Supplier's Efficiency and Performance Evaluation using DEA-SVM Approach

Bo Jiang*

School of Computer and Information Engineering, Zhejiang Gongshang Uiniversity, Hangzhou, China
Email: nancybjiang@mail.zjgsu.edu.cn

Wei Chen, Hua Zhang, Weifeng Pan

School of Computer and Information Engineering, Zhejiang Gongshang University, Hangzhou, China
Email: chenweishaoxing@163.com, zerozhua@126.com, panweifeng1982@gmail.com

***Abstract*—Supplier evaluation is an important process in supply chain. To our best knowledge, we firstly report a study on supplier classification problem for efficiency and performance in the meanwhile, which is to aim at reducing the risk of enterprises and finding the suppliers with both high efficiency and performance. This paper proposed an integrated model, which hybridized data envelopment analysis (DEA) and support vector machine (SVM) together, to predict the four-class problem according to their efficiency and performance. The proposed approach is a two-step process. The first step groups them into the efficient and the inefficient according to a new metric (i.e., efficient score) computed by DEA. Then the second step will use efficient score as a new feature introduced into the data set to train SVM model and further to forecast new supplier's classification. The proposed approach shows comparable performance when compared with several existing approaches.**

Index Terms---supplier evaluation; classification; support vector machine(SVM); efficiency and performance; data envelopment analysis（DEA）

I. INTRODUCTION

Supplier evaluation is one of the most important activities in supply chain, which can assess the relative capability of suppliers and their comprehensive performance. It is also a multi-criterion decision making problem including both qualitative and quantitative factors [1, 2]. Thus, neither pure mathematical model nor pure conceptual model is appropriate to model the real supplier selection problem.

In the literatures concerning supplier evaluation, mathematical and statistical methods are usually used to assess the efficiency of suppliers. For instance, data envelopment analysis (DEA) is a popular method that is widely used to measure the efficiency of alternative suppliers [3-5]. Sometimes, it is also applied to the performance evaluation of suppliers [6, 7]. Peng [8] proposed a model aiming at optimizing the suppliers by combining analytical hierarchy process (AHP) and grey relational analysis (GRA). However, these methods are almost applied to the known suppliers in the supply chain, and thus they are not appropriate to predict and evaluate new suppliers.

Machine learning is an alternative methodology for classification problems where the model is trained based on the historical data and then it is applied to decision making on new candidates. Recently, Wu [9] adopted a hybrid model composed of both statistical and machine learning methods to evaluate the performance of suppliers and select the best one. The classification process is too simple to discover the potential suppliers that deserve selection for enterprises. As one of machine learning methods, support vector machine (SVM) has been successfully applied to a lot of classification problems [10-12]. To our best knowledge, however, there exists few focuses on using SVM to train model for supplier evaluation and prediction.

In most firms, the evaluation process is only based on suppliers' performance outcomes such as prices, quality and delivery. Thus, it only deals with part of the supplier evaluation problem. For example, a supplier may acquire high level in performance by using enormous amounts of resources like human resources and equipment resources, but it is an inefficient performer [13]. In this work, we firstly use the data mining technique to classify the supplier clusters, which are categorized into high performers and efficient (HE), high performers and inefficient (HI), low performers and efficient (LE), and low performers and inefficient (HI). We proposed a DEA-SVM approach to model this multi-class prediction problem and to further identify a new supplier. Detailed methods and results are described and discussed in the following sections.

II. DEA AND SVM

A. Data Envelopment Analysis

Data envelopment analysis (DEA) is a non-parametric mathematical programming tool that is able to determine the efficient frontier of the most efficient decision making

*Corresponding author, email: nancybjiang@mail.zjgsu.edu.cn

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units (DMUs) and to calculate the efficiency of each DMU with respect to the efficient frontier based on multiple inputs and outputs. The basic ideas of DEA can date back to Farrell [14] and the recent series of discussions started with the article by Charnes, Cooper, and Rhodes [15]. More detailed information can be found else where [16, 17].

