example, minimize the number of modifications).

Network completion has been the subject of numerous recent works. In [3], the authors targeted the completion of stationary Boolean networks. This method has been further refined along the years. Latest works [18] focus on completion in Time Varying Genetic Networks. These are networks whose topology does not change through time, but the nature of the interactions (activation, inhibition, or no interaction) between components may change at some (finite number of) time points. The completion approach (which, in these authors' papers, refers to both addition and deletion of interactions, making it a synonym of revision) has been successfully applied to biological case-studies, for example the DREAM4 Challenge [20], and the implementation has been improved through heuristics [19]. The method however is limited to acyclic networks.

Logical-based approaches may be also fruitful to network revision. It has been successfully applied to causal networks [15] and molecular networks represented with the SBGN-AF language [26].

Despite being a proper research area, revision is strongly connected to model inference. Starting from an empty model, revision may indeed be used to model from gene expression data. On the reverse, existing inference algorithms may be an inspiration for new revision methodologies. In particular, Answer Set Programming (ASP), a form of declarative programming that has been successively used in many knowledge representation and reasoning tasks [21,4,5] has been proven useful for network reconstruction [9] and inference of metabolic networks [25].

To our knowledge, no works have been led so far in the field of revision of timed models, without any restriction on the structure of the network.

In this paper, we aim to provide a logical approach to tackle the revision of qualitative models of biological dynamic systems, like gene regulatory networks. In our context, we assume the set of interacting components as fixed and we consider potential additions/deletions of interactions between components. The main originality of our work is that we address this problem in a timed setting, with quantitative delays potentially occurring between the moment an interaction activated and the moment its effect is visible. It allows for example to catch delays between the activation of a gene, and the moment the concentration of a gene reaches a qualitative threshold.

During the past decade, there has been a growing interest for the hybrid modeling of gene regulatory networks with delays. These hybrid approaches consider various modeling frameworks. In [17], the authors hybrid Petri nets: the advantage of hybrid with regard to discrete modeling lies in the possibility of capturing

biological factors, e.g., the delay for the transcription of RNA polymerase. The merits of other hybrid formalisms in biology have been studied, for instance timed automata [24] and hybrid automata [2]. Finally, in [8], the authors investigate a direct extension of the discrete René Thomas’ modeling approach by introducing quantitative delays. These delays represent the compulsory time for a gene to turn from a discrete qualitative level to the next (or previous) one. They exhibit the advantage of such a framework for the analysis of mucus production in the bacterium *Pseudomonas aeruginosa*. The approach we propose in this paper inherits from this idea that some models need to capture these timing features.

In order to address the formal checking of dynamical properties within very large BRNs, we previously introduced in [22] a new formalism, named the “*Process Hitting*” (PH), to model concurrent systems having components with a few qualitative levels. Being a particular restriction of asynchronous automata networks or safe Petri nets, Process Hitting can be applied to complex dynamical systems with a very large number of interacting components, where each of these components can be described with a few internal states. In this paper, following recent works enriching (by adding priorities) the expressivity of PH while preserving its efficiency [12], we extend PH with quantitative timing features and exhibit efficient ASP-based approaches to perform network revision.

As readers may not be familiar with PH, we briefly introduce it in section 2, then give in section ?? some preliminary insights about recent translation of PH into ASP presented in [6]. All theoretical and practical notions are then settled to introduce our timed extension of PH, and related completion algorithm in section 3. Then we illustrate the merits of our approach in section 4 by first applying it on a simplified model of mammalian circadian clock [7], then discussing the practical results on a range of benchmarks from bioinformatics literature. Finally, in section 5, we summarize our contribution and give some perspectives for future works.

2 Process Hitting

Definition 1 introduces the Process Hitting (PH) framework [22] which allows to model a finite number of local levels, called *processes*, grouped into a finite set of components, called *sorts*. A process is noted a_i , where a is the sort’s name, and i is the process identifier within sort a . At any time, exactly one process of each sort is *active*, and the set of active processes is called a *state*.

