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Bankruptcy Prediction on Margin Trading and Applications

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Abstract Although bankruptcy and default are well known as critical factors leading to various financial recessions or financial bubbles, such as the Great Depression in the USA that began in 1929 and the Lost Decade of Japan in the 1990s, predicting when they will occur has not been studied sufficiently. In this paper, we propose a method that filters out risky investors and keeps good investors in a margin-trading simulation. Investors are divided into three classes (bankrupt, surviving and profitable) instead of the standard two (bankrupt/bad and surviving/good). As a result, bubble bursting can be thwarted, since maintaining credit absorption for the qualified investors can prevent the collapse of prices. We expose the problems with using the minimum margin as the de facto tool for controlling trading on the margin. We compare the results of four well-known data classification methods (multiple discriminant analysis, neural networks, decision trees and support vector machines) in order to determine the one that is most suitable for building a credit-scoring schema. Of the methods considered, the C4.5 algorithm for building decision trees was found to be the best. Our proposed strategy can successfully use credit scoring to tame the bubble phenomenon.

Keywords. margin trading, credit scoring, bankruptcy prediction, stock market simulation, bubble bursting.

1 Introduction

Bankruptcy prediction is a challenging topic in business analytics because of the importance of precise and timely strategic business decisions and their impact on the corporation, society and the country and even globally. In the United States, the Great Depression that began 1929 and the 2008 financial crisis when the housing bubble

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burst and in Japan, the Lost Decade of the 1990s were ignited by the inability to accurately predict bankruptcy [6].

Following these recessions, various regulations were established to ensure the stability of the market and to prevent another collapse [31]. Because buying on the margin is correlated with financial distress, it can be used as an indicator for detecting an imbalanced financial market [19]. Margin requirements are used to control price volatility and to prevent investors from going into debt to engage in reckless speculation. It is also used to ensure sufficient liquidity in the market that prices are established fairly and smoothly. Relaxing requirements for investing on the margin holds great appeal for the investors, but it is a double-edged sword. Although it increases liquidity, it is also likely to increase volatility [36]. On the other hand, tight requirements restrict volatility, but the liquidity will be low, because many investors will default. Some of the investors who will be defaulted or file to bankruptcy should be well predicted to manage the risk as instructed on Basel II accord [15]. For a bank or lender, increasing the margin requirements is an effective tool for mitigating risk. However, good investors may also be filtered out since only investors who have sufficient working capital are retained, but, unfortunately, this tool cannot predict which investors will perform well.

In this paper, we develop a new method for using credit scoring to predict an investors' performance when trading on the margin. Compared to a margin requirement that screens investors merely by their capital and collateral, credit scoring can extend the scope of the evaluation to include the character, capacity and condition of the trader. The simulation presented here was developed from the stock market simulation that was studied by Nakatani et al. [23, 25] and Zhu [40]. The bank agent in that model did not have intelligence and considered only the ratio of debt to working capital. We implemented an artificial intelligence approach to credit scoring for granting loans. We used a statistical method, multiple discriminant analysis [2] and artificial neural networks, decision trees and support vector machines to create our credit-scoring schema.

In the financial industry, credit scoring is well known as a way to predict bankruptcy and thus our research appears to be similar to that of others; however, to the best of our knowledge, there have been no scientific studies of using credit scoring for margin trading. Most of the related research considers ways to predict bankruptcy of companies [12, 14, 20, 22, 27, 32, 39]. However, Wang [35] used an analytical approach to measuring the credit risk for margin trading and calculated the threshold-breaking probability, the default probability and loss given default. In that study, financial ratios were not used to predict bankruptcy, whereas we use the investors' financial ratios and an artificial intelligence approach to predict the status of each investor. We developed a method for credit scoring that uses three classes ("bankrupt", "surviving" and "profitable"), although most known methods use only two classes ("bankrupt" and "surviving" or good and bad). The "profitable" class is useful for maintaining market liquidity when a bubble occurs. Banks can deliver their loans to investors who will help maintain market liquidity. We consider the impact of credit scoring on price movement and its effect on controlling bubbles.

