Expert Systems with Applications 40 (2013) 162–167

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A proposed validation framework for expert elicited Bayesian Networks

Jegar Pitchforth *, Kerrie Mengersen

Queensland University of Technology, Lvl 11, 126 Margaret St., Brisbane 4000, Australia

ARTICLE INFO

Keywords:
Expert
Validation
Bayesian Network
Sensitivity

ABSTRACT

The popularity of Bayesian Network modelling of complex domains using expert elicitation has raised questions of how one might validate such a model given that no objective dataset exists for the model. Past attempts at delineating a set of tests for establishing confidence in an entirely expert-elicited model have focused on single types of validity stemming from individual sources of uncertainty within the model. This paper seeks to extend the frameworks proposed by earlier researchers by drawing upon other disciplines where measuring latent variables is also an issue. We demonstrate that even in cases where no data exist at all there is a broad range of validity tests that can be used to establish confidence in the validity of a Bayesian Belief Network.

1. Introduction

Bayesian Networks (BNs) are an increasingly popular tool for modelling complex systems, particularly in the absence of easily accessed data. A BN describes the joint probability distribution of a network of factors using a Directed Acyclic Graph (Pearl, 1988). Factors that influence the likelihood of the outcome node being in any given state are represented as nodes on the graph. If the state of one model factor influences the state of another a directional arc is drawn between the two nodes representing these factors in the model. The combination of the nodes and their relationships is the BN structure. Each node in the graph can adopt any one of a finite set of states. For example, a factor representing magnitude could be classified as 'high' or 'low'. While nodes do not strictly have to be discretised the practice is by far more commonly undertaken than not due to its computational convenience, and as such we do not discuss models that include non-discretised nodes in this paper. Finally, each node and relationship between nodes is quantified according to the likelihood of the node adopting a given state. In the case of input nodes these probabilities are seen as unconditional, whereas nodes internal to the model are dependent upon the states of the preceding nodes. The strength and direction of the relationship between model factors is defined in the conditional probability table associated with the child node.

BNs are often created through a process of expert elicitation, in which experts are asked to create a complex systems model by giving their opinions on the model structure, discretisation, and parameterisation. The validity of these models is generally tested through one of two procedures: by comparing the model predictions to data available for the subject matter, or by asking the experts who contributed to the model creation to comment on its accuracy. This paper argues that these tests are limited in their ability to accurately test the validity of BNs, and presents a framework for more thorough validity testing. The work presented here stems from questions raised during the creation of a BN from expert elicitation to model the inbound passenger processing time at Australian airports. The network was elicited in collaboration with managerial and operational experts from Australian Customs and Border Protection Service (ACBPS) for the purpose of gaining more informative reporting of key performance indicators. In particular, the modelling of critical infrastructure underlined the importance of establishing that both experts and modellers have confidence in the final model produced. The paper is structured as follows. First, the concept of validation as it applies to BNs is introduced in Section 1.1. Second, the sources of confidence in BN validity are discussed, including network structure, discretisation, and parameterisation in Section 1.2. Third, prior approaches to validating latent and expert elicited scales and models are introduced, drawing from psychometrics, system dynamics and other BN research in Section 2. These principles are then applied to BNs with examples from the airport inbound passenger processing model in Section 3.

1.1. Confidence in Bayesian Belief Network validity

Model validity is often conceptualised as a simple test of a model's fit with a set of data. However validity is a much broader construct: in essence, validity is the ability of a model to describe the system that it is intended to describe both in the output and in the mechanism by which that output is generated. In this paper we consider this broader definition of validity. The need for an explicit

* Corresponding author. Tel.: +61 403 961 878.
E-mail address: jegar.pitchforth@qut.edu.au (J. Pitchforth).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2012.07.026

set of validity tests for BNs over and above comparisons with data is clear. In current practice, where data are available on the phenomenon of interest, these data may be used to validate model predictions. Several tests of this nature exist, such as a variety of Normal Maximum Likelihood model selection criteria (Silander, Ross, & Myllymaki, 2009). However, a common reason for using BN models is a lack of available data. Examples of phenomena for which data are scarce include population characteristics in many developing countries (Shakoor, Taylor, & Behrens, 1997), global epidemiological phenomena (Masoli, Fabian, Holt, & Beasley, 2004), organised crime (Sobel & Osoba, 2009), conservation (Johnson, 2009) and biosecurity risk analysis (Barrett, Whittle, Mengersen, & Stoklosa, 2010). In such cases, expert opinion can be elicited to create a Bayesian Belief Network (BBN). A common technique for validating BBNs based on expert opinion in the absence of data, is simply to ask the experts whether they agree with the model structure, discretisation, and parameterisation (see Korb & Nicholson (2010) for an excellent overview of BN applications and methods). This simple test is necessary, but not sufficient, to independently verify the validity of a complex model. Even where data are available, model fit is only a part of the model's overall validity. These considerations lead to this paper's proposition of a general validity framework for BNs.