The concurrent interactions between processes are defined by a set of *actions*. Each action is responsible for the replacement of one process by another of the same sort conditioned by the presence of at least one other process in the current state. A normal action is denoted by $a_i \rightarrow b_j \uparrow b_k$, which is read as a_i *hits* b_j to make it *bounce* to b_k , where a_i , b_j , b_k are processes of sorts a and b , called respectively *hitter*, *target* and *bounce* of the action. We also call a *self-hit* any action whose hitter and target sorts are the same, that is, of the form: $a_i \rightarrow a_i \uparrow a_k$. The original Process Hitting framework contains only actions with

one hitter but it should be noted that during these last years it was gradually enriched with new type of sorts like cooperative sorts and new actions like plural actions [11] (at least 2 hitters), actions with priority [13] and actions with delay.

The PH is therefore a restriction of asynchronous automata, where each transition changes the local state of exactly one automaton, and is triggered by the local states of at most two distinct automata. This restriction in the form of the actions was chosen to permit the development of efficient static analysis methods based on abstract interpretation [23].

Definition 1 (Process Hitting). A Process Hitting is a triple $(\Sigma, \mathcal{L}, \mathcal{H}_p)$ where:

- $\Sigma = \{a, b, \dots\}$ is the finite set of sorts;
- $\mathcal{L} = \prod_{a \in \Sigma} \mathcal{L}_a$ is the set of states where $\mathcal{L}_a = \{a_0, \dots, a_{l_a}\}$ is the finite set of processes of sort $a \in \Sigma$ and l_a is a positive integer, with $a \neq b \Rightarrow \mathcal{L}_a \cap \mathcal{L}_b = \emptyset$;
- $\mathcal{H}_p = \{A \rightarrow b_j \uparrow b_k \text{ with } A \in \mathcal{L}^\diamond \wedge b \in \Sigma \wedge b_j \neq b_k \wedge \text{if } b_j \in A \Rightarrow A = b_j\}$ is the finite set of actions. With \mathcal{L}^\diamond the set of all the sub-states of \mathcal{L} .

Example 1. The figure 1 represents a $\mathcal{PH}(\Sigma, \mathcal{L}, \mathcal{H})$ with three sorts ($\Sigma = \{a, b, c\}$) and: $\mathcal{L}_a = \{a_0, a_1\}$, $\mathcal{L}_b = \{b_0, b_1\}$, $\mathcal{L}_z = \{z_0, z_1, z_2\}$.

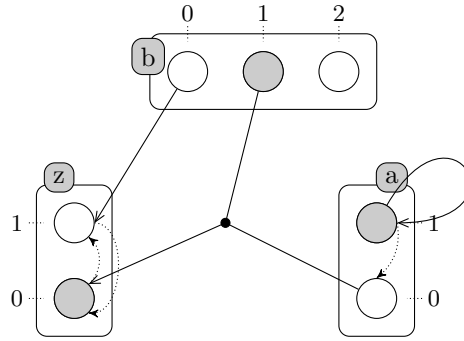


Fig. 1. A PH model example with three sorts: a , b and z (a is either at level 0 or 1, b at either level 0, 1 or 2 and z at either level 0, or 1). Boxes represent the *sorts* (network components), circles represent the *processes* (component levels), and the 3 *actions* that model the dynamic behavior are depicted by pairs of arrows in solid and dotted lines. A self-action: $a_1 \rightarrow a_1 \uparrow a_0$, a mono-action: $b_0 \rightarrow z_1 \uparrow z_0$ and plural action $a_0 \wedge b_1 \rightarrow z_0 \uparrow z_1$. The grayed processes stand for the possible initial state: $\langle a_1, b_1, z_0 \rangle$.