The DEA formulation is given as follows. Given a set of n DMUs to be analyzed, each uses m common inputs and s common outputs. Let k ($k=1, 2..., n$) denote the DMU whose relative efficiency or productivity is to be maximized.

$$Max\ h_k = \frac{\sum_{r=1}^{s} u_{rk} y_{rk}}{\sum_{i=1}^{s} v_{ik} x_{ik}}, \tag{1}$$

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{r=1}^{m} v_i x_{ij}} \le 1, \quad \begin{matrix} i = 1, 2, \dots, m \\ r = 1, 2, \dots, s \\ j = 1, 2, \dots, n \end{matrix} \tag{2}$$

where u_{rk} is the variable weights of given to the rth output of the kth DMU, v_{ik} is the variable weights of given to the ith input of the kth DMU, u_{rk} and v_{ik} are decision variables determining the relative efficiency of DMUk, Y_{rj} is the rth output of the jth DMU, and x_{ij} is the ith input of the jth DMU.

It assumes that all Y_{rj} and X_{ij} are positive, and h_k is the efficiency score and is less than or equal to 1. When efficiency score of h_k is 1, DMUk is called the efficient frontier and the other is called the inefficient frontier. There are two types of CCR models. In this paper, we apply the output oriented CCR model since we focus on maximizing the multiple outputs.

B. Support Vector Machines

Support vector machine (SVM) developed by Vapnik [18] has gained popularity due to many attractive features and excellent generalization performance. It is one kind of new machine learning algorithm in the statistical learning theory. SVM formulation is given as follows:

Given a training data set $\{(x_i, y_i)\}$, x_i is the weighted feature vector of the ith and $y_i \in \{1, -1\}$ is the label of this sample. For linearly separable problem, we can determine a hyperplane $f(x)=0$ which separates the positive and negative samples.

$$f(x) = \sum_{i=1}^{n} w_i x_i + b = 0 \tag{3}$$

where w is a n-dimension vector and b is a scalar value. Meanwhile, each sample follows the below formula,

$$\begin{cases} w \cdot x_i - b \ge 1 & \text{for } x_i \text{ of the first class} \\ w \cdot x_i - b \le -1 & \text{for } x_i \text{ of the second class} \end{cases} \tag{4}$$

The plane creating the maximum margin is named as the separating hyperplane which can be confirmed by the vector w and the scalar b. By introducing slack variables ξ_i and penalty parameter of the error term C (C>0), the optimal hyperplane can be found by solving the following problem.

$$\underset{w,b,\xi}{Min}\ p(w,b,\xi) = \frac{1}{2}(w \cdot w) + \frac{C}{2}\sum_{i=1}^{n} \xi_i^2 \tag{5}$$

where ξ is the distance lying on the wrong side of the margin between the margin and example x_i. SVM requires solving the following optimization problem [19].

$$V(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j k(x_i \cdot x_j) \tag{6}$$

Subject to

$$\sum_{i=1}^{l} y_i \alpha_i = 0,\ \mathrm{C} \ge \alpha \ge 0, i = 1, 2, \dots l. \tag{7}$$

where α_i is the Langrage multiplier for each training sample i. The function k (x_i, x_j) returning a dot product of feature space mappings of the original data points is called a kernel function which can map the training vectors x_i into a higher dimension space, and the SVM model finds a linear hyperplane which has the maximal margin boundary in order to separate the data. There are three popular kernels, namely linear, polynomial and radial basis function (RBF), which are showed as follows:

1. Linear: $k(x_i, x_j) = x_i^T x_j$ (8)
2. Poly: $k(x_i, x_j) = (\gamma x_i^T x_j + r)^d$ (9)
3. RBF: $k(xi, xj) = \exp\left(-\gamma \| xi - xj \|^2\right)$ (10)

where γ, r and d are kernel parameters, and γ must be larger than zero. The most commonly used and effective kernel is the RBF kernel. In this work, we consider above three commonly used kernel functions to train the model. The final decision function for a new sample x has the following form:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i y_i k(x_i, x) + b\right) \tag{11}$$

where b is a threshold term computed as

$$b = \sum_{i=1}^{n} \alpha_i y_i k(x_i, x_j) \tag{12}$$

For any $j \in \{1, 2, \dots, n\}$.

