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# A method for root cause analysis with a Bayesian belief network and fuzzy cognitive map

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ABSTRACT

People often want to know the root cause of things and events in certain application domains such as intrusion detection, medical diagnosis, and fault diagnosis. In many of these domains, a large amount of data is available. The problem is how to perform root cause analysis by leveraging the data asset at hand. Root cause analysis consists of two main functions, diagnosis of the root cause and prognosis of the effect. In this paper, a method for root cause analysis is proposed. In the first phase, a causal knowledge model is constructed by learning a Bayesian belief network (BBN) from data. BBN's backward and forward inference mechanisms are used for the diagnosis and prognosis of the root cause. Despite its powerful reasoning capability, the representation of causal strength in BBN as a set of probability values in a conditional probability table (CPT) is not intuitive at all. It is at its worst when the number of probability values needed grows exponentially with the number of variables involved. Conversely, a fuzzy cognitive map (FCM) can provide an intuitive interface as the causal strength is simply represented by a single numerical value. Hence, in the second phase of the method, an intuitive interface using FCM is generated from the BBN-based causal knowledge model, applying the migration framework proposed and formulated in this paper.



## 1. Introduction

Identifying the root cause and effect of an event has become a very important issue in some domains such as security, medical, mechanical and others. Root cause analysis (RCA) is able to identify the relationship between the causes and effects of an event and perform diagnosis and prognosis. Diagnosis means finding the cause and prognosis means predicting the effect. The fuzzy cognitive map (FCM) and the Bayesian belief network (BBN) are the two major frameworks used in RCA. BBN is a powerful modelling tool in data-rich domains. It has an ability to learn from data. In addition, it supports an efficient evidence propagation mechanism, which is very useful in the RCA process. Moreover, BBN is a more mature framework than other RCA frameworks because many BBN software tools have been introduced to and commercialised in today's market, such as Hugin, Netica, BayesiaLab and others.

After the causal model of a domain is constructed, the presentation of causal knowledge is the next concern in this study. Representing causal knowledge in an intuitive way is vital, especially for knowledge acquisition and information sharing. FCM is simpler and more intuitive in interpreting causal knowledge than BBN (Cheah, Kim, Yang, Choi, & Lee, 2007). A good understanding of causal knowledge enables us to make successful causal reasoning and strategic decisions manually. A method which integrates the BBN and FCM is proposed in this paper to leverage the merits of both causal modelling approaches within a unified framework. The reasons for the integration are to reduce the human effort by learning the causal model from the data automatically and to present the model in an intuitive way. BBN is used to learn the causal model and to perform the RCA because of its expressiveness and powerful causal reasoning capability. FCM is used to present the causal knowledge in an intuitive way because of its simplicity.

In order to provide a powerful RCA capability using BBN and an intuitive presentation of causal knowledge using FCM, a method to migrate BBN to FCM is proposed. Although BBN and FCM are causal knowledge approaches which share some common features in their representation, there are also some differences between them. Hence, some modifications need to be made before the migration takes place. The first step of the method involves discovering the individual causal effects from a conditional probability table (CPT) as CPT represents the combination of multiple causal effects. Therefore, migration of BBN to FCM involves transforming a quantitative to a qualitative representation. A conditional probability equation

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is used to discover the probability of the increase for an event when the cause event has increased. The value is stored in a new CPT and the combination of positive influences calculated for subsequent use. The next step of the method generates an FCM-compatible BBN to address the range of difference between BBN and FCM by using Pearson's correlation coefficient equation. Once the fuzzy-compatible probability has been constructed and reorganised, the transformation from probability to possibility by adoption of Klir's equation will be performed. The causality sign will be determined at the last stage to generate a proper FCM.

## 2. Literature study

### 2.1. Root cause analysis (RCA)

There is a cause behind every problem. To avoid the problem persisting, localisation and elimination of its cause is of the utmost significance. RCA is there to address the problem or non-conformance by localising the true cause and implementing corrective action to prevent recurrence of the problem (Rooney & Heuvel, 2004). In the past, RCA was well-known in industrial psychology and was utilised in the analysis of many important industrial accident cases. RCA is alternatively referred to as error analysis, root cause localisation, root cause diagnosis, fault localisation, causal reasoning, causal discovery and problem determination (Reason, 2000). Kiciman and Subramanian (2005) claimed that the process of localising the root cause is extremely important, especially in large-scale systems. The evolution of communication systems has contributed to unprecedented growth in the number of internet users, which has in turn produced a large amount of data flow. As a result, identifying the cause of a system which fails to function properly is a very challenging task. In addition, identification of the root cause in today's enterprise systems is still usually performed manually (Wong & Debroy, 2009). Identifying the causes manually in such a data-rich domain is very time-consuming and experienced technical experts are needed. Moreover, the reliability and performance of a system are always a prerequisite in the globalised world. Detection and diagnosis of causes or faults must be accurately performed and completed in a short period of time.