We also present a new banking strategy for taming bubbles [24]. Most economists use financial regulations and macroeconomic policies in their attempts to tame the crashes that follow bubbles. For example, Danthine [9] used capital buffers to mitigate systemic risk and Sornette [33] developed a method for detecting bubbles and predicting crashes. In our bubble-taming strategy, we use artificial intelligence, credit scoring, bubble detection and loan adjustments. We verified in our cases that if a bank uses our strategy, it can prevent the bubble from bursting.

The remainder of this paper is organized as follows. In Section 2, we explain the use of the simulation model for discovering problems and finding critical factors. In Section 3, we briefly describe the theoretical background of various classification methods that are used to predict bankruptcy. In Sections 4 and 5, we discuss the result of the simulations. In Section 6, we make some remarks and present our conclusions.

2 Model

2.1 Investor Behavior

We assume that there are two types of investors (or players) in the stock market, that is, players with artificial intelligence (AI players) and players with random behavior (random players). *AI players* are big players who are smart and have large assets, whereas *random players* are small, speculative traders. AI players create trends, while random players create noise. AI players create price movement, since they make effective order decisions and are able to capitalize them. On the other hand, the decisions of random players are made by a random walk with a Gaussian distribution. AI players are given loans and this leverages their actions; random players are not given loans. When AI players collapse, this will cause price movement and it may even cause prices to crash, since AI players have large capitalization in the market. Therefore, in order to avoid sinking prices, it is important that bank agents properly analyze the situation before granting their loan applications.

The algorithm we used for the AI player's decisions is based on the back-propagation neural network (BPNN) rules, which were developed by Nakatani et al. [23, 25] and Zhu [40]. The BPNN is made up of three layers (input, hidden and output). The input data consisted of 53 items, it learned from 51 historical transactions and the information includes the amount of cash and number of shares of stock possessed by the investor being evaluated. The hidden layer contains 60 neurons and the transfer function that is applied is a sigmoid function. The output of the BPNN are buying and selling signals and the result is the larger of the two. A market order occurs when the buying or selling signal is greater than 0.99; otherwise, there is a limit order or a bid order. In order to determine the signal to buy or sell, the BPNN evaluates the following function as a measure of wealth in future:

$$Q_p = \sum_{n=0}^{n} \Delta V_{p+n} \gamma^n.$$

$\Delta V = V(t_{p+n}) - V(t_{p+n-1})$, γ is a future discount factor $(0 < \gamma < 1)$ and V is an evaluation function of investor's assets. Here, $\Delta V > 0$ signifies that the investor's wealth increases as the price rise and $\Delta V < 0$ signifies that the investor's wealth decreases as the price decline. A decreasing price is a signal for applying a short-sale strategy. The teacher signal t_{ip} is determined by Q_p as follows:

$$t_{ip} = \sigma(Q_p),$$

where σ is a sigmoid function with $\alpha = 0.5 \times 10^{-6}$

$$\sigma(x) = \frac{2}{1 + \exp(-\alpha x)} - 1.$$

The random player's orders are based on the normal distribution:

$$f(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \tag{2.1}$$

where μ is the mean order and σ is its standard deviation. We used a Gaussian distribution, because we believe that this best approximates the value of the price bids and asks of random players. We assume that the probability that they decide to invest all of their money is smaller than the probability that they invest only a part. If the standard deviation is equal to half of a player's working capital, it means that the probability that they invest half of their wealth is around 70%. A positive value indicates buying and a negative value indicates selling. When this value is less than the minimum transaction, a hold results. The minimum transaction was set at 100 shares.

Some of the random players use a buy-and-hold strategy. This simple approach attempts to create profit by only selling shares when the price is higher than it was when the shares were purchased. This is a common strategy for the average investor.

2.2 Simulation Model

There are two main phases in the simulations: credit scoring and taming the bubble.

1. Credit Scoring
   In the first step, we will formulate a credit-scoring schema to describe how credit scoring is developed and in the second part, we will explain how bank uses credit scoring.