III. Classification Task And Hybrid Model

A. Supplier Classification

The supplier evaluation consists of performance and efficiency. Performance reflects the relationship between suppliers and enterprises. The better performance, the better services can suppliers provide, such as accurate delivery time, preferential price, enough goods, and so on. The enterprises can build the robust supply chain, which help enterprise operate normally and gain more profit. Efficiency reflects the competitiveness of the suppliers' own. The higher the efficiency, the stronger the competitiveness for a supplier to occupy the market position. Figure 1 shows the relationship of performance and efficiency [13]. The proposed division for supplier clusters concerning four classifications is described as follows:

1) High performance and efficient (*HE*): These kinds of suppliers have miraculous industry, positive credit and healthy development. They are the best choice for enterprise. In the long-term cooperation, the enterprises need a supplier with high performance, who have perfect operation system and supply system to provide services. They both make the profit balance which can keep the health cooperation and harmonious development to obtain win-win results.

2) High performance and inefficient (*HI*): The supplier of this class is also suitable for enterprises, but when they provide service, they also consume a lot of resources, like more human resource. From a view of long-term trend, it will undermine the cooperation between them, breaking the enterprise supply chain, so they are not the best options for enterprises.

3) Low performance and efficient (*LE*): This class of supplier is competitive enough, but it does not provide a good service and thus is not conducive to the supply chain. In the long-term cooperation, they will affect the development of the whole supply chain。

4) Low performance and inefficient (*LI*): This type of supplier is not competitive and they can not provide great services for the enterprise. The enterprise should consider giving up the cooperative relationship with their suppliers.

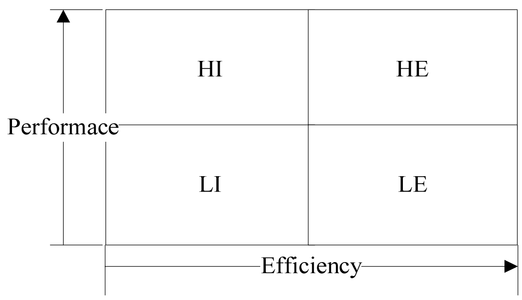

Figure 1. Performance and efficiency of suppliers.

B. Hybrid Model

In this work, a hybrid method combining DEA and SVM is proposed to model the four-class supplier problem in terms of efficiency and performance in different levels. The model consists of two steps. Step 1 classified the suppliers as efficiency or inefficiency in terms of the efficient scores derived by DEA. Then the second step regarded the efficient score as a new feature and added it into the previous feature vector. Based on the new feature set, SVM was applied to train the model that can be used to evaluate any new suppliers. Figure 2 depicts the conceptual procedure for supplier evaluation using the proposed DEA-SVM approach.

IV. Dataset And Experiments

A. Dataset

The exiting experimental dataset for research is taken from Narasimhan and Talluri [13]. The data is derived from a large, multinational company, which is a global leader in design, production, and marketing of communication systems. In this set, each supplier has 11 attributes, which are divided into two categories: the capability attributes and performance attributes. Table I shows the detailed descriptions for capability attributes in the left and performance attributes in the right.

TABLE.I
CAPABILITY AND PERFORMANCE ATTRIBUTES

Capability attributes	Performance attributes
Quality management practices and systems (QMP)	Cost Reduction Performance (CRP)
Documentation and self-audit (SA)	Price
Process manufacturing capability (PMC)	Delivery
Management of the firm (MF)	Quality
Design and development capabilities (DDC)	Other
Cost reduction capability (CRC)	

We use the output oriented CCR (Charnes, Cooper, and Rhodes) model to get the DEA score (DS) as a new feature, where the six capability attributes are used as input and the five performance attributes are regarded as output for DEA model. We refer to the original feature set as FS and the new one including DEA score attribute as FS+DEA. All attribute values for 23 suppliers are listed in Table II. The label attribute values representing the four classifications of suppliers are also listed in the last column of Table II.

