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Multi-criteria ABC analysis using artificial-intelligence-based classification techniques

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ABSTRACT

ABC analysis is a popular and effective method used to classify inventory items into specific categories that can be managed and controlled separately. Conventional ABC analysis classifies inventory items three categories: A, B, or C based on annual dollar usage of an inventory item. Multi-criteria inventory classification has been proposed by a number of researchers in order to take other important criteria into consideration. These researchers have compared artificial-intelligence (AI)-based classification techniques with traditional multiple discriminant analysis (MDA). Examples of these AI-based techniques include support vector machines (SVMs), backpropagation networks (BPNs), and the *k*-nearest neighbor (*k*-NN) algorithm. To test the effectiveness of these techniques, classification results based on four benchmark techniques are compared. The results show that AI-based techniques demonstrate superior accuracy to MDA. Statistical analysis reveals that SVM enables more accurate classification than other AI-based techniques. This finding suggests the possibility of implementing AI-based techniques for multi-criteria ABC analysis in enterprise resource planning (ERP) systems.

1. Introduction

Effective inventory management has played an important role in the success of supply chain management. For organizations that maintain thousands of inventory items, it is unrealistic to provide equal consideration to each item. Managers are required to classify these items in order to appropriately control each inventory class according to its importance rating.

ABC analysis is one of the most commonly employed inventory classification techniques. Conventional ABC classification was developed for use by General Electric during the 1950s. The classification scheme is based on the Pareto principle, or the 80/20 rule, that employs the following rule of thumb: "vital few and trivial many." The process of ABC analysis classifies inventory items into A, B, or C categories based on so-called annual dollar usage. Annual dollar usage is calculated by multiplying the dollar value per unit by the annual usage rate (Cohen & Ernst, 1988; Partovi & Anandarajan, 2002). Inventory items are then arranged according to the descending order of their annual dollar usage. Class A items are relatively small in number, but account for the greatest amount of annual dollar usage. In contrast, class C items are relatively large in number, but make up a rather small amount of annual dollar usage. Items between classes A and C are categorized as class B.

Although ABC analysis is famed for its ease of use, it has been criticized for its exclusive focus on dollar usage. Other criteria such as lead-time, commonality, obsolescence, durability, inventory cost, and order size requirements have also been recognized as critical for inventory classification (Flores & Whybark, 1987; Jamshidi & Jain, 2008; Ng, 2007; Ramanathan, 2006). In order to accommodate multi-criteria inventory classification, many researchers have proposed methods that consider factors other than annual dollar usage. Flores and Whybark (1987) developed a cross-tabulation matrix method for use in bi-criteria inventory classification; they found that the method becomes increasingly complicated when three or more criteria are involved in evaluations.

Cohen and Ernst (1988) implemented a statistical clustering technique to classify inventory items with multiple attributes; however, a substantial amount of inventory data is required to execute this technique. Sophisticated statistical procedures such as factor analysis are also necessary. Every time a new inventory item is stored in a warehouse, the clustering process must be repeated, and there is a possibility that previously classified items may end up with different classes.

Partovi and Burton (1993) applied the analytic hierarchy process (AHP) to inventory classification in order to include both quantitative and qualitative evaluation criteria. AHP has been praised for its ease of use and its inclusion of group opinions; however, the subjectivity resulting from the pair-wise comparison process of AHP poses problems. Bhattacharya, Sarkar, and

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Mukherjee (2007) developed a distance-based multiple-criteria consensus framework utilizing the technique for order preference by similarity to ideal solution (TOPSIS) for ABC analysis. TOPSIS (Hwang & Yoon, 1981) evaluates the distance of each alternative from both the most ideal and least ideal solutions. Alternatives that are closest to the most ideal situation, while being furthest from the least ideal situation, are considered optimal.

To offset the impact of subjectivity, Ramanathan (2006) and Ng (2007) proposed methods similar to data envelopment analysis (DEA). These methods maximize the artificial inventory score that is used to classify each inventory item. Unlike AHP, the weights given to classified criteria are solved automatically when the DEA model is optimized. Like the statistical clustering technique, this model must be reprogrammed and solved whenever a new inventory item is introduced.

AI-based techniques for inventory classification are gaining popularity. Guvenir and Erel (1998) proposed the genetic algorithm for multi-criteria inventory classification (GAMIC) to calculate the weight of criteria, along with the AB and BC cut-off points of classified inventory items. Similar to the AHP, criteria hierarchy is utilized to compute weighted scores of the inventory items. The items with scores greater than the AB cut-off point are classified as A; similarly those between AB and BC are classified as B, and those below BC as C. A chromosome encodes the weight vector, along with the two cut-off points for classification. Standard genetic operators such as reproduction, crossover, and mutation are applied to the chromosomes. GAMIC improves the quality of criteria weights previously obtained through pair-wise comparisons between two criteria.