(a) Credit Scoring Schema

A *credit score* is a model that predicts whether an applicant will be able to repay a loan [12]. It transforms the relevant data pertaining to the applicant into numerical measures that are used to guide credit decisions [4]. Credit scoring is used to predict the investor status, which is determined from their *working capital* ($w(t)$), defined as

$$w(t) = \text{cash}(t) + \text{price}(t) \times \text{share}(t) - \text{debt}(t), \qquad t\text{: time.}$$

The investor status is classified as bankrupt, surviving, or profitable. Investors are said to be *bankrupt* if and only if their working capital is less than or equal to zero. Investors are said to be *profitable* if and only if their working capital has increased by at least 40% in the previous month (22 days). Investors are said to be *surviving* if their working capital is greater than zero and less than 1.4 times their working capital in the previous month:

$$status = \begin{cases} \text{bankrupt,} & \text{if } (w(t) \leq 0) \\ \text{surviving,} & \text{if } (0 < w(t) < 1.4w(t-22)) \\ \text{profitable,} & \text{if } (w(t) \geq 1.4w(t-22)). \end{cases}$$

To predict the status of investors, we used four well-known methods to develop credit scores. These methods include multiple discriminant analysis (MDA) from statistics, C4.5 from the field of decision trees, resilient propagation neural networks (RPNN) and the support vector machine (SVM) from the field of machine learning. Each of these methods used the following eight ratios to predict the status of investors.

i. (market value)/(total assets) = v_1
ii. (profit or loss)/(total assets) = v_2
iii. (liabilities)/(working capital) = v_3
iv. (cash)/(working capital) = v_4
v. (market value)/(working capital) = v_5
vi. (profit or loss)/(working capital) = v_6
vii. (liabilities)/(total assets) = v_7
viii. (cash)/(total assets) = v_8

In the AI approach, we use a vector-valued function $f(v)$ with eight arguments $(v_1, \ldots, v_8)$. The output data are normalized to be in the range $[-1, 1]$.

$$Y = (y_1, y_2, y_3) = f(v_1, \ldots, v_8), \qquad -1 \leq y_i \leq 1 \ (i = 1, 2, 3). \quad (2.2)$$

Each output $(y_i+1)/2$ $(i=1,2,3)$ can be regarded as the probability of investor status which is bankrupt, surviving and profitable. The maximum output of the prediction indicates whether the investor is bankrupt, surviving, or profitable. The status of each investor is determined by

$$g(Y)=\begin{cases}\text{bankrupt}, & \text{if } (y_1=\max Y)\\ \text{surviving}, & \text{if } (y_2=\max Y)\\ \text{profitable}, & \text{if } (y_3=\max Y).\end{cases}$$

In the AI approach, the training data included bankrupt data, which included the values of eight variables for one week (five days) before bankruptcy; profitable data, which included the values of eight variables for one month (22 days) before the profit exceeded 40%; and surviving data, which included the data of any surviving investors.

(b) Credit Scoring Application
When a loan is requested, the bank agent will check the investor's credit score. If the investor status is surviving or profitable, then their loan proposal will be granted. If an investor is identified as bankrupt, the bank then checks whether that investor's working capital > debt. If true, then the player is considered likely to default and the bank agent will send a payback request that forces the sale of all of their assets in order to repay the loan. The function for the bank's action based on the investor status is

$$\Phi=\begin{cases}\text{loan}, & \text{if } g(f(v))=\text{profitable or } g(f(v))=\text{surviving}\\ \text{request pay back}, & \text{if } g(f(v))=\text{bankrupt}.\end{cases}$$

If the investor's working capital $\leq$ debt, the investor will be liquidated and removed from the market. *Liquidated* means that all of the investor's capital and stocks are used to pay the debt; the stocks are sold through the market. If a liquidated investor cannot recover his debt, the bank loses its money. This threshold for checking bankruptcy is called the margin ratio and it is defined as the value of the collateral over the total liabilities:

$$R(t)=\frac{\text{(working capital)}}{\text{(debt)}+\text{(interest)}}.$$

If this is equal to unity, or the maximum debt of the player is equal to the working capital, bankruptcy can be defined as

$$\frac{\text{(total cash)}+\text{(total stocks market value)}}{\text{(total debt)}}\leq 2.$$

2. Taming The Bubble
   In the final phase, we consider how a minimum margin adjustment can be used to control the price movement in a bubble and then we replace it with credit scoring. We then perform a simulation and analyze the impact of credit scoring and loan adjustments on the price movement. Finally, we explore a strategy for maintaining a bank's reserves.

   (a) Minimum margin evaluation
   Minimum margin is minimum payment or collateral that investor has to provide at a margin trading transaction. We compared the minimum margin to the credit score as a tool for identifying bankruptcy. We carried out an experiment to calculate how many investors had been correctly or incorrectly classified either using minimum margin or credit scoring. The result is presented in the Experiment 3.

