Support Vector Machines for Multi-Attribute ABC Analysis

Hasan Basri Kartal and Ferhan Cebi

Abstract—**This paper examined the classification performance of Support Vector Machines (SVMs) on multi-criteria inventory analysis. The ABC analysis using the Simple Additive Weighting (SAW) method was employed to determine inventory classes of items held in inventory of a large scale automobile company operating in Turkey. The provided data set was analyzed with SVMs to obtain classification performance of the SVM learning algorithm. The results showed that SVM is highly applicable to the inventory classification problem.**

Index Terms—**ABC analysis, multi-criteria inventory classification, support vector machine (SVM).**

I. Introduction

Inventory management is a crucial issue requiring managerial concerns because of its effects on operational performance and competitiveness of organizations. Organizations need managerial tools in analyzing inventory efficiently. ABC analysis is one of the most commonly used methods to classify items held in inventory with regard to their relative importance. This kind of classification provides the organizations determine the most important items in inventory which the organizational resources will focus on [1].

ABC analysis classifies inventory items into three different groups as A, B, and C by their relative significance based on well-known Pareto principle. In conventional ABC *Group A* items are relatively few in number of unites but consist of the large amount of annual usage dollar value, whereas *Group C* items are relatively large in number of units but consists few of the amount of annual usage [2]. The remaining items between the two groups are *Group B*. Traditional ABC analysis is commonly applied to split inventory items into groups because of its simplicity and ease of use. However, the analysis has been criticized because it considers only a single dimension, the total amount of usage cost [3]-[5]. Thus, in many cases that other attributes can also be important, classical ABC inventory analysis becomes insufficient. Hence, multi-criteria inventory classification provides an opportunity to consider additional criteria such as criticality, lead time, substitutability, commonality, repairability, storage cost, scarcity cost, payment options, supplier alternative, unite size, order size, or such others [6], [7]. Therefore, multi-criteria ABC analyses have been getting attractions for more than two decades.

There are many multi-criteria ABC analysis models in the literature such as matrix-based methodologies, analytical hierarchy process (AHP) based and linear optimization based models, and meta-heuristic approaches. A joint criteria matrix approach applied via bi-criteria as in [2], [8] can be given as examples of matrix-based models. Reference [2] extended a previous study and suggested the use of AHP to integrate the given multiple criteria and to rank the items in inventory. Reference [8], [9] used an AHP based model to classify inventory items. Unit cost, annual dollar usage and several additional criteria such as critical factor and lead time were considered in the classification of items in [9]. Reference [10] applied a fuzzy AHP based model for classifying the inventory items to be hold in a distributing firm. In the study [10], fuzzy theory was used to overcome the difficulty on determining the importance of the conflicting attributes. Reference [11] proposed another approach named as *ABC–FC* approach by combining ABC analysis and fuzzy theory for classification of items.

Data envelopment analysis (DEA) based models such as weighted linear optimization [7], [12] were also used in ABC inventory classification by considering multiple criteria. Reference [13] proposed a modified version of a common weight DEA-like model by applying a few concepts in DEA models to use linguistic terms in the model. Whereas [7] proposed a weighted linear optimization model which is likely to the method of data envelopment analysis, [12] provided an extended version of a previous model by using two sets of weights as both most favorable and less favorable for each inventory item. The literature also introduced the applications based on heuristic techniques for classifying inventory items based on multiple criteria. Reference [14], for example, employed SVM and k-nearest neighbor to classify the inventory items. Reference [15] proposed an artificial neural network (ANN) to address the problem of inventory classification of a company in a pharmaceutical industry. Reference [3] used the genetic algorithm to find a solution to multi-attribute classification problem by optimization a set of parameters representing the weights of criteria.

The purpose of this paper is to investigate SVMs performance in inventory classification based on multiple attributes. The remaining of the paper is organized as follows. The next section gives brief information on SVMs. Section III introduces a real case study of an automobile company as an application; Section IV discusses the results of the application. Finally, the last section presents the conclusion section based on the findings.

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II. Support Vector Machines

SVMs are a set of related machine learning methods based on Vladimir Vapnik's statistical learning theory. A SVM classifier takes a set of inputs which belong to different classes, builds a model that predicts any given instance belongs to which class [16], [17]. It determines an optimal hyperplane to separate different classes in the data set. The hyperplane is placed at the maximum distance from the nearest points of a given data set [18].

A SVM model represents the training examples into separated categories in a mapped space as certain points [17]. In this space, finding the hyperplane requires to solve a quadratic optimization problem by using Lagrange multipliers [18]. The points, which determine the hyperplane, are called Support Vectors. Thus, the vectors are critical elements to train the classifying algorithm. It determines an optimal hyperplane to separate different classes in a data set [19].

