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Linking Bayesian networks and PLS path modeling for causal analysis

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ABSTRACT

Causal knowledge based on causal analysis can advance the quality of decision-making and thereby facilitate a process of transforming strategic objectives into effective actions. Several creditable studies have emphasized the usefulness of causal analysis techniques. Partial least squares (PLS) path modeling is one of several popular causal analysis techniques. However, one difficulty often faced when we commence research is that the causal direction is unknown due to the lack of background knowledge. To solve this difficulty, this paper proposes a method that links the Bayesian network and PLS path modeling for causal analysis. An empirical study is presented to illustrate the application of the proposed method. Based on the findings of this study, conclusions and implications for management are discussed.

1. Introduction

In recent years, knowledge management and related strategy concepts are often promoted as important components of organizations' survival strategies (Martensson, 2000). Knowledge management is regarded as a key source of sustainable competitive advantage (Holsapple & Singh, 2001; Liao, 2003), and is also seen as playing a fundamental role in the process of transforming individual knowledge into organizational knowledge (Liebowitz, 2001).

Knowledge is generally considered as intangible, and is difficult to measure, but it is generally accepted that it sometimes increases through use (Wiig, Hoog, & Spek, 1997). More importantly, for the purpose of advancing the quality of decision-making and thereby facilitating a process of transforming strategic objectives into effective actions, causal knowledge based on causal analysis is needed (Lin & Wu, 2008; Nadkarni & Shenoy, 2004; Tan & Platts, 2003). Several creditable studies have placed emphasis on the usefulness of causal analysis techniques. Tan and Platts (2003) conduct an appraisal of causal analysis techniques ranging from fishbone (Ishikawa) diagrams, Why/Why diagrams, influence diagrams, mind maps, to cognitive maps. In an especially relevant study, Lin and Wu (2008) implement a fuzzy DEMATEL method to produce a causal diagram. In addition, Bayesian networks and PLS path modeling are popular causal analysis techniques. Through these causal analysis techniques, causal maps can be created. Causal maps represent the causal knowledge of subjects in a specific domain, and they have been applied widely in the areas of policy analysis and management sciences to demonstrate the relationships between relevant factors, knowledge, and conditions (Nadkarni & Shenoy, 2004).

Among causal analysis techniques, the PLS path modeling is particularly famous for its successful applications in customer satisfaction analysis; both the American Customer Satisfaction Index (ACSI) and the European Customer Satisfaction Index (ECSI) were constructed using PLS path modeling. However, many researchers and experts have experienced a certain amount of difficulty regarding how to establish the causal directions between constructs, due to lack of background knowledge or previous theoretical support. To deal with this difficulty, this paper proposes using the Bayesian network prior to implementing PLS path modeling for causal analysis.

The Bayesian network is a causal map, a kind of graphical representation of an expert's knowledge, based on probability theory (Nadkarni & Shenoy, 2004). The Bayesian network enjoys the advantage that it needs no rigid statistical assumptions: it graphically displays as a directed acyclic graph (DAG), and represents a set of conditional independence constraints among a given number of variables and their related conditional probability distributions (Lauria & Duchessi, 2007). Because of the special nature and merit of the Bayesian network, the DAG can serve as a guide to help us decide the causal directions between constructs when using PLS path modeling. This paper, therefore, suggests a method that links the Bayesian network and PLS path modeling for causal analysis. An empirical study is presented to illustrate the application of the proposed method. The remainder of this paper is organized as follows. In Section 2, the proposed method is presented. In Section 3, the Bayesian network and PLS path modeling are discussed. In Section 4, an empirical study is presented by way of illustration. Finally, based on the findings of this research, conclusions and implications for management are presented.

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2. The proposed method

According to Al-Tabtabai (1998), causal knowledge is a kind of knowledge structure which is concerned with the configuration of a given system and the way its components work together to perform a specific task. Through the use of a causal analysis technique we may obtain a causal map where causal knowledge is exhibited. A causal map is a kind of compact diagram, which captures causal knowledge by picturing relationships among concepts connected with labeled arrows. It is also a method for visualizing the relationships among different concepts within a downward-branching hierarchical structure. A causal map, with its embedded causal knowledge, is an important and useful tool, because it helps us stimulate the generation of ideas, promote creativity, communicate complex concepts, and transform an individual's tacit knowledge into a team's explicit knowledge.

Lin and Wu (2008) note that: (1) cause and effect are two different concepts; (2) causes tell the reason why something happened, whereas effects are the results of that happening; and (3) to capture the cause–effect relationship is not an easy task, because the interaction between cause and effect is often complex and subtle. Fortunately, several causal analysis techniques can be used to produce causal maps (Lin & Wu, 2008; Nadkarni & Shenoy, 2004; Tan & Platts, 2003). Among them, the Bayesian network and PLS path modeling are vital, trend-setting techniques. The former is currently gaining importance as a data mining technique, while the latter is becoming popular as a modeling method.

