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Multi Criteria ABC analysis using artificial – intelligence-based classification techniques – case study of a pharmaceutical company

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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. In traditional ABC analysis the inventory items are categorized in to A ,B and C classes based on the annual dollar usage. The annual dollar usage is determined as the product of unit cost of each item and its annual demand. The items are arranged in the descending order of annual dollar usage. In traditional ABC analysis annual demand and Unit cost are the only criteria for classification. Researchers have been developing multi – criteria ABC classification models to include criteria such as criticality, Lead time and ordering cost etc. Several classification methods have been proposed in the literature like Analytical Hierarchy process (AHP), Data Envelopment analysis (DEA) and TOPSIS, etc. In this paper the authors have applied artificial-intelligence –based classification methods for the inventory classification of a pharmaceutical manufacturing company. The AI methods proposed in this paper are Back-propagation (BP) artificial neural network, Support Vector Machines (SVM), K-Nearest neighbor and Multiple Discriminant Analysis (MDA). Out of the above methods SVM enables higher classification accuracy than the others. This finding suggests the possibility of implementing AI – based techniques for multi-criteria ABC analysis in enterprise resource planning (ERP) systems

Key Words: - **ABC Classification, ANN, SVM, KNN, MDA.**

I. 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; Partovi & Anandarajan, [1]. 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.

Al-based techniques for inventory classification are gaining popularity. Guvenir and Erel [2] 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 [3] 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 [1] utilized back propagation (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.

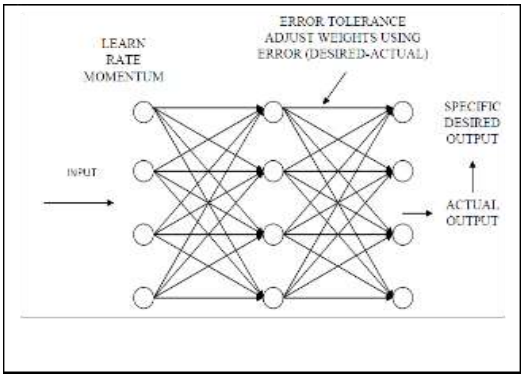
The support vector machine (SVM) is a powerful novel learning algorithm introduced by Vapnik [4]. A SVM is based on the structural risk minimization principle. SVM is utilizes a hypothesis space of linear functions in a high dimension space. In the high dimension space, an optimal separating hyper plane 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, [5]. k-Nearest neighbors (k-NN) is another popular method for classification and pattern recognition; it was first introduced by Fix and Hodges [6], and later adapted by Cover and Hart [7] 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.

II. 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 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.

A. Back propagation 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 (Fig1) is composed of three layers of neurons: the input layer, the hidden layer, and the output layer. The input layer is considered the mode 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,[3] 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} The sum of modified signals is again activated by a sigmold signal function and the output is collected. The weights of input-hidden and hidden –output layers are modified by a specific learning function, such as gradient descent based algorithms, as shown in Fig. 1.



Input Layer - Hidden Layer - Output Layer.

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B. Support Vector machines

SVMs were originally developed by Vapnik and co-workers [4] at Bell Laboratories. A SVM employs structural risk minimization rather than the empirical risk minimization used by conventional neural networks. SVMs use a linear model to implement nonlinear class boundaries via the nonlinear mapping of input vectors into a high-dimensional feature space. In this high-dimensional space, the maximum margin hyper plane is found so that the separation between decision classes can be maximized. Support vectors are defined as the training example closest to the maximum margin hyper plane.

Given a training set of instance-label pairs (x_i y_i), i=1,2, ……,n. where the input is labeled $x_1 € R^n$ and the output is labeled $y_i €$ (-1,+1), the SVM classifier satisfies the following conditions:

$$\begin{cases} w^T \phi(x_i) + b \geq +1, \text{ if } y_i = +1 \\ w^T \phi(x_i) + b \leq -1, \text{ if } y_i = -1 \end{cases}$$

Where w denotes the weight vector and b the bias. $\phi(.)$ is a nonlinear function that maps the input space to a high-dimensional feature space. $w^T \varphi(x) + b=0$ is represented as the linear separating hyperplane that separates two hyper planes with the margin width equal to $\frac{2}{\|w^2\|}$.