As m labels the given training examples in a given set where x_i is the feature of the *i*th example, y_i defines the output for *i*th example as a binary value, and w denotes the weight and b the bias in (1) and (2).

$$wX_i + b \geq +1 \quad for \;\; y_i = +1 \tag{1}$$

$$wX_i + b \leq -1 \quad for \;\; y_i = -1 \tag{2}$$

If these conditions in (1) and (2) are considered for each pairs of (x_i, y_i) while i=1, 2… m we can form it as in (3).

$$\{(x_i, y_i) | x_i \in R^N, y_i \in \{-1,1\}\}_{i=1}^m \tag{3}$$

In order to determine the hyperplane which was established as far from the support vectors as possible, the margin supposed to be maximized. Thus maximization of the margin is equivalent to minimization of $\|w\|$. We may get the minimum $\|w\|$ by quadratic programing as shown below.

$$\min \frac{1}{2} w^T w \tag{4}$$

$$\text{s.t.} \;\; y_i(w^T x_i + b) \geq 1 \;\; \text{and} \;\; i = 1,2,...,m \tag{5}$$

This quadratic problem can be solved by introducing Lagrange multipliers using the Karush-Kuhn-Tucker theory. C in (7) is a penalty parameter [20].

$$\max \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{i=1}^{m} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{6}$$

$$\text{s.t.} \;\; \sum_{i=1}^{m} \alpha_i y_i = 0 \;,\;\; 0 \leq \alpha_i \leq C \;\; \text{and} \;\; i = 1,2,...,m \tag{7}$$

SVM algorithms use also kernels to reduce the complexity of problems as mapping them in a high dimensional space [21]. A kernel function makes easier to classify the inputs using the kernel trick as follows:

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \tag{8}$$

To find the optimal hyperplane we can reform the problem in a new quadratic model as follows:

$$\max \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{i=1}^{m} \alpha_i \alpha_j y_i y_j \varphi(x_i)^T \varphi(x_j) \tag{9}$$

$$\text{s.t.} \;\; \sum_{i=1}^{m} \alpha_i y_i = 0 \;,\;\; 0 \leq \alpha_i \leq C \;\; \text{and} \;\; i = 1,2,..,m \tag{10}$$

For each of the n support vector, the decision function *D(x)* which is not a magnitude but the sign becomes as in (11).

$$D(x) = sign(\sum_{k=1}^{n} a_k y_k K(x, x_k) + b) \tag{11}$$

There are various kernel functions used by SVM such as radial basic function, sigmoid function and polynomial function. More information on SVM algorithms and applications can be found in [19], [22] and details of the statistical learning theory are available in [21], [23].

III. Application of SVM Classification

This study aimed to investigate SVMs' applicability in multi-attribute ABC inventory analysis. First the simple additive weighting (SAW) method was implemented to classify inventory items based on the multiple attributes. Then SVMs were applied for measuring its classification performance.

The multi-attribute inventory classification was applied to 715 industrial inventory items of a large scale automotive company operating in Turkey [24]. The attributes used in the analysis were realized by discussing with the engineers in the related department. These attributes were illustrated in Fig.1.

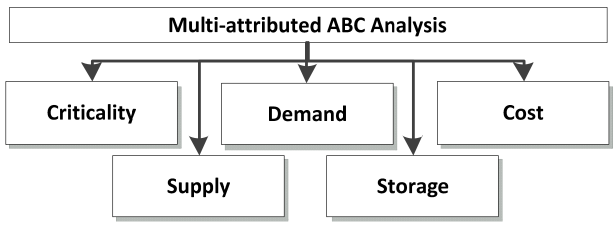

Fig. 1. The attributes of the applied multi-attributed ABC analysis model

Criticality is a factor referring the importance of the inventory items with respect to ongoing and planned production processes [8]. An item with a high level of criticality has more importance to the continuity of the production and to overall manufacturing efficiency.

Demand describes the total number of usage for each item which was consumed in a year [10]. The higher number it is used the higher importance it has.

Cost refers to the unit cost of an inventory item as an amount of money. It is considered as the purchase price of an item to the company [8], [10].

Supply attribute was defined as a value based on the supplying related importance of an inventory item. The inventory in the industrial material warehouse is a group of inventory that consists of items that their being supplied on time is significance, and both the supplier and lead time for an item are important in an adequate supply of an item on time without extra stocking and without excessive costs [25]. The value for the supply attribute is a number between zero and one that was determined by an item's condition of supplier and average lead time in last year's inventory records. Lead time was considered as the time interval between ordering and receiving an order. A longer lead time and an unsecure supplier caused a bigger number on supply attribute. A higher value for supply attribute means a higher level of importance in inventory management; and it requires more care to make improvement because the stability of supplier and length of the lead time are important for safety of supply to provide desired service level from storage to the production processes [26], [27].

Storage is the last attribute, and it is crucial for the warehouse due to the limited capacity. It refers to the storing conditions of an item, basically to the volume occupied by an item and its holding costs in the storage [25], [28]. An item which requires a larger space and a higher holding cost gets a higher value for the storage feature. It was determined similarly as a number between zero and one for each item.