A state of a given PH consists in a set of active processes containing a single process of each sort. The active process of a given sort $a \in \Sigma$ in a state $s \in \mathcal{L}$ is noted $s[a]$. For any given process a_i we also note: $a_i \in s$ if and only if $s[a] = a_i$. The dynamic of the PH networks is performed thanks to the actions. Indeed, the transition from one state s_1 to its successor s_2 is done when there is a playable

action (definition 4) at s_1 . After each transition only one sort, or one component, changes its level from one process to another.

In some dynamics it is crucial to have information about the delays between two events (two states of a PH). Classic actions cannot exhibit this information: we just know chronology, i.e., that the state s_2 will be after s_1 in the next step but it is not possible to know chronometry, i.e., how much time this transition takes to occur. We propose to add the delay in the action attributes which is responsible of the transition between the two states. That means that this action needs to be played during a specific time so that the system does not change its state (Definition 2).

Definition 2 (Timed action). Let $\mathcal{PH} = (\Sigma, \mathcal{L}, \mathcal{H})$ be a process hitting and \mathcal{L}^\diamond be the set of all the sub-states of \mathcal{L} . A timed action of \mathcal{PH} is a action with a delay D : $A \xrightarrow{D} b_i \uparrow b_j$ where $D \in \mathbb{R}^+$, $A \in \mathcal{L}^\diamond$, and b_i, b_j where $b_i \neq b_j$ are two processes of the target sort b . If $b_i \in A$, $A = b_i$.

To model biological networks, we used the PH framework with timed actions (Definition ??). Indeed, in the biological models that we studied we need to present not only the cooperation between the components to influence another one (action), but also the time that this action need to take place (delays).

Definition 3 (Process Hitting with Timed Actions). A Process Hitting with timed actions is a triple $(\Sigma, \mathcal{L}, \mathcal{H}_{tp})$ where:

- $\Sigma = \{a, b, \dots\}$ is the finite set of sorts;
- $\mathcal{L} = \prod_{a \in \Sigma} \mathcal{L}_a$ is the set of states where $\mathcal{L}_a = \{a_0, \dots, a_{l_a}\}$ is the finite set of processes of sort $a \in \Sigma$ and l_a is a positive integer, with $a \neq b \Rightarrow \mathcal{L}_a \cap \mathcal{L}_b = \emptyset$;
- $\mathcal{H}_{tp} = \{A \xrightarrow{D} b_j \uparrow b_k \mid A \in \mathcal{L}^\diamond, b_j \neq b_k, b_i \in A \Rightarrow A = b_j\}$ is the finite set of timed actions.

Duration of actions can now be represented in a Process Hitting model thanks to timed actions. Note that if all actions delays are set to 1 it is equivalent to Process Hitting without delays (original PH). The way these new actions should be used is described as follows.

Definition 4 (Playable timed action). Let $\mathcal{PH} = (\Sigma, \mathcal{L}, \mathcal{H}_{tp})$ be a PH with timed actions and $s \in \mathcal{L}$ a state of PH. We say that the action $h = A \xrightarrow{D} b_i \uparrow b_j$ is playable in state s if and only if $A \subseteq s$ and $b_i \in s$.

Even if there already exists a few hybrid formalisms, we chose to propose this extension of the PH framework for several reasons. First, PH is a general framework that, although it was mainly used for biological networks, allows to represent any kind of dynamical models, and converters to several other representations are available. Although an efficient dynamical analysis already exists for this framework, based on an approximation of the dynamics, it is interesting to identify its limits (especially the fact that previous studies were focusing only on discrete, not timed, dynamics) and compare them to the approach we present

later in this paper. Finally, the particular form of the actions in a PH model allows to easily represent them in ASP, with one fact per action, as described in the next section. Other representations may have required supplementary complexity; for instance, a labeling would be required if actions could be triggered by a variable number of processes. We now show how to represent the previous definitions through ASP.

