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Procedia Engineering 15 (2011) 3526 - 3530

Procedia Engineering

www.elsevier.com/locate/procedia

Advanced in Control Engineeringand Information Science

Quantitative Combination of Different Bayesian Networks

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Abstract

Bayesian network is a directed acyclic graph that each node has a conditional probability table. It is a knowledgebased system and could reason effectively under uncertainty. In most times, knowledge-based system will face the task of combining several systems from different sources or from the same source at different times. As a knowledgebased system, Bayesian network will also face the same problem. This paper presents a novel method to combine several Bayesian networks based on the research of property of conditional probability.

© 2011 Published by Elsevier Ltd. Selection and/or peer-review under responsibility of [CEIS 2011]Keywords: Bayesian network;

Knowledge-based system; Property of conditional probability

1. Introduction

Bayesian network was first proposed [1] by Pearl in 1986, and Jensen gave a straightforward definition [2] in 2001. Bayesian network can be expressed as: $B = (G, \Theta)$, where G is a directed acyclic graph, and each directed edge in the graph represents a dependence; Θ is a group of conditional probability tables (CPTs) corresponding to a node set which represents a set of variables. In the past few years, more and more scholars began to study it. Therefore a variety of effective algorithms of structure learning in Bayesian network has been proposed, among these, there are two classical algorithms: Cooper's method based on score and search (K2 algorithm) [3] and Cheng's method based on information-theory [4]. Although a large number of algorithms have been proposed, it is hard to decide which network obtained by these algorithms is absolutely reliable.

Currently researchers begin to realize the importance and necessity of combining two or even more Bayesian networks. Sagrado et al. proposed a method to combine Bayesian networks based on the union and intersection of independencies [5]. Li et al. proposed a method to combine Bayesian networks [6] based on the theorems proved by Wong: probabilistic conditional independence is equivalent to the

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notion of generalize multivalued dependency and a generalized acyclic join dependency is equivalent to a triangulated Markov network [7].

This paper presents a novel method to combine Bayesian networks based on the research of property of conditional probability. Section 2 describes the property of conditional probability; Section 3 describes the addition of conditional probability; Section 4 describes the learning procedure of combining two Bayesian networks; Section 5 concludes this work.

2. Property of conditional probability

Theorem 1 Given variables A and B, if A and B are independent then it meas P(A|B) = P(A). **Proof.** If A and B are independent, then the following equation holds

$$P(AB) = P(A)P(B) \tag{1}$$

and according to Bayes theorem, we have

$$P(AB) = P(A \mid B)P(B)$$
⁽²⁾

Compared Eq.(1) with Eq.(2), we can have P(A|B) = P(A). End of the proof.

Theorem 2 Given variables A and B, and any other variable C, if A and B are independent given C then it meas P(A|B,C) = P(A|C).

Table 1. The CPT of P(A|B)

P(A B)	b_0	b_I	
c_0	X_{00}	X_{10}	
c_1	X_{0I}	X_{II}	

Table 2. The CPT of P(A)



Theorem 1 and Theorem 2 are useful. If *A* and *B* are independent of each other, and the probability distribution of node *A* is shown in Table 2. It can be expressed in the form shown in Table 3. Since *A* and *B* are independent, then *B* can not affect the probability distribution of *A*, for $\Box b_j \in B$, $P(A = a_i | B = b_j) = P(A = a_i)$ always holds. According to that, two CPTs of same node can be combined by extending them into the same form, even if they are from different Bayesian networks and have different parent node set.

Table 3. The CPT of P(A) after extension

P(A B)	b_0	b_I	
a_0	X_0	X_0	
a_1	X_{l}	X_{I}	

Table 4. The CPT of P(A|B) after simplification

	a_0	a_1	
P(A)	X_{00}	X_{0I}	

Theorem 3 Given variables A, B and A is independent of B, if B takes different values, the distribution of A does not change.

(1)

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