The values for the related attributes of each inventory items were listed on an excel sheet as a data set. The data set consists of values which were provided by the company's last year's inventory records and values were recently assigned by warehouse technicians. The SAW method, which is a commonly known and widely used method for multi-attribute decisions, was applied to the inventory. It was chosen as a model to produce the analysis results because it is very easy to apply and simple to evaluate [23]. The weights of each attributes determined by directly interviewing with the engineers of related department as 0.3 for criticality, 0.1 for cost and 0.2 for demand, supply and storage attributes.

The values in data set were normalized by linear normalization to relatively calculate the contribution of each feature to the item's importance. For each inventory item, the normalized values of attributes were weighted by the determined weights. Then as summing the simple weighted values for each item, the overall importance values have been obtained as the final scores shown blow on Table I.

TABLE I: THE EXAMPLES OF DATA AND FINAL SCORES

Cri.	Demand	Cost	Sup.	Sto.	Final Scores
0.184	0.3970	0.0001	0.3210	0.31	0.21859
0.428	0.0154	0.0065	0.1871	0.31	0.23071
0.352	0.0001	0.6990	0.1790	0.56	0.25981
0.402	0.4304	0.0002	0.2403	0.31	0.27368
0.428	0.0004	0.0553	0.1871	0.13	0.20297
0.317	0.0056	0.0018	0.2194	0.31	0.19925
0.335	0.2612	0.0014	0.3290	0.56	0.30459
0.352	0.0001	0.1413	0.3129	0.31	0.28130
0.335	0.1025	0.0016	0.3290	0.56	0.28876
0.335	0.0852	0.0006	0.0500	0.31	0.18102

After the final scores were calculated and the results were sorted in order of descending as illustrated in Table II, to classify inventory items into groups A, B, and C, Pareto's 80-20 rule [29] applied to the final importance scores. The top 20% of the inventory were assigned to group A; the bottom 50% were assigned to group C, and the between 30% were assigned to group B. Hence, we obtained a data set of inventory that consist the multiple attributes and classes of each inventory items.

Once classes of the items determined by the model, to analyze the data by SVM a popular data mining software WEKA 3.6.8 [30] has been used. It contains various visualization tools and machine learning algorithms including SVM [31]. In order to measure SVM's classification performance, poly kernel SVM and normalized poly kernel SVM algorithms of SMO function implemented in WEKA have been used. Its implementation transforms nominal attributes into binary values and provides results by normalizing the attributes [30], [32]. Required parameters such as complexity and gamma parameter etc. were assigned as default values.

TABLE II: THE RANKING AND CLASSES OF ITEMS

ID	SAW score	Cumulative SAW score	Cumulative % of items	Class
485	0.427662	0.427662	0.14%	A
442	0.408145	0.835807	0.28%	A
73	0.241266	37.230168	20.06%	B
30	0.240499	37.470667	20.20%	B
142	0.240303	37.710970	20.34%	B
568	0.203067	83.865079	50.14%	C
569	0.203067	84.068147	50.28%	C
377	0.111196	144.944232	99.72%	C
122	0.108239	145.052470	99.86%	C
494	0.108014	145.160484	100.00%	C

IV. RESULTS

The performance results of SVM have been evaluated by three performance modes as the percentages of correctly classified items. These modes are training set, cross validation, and percentage split test.

First, all of the data has been used both to train the algorithm and to predict the classes. The simple attributes of the items were taken as inputs, and then the classes of each item were predicted. Secondly, inventory items were divided into 11 folders of nearly equal size of instances for cross-validation. Finally, the data split into two parts as 66.66% of training set and 33.33% of test data for percentage split test. The classification performance results by training set, cross-validation, and percentage split test using both the poly kernel SVM and normalized poly kernel SVM are shown in Table III.

TABLE III: THE RESULTS FOR SVM'S CLASSIFICATION PERFORMANCE

Performance mode	Poly kernel SVM	Norm. poly kernel SVM
Training set	90.396 %	86.299 %
Cross-validation	88.418 %	84.887 %
Percentage split test	90.456 %	86.307 %

As seen in the first column of the table above, poly kernel SVM approximately 90% correctly classified the instances for the three tests mentioned above, whereas as seen in the second column of the table above normalized poly kernel SVM about 85% correctly classified the instances for the same tests. Although the classification performance for each type of test in both columns varies from 84.3% to 90.4%, reasonable accuracy results obtained for all the tests in the table.

V. CONCLUSION

This paper presents a support machine application in multi-attribute ABC analysis based on the SAW method. In the ABC analysis inventory classes are obtained by considering multiple criteria such as criticality, demand, cost, supply and storage. By employing the raw inventory data as inputs and the produced classes as outputs, the study utilizes SVMs to measure the algorithm's classification performance. The results indicate that SVMs can be successfully applied to inventory classification problems. However, there is a limitation of the study to generalize the results because only one specific application was conducted in the study. In the case of the usage different inventory data set, similar results from SVMs applications in multi-attribute ABC analyses may not be obtained. The other SVM applications can be useful to improve inventory classification performances. For further studies, several kernel SVMs can be used, and their performance can be compared to achieve better results. Similarly, the studies using various ABC inventory analysis models may be conducted.

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