3 Revision of PH networks

3.1 Algorithm

In this section we propose a simple algorithm to revise Process Hitting networks. We assume that new observation data are provided as a *chronogram* of size T : the value of each variable is given for each time step t , $0 \leq t \leq T$, through a time interval discretization. This algorithm takes as input a Process Hitting and a chronogram of genes evolutions of this network. Knowing the genes' influences (or assuming all possible influences), this algorithm will complete the input network by adding the delayed actions that could have realized the changes observed in the chronogram. Algorithm 1 shows the pseudo code of our algorithm. If the observations are perfect, it will generate all possible actions that can realize each change observed. Because of the delayed semantics, it is not possible to decide whether an action is correct or not. But we can output the minimal sets of actions necessary to realize the changes observed. If the observations are not perfect, we can merge actions by replacing the one that only differs by the delay by one action whose delay is the average one. The intuition is that, in practice, if there are enough observations, the delay of those actions should tend to the real value.

Theorem 1 (Completeness). *Let PH be a Process Hitting, C be a chronogram of the genes of PH and A be the set of actions of PH that realized the chronogram C . Let PH' be a Process Hitting and A' be the set of actions of PH' such that $A' \subseteq A$. Given PH' and C as input, Algorithm 1 (without step 2) is complete: it will output a set of process hitting S , such that $\exists PH'' \in S$ with A'' the set of actions of PH'' such that $A'' = A' \cup A$.*

Proof. Let us suppose that the algorithm is not complete, then there is an action $a \in A$ that realized C and $a \notin A''$. After step 1.2, PH'' contains all actions that can realized each gene change. Here there is no action $a \in A$ that realized C which is not generated by the algorithm, so $a \in A''$. Then it implies that at step 3, the action a is removed from A'' . But since a realized one the change of C and a is generated at step 1, then it will be present in one of the minimal subset of actions. And a will be in one of the network outputted by the algorithm. \square

Theorem 2 (Complexity). *Let PH be a Process Hitting, S be the number of sorts of PH and P be the maximal number of processes of a sort of PH . Let C be a chronogram of the genes of PH over T units of time, such that c is the number of gene change of C . The memory use of our algorithm belongs*

Algorithm 1 PH-Completion($PH, Chronogram, Influences, indegree$)

- INPUT: a Process Hitting PH , a chronogram C of the genes evolution of PH , the genes influences and a maximal action in-degree i .
- Let $A := \emptyset$
- Step 1: For each time where a gene G changes its value from P to P' in C :
 - Let D be the delay since the last time a gene has changed.
 - Generate all actions with delay D which involve all subsets of size i of the genes S_1, \dots, S_n having an influence on G :

$$a := action(S_1, P_1, \dots, S_n, P_n, G, P, P', D)$$

- Add all action a in A
 - Step 2 (optional): Merge each action with the same hitters, $S_1, P_1, \dots, S_n, P_n$ and the same target, G, P, P' , into one action where the delay is the average.
 - Step 3: Generate S the set of all subsets of actions of A that realize C such that:
 - A is minimal:

$$\forall A \in S, \nexists A' \in S, A' \subset A$$
 - Atmost one delay per action: $\forall h \in A$, where $h = A \xrightarrow{D} b_j \uparrow b_k$, $\nexists h' \in A$, such that $h' = A \xrightarrow{D'} b_j \uparrow b_k$, $D \neq D'$.
 - OUTPUT: S a set of completed Process Hittings that realize the chronogram.
-

to $O(T \times P \times i^S \times 2^{T \times P \times i^S})$ that is bound by $O(T \times P^{S+1} \times 2^{T \times P^{S+1}})$. The complexity of completing PH by generating actions from the observations of C with Algorithm 1 belongs to $O(c \times i^S + (T \times P \times i^S)^2 + 2^{2 \times T \times P \times i^S} + c \times 2^{T \times P \times i^S})$ that is bound by $O(2^{3 \times T \times P^{S+1}})$.