Artificial neural networks have been widely applied for classification purposes, as well as for forecasting problems in a variety of applications. They are useful for finding nonlinear surfaces and separating the underlying patterns. Paliwal and Kumar (2009) delivered a comprehensive survey of neural network articles, categorizing the application of networks into categories: accounting and finance, health and medicine, engineering and manufacturing, and marketing. Accounting and finance is the category with the greatest number of applications, especially with regard to bankruptcy prediction, credit evaluation, fraud detection, and property evaluation finance.

Partovi and Anandarajan (2002) utilized backpropagation (BP) and genetic algorithm (GA)-based learning methods to develop an artificial neural network for inventory classification. Real-world inventory data from a large pharmaceutical company were used to compare the accuracy of the proposed neural network methods with that of multiple discriminant analysis (MDA), a statistical classification technique. Multiple attributes including unit price, ordering cost, demand range, and lead-time were used to classify the inventory items. The results showed that neural network–based classification models have a higher predictive accuracy than the conventional MDA technique. Between the two neural network–based techniques, the GA demonstrated slightly better classification accuracy than BP.

The support vector machine (SVM) is a powerful novel learning algorithm introduced by Vapnik (1995). A SVM is based on the structural risk minimization principle. SVM utilizes a hypothesis space of linear functions in a high dimension space. In the high dimension space, an optimal separating hyperplane is constructed to give the maximum separation between decision classes. SVMs have recently proved popular machine learning tools for classification and regression. Application of SVMs has enabled significant progress in a variety of fields, including image detection, text categorization, bioinformatics, fault diagnosis, and financial analysis (Hu & Zhang, 2008).

k-Nearest neighbors (k-NN) is another popular method for classification and pattern recognition; it was first introduced by Fix and Hodges (1951), and later adapted by Cover and Hart (1967). In this method, a newly introduced item is classified into the class with the most members present among the k-nearest neighbors. Applications of k-NN can be found in various pattern recognition and classification problems.

The rest of this paper is organized as follows. Section 2 reviews the concepts of several AI-based techniques. Benchmark classification techniques that were found in the literature are discussed and demonstrated in Section 3. In Section 4, the AI-based inventory classification techniques used in this research are described. An illustration is provided in Section 5 that compares the accuracy of various classification techniques. The paper concludes in Section 6 with a discussion of the application of the AI-based techniques to multiple-criteria inventory classification problems.

2. Artificial-intelligence-based classification techniques

Inventory classification problems deal with the assignment of inventory items to a group so that they can be appropriately managed. Artificial-intelligence (AI)-based techniques take advantage of symbolic logic and advanced computer technology when developing various learning algorithms for classification. In this paper, three AI-based classification techniques will be utilized for inventory classification: BP networks (BPNs), SVMs, and the k-NN algorithm. The accuracy of each technique will be compared with the others.

2.1. Backpropagation networks

BPNs are the most widely used classification technique for training an artificial neural network. A BPN utilizes supervised learning methods and feed-forward architecture to perform complex functions such as pattern recognition, classification, and prediction. A typical BPN (Fig. 1) is composed of three layers of neurons: the input layer, the hidden layer, and the output layer. The input layer is considered the model stimuli, while the output layer is the associated outcome of the stimuli. The hidden layer establishes the relationship between the input and output layers by constructing interconnecting weights.

Input layer neurons are linear, while neurons in the hidden and output layers have sigmoidal signal functions (Kumar, 2005). The input signals are modified by the interconnected weights W_{ih}. A sigmoidal signal function is used to activate the sum of the modified signals. It also converts the output of the hidden layer into the input signals of the output layer. Similarly, the input signals of the output layer are modified by the interconnected weights W_{hj}.

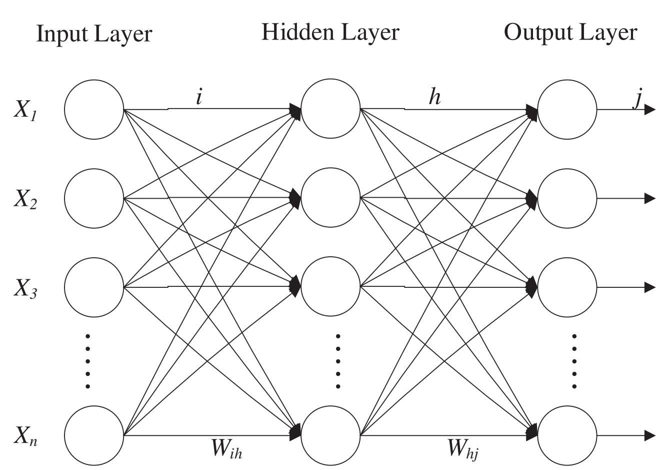

Fig. 1. Back propagation network architecture.