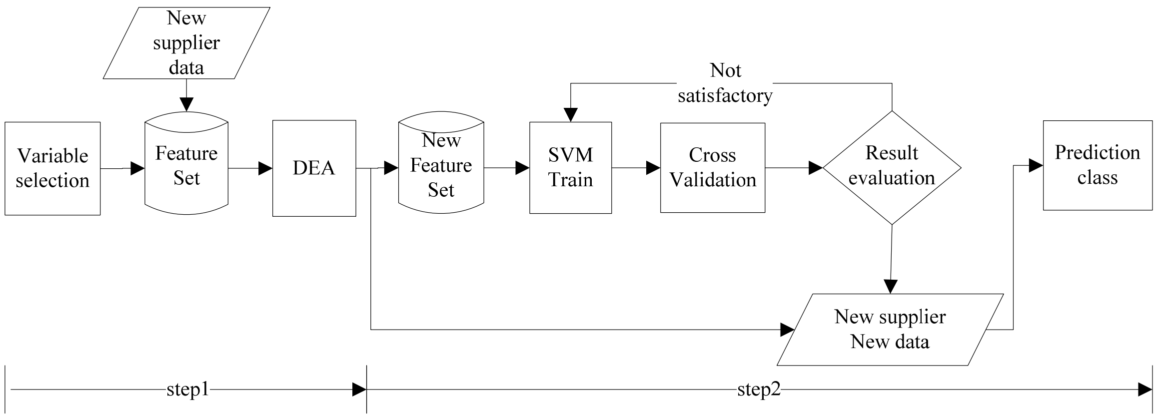

Figure 2. The DEA-SVM Hybrid model.

TABLE.II
THE DATA SET COMPOSED OF 23 SUPPLIERS FOR EXPERIMENTS

#Supp	QMP	SA	PMC	MF	DDC	CRP	Quality	Price	Delivery	CRP	Other	DEA Score	Label
1	0.9662	0.9742	1.0385	1.0808	1.1417	0.7839	0.6211	0.8922	0.1284	1.2107	0.6359	0.602	LI
2	0.7054	1.0438	0.7500	0.8782	0.0000	0.8750	0.6932	0.8922	0.3855	0.0000	0.3179	1.000	LE
3	0.5611	0.8947	0.7789	0.7205	0.8372	0.7404	1.0205	0.4341	1.5420	0.0000	1.2719	1.000	LE
4	1.1272	1.0438	0.9520	0.9607	0.9661	1.1402	1.6639	1.1333	1.5420	1.2107	1.8019	1.000	HE
5	1.1272	1.0438	1.1251	1.0808	1.2560	1.2115	0.9983	1.3503	1.1565	1.2107	0.9540	0.855	HI
6	0.9877	1.0438	0.9376	1.0808	1.0466	0.9422	1.0426	1.3263	1.7990	2.4214	0.9877	1.000	HE
7	0.8051	0.8351	1.0385	0.9607	1.2560	1.0768	1.2201	1.2056	0.7710	2.4214	1.2719	1.000	HE
8	1.1809	1.0438	1.1251	1.0208	1.0627	1.0096	0.8429	1.1333	0.6424	1.2107	0.8479	0.723	LI
9	1.2346	1.0438	1.1251	1.0808	1.2560	1.1442	0.6433	0.8922	0.3855	0.0000	0.5299	0.562	LI
10	0.5904	1.0438	0.6058	0.7629	0.5796	0.4038	1.4419	0.4341	1.4135	0.0000	1.2719	1.000	HE
11	0.8642	0.8118	0.8182	0.9536	0.9661	0.8076	0.4215	0.8922	1.0279	0.0000	0.8479	0.805	LI
12	0.6441	0.8351	1.0227	1.0208	0.9661	1.0768	1.0205	1.3263	0.7710	1.2107	0.7418	1.000	LE
13	1.2346	1.0438	1.1251	1.0808	1.2560	1.2115	0.5546	1.1092	1.0279	1.2107	1.1660	0.773	LI
14	1.0662	1.0438	1.1251	1.0808	1.1593	1.2115	0.8208	0.8922	0.8994	1.2107	0.8479	0.609	LI
15	1.0100	1.0438	0.8654	1.0208	0.7322	0.6815	1.2423	1.5674	1.4135	2.4214	1.2719	1.000	HE
16	0.8978	0.9742	1.0385	1.0208	0.9420	0.8076	1.0205	0.8922	0.3855	0.0000	0.4240	0.764	LI
17	1.1272	0.9742	1.0385	1.0208	1.2560	1.0768	1.0205	0.8681	0.7710	0.0000	0.5299	0.702	LI
18	1.1809	1.0438	1.1251	1.0808	1.2560	1.2115	1.2201	0.2411	0.0000	0.0000	0.4240	0.733	LI
19	1.0735	1.0438	1.1251	0.9007	1.1593	0.9422	1.1647	0.8922	1.4135	1.2107	1.0599	0.904	HI
20	1.0735	1.0438	1.1251	1.0808	0.6762	1.1442	0.8429	1.0550	1.4135	1.2107	1.4839	1.000	HE
21	1.2346	1.0438	1.1251	1.0133	1.2560	1.2115	0.7764	0.8922	1.0279	0.0000	0.9540	0.658	LI
22	1.2346	1.0438	0.9520	1.0808	1.0466	1.2115	1.4642	1.3263	1.7990	2.4214	1.4839	1.000	HE
23	1.0735	1.0438	1.0385	1.0172	0.8695	1.0768	1.2423	1.3503	1.2849	2.4214	1.5900	1.000	HE