Many studies have attempted to advance the usefulness of the Bayesian network. Barrientos and Vargas (1998) combine Bayesian networks and case-based reasoning to create a knowledge representation scheme capable of dealing with time-varying processes; Sucar and Martínez-Arroyo (1998) propose a hybrid approach for structure learning of Bayesian networks; Garside, Rhodes, and Holmes (1999) discuss the efficient estimation of missing information in causal inverted multiway trees, and propose a simplified Maximum Entropy model; Kang and Golay (1999) present a Bayesian network-based advisory system for operational availability in complex nuclear power plant systems; Nadkarni and Shenoy (2001) present a Bayesian network approach to making inferences in causal maps; Jurgelenaite and Lucas (2005) propose a method of using equivalence classes of binomial distributions as a means to define very large Bayesian networks; Viaene, Dedene, and Derrig (2005) use Bayesian learning neural networks for auto claim fraud detection; Liu, Sung, and Mittal (2006) propose a semi-fixed model to represent the gene network as a Bayesian network with hidden variables; Cho (2006) uses the linear Bayesian approach to update the distribution of activity duration; Lauria and Duchessi (2007) suggest a methodology for developing Bayesian networks; De Melo and Sanchez (2008) present a knowledge-based representation for maintenance project delays, etc.

As for PLS path modeling, it has been successfully applied to a variety of areas, such as: exploring the human side of client/server system success (Guimaraes & Igbaria, 1997); examining the impact of poor performance on risk-taking attitudes (Lee, 1997); investigating effects of source and participant anonymity and difference in initial pinions in an EMS context (Kahai, Avolio, & Sosik, 1998); performing the technological aspect of environmental scanning (Raymond, Julien, & Ramangalahy, 2001); examining the impact of shared domain knowledge and its unit structure (Ranganathan & Sethi, 2002); satisfying and retaining customers through independent service representatives (Brown & Chin, 2004); discussing the extensions of PLS path modeling (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005); testing the influence of technology on user expectancies (Looney, 2006); investigating the relationship between interpersonal trust, employee satisfaction, and employee loyalty (Matzler & Renzl, 2006); defining relationship quality for customer-driven business development (Roos, Gustafsson, & Edvardsson, 2006); arguing the error term in formative measurement models (Diamantopoulos, 2006); examining the determinants of students' satisfaction and their perceived learning outcomes (Eom, Wen, & Ashill, 2006); arguing the issue of strategic sourcing (Kocabasoglu & Suresh, 2006); making decisions for resource allocation (Andreou & Bontis, 2007); assessing the performance of business unit managers (Bouwens & Vanlent, 2007); performing a modified PLS path modeling algorithm handling reflective categorical variables (Jakobowicz & Derquenne, 2007); examining the role of problem recognition and cognitive bias (Keil, Depledge, & Rai, 2007); discussing competitive and cooperative positioning in supply chain logistics relationships (Klein, Rai, & Straub, 2007); and discussing the relationships among latent variables and residuals in PLS path modeling (Vittadini, Minotti, Fattore, & Lovaglio, 2007); performing a trust-based consumer decision-making model in electronic commerce (Kim, Ferrin, & Rao, 2008); developing an index for online customer satisfaction (Hsu, 2008), and so on.

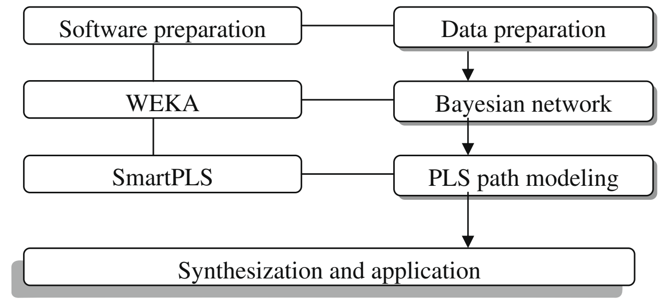

Fig. 1. Causal analysis process.

However, few studies have dealt with the issue of 'theory dependency'. Regarding theory dependency, the Bayesian network is data driven with no restrictions, while PLS path modeling is based on theory (Lauria & Duchessi, 2007). If one uses PLS path modeling in a situation lacking a previous theory, serious problems arise. For example, the task of deciding the causal direction between constructs would become excessively complicated because we need to guess at a huge number of possibilities in terms of causal directions between several constructs. To solve this problem, this paper proposes an effective way to implement the Bayesian network prior to conducting PLS path modeling. Using the proposed method, the execution of PLS path modeling, according to the DAG of the Bayesian network, can be performed smoothly and effectively. For this scenario, the proposed method is shown in Fig. 1. Before carrying out the causal analysis, software preparation is needed. For this purpose, there are a number of free software packages available, such as 'WEKA' for the Bayesian network, and 'SmartPLS' for PLS path modeling.

The proposed method for causal analysis consists of four phases: 'Data preparation', 'Bayesian network', 'PLS path modeling', and 'Synthesization and application'. Data preparation is the preparation phase, in which we are required to cleanse and format the data for the use of the chosen software. The next step is to employ 'WEKA' to obtain a DAG through Bayesian network classifiers with a search algorithm. Based on the DAG, the PLS path modeling phase can be implemented with 'SmartPLS'. Finally, synthesization and application are conducted to support better decision-making and to apply in problem-solving.

3. Bayesian networks and PLS path modeling

Popular data-mining techniques include *K*-means clustering, decision trees, Bayesian networks, regression models, and neural networks. Such data mining techniques are supported by the