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Technology forecasting in the National Research and Education Network technology domain using context sensitive Data Fusion

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ABSTRACT

Using inductive reasoning this paper develops a framework for the Structural Equation Modeling based context sensitive Data Fusion of technology indicators in order to produce Technology Forecasting output metrics. Data Fusion is a formal framework that defines tools, as well as the application of these tools, for the unification of data originating from diverse sources. Context sensitive Data Fusion techniques refine the generated knowledge using the characteristics of exogenous context related variables, which in the proposed framework entails non-technology related metrics. Structural Equation Modeling, which is a statistical technique capable of evaluating complex hierarchical dependencies between latent and observed constructs, has been shown to be effective in implementing context sensitive Data Fusion. For illustrative purposes an example model instantiation of the proposed framework is constructed for the case of the National Research and Education Network technology domain using knowledge gained through action research in the South African National Research Network, hypotheses from peer-reviewed literature and insights from the Trans-European Research and Education Network Association's annual compendiums for National Research and Education Network infrastructure and services trends. This example model instantiation hypothesizes that a National Research and Education Network's infrastructure and advanced services capabilities are positively related to one another, as well as to the contextual influence it experiences through government control. Also, positive relationships are hypothesized between a National Research and Education Network's infrastructure and advanced services capabilities and its usage, which is defined as the technology forecasting output metric of interest for this example. Data from the 2011 Trans-European Research and Education Network Association compendium is used in the Partial Least Square regression analysis of the example model instantiation, which confirms all hypothesized relationships, except the postulation that a National Research and Education Network's infrastructure and advanced services capabilities are positively related. This latter finding is explained by observing the prevalence of technology leapfrogging in the National Research and Education Network global community.

1. Introduction

Technological advancement continues at an astounding rate, seemingly following exponential growth models such as Moore's (Mack, 2011), Nielsen's Law (Nielsen, 1988) and Metcalfe's Law (Metcalfe, 1995). Driven not only by the invention, innovation and diffusion of new technologies, but also by the move to the paradigms of globalization and open innovation (Nyberg and Palmgren, 2011), this has created highly competitive global markets for technology based products and services (Porter, 2007). Hence, the survival, growth and profitability of firms that play in these markets depend highly on their ability to monitor current, as well as predict future technological changes in order to create a solid and sustainable technological base that can withstand, or adapt to rapidly changing market requirements (Porter, 2007). Moreover, firms need to effectively and efficiently manage technological changes both internally and externally if they are to create sustainable competitive advantages in rapidly high-tech markets (Lichtenthaler, 2004). Technology Intelligence (TI), which is a core process within the discipline of technology management, involves the process of capturing technology related data, converting this data into information by determining relational connections and refining information to produce knowledge that can guide strategic decision makers during strategic planning (Lichtenthaler, 2004; Chang et al., 2008). Technology indicators, such as technology maturity and degree of innovation, are those measureable sources of technology related data that allow for the direct characterization and evaluation of technologies over their whole life

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cycle (Chang et al., 2008). Scrutinizing the information that has been distilled from a set of technology indicators in a forward-looking approach, commonly referred to as Future-oriented Technology Analysis (FTA), can potentially provide decision makers with Technology Forecasting (TF) knowledge, amongst others (Porter, 2005).

Buchroithner (Buchroithner, 1998) and Wald (Wald, 1997) define Data Fusion (DF), which was developed in the military domain for the generation of quality tactical knowledge through the multi-layered processing of sensor data (Wald, 1999), as "… a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application." Within the discipline of DF, context can be viewed as synonymous with a situation, which in turn is defined as a set of relational connections (i.e. instantiated relations) (Steinberg, 2009). Context can be used in each level of the DF process in order to refine data alignment and association, as well as during situation state estimation (Steinberg, 2009). Recently, context sensitive DF techniques have been explored which effectively refine the generated knowledge at each level of processing based on the characteristics of exogenous context-related variables (Steinberg, 2009).