Proof. Let i be the maximal indegree of an action in PH, $0 \leq i \leq P$. Let p be a process of PH and n be the number of sorts that can influence p . There is i^S possible combinations of those process that can hit p , each of those can form an action. There is P process and at most T possibles delay, so that there are $T \times P \times i^S$ possibles actions, thus at step 1, the memory of our algorithm is bound by $O(T \times P \times i^S)$, which belongs to $O(T \times P^{S+1})$ since $0 \leq i \leq P$. Generating all minimal subsets of actions A of PH' that realize C can require to generate at most $2^{T \times P \times i^S}$ set of rules. Thus, the memory of our algorithm belongs to $O(T \times P \times i^S \times 2^{T \times P \times i^S})$ and is bound by $O(T \times P^{S+1} \times 2^{T \times P^{S+1}})$.

Merging the actions at step 2 is polynomial in the number of actions and the complexity of this operation belongs to $O((T \times P \times i^S)^2)$. The complexity of this algorithm belongs to $O(c \times i^S + (T \times P \times i^S)^2)$. Since $0 \leq i \leq P$ and $0 \leq c \leq T$ the complexity of Algorithm 1 is bound by $O(T \times P^S + (T \times P \times P^S)^2) = (T \times P^S + T^2 \times P^{2S+2})$.

Generating all minimal subsets of actions A of PH' that realize C can require to generate at most $2^{T \times P \times i^S}$ set of rules. Each set has to be compared with the others to keep only the minimal ones, which costs $O(2^{2 \times T \times P \times i^S})$. Furthermore, each set of actions has to realize each change of C , it requires to check c changes and it costs $O(c \times 2^{T \times P \times i^S})$. Finally, the total complexity of completing PH by generating actions from the observations of C belongs to $O(c \times i^S + (T \times P \times i^S)^2 + 2^{2 \times T \times P \times i^S} + c \times 2^{T \times P \times i^S})$ that is bound by $O(T \times P^S + (T \times P^{S+1})^2 + 2^{2 \times T \times P^{S+1}} + T \times 2^{T \times P^{S+1}})$ □

4 Evaluation

4.1 Application: Circadian clock

Figure 2 shows the circadian clock model of [7]. The right part shows a chronogram of the gene evolution of the circadian clock. The abscisse axe represents time steps in hours and ordinate represents the gene value. In this example we observe the evolution of genes G and PC during the night (L is fixed to 0). Here we can see the 7 (resp. 5) hours of delay shift of PC (resp. G) from 1 to 0 and vice versa. Indeed, PC and G respectively change their state 7 hours and 5 hours after a change occurs in the system.

The left part of Figure 3 shows the circadian clock represented as a Process Hitting with timed plural actions. Here, the light L , the gene PC and G are represented by sorts with two processes. The light clock is represented by an autonomous temporized sort: there are only auto-actions. Actions are represented by edges as follows: when a node have incoming edge its the target of an action and the hitters of this action are the nodes where those edges are coming. Each

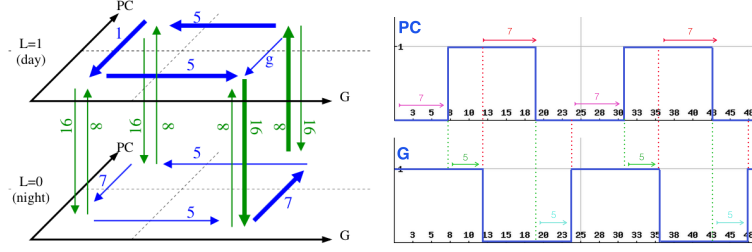


Fig. 2. The first figure is taken from [8], it presents the qualitative model of the mammalian circadian cycle during the summer. The second one is a chronogram corresponding to the discretization of the observed data set of a circadian clock components during the night ($L=0$).

action is labelled by its delay. Right part of the figure shows the representation of the circadian clock with the ASP formulation we presented in section ??.