### 2.2. RCA with BBN and FCM

Though BBN and FCM have been applied in various domains, BBN is selected by many researchers for building causal models because of its soundness and expressiveness. A causal model can be built by two methods, manual and automated (Korb & Nicholson, 2003). Manual construction of a causal model is a way to acquire knowledge from experts in a particular domain. Construction of BBN by hand involves several development stages. First, the relevant variables of the event need to be selected and captured by interviewing experts in particular domains. In the second stage of the construction, the conditional independence or dependence relationships among the variables will be identified and represented in a graphical structure. The causality relationships obtained are based on the interviews with the domain experts and represented in a graph by taking the causality sign to determine the arcs direction between the variables. Next, the assessment and verification of the probabilities needed for the network under development will be facilitated because the probabilistic and logical constraints among the domain variables are known. Once the graphical structure has been constructed, the CPT for each variable needs to be built. The conditional probabilities can be obtained from the domain expert. Finally, an assessment of the completed BBN will be done by performing a sensitivity analysis.

The automated method of BBN construction involves learning the BBN causal model from data. This method significantly reduces the effort required for eliciting causal knowledge from the domain experts. There are two stages of learning in BBN, structure learning and parameter learning. In BBN, the DAG is called the structure and the values in the conditional probability distribution are called the parameters (Neapolitan, 2003). Structure learning in BBN is a harder problem algorithmically than parameter learning. BBN parameter learning means learning the strength of dependencies as encoded by the entries in the CPT.

A new method for acquiring probabilities from domain experts has been designed to elicit big number probabilities in reasonable time and tested in oesophageal cancer analysis (Van der Gaag, Renooij, Witteman, Aleman, & Taal, 2002). Though the assessment rate by the domain expert can hit 150 probabilities per hour with the proposed method, the accuracy of probabilities is not absolute. Furthermore, finding an expert in a particular domain is always a big challenge, especially unpopular domains. However, Yet, Perkins, Marsh, and Fenton (2011) presented a method of building causal BBN by knowledge elicitation with a clinician as domain expert. Three stages of knowledge modelling are outlined to decrease the semantic mistakes in the final BBN model and provide understandable immediate models. However, the method proposed has not been completely developed and is only applicable to a few attributes. Other than that, causal probabilistic graphical models can be built with an expert system approach. Athanasiou and Clark (2009) built a causal model based on the rule-based DIMITRA system for the caring procedure to be followed for wheelchair users with spinal injury. Eleven qualified staff nurses participated in the elicitation of the conditional probabilities of signs and symptoms given specific diagnoses. The diagnostic performance tested by the causal BBN built is equally promising but each expert may have different assumptions and this could lead to bias when the diagnostic performance test is performed. Moreover, manual construction of BBN needs to elicit knowledge from human experts and could be very time-consuming.

The data mining approach is the other method which is commonly used in BBN without explicit access to the knowledge of human experts. However, several requirements need to be fulfilled in order to construct a good BBN with this approach. The domain has to be a data-rich domain which can provide enough data and valuable information for the analysis and construction of the causal model. The data must be collected very carefully to permit reliable identification of likelihood relationships. Moreover, the missing values in the dataset have to be filled in based upon estimated probabilities of these values or amputated from the dataset. Learning BBN from data involves two stages which are structure learning and parameter learning. Medina-Oliva, Iung, Barberá, Viveros, and Ruin (2012) integrated several RCA methods to identify the bad physical actors which cause performance deviations in an industrial system. They compared BBN with other RCA methods and concluded that BBN is able to deal with issues such as prediction or diagnostic optimisation, data analysis of feedback, experience, deviation detection and model updating and multi-state elements. Jiang, Neapolitan, Barmada, and Visweswaran (2011) designed a combinatorial epistasis learning method called BNMBL to construct BBN epistatic models. They concluded that representing epistatic interactions with BBN models and scoring them with a BBN scoring criterion holds promise for identifying epistatic genetic variants in data. The data mining approach allows BBN to learn structure from a large number of variables in the shortest time (Cussens, 2012) compared with knowledge-based BBN. Although the data mining approach has been widely applied in BBN, the capability of BBN has not been fully exploited. This literature applied BBN only in the structure learning process, which is only a part of BBN's capabilities. The powerful root cause analysis