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Learning temporal nodes Bayesian networks

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ABSTRACT

Temporal nodes Bayesian networks (TNBNs) are an alternative to dynamic Bayesian networks for temporal reasoning with much simpler and efficient models in some domains. TNBNs are composed of temporal nodes, temporal intervals, and probabilistic dependencies. However, methods for learning this type of models from data have not yet been developed. In this paper, we propose a learning algorithm to obtain the structure and temporal intervals for TNBNs from data. The method consists of three phases: (i) obtain an initial approximation of the intervals, (ii) obtain a structure using a standard algorithm and (iii) refine the intervals for each temporal node based on a clustering algorithm. We evaluated the method with synthetic data from three different TNBNs of different sizes. Our method obtains the best score using a combined measure of interval quality and prediction accuracy, and a competitive structural quality with lower running times, compared to other related algorithms. We also present a real world application of the algorithm with data obtained from a combined cycle power plant in order to diagnose temporal faults.

1. Introduction

Bayesian Networks [18] have been studied as a popular technique to deal with uncertainty. They have proven to be successful in different applications, such as medical diagnosis, crime risk factor analysis, sensor validation and customer analysis [19,20,12,7], among others. However, traditional Bayesian Networks cannot deal with temporal information. For this reason, an extension called Dynamic Bayesian Networks (DBNs) [5] was introduced. DBNs can be seen as multiple slices of a *static* BN over time, with links between adjacent slices. Nonetheless, these models may become quite complex, in particular when only a few important events occur over time.

Temporal Nodes Bayesian Networks (TNBNs) [1] are another extension of Bayesian Networks. They belong to a class of temporal models known as *Event Bayesian Networks* [10]. TNBNs were proposed to manage uncertainty and temporal reasoning. In a TNBN, each Temporal Node has intervals associated to it. Each node represents an event or state change of a variable. An arc between two Temporal Nodes corresponds to a causal-temporal relation. One interesting property of this class of models, in contrast to Dynamic Bayesian Networks, is that temporal intervals can differ in number and size.

TNBNs have been used in diagnosis and prediction of temporal faults in a steam generator of a fossil power plant [1]. The problem is that there does not exist an algorithm to learn TNBNs models, so the model has to be obtained from external sources such as domain experts. This can be a hard and prone to error task.

In this paper, we propose a learning algorithm to obtain the structure and the temporal intervals for TNBNs from data. The learning algorithm consists of three phases. In the first phase, we obtain an approximation of the intervals using a simple algorithm such as equal-width discretization (EWD) or a K-means clustering approximation. For the second phase, the BN structure is obtained with the structure learning algorithm introduced in [3]. The last step is performed to refine the intervals for each Temporal Node. This refinement uses the structure obtained in the previous step in order to improve the

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intervals. For this, our algorithm obtains a number of possible sets of intervals for each configuration of the parents. We used a clustering approach to obtain the intervals, more specifically the algorithm models the data based on a Gaussian mixture model. Each component of the mixture corresponds to an interval. Given that our algorithm obtains different intervals, we applied two pruning techniques to discriminate some intervals and to increase the efficiency of our algorithm. From the remaining intervals, our algorithm selects the set of intervals that maximizes the prediction accuracy.

We evaluate our algorithm with three synthetic examples of TNBNs. The data was generated with different distributions. We compare our algorithm with two baselines: K-means and Equal-width discretization. We also compare it to the algorithm proposed in [9]. In the experiments, our algorithm obtains the best score in terms of a combined measure that takes into account predictive accuracy and interval quality. Our algorithm also obtained lower running times. Finally, we present an application of the algorithm with real data obtained from a power plant simulator in order to diagnose and predict temporal faults.

The paper is organized as follows. In Section 2, the Temporal Nodes Bayesian Network model is described. In Section 3, we present related work about learning TNBNs. In Section 4, we introduce the proposed learning algorithm called LIPS (Learning Intervals-Parameters-Structure). In Section 5, we present an overview of experiments and measures used to evaluate our algorithm. The results of the algorithm with synthetic data are described in Section 6. In Section 7, we show the results of applying LIPS to a real world application. In Section 8, we present our conclusions and ideas for future research.

2. Temporal nodes Bayesian networks

Bayesian networks (BNs) are a successful model for dealing with uncertainty. However, *static* BNs are not suited to deal with temporal information. For this reason, Dynamic Bayesian Networks [5,4] were introduced. In a DBN, a copy of a base model is made for each time stage. These copies are linked via a transition network. In this transition network it is common that only links between consecutive stages are allowed (Markov property). The problem is that DBNs can become very complex. This is unnecessary when dealing with problems for which there are only a few changes for each variable in the model. Moreover, DBNs are not capable of managing different levels of time granularity. They usually have a fixed time interval between stages.

A Temporal Nodes Bayesian Network (TNBN) [1,10] is composed of a set of Temporal Nodes (TNs). TNs are connected by edges, each edge represents a causal-temporal relationship between TNs. There is at most one state change for each variable (TN) in the temporal range of interest. The value taken by the variable represents the interval in which the event occurs. Time is discretized in a finite number of intervals, allowing a different number and duration of intervals for each node (multiple granularity). Each interval defined for a child node represents the possible delays between the occurrence of one of its parent events (cause) and the corresponding child event (effect). Some Temporal Nodes do not have temporal intervals, these correspond to Instantaneous Nodes. Root nodes are instantaneous by definition [1]. Formally, a TNBN is defined as follows.

Definition 1. A TNBN is defined as a pair $B = (G, \Theta)$. G is a Directed Acyclic Graph, $G = (\mathbf{V}, \mathbf{E})$. G is composed of $\mathbf{V}$, a set of Temporal and Instantaneous Nodes; $\mathbf{E}$ a set of edges between Nodes. The Θ component corresponds to the set of parameters that quantify the network. Θ contains the values $\Theta_{v_i} = P(v_i|Pa(v_i))$ for each $v_i \in \mathbf{V}$; where $Pa(v_i)$ represents the set of parents of v_i in G.

Definition 2. A Temporal Node, v_i, is defined by a set of states $\mathbf{S}$, each state is defined by an ordered pair $S = (\lambda, \tau)$, where λ is the value of a random variable and $\tau = [a, b]$ is the interval associated, with an initial value a and a final value b.These values correspond to the time interval in which the state change occurs. In addition, each Temporal Node contains an extra default state $s = (\text{“no change”}, \emptyset)$, which has no interval associated. If a Node has no intervals defined for any of its states, then it receives the name of Instantaneous Node.

The following is an example based on [1], its corresponding graphical representation as a DBN and a TNBN are shown in Fig. 1.

Example 1. Assume that at time $t = 0$, an automobile accident occurs, a Collision. This kind of accident can be classified as *severe*, *moderate*, or *mild*. To simplify the model, we will consider only two immediate consequences for the person involved in the collision, Head Injury and Internal Bleeding. Head Injury can bruise the brain, and chest injuries can lead to internal bleeding. These three are instantaneous events that will generate subsequent changes, for example the Head Injury event might generate Dilated Pupils and unstable Vital Signs. Suppose that we gathered information about accidents occurred in a specific city. The information indicates that there is a strong casual relationship between the severity of the accident and the immediate effect of the patient's state. Additionally, a physician domain expert provided some important temporal information: If a head injury occurs, the brain will start to swell and if left unchecked the swelling will cause the pupils to dilate within 0 to 60 min. If internal bleeding begins, the blood volume will start to fall, which will tend to destabilize vital signs. The time required to destabilize vital signs will depend on the bleeding severity: if the bleeding is gross, it will take