

# Asset Evaluation Model Based on SVM Algorithm

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**Abstract.** The purpose of asset write-offs by a firm is to provide an accurate valuation of the firm and to reveal its true business performance from the perspective of economic conditions. However, the decision to write-off assets might be manipulated by the manager of the firm and thus misguide the public to an incorrect firm value. The aim of this study is to provide quantitative prediction models for asset write-offs based on both firms' financial and managerial incentive factors. The prediction is achieved in two stages, where the first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such asset write-offs if they took place. The prediction models are constructed by support vector machine (SVM) and logistic regression for the binary decision of asset write-offs, and support vector regression (SVR) and linear regression for the write-off magnitude. The performances of different models are compared in terms of various criteria. Moreover, the bagging approach is used to reduce the variance in samples to improve prediction performance. Computational results from empirical data show the prediction performances of SVM/SVR are moderately superior to their counterpart legit/linear models. Moreover, the prediction accuracy varies with the distinctive types of asset write-offs.

**Keywords:** Asset write-offs; support vector machine; bagging.

## 1. Introduction

The decision of asset write-offs is considered relevant to a firm financial performance or economic factors<sup>1</sup>. Previous studies have attempted to explore the managerial incentive factors behind the asset write-offs decision. Nonetheless, these studies generally focused on the timing of the asset write-offs or the factors leading to this decision. Seemingly, quantitative prediction models would be more useful to investors and market participants for their ability to provide incremental information about a firm potential recognition of an asset write-offs and the appropriate magnitude of asset impairments. There were a few studies that employed regression analysis, logistic regression, or the Tobit model to build an asset write-offs models. Nevertheless, they generally focused on justifying the relationship between the asset write-offs decision and the designated financial factors. The aim of this study is to establish prediction models for asset write-offs decisions. The prediction is achieved in two stages, where the first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such impairment.

Two types of approaches are used to construct the prediction models in this study; one is regression analysis in the statistical approach, and the other is the support vector machine in the machine learning field. In the statistical approach, the logistic regression is employed to construct the binary decision model and ordinary regression analysis is used for predicting the write-off amount. In the machine learning approach, the standard SVM is used to construct the binary decision model, and the support vector regression is used for predicting the write-off amount. Performance comparisons of these two approaches are provided based on the computational results from an empirical study.

## 2. Prediction Models

### 2.1 Logistic Regression

Logistic regression or called legit analysis is a popular tool for binary prediction and is defined as:

$$p = \frac{\exp(\beta_0 + \beta_1 x_1 + \dots + \beta_m x_m)}{1 + \exp(\beta_0 + \beta_1 x_1 + \dots + \beta_m x_m)}$$

P: the probability of occurrence

$x_i$ : Explanatory variables of the prediction model,  $i=1, m$

$\beta_0$ : Regression intercept  $\beta_i$ : coefficients of the explanatory variables  $i=1, m$ .

## 2.2 Support Vector Machine

Machine learning approaches, such as decision tree, case-based reasoning, and artificial neural networks (ANNs), have been widely applied to the research area of financial management. For example, Borat and Kennedy used the back propagation neural network for firm bankruptcy prediction; Oakley and Brown reviewed the literature on ANNs applied to accounting and finance problems and suggested criteria that should be used to determine whether using an ANN is appropriate; and Cheng also presented a radial basis function neural network for financial distress prediction.

In recent years, a particular type of neural network known collectively as support vector machines is widely accepted as an efficient tool for prediction due to its advantages in global optimization and model generalization. The ordinary SVM is a binary learning machine based on statistical learning theory. The basic idea behind SVM is to construct an optimal hyper plane as the decision surface so the margin of separation between positive and negative training examples is maximized.

## 3. Research Design

### 3.1 Data Collection

The sample used in this study consists of the listed companies in Taiwan's stock market between 2005 and 2007. Company information and financial data are from the database of Taiwan Economic Journal Corporation (TEJ). Missing data are verified with reports published by Taiwan Stock Exchange Corporation (TSE) and Grew Tai Securities Market (OTC). The initial sample contains 1,358 firms in each year. After discarding the outliers, the resulting sample consists of 1,092 firms in 2005, 1,132 firms in 2006, and 1,174 firms in 2007. Classified by year and industry, the sample data are presented in Table 1.

Table 1. Distribution of firms in the sample

Industry	2005 (N=1,092)			2006 (N=1,132)			2007 (N=1,174)		
	Non-WO	WO	Total	Non-WO	WO	Total	Non-WO	WO	Total
Cement	2	5	7	2	5	7	4	3	7
Foods	11	10	21	14	7	21	12	9	21
Plastics	15	8	23	13	10	23	15	9	24
Textiles	27	23	50	33	21	54	33	20	53
Electric Machinery	53	17	70	47	25	72	52	22	74
Electric Appliance	9	5	14	8	6	14	4	10	14
Chemical & Biotech.	57	20	77	62	18	80	54	24	78
Glass & Ceramic	3	2	5	3	2	5	3	2	5
Paper Pulp	3	4	7	4	3	7	2	5	7
Iron & Steel	18	14	32	20	15	35	24	13	37
Rubber	7	4	11	8	4	12	10	2	12
Automobile	3	1	4	1	2	3	1	4	5
Electronics	441	163	604	460	169	629	468	192	660
Construction	29	20	49	25	24	49	37	14	51
Shipping	19	2	21	20	2	22	15	8	23
Tourism	10	1	11	11	1	12	11	2	13
Trade	15	3	18	14	6	20	11	8	19
Oil, Gas and Electricity	7	4	11	10	1	11	11	1	12
Others	40	17	57	30	26	56	43	16	59