4.2 Experiments

In this section, we evaluate our approach on learning the circadian clock actions. All experiments are run with a ASP implementation of Algorithm 1 on a processor Intel Xeon (X5650, 2.67GHz) with 12GB of RAM.

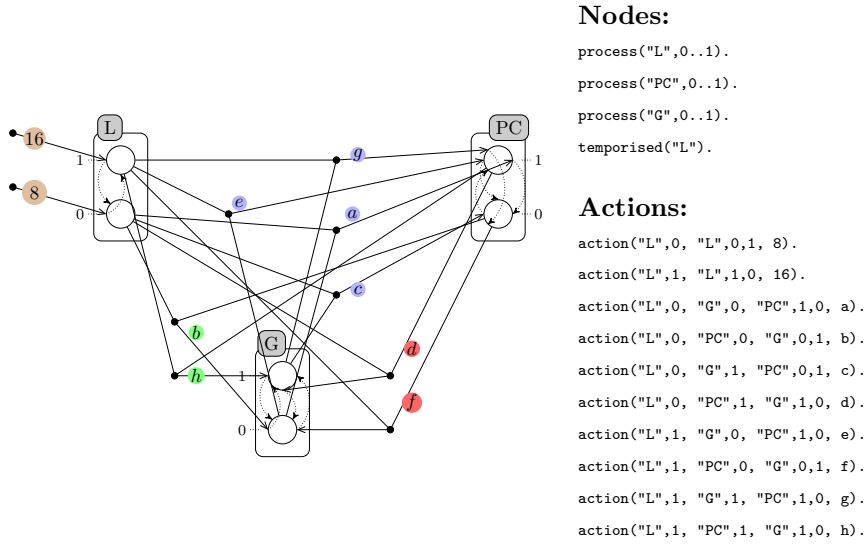


Fig. 3. Representation of circadian clock in Process Hitting (left) and the equivalent ASP representation (right). The value "a", "b", ..., "h" represent the delays in actions.

When the ASP representation of a chronogram like the one of Figure 2 is given as input to Algorithm 1 it will generate all the timed actions that can induce the observed changes. The delay of the action is simply determined from the time delay between two changes.

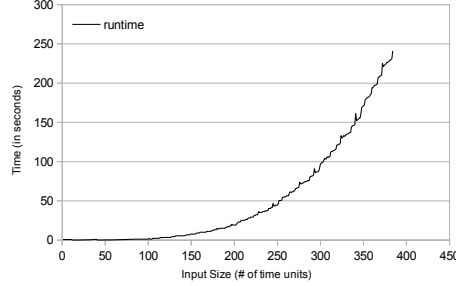


Fig. 4. Run time of the application of Algorithm 1 on circadian clock chronograms varying the number of time steps.

Figure 4 shows the evolution of run time of our ASP implementation of Algorithm 1 on the inference of the circadian clock actions regarding the quantity of input data. In this experiment, we analyse the scalability of our approach by varying the number of time units of the input, i.e. the size of the chronogram. Here we can see that the time needed to analyse the input data grows exponentially. The experiments stop at 384 because the memory required by the ASP solver reached the 12GB of RAM we have. It is currently quite difficult to obtain real data from biological system with chronogram exceeding 100 points. In work like [10] the considered chronograms are only composed of about 10 points. Regarding the circadian clock, a chronogram of 100 data points is about 4 days of data, that is not much information, especially in cases where we want to analyze the effect of perturbations (for example, understand the recoverability phase in case of jet-lag).

5 Conclusion and perspectives

In this paper, we proposed an approach to automatically infer timed models of Process Hitting from time series data (expressed as chronograms). To do so, we implemented our algorithm in ASP. We illustrated the applicability and limits of the method through various benchmarks. This opens the way to promising applications in the connection between biologists and computer scientists. Further works will now consist in discussing the kind of information one can get on timed Process Hitting by analyzing the associated untimed model. We also plan to improve our implementation to make it robust against noisy data.

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