

# Abductive inference in bayesian networks

David Quesada López

Computational Intelligence Group, Departamento de Inteligencia Artificial, Universidad Politécnica de Madrid, Spain

## Abstract

Abductive inference in bayesian networks solves the problem of obtaining the most probable explanation (MPE) of a network given some evidence of its nodes. This inference can be total, if you aim to obtain the MPE of the whole network, or partial, if you are only interested in some of the nodes. In this state of the art we will cover both approaches and the methods used to solve them.

KEY WORDS: Bayesian networks; Abductive inference; Approximate inference

## 1 Introduction

A Bayesian network is a directed acyclic graph (DAG) where you represent each node as a random variable and the edges represent the dependence or independence among them. Each node also has associated a conditional probability distribution conditioned to its parents that represents the probability distribution of the node's variable.

One of the problems associated with BNs is abductive inference, which consists in finding the maximum *a posteriori* probability (MAP) state of the network given some evidence on the state of variables of the network. In general, we are interested in the  $K$  most probable explanations (k-MPE). This problem is known to be NP-hard (Shimony (1994)), and most of the times trying to obtain an exact MPE turns out to be intractable. This is the reason why most researchers focus on getting  $K$  approximate MPEs instead of the exact one.

Abductive inference can also be called total, when we want to know the whole network's k-MPEs, or partial, when we only want the  $K$  most probable state assignments for a subset of the variables known as the explanation set (Fortier *et al.* (2013)).

In this state of the art, we will review some methods to perform total and partial abductive inference on a Bayesian network.

## 2 State-of-the-art

We can formally describe the problem of the k-MPE as: given a set of unobserved variables  $p(X_u)$ , a set of observed variables  $p(X_o)$ , we want to find the configuration  $p(x_u^*)$  such that:

$$x_u^* = \arg \max_{x_u} P(x_u | x_o) \quad (1)$$

Which means we are aiming to maximize the MAP state of the network by finding an appropriate  $p(x_u^*)$  (De Campos *et al.* (2002)).

Traditionally, there has been three solutions to this problem (De Campos *et al.* (2001)):

- Through the computation of the *chain rule*, which is intractable in even the simplest of networks

- Through belief propagation.
- Through abductive inference.

## 2.1 Total abductive inference

It has been proven that belief propagation and abductive inference are both equal in complexity when finding the MPE of a network (Dawid (1992)), however the problem of finding the k-MPE is a more complex one.

There are two ways of tackling this problem:

- With exact computation. This is the case of Dawid (1992), where a belief propagation algorithm was adapted to find the MPE of a network by replacing the summation by maximum in the message passing. This method was able to only find the first 3 MPEs of the network (Nilsson (1998)), so it had to be modified to be able to find the k-MPE.
- With approximate results. Here, we treat the problem as an optimization one. One approach was performed by Gelsema (1995) using a genetic algorithm (GA). In this method, each individual of the population represents a possible state of the network by representing the presence or absence of the nodes with a binary vector. Genetic programming is also used by Rojas and Kramer (1993) to solve this problem. Here, they represent the network's graph in each individual. Another method was proposed by Welch (1996), where he used a Montecarlo simulation to initialize the population and then used a GA similar to that of Gelsema.

## 2.2 Partial abductive inference

## 3 Conclusions and future research

What are the main open lines for research.

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