B. Experiment Steps

Given the data set as shown in Table II, we implemented the algorithm proposed in Figure 2, from step 1 to step 3:

Step 1: *DEA score generation*. We chose capability attributes as input and performance attributes as output for CCR model, and used software Lingo (version 6.1) to calculate the DEA scores.

Step 2: *Training*. We mainly applied SVM to train the model with the same data set using two feature sets FS and FS_DEA, respectively. Suitable selection of kernel function and the related parameters may largely improve the prediction accuracy. To this end, we performed grid search to optimize the parameters C, γ associated with RBF kernel, and d associated with polynomial kernel based on 5-fold cross validation with 20 runs, where one run represents a new random subset split of the entire data set. Multiple runs are to aim at eliminating the instability of predictions arising from the small size of the data set. Similar experiments were also performed using alternative machine learning methods including decision tree (DT), logistic regression (LogR), naïve Bayes (NB), and RBF network (RBFN) for the purpose of a comprehensive comparison. Here, the SVM was performed using LIBSVM [20] and other methods were implemented using WEKA [21].

Step 3: *Evaluation for new suppliers*. Given a new supplier and the corresponding attribute values, the DEA score is firstly calculated based on *Step 1*. Then, the model trained on the entire data set is performed to identify the class that the new supplier belongs to.

V. Results Analysis

Since cross validation is reported as an effective way to minimize data dependency and to improve the reliability of the results [22], 5-fold cross validation was applied in this paper. With the utilization of multiple runs, the average accuracy (ACC) over 20 runs and its standard deviation (std) were computed as two criterias to evaluate the performance of the proposed method. The highest accuracy value via optimizing the parameters using grid search was obtained for each run (i.e. one 5-fold cross validation), and the ACC value and its standard deviation were averaged over 20 independent runs. In addition, similar procedures were also performed on all alternative methods for a comprehensive comparison.

TABLE.III
THE ACC AND STD VALUES USING THE FEATURE SET FS

Method	ACC (%)	std
SVM--Linear	74.78	0.0174
SVM--RBF	**75.65**	**0.0212**
SVM--POLY(2)[a]	72.39	0.0257
SVM--POLY(3)[a]	70.26	0.0350
RBF Network	58.48	0.0819
Logistic Regression	66.09	0.0488
Naive Bayes	63.70	0.0634
Decision Tree	61.30	0.0531

Note: [a]SVM--POLY(*d*), where *d* is the degree of the polynomial kernel function.

A. Classification Performance upon the Feature Set FS

Table III shows the ACC and std values of all methods inlcuding SVM, DT, LogR, NB and RBFN using the feature set FS. It can be observed that the difference between SVM and other machine learning methods is significant. SVMs with different kernel functions achieve the ACC values of above 70%, while those for other machine learning methods are all lower than this threshold. When using the RBF kernel, the ACC value of SVM achieved 75.65% that is the highest and the improvement is at least by 10% higher than other methods. In addition, the standard deviation values of SVMs are also relatively lower than other methods, which implies that SVM is a better choice for supplier classification and evaluation problem when compared with other methods. Moreover, different results can also be observed for SVMs with different kernel functions. The ACC value of SVM with quadratic polynomial kernel function is 72.39%, which is larger than the ACC value of SVM with the cubic polynomial kernel function. However, the ACC value of SVM with quadratic polynomial kernel is lower than that with linear kernel which is equivalent to a polynomial kernal with degree of 1. It means the performance of low degree's polynomial kernel is better than that of high degree's polynomial kernel.