## 3.2 Empirical Models

### 3.2.1 Statistical Regression

There are 15 explanatory variables in total, as discussed earlier. The resultant model is as follows.

$$P(D\_WOTA = 1 | x) = \frac{e^z}{1 + e^z}$$

The amount of data is relatively scarce compared to the number of variables used in the model. Thus, only those significant variables are kept by the both forward and backward stepwise method when conducting an empirical analysis.

### 3.2.2 SVMs

To reduce the prediction variances of the models, we use the bagging method to construct the prediction models. Let  $M$  denote a general model, i.e., Legit or SVM,  $S = (x_i, y_i)$ ,  $i = 1, \dots, N$  be  $N$  pairs of input-output data. The steps of the bagging method are as follows.

Step 1. Bootstrap

Number of training times =  $T$

For  $j=1$  to  $T$

Randomly draw  $N$  pieces of data with replacement from  $S$  to form a sample  $S_i$

Training  $M$  with  $S_i$  to obtain a trained model  $M_j$

Next  $j$

Step 2. Bagging

Let  $x$  be the input vector.

Case of binary prediction:

The final prediction with  $x$  is determined by a majority voting

$$M_{Bagging(x)} = \arg \max_k \{C_k\}, k \in \{0,1\},$$

Where  $C_k$  is the number of  $M_j$  whose prediction is class  $k$  for a given input  $x$ .

Case of write-off magnitude prediction:

$$M_{Bagging(x)}(x) = \frac{1}{T} \sum_{j=1}^T M_j(x)$$

### 3.2.3 Prediction Performance Criteria

The performance evaluation of the binary prediction is based on the prediction error rate, i.e., the ratio of number of error prediction to the total number of firms in the prediction sample. The prediction error rate must be less than the random error, i.e., the number of asset write-offs firms divided by the total number of firms in the sample, for the prediction models to be effective. MSE, NMSE, and MAPE can measure the difference between the actual write-off magnitudes and the predicted ones. The lower these values, the more accurate the prediction models are. MSE, NMSE, and MAPE are defined as:

$$MSE = \frac{\sum_{i=1}^n (A_i - F_i)^2}{n} \quad NMSE = \frac{\sum_{i=1}^n (A_i - F_i)^2}{n\delta^2} \quad MAPE = \frac{\sum_{i=1}^n \left| \frac{A_i - F_i}{A_i} \right|}{n}$$

## 4. Empirical Result Analysis

As discussed previously, the asset write-offs decisions are also influenced by macroeconomic conditions, which are not considered in our models. To exclude this factor, prediction models are constructed for respective years. As shown in Table 3, the prediction error rates of the single logic model are 0.2918, 0.3033, and 0.2890, for years 2005, 2006, and 2007, respectively, which are all less than the random errors. Though the error rate for year 2006 is greater than the random error, the error rates for years 2005 and 2007 are both slightly less than that by the legit model. Though these results did not show SVM significantly outperforms the legit model, the performance deviation of SVM was less than the legit model, implying SVM can provide more robust prediction performance.

Table 2. Performance comparison of various models

	model	Year 2005		Year 2006		Year 2007	
		Mean	SD	Mean	SD	Mean	SD
Single	Random	0.2941		0.3050		0.2904	
	Logit	0.2918	0.01371	0.3033	0.01609	0.2890	0.0133
	SVM	0.2863	0.01078	0.3130	0.00976	0.2793	0.0091
Ensemble	Logit	0.2926	0.01436	0.3033	0.01511	0.2892	0.0137
	SVM	0.2854	0.01099	0.3130	0.00995	0.2797	0.0091

From the performance comparisons presented in Tables, it is seen that SVR model generally performs better than the regression model in the measure of NMSE. This result implies that the performance of SVR is not affected by the value range of dependent variable, which happens to be the deficit of linear regression models. It is also noted that the effect of ensemble sampling is not significant as demonstrated in Tables. A possible reason is the number of data used in bagging the training sample is insufficient to produce a well generalized model. This argument will be further studied in our future research.

## 5. Summary

This study has established asset write-offs prediction models using two types approaches, namely regression analysis and support vector machines. The prediction is achieved in two stages, where the first stage conducts a binary prediction of the occurrence of asset write-offs by a firm, while the second stage predicts the magnitude of such asset write-off if one exists. In the first stage, the logistic regression and the SVM are used to construct models for predicting the binary prediction of asset write-offs, while in the second stage the linear regression and the SVR are used to predict the magnitude of asset write-offs.

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