For classification problems that are linearly non-separable. Incorrect classification is unavoidable. To allow for incorrect classification, a slack variable ξ_i is introduced to the prime optimization model and is defined as:

$$\text{Min} \quad \frac{1}{2} w^T w + c \sum_{i=1}^{N} \xi_i$$

Subject to $\{y_i (w^T \phi(x_i)+b) \geq 1- \xi_i$,i=1,….N xi$_i \geq$ 0, 1,……….N

Where C is a penalty parameter, which is a regularized constant that determines the trade-off between training error and model flatness.

In order to solve this quadratic optimization problem, the Lagrangian method is used. Lagrangin multipliers α_i (i.e., support vectors) are introduced to construct the Lagrangian function used to find the saddle point:

$$L_p(w,b,x) = \frac{1}{2} w^T w - \sum_{i=1}^{m} (\alpha_i y_i (wx_i + b) - 1)$$

By applying Karush Kuhn-Tucker (KKT) conditions for the optimum constrained function, L_p can be transformed to the dual Largrangian $L_D(\alpha)$:

$$L_D(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{ij=1}^{m} \alpha_i \alpha_j y_i y_j (x_i x_j)$$

The dual form of the primal optimization model can be transformed as

$$\text{Max} \quad L_D(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{ij=1}^{m} \alpha_i \alpha_j y_i y_j (x_i x_j)$$

Subject to $0 \leq \alpha_i \leq C$ i = 1, ……m

$$\sum_{i=1}^{m} \alpha_i y_i = 0$$

The inner products in the objective function of the dual Lagrangian are replaced by the kernel function in order to map the instance data into a high-dimensional feature space:

$K(x_i, x_j) = \phi(x_i).\phi(x_j)$

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$$L_D(\alpha)=\sum_{i=1}^{m}\alpha_i-\frac{1}{2}\sum_{ij=1}^{m}\alpha_i\alpha_j y_i y_j k(x_i,x_j)$$

The selection of kernels is important in order to obtain robust classification results. The most popular kernel function are linear, polynomial, radial basis functions (RBFs), and sigmoid.

Let α^* be the optimal solution for the dual optimization problem. The decision function for classification can be defined as:

$$\text{Sgn}\left(\sum_{i=1}^{m} y_i\alpha_i^* k(x,x_i)+b^*\right)$$

C. k- Nearest neighbors

K-NN is a non parametric technique for classifying observations Cover & Hart, [7]. Computations of the measure of distance or similarity between observations are conducted prior to classification. A newly introduced item is then classified to the group where the majority of k-NNs belong. Use of k-NN requires an appropriate value of k. Loftgaarden and Queensbrerry [8] proposed that a reasonable k could be obtained by calculating the square root of the number of observations in a group. Hand [9] suggests that a trial and error approach might be more effective in identifying the value of k that incurs the lowest classification error. Malhotra, Sharma, and Nair [10] conducted a sensitivity analysis to compare the classification accuracy among various values of k to conclude that a value of 3 gives that highest correct classification rate:

D. Multiple Discriminant Analysis (MDA)

In this paper, an MDA model is used as a benchmark. In building the MDA model for classification of inventory Items, we need to forecast a precise cut-off value showing a clear distinction between samples. An MDA is a useful technique for classification of inventory items. An MDA function is represented as follows.

$$Z - W1X1 + \beta2X2 + \beta3X3 + \cdots\cdots\cdots + \beta iXi$$

Where Z-scores refer to a discriminant score and W represents cut-off values. Z and Xs indicate dependent and independent variables respectively. Statistical analyses were done using SPSS.