B. Performance upon the Feature Set FS+DEA

To observe the impact of DEA score on the improvement in prediciton ACC values, we performed the same cross validation experiments using the feature set FS+DEA. Table IV shows the ACC and std values of all methods inlcuding SVM, DT, LogR, NB and RBFN. From Table IV when compared with Table III, most of all methods show increase in ACC value except the SVM with the linear kernel whose ACC descends from 74.78% to 74.35%. At the same time, most of methods also show decrease in the standard deviations of accuracy values. The most important finding is that the SVM with RBF kernel retains the improvement and the best performance.

TABLE.IV
THE ACC AND STD VALUES USING THE FEATURE SET FS+DEA

Methods	ACC (%)	std
SVM--Linear	74.35	0.0130
SVM--RBF	**77.17 ↑**	**0.0188 ↓**
SVM--POLY(2)	72.83	0.0233
SVM--POLY(3)	71.95	0.0256
RBF Network	62.39	0.0664
Logistic Regression	68.48	0.0686
Naive Bayes	64.78	0.0548
Decision Tree	60.22	0.0664

Moreover, we performed the paired t-test at the 95% significance level for the accuracy index, in which we compare the corresponding pairs in the 20 runs using different feature sets. Table V lists the *p*-values of the t-test for all methods. The output values (*p*-values) of the paired t-test result in that the improvements of four methods including SVM with linear kernel (p=0.330), SVM with cubic polynomial kernel (p=0.304), logistic regression (p=0.281) and decision tree (p=0.315) are not significant. However, the predictions of SVM with RBF kernel (p=0.005), SVM with quadratic polynomial kernel (p=0.000) and RBF network (p=0.014) provide statistically significant higher ACC values. Consequently, of all methods, the SVM with RBF kernel achieves the highest ACC with significant improvement by adding DEA score into the raw feature set.

The above analysis implies that SVM is suitable for the classification task of the supplier selection problem. In particular, the integration of SVM with the RBF kernel and DEA method achieved the best results. Proper method selection is necessary for the supplier evaluation which may guarantees supplier evaluation optimum solutions when compared with other artificial intelligence approaches. Especially for SVM, making an appropriate choice for kernel function is the key to construct an excellent classification model which may enhance the prediction performance according to the above experimental results. Valid experiments using statistical test suggest that DEA score is a useful feature to improve the classification performance. We conclude that the hybrid DEA-SVM model is a promising method that can be utilized as a competitive solution in the supplier evaluation area. An important advantage of this method is that it can be applied to identifications on new suppliers whether they deserve consideration for a firm.

TABLE.V
THE P-VALUES PERFORMED WITH PAIRED T-TEST FOR DIFFERENT PREDICITONS USING FEATURE SETS FS AND FS+DEA

Method	SVM--Linear	SVM--RBF	SVM--POLY(2)	SVM--POLY(3)	RBF Network	LogR	Naive Bayes	Decision Tree
p-value	0.330	0.005	0.000	0.304	0.014	0.281	0.056	0.135

VI. CONCLUSIONS

We proposed a DEA-SVM model with the purpose of classifying the suppliers into four categories: (i) high performance and efficient (HE), (ii) high performance and inefficient (HI), (iii) low performance and efficient (LE), and (iv) low performance and inefficient (LI). To verify the feasibility of the proposed DEA-SVM model, supplier evaluation is performed on an existing dataset [13]. The contribution of this study can be summarized as follows: Firstly, DEA method does provide valuable information in the supplier evaluation. Secondly, the proposed DEA-SVM hybrid method provides better classification results than decision tree logistic regression, RBF network, and naive Bayes. Hence, SVM method has better capacity on handling classification problems on a small dataset. Although the dataset of suppliers is very small, the results show that a very small-sized data set can give meaningful results in training DEA-SVM. The above-mentioned findings suggest that the DEA-SVM model should be a better alternative to conduct the supplier evaluation tasks.

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