1.2. Sources of confidence in Bayesian Network validity

In order to approach a validation framework for BNs, a short discussion of the background assumptions of this framework is required. First, we assume there exists a latent, unobservable 'true' model (or set of acceptable 'true' models) for the phenomenon of interest against which the expert elicited model can be compared. Second, for the purposes of the validity framework presented in this paper, we consider a BN model to consist of four elements: model structure (Section 1.2.1), node discretisation (Section 1.2.2), and discrete state parameterisation(Section 1.2.3). Each of these elements has been raised as a source of uncertainty in BN modelling. We provide a discussion of each element and consider the importance of validity within each model element, and within the model as a whole. The model elements are summarised in Fig. 1.

1.2.1. Structure

There are a number of questions when creating the structure of a BN. The first is the appropriate number of nodes to include which is a question of the modelling domain, level and scope. It is widely acknowledged that networks with a large number of nodes can easily become computationally intractable, as can networks with a large number of arcs between nodes (Koller & Pfeffer, 1997).

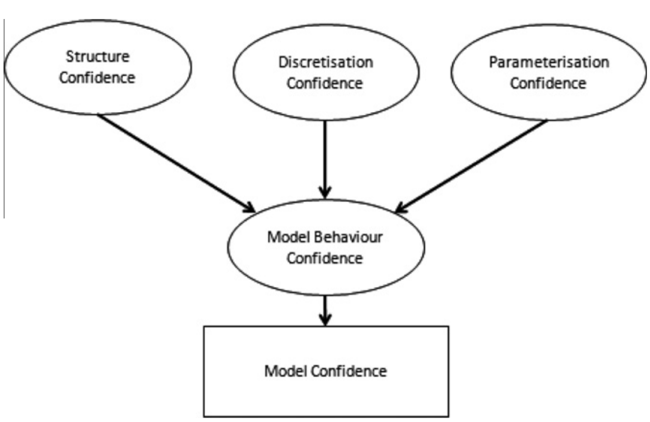

Fig. 1. Sources of confidence in Bayesian Network validity.

The BN creator should ensure that the model is neither too simple nor too complex in its explanation of the system.

1.2.2. Discretisation

The discretisation process allows us to model systems probabilistically by taking continuous factors and assigning them intervals, ordinal states or categories, then modelling over the discrete domain. In more recent research, Uusitalo (2007) pointed out that such discretisation is a major disadvantage of BN modelling if it is necessary for the model, and Myllymaki, Silander, Tirri, and Uronen (2002) outlines how the process has the potential to destroy useful information. Given the information loss inherent in the discretisation process, ensuring that the states are a valid interpretation of the state space of the node is critical for a defensible network.

1.2.3. Parameterisation

Parameterisation refers to adding the values elicited from experts to the belief network (Woodberry, Nicholson, Korb, & Pollino, 2005). Much work has been conducted on controlling this stage of the process (Renooij, 2001), but little has been written about how to validate expert responses post-elicitation.

1.2.4. Model behaviour

Finally, the behaviour of the model can be seen as the joint likelihood of the entire network as well as its sub-networks and relationships, hence confidence in model behaviour is founded upon the validity of the other three dimensions of the model. It is important to note that in the case of BNs, we are not only interested in whether the model can tell us what a system is doing under certain conditions, but also the factors and relationships that bring about this behaviour. This makes the problem of validating the model incredibly complex when attempted wholesale and justifies the need for partitioning the dimensions of uncertainty for BNs. As such it is recommended that the structure, discretisation and parameterisation are tested for validity before any model behaviour tests can be run.

2. Previous approaches to validity

2.1. Psychometrics

The discipline of psychometrics arose as a counterpart to the field of psychology, which at its foundation attempts to measure latent, unobserved, 'true' variables such as intelligence. Due to this rich tradition, the foundations of measurement validation in psychometry are particularly solid, and serve as a useful base to begin discussion of a similar framework for BNs. Psychometrics first identified four types of validity (Cronbach & Meehl, 1955); more recent research has reclassified and added dimensions of validity to establish a full validation framework (Trochim, 2001). Based on the framework depicted in Fig. 2, a psychometric test can pass all these tests of validity to varying degrees, providing a multidimensional measure of how well a particular test measures a latent variable. In psychometric testing there are seven commonly tested dimensions of validity: nomological validity, face validity, content validity, concurrent validity, predictive validity, convergent validity, and discriminant validity. In psychometrics, before any other tests of validity can be undertaken, the nomological validity of the validity domain should be established. High nomological validity indicates that the measurement sits well within current academic thought on the subject. Face validity refers to the heuristic interpretation of a measure as a valid representation of the underlying psychometric construct. Content validity describes both the inclusion of all variables believed to be within a domain and the