   (b) Margin trading with credit scoring
   We analyzed the impact of credit scoring and loan amount adjustments on the price movement in the simulation. We will compare four methods for developing credit scoring and discuss loan absorption in Experiment 4. Figure 1 provides an overview of the simulation model.

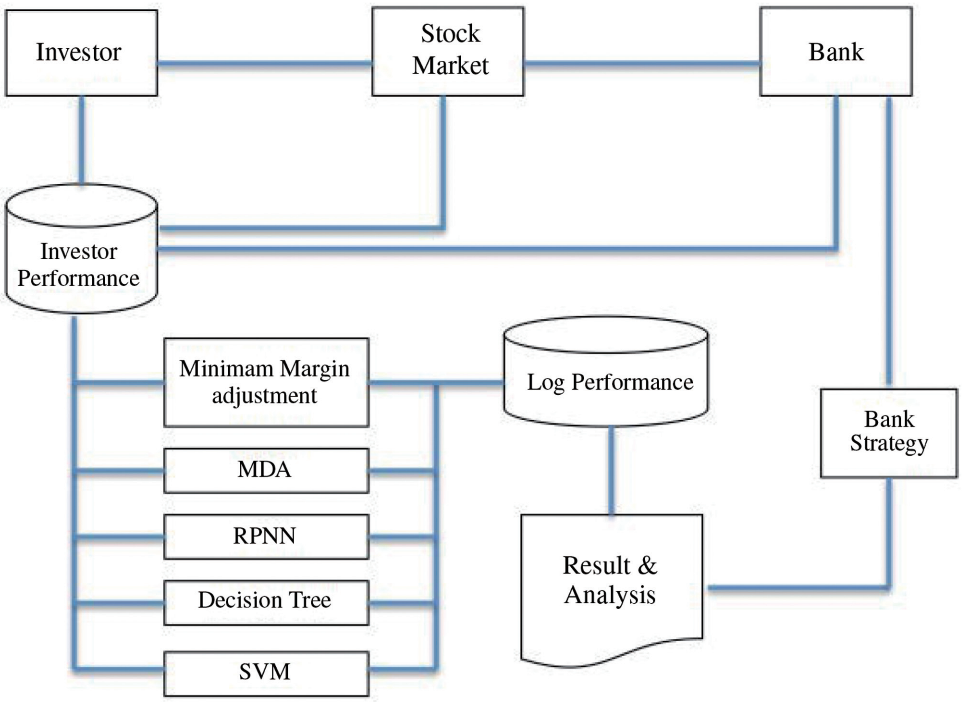


Figure 1: Overview the simulation model

3. Bank's Reserve

   We created a strategy for taming bubbles by comparing the simulation of a smart bank to a non-smart bank when there are both static and dynamic reserves. A *smart bank* is one that has already been trained or uses AI to evaluate loan requests; a *non-smart bank* is one that is not trained or that does not use credit scoring. In the simulation, the smart banks used the AI method which had the best accuracy in Experiment 1 and 2; this was the C4.5 decision tree method.

   Static reserves are the resources that maintain a constant monetary value. A bank's static reserves depend on the total credit extended to all investors. *Dynamic reserves* are resources which depend on the *total market value*, which is total number of investor's shares $\times$ the market price. We consider the dynamic reserves because some banks have enormous amounts of reserve capital; their capitalization is higher than the margin-trading capitalization market. Thus, they can provide reserve money as the total market value to be used in margin trading and gain profit from the interest.

   The smart bank has the functions of credit scoring, bubble detection and loan adjustment.

   (a) Credit Scoring

   In the simulation, the smart bank uses the AI approach for determining credit scoring. The initial data for training is generated by using the result of Experiment 3. When the market is closed in midnight, the artificial intelligence is updated.

   (b) Bubble Detection

   Denote by t_i the noon of i-th day in the trading period. Let $S(t)$ be the stock price at the time t and $R(t_i)$ the daily logarithmic return, that is, $R(t_i) = \log S(t_i) - \log S(t_{i-1})$. As a simplification of Sornette's method for bubble detection [33], we identify the bubble when $B(t_i) \geq 2$, where

$$B(t_i) = \frac{EMA(t_i, 5)}{EMA(t_{i-5}, 5)}$$

   and