Chapter 71
Using Hybrid Classifiers to Conduct Intangible Assets Evaluation

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ABSTRACT

Traditional financial reporting usually ignores intangible assets, even though these assets play an increasingly important role in today's knowledge-based economy. As such, the valuation of intangible assets, while typically overlooked in traditional reporting, has nonetheless garnered widespread interest. This paper uses data-mining technologies to identify important valuation factors and to determine an optimal valuation model. In the feature selection process, the paper focus on three methods, namely, decision trees, association rules, and genetic algorithms in data mining, to identify important valuation factors. The results show that decision trees have approximately 75% prediction accuracy and select seven critical variables. In the prediction process, the paper constructs and compares many kinds of evaluation and prediction models. The results show that hybrid classifiers (i.e., k-means + k-NN) perform best in terms of prediction accuracy (91.52%), Type I and II errors (11.17% and 7.15%, respectively), and area under ROC curve (0.908).

1. INTRODUCTION

The knowledge-based economy has evolved in recent decades, making capability and efficiency in creating, expanding, and applying knowledge important success factors for companies. Today, the primary method for creating firm value involves converting traditional physical production factors into intangible knowledge (Kessels, 2001; Tsai, Lu, & Yen, 2012). For this reason, the values of research and development (R&D), advertising, brand equity, and other intangible assets have increased relative to the value of physical capital as inputs in the production processes of advanced economies (Giglio & Severo, 2012). As a result, a large part of a firm's value may come from a wide range of intangible as-

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sets. For example, Demers and Lev (2001) and Trueman, Wong, and Zhang (2000) found that website traffic of internet firms is positively related to the respective values of the firms. A strong positive relation between intangible R&D assets and stock value also exists, according to Chan, Lakonishok, and Sougiannis (1999) and Eberhart, Maxwell, and Siddique (2004). To evaluate a firm's overall value, we therefore should consider not only the value of tangible assets, but also the value of intangible assets (Chan et al., 1999; Eckstein, 2004).

However, the nature of current disclosure regulations means that financial statements do not always reflect the value of intangible assets. This creates information asymmetry between management (i.e., insiders) and shareholders or investors (i.e., outsiders) (Gupta & Golec, 2012; Vergauwen, Bollen, & Oirbans, 2007). Lev and Daum (2004) suggest that to improve investors' understanding of firm performance, managers need to supplement the accounting and financial information already available with more detailed disclosures about their intangible assets.

Therefore, in order to provide useful information to investors or creditors, it is important to understand what factors might affect the value of intangible assets. Accordingly, we follow Tsai et al. (2012) and review related literature from diverse domains to identify a large array of factors affecting intangible assets. Then, we use data-mining technologies to extract the most important features (or factors) from a given dataset. We then use these critical factors to construct prediction models by employing four well-known classification technologies in data-mining.

Prior studies use data-mining techniques to build prediction models, but they have some limitations when using single-classification techniques. Therefore, recent studies use multiple classifiers, such as hybrid classifiers, to achieve better prediction performance (Hsieh, 2005; Huysmans, Baesens, Vanthienen, & van Gestel, 2006). In general, hybrid classifiers combine two different machine-learning techniques sequentially. Therefore, there are four combination methods in hybrid systems: combining a classifier technique with a clustering technique (i.e., classifier + clustering), combining a clustering technique with a classifier technique (i.e., clustering + classifier), combining two different classification techniques (i.e., classifier + classifier), and combining two different clustering techniques (i.e., clustering + clustering). For example, they start with clustering and then use the result to construct the classifier (Chandra, Ravi, & Ravisankar, 2010; Chauhan, Ravi, & Karthik Chandra, 2009; Verikas, Kalsyte, Bacauskiene, & Gelzinis, 2010). However, researchers have not examined the use of such hybrid classifiers for predicting the value of intangible assets. As such, this paper develops prediction models using single-classification and hybrid-classifier techniques. In addition, the paper evaluates whether hybrid classifiers have higher prediction accuracy and result in fewer Type I/II errors for intangible-assets prediction.

This paper uses data-mining technologies to identify important valuation factors and to determine an optimal valuation model. Our experiment has two processes. The first process consists of feature selection, in which we use feature selection techniques to choose the critical factors affecting the value of intangible assets from a large number of variables in the current literature. Then we use three feature selection methods, namely, decision trees (DT), association rules (AR), and genetic algorithms (GA) in data mining, to identify important valuation factors. This paper also compares various machine learning techniques to construct a more accurate evaluation and prediction model after the feature selection process. By following the aforementioned steps, we determined that the features selected by the DT method are the most important factors affecting intangible assets and the market-based value of firms in Taiwan. Those features are as follows: *BOARD INDEPENDENCE*, *CAPITAL INTENSITY*, *PROFITABILITY*, *AGE*, *CONCENTRATION*, *SEMICONDUCTOR INDUSTRY*, and *ANALYST FOLLOWING*. The second process consists of prediction, in which we construct and compare many kinds of evaluation and pre-