III. RESEARCH METHODOLOGY

In our research, the AI-based classification techniques BPN, SVM, and KNN were implemented to classify inventory items of a pharmaceutical manufacturing company. In order to study the effectiveness of these classification techniques, the classification results were compared with traditional MDA. Four classification criteria viz., annual demand, ordering cost, unit price and lead time were selected as inputs. The data set was adopted from a journal paper [1].Univariate analysis has been applied to the data set on the four criteria for the three classes ,A,B,and C (Table.1). The analysis revealed that the three classes (A,B and C) belong to different populations. In that paper the authors have applied ANN (BP), ANN (GA) and MDA methods to the data set. In the present paper, the author is using ANN(BP), SVM, KNN and MDA methods for classification of the inventory items(data set).This author has got better classification accuracy with SVM than the authors of the paper [1].

The BPN and SVM for this study were implemented using Neurosolutions soft ware package. The KNN and MDA were implemented using SPSS soft ware package. The BPN used in this study consists of 3 layers with 3 neurons in the input layer, 16 neurons in the hidden layer and 3 neurons in the output layer. Sigmoid activation function and learning with momentum was used. The data was divided in to 3 sets for training, validating and testing respectively. 60% of the data is used for training and 40% of data is used for testing. After training, the inventory data from another pharmaceutical company was used for validation As regards the SVM, Kernel adatron algorithm is used as the kernel function of the SVM. . The selection of the optimal values of the neighborhood parameter k is critical when classifying with K-NN. In this study, the neighborhood parameters k was assigned a value of 3, as suggested by Malhotra et al [10]. The K-NN classifier was then implemented using SPSS.

The holdout sample of the pharmaceutical company consists of 95 inventory items. Sixty percent of this data is used for training the network and the remaining forty percent of the data is used for testing. For validatation the inventory data of another pharmaceutical company is used. The classification accuracies of various AI methods and MDA method are shown in Table. 2. The holdout data and external data is very large (occupying 6-7 pages) and hence to save the space they are not shown here.

Table.1.Univariate analysis of variables used in the study (SD : Standard deviation)

Variables	Classification of inventory items						F
	Item A (12 Units)		Item B(34 units)		Item C(49 units)		
	Mean	SD	Mean	SD	Mean	SD	
Unit Price	1356.67	2097.37	147.02	275.53	16.42	33.04	15.19
Ordering Cost	53.33	81.76	5.96	9.64	0.78	1.48	15.47
Demand	17.13	15.99	25.63	18.87	31.76	18.90	13.75
Lead Time	31.20	21.04	10.88	11.96	3.05	2.46	36.91

IV. RESULTS

The classification accuracies of various AI methods and MDA method for the inventory data of the pharmaceutical manufacturing are shown in Table. 2. From the table it is observed that all the AI methods (BP, SVM, and KNN) performed better when compared to MDA method. Among the AI methods SVM method performed better when compared to other AI methods.

Table.2.Prediction accuracy of ANN (BP), SVM, KNN and MDA for inventory classification

	BP	SVM	KNN	MDA
Overall Training Sample	80.15	84.69	76.73	71.45
Holdout Sample Overall Classification	86.24	87.39	80.59	73.52
Item A	81.75	89.65	81.12	75.16
Item B	85.16	85.68	83.20	82.17
Item C	88.09	88.02	78.65	67.12
External Sample Overall Classification	73.72	81.85	72.66	69.27
Item A	75.05	81.85	72.66	69.27
Item B	71.89	80.58	70.16	70.53
Item C	72.72	81.01	71.15	66.73

V. CONCLUSIONS

In today's manufacturing environment, an organization needs to maintain the delicate balance between critical stock-outs and minimizing inventory costs. Researchers have developed various types of classification models to achieve this balance. This paper presents a new approach for ABC classification of various SKUs. We have used AI-based techniques in terms of ANN, SVM and KNN to classify SKUs in a pharmaceutical industry. The classification results of these methods were compared to the traditional statistical technique of MDA. The AI-based methods (BP, SVM, and KNN) performed better compared to MDA. Among the AI-based methods, SVM outperformed other AI-based methods. The findings suggests the scope to provide AI-based technologies for classifying the inventory in ERP packages, in which so far no step has been done in this direction.

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