Regression analysis constitutes a family of statistical techniques geared at modeling and analyzing the relationship between dependent and independent variables from empirical data (Haenlein and Kaplan, 2004). Moreover, regression analysis attempts to explain the variations in dependent variables as functions (commonly referred to regression functions) of variations in independent variables (Haenlein and Kaplan, 2004). With this knowledge it is then possible to perform prediction and forecasting of the values that dependent variable will assume for specific independent variable values (Haenlein and Kaplan, 2004). Classic regression techniques (such as multiple regression, discriminant analysis, logistic regression and analysis of variance) can be classified as first generation techniques, since these techniques explicitly assume independence between multiple dependent variables (Haenlein and Kaplan, 2004). This, unfortunately, limits the ability of such techniques to comprehensively model complex interrelationships, such as the interplay between two or more output variables in a TF model. More specifically, classic first generation regression techniques are not able to model the potential mediating or moderating effect that output variables could have on one another. To overcome this limitation, Jöreskog (Jöreskog, 1973) proposed covariance based Structural Equation Modeling (SEM) as a second-generation technique, which allows for the simultaneous modeling of relationships amongst multiple dependent and independent constructs. A further inherent limitation of first generation regression techniques is their explicit assumption that all dependent and independent variables are directly observable (Haenlein and Kaplan, 2004). This assumption implies that all variables' values can be directly obtained from real-world sampling experiments (Haenlein and Kaplan, 2004). As such, any variables that cannot be directly observed need to be considered unobservable and have to be excluded from first generation regression models (Haenlein and Kaplan, 2004). However, such unobservable variables, commonly referred to as latent constructs, are supported by SEM. Steinberg postulated that SEM is ideally suited to implement context sensitive DF (Steinberg, 2009; Steinberg and Rogova, 2008). Not only does SEM support the complex structural models used in situation state estimation (as is required in TF), it also allows for non-linear and non-Gaussian factors and cyclical dependencies amongst model variables that can be either latent or directly observable (Steinberg, 2009).

According to Sohn and Moon (Sohn and Moon, 2003) most TF techniques rarely take into account the structural relationships amongst technology indicators and TF output metrics. SEM, however, provides an advantage over these limited TF techniques by allowing for the modeling of complex hierarchical relationships between technology indicators and TF outputs metrics. Sohn and Moon (Sohn and Moon, 2003) have shown that SEM, which can be viewed as a generalization of factor and path analysis methods such as Bayesian Networks (Steinberg, 2009), can successfully implementing TF of the Technology Commercialization Success Index (TCSI) TF output metric.

An NREN is a specialized broadband network connectivity and service provider that explicitly caters for the needs of the research and education communities of a country (TERENA COMPENDIUM of National Research and Education Networks in Europe, 2012). In some instances, NRENs also service the needs of other public sector entities, such as hospitals, municipalities and libraries. Typically, one NREN is present per country (for example SANReN (The South African National Research Network (SANReN), 2013) in South Africa and the Joint Academic Network (JANET) in the United Kingdom), although separate NREN entities could potentially exist to service distinct in-country research and education sectors or geographic areas, for example the Energy Sciences Network (ESnet) and Kansas Research and Education Network (KanREN) in the United States (TERENA COMPENDIUM of National Research and Education Networks in Europe, 2012). NREN'si are built primarily on fiber optic cabling infrastructure and provide researchers, educators and students with unparalleled connectivity speeds and advanced services at a fraction of the price of commercial network providers (TERENA COMPENDIUM of National Research and Education Networks in Europe, 2012). These networks are currently experiencing rapid technology driven changes, resulting in evolving business models, innovative infrastructure solutions and service offerings, as well as increased international collaboration (TERENA COMPENDIUM of National Research and Education Networks in Europe, 2012; TERENA COMPENDIUM of National Research and Education Networks in Europe, 2011).

The objectives of this paper are twofold: Firstly, the paper builds on the work of Steinberg (Steinberg, 2009; Steinberg and Rogova, 2008), as well as Sohn and Moon (Sohn and Moon, 2003), by proposing a framework for the SEM based DF of technology indicators in order to produce TF output metrics. The proposed framework is an evolved and improved version of the framework first proposed in (Staphorst et al., 2013). Secondly, application of the proposed framework is illustrated by through the use of a model instantiation example in the NREN technology domain. The proposed NREN example model instantiation was constructed using insights gained through action research in the South African National Research Network (SANReN) (The South African National Research Network (SANReN), 2013), insights from Trans-European Research and Education Network Association's (TERENA) NREN compendium for 2012 on global NREN infrastructure and services trends (TERENA COMPENDIUM of National Research and Education Networks in Europe, 2012), as well as hypotheses and postulations in peer-reviewed literature. It is important to view the example NREN model instantiation presented in this paper as a mere illustrative example of the use of the proposed framework, not as a definitive platform for TF in the NREN domain.

The paper is structured as follows: Firstly, a theory review is presented on the use of SEM for context sensitive DF and the use of SEM in TF, as well as taxonomy of technology indicators and forecasting output metrics. An evolved version of the framework for SEM based DF for TF proposed by Staphorst, Pretorius and Pretorius in (Staphorst et al., 2013) is then developed through inductive reasoning. The example NREN model instantiation of the framework is then presented, including the definition of a number of research propositions relevant to this example model instantiation. This is followed by a quantitative evaluation of the example model instantiation using cross-sectional data extracted from TERENA's NREN compendiums for 2011 (TERENA COMPENDIUM of National Research and Education Networks in Europe, 2011), including an evaluation of the research propositions defined for the example model instantiation. Lastly, the paper presents an evaluation of the reliability and the validity of the example NREN model instantiation.

2. Theory and framework development

Steinberg postulated that SEM is one potential statistical tool that lends itself naturally to implement DF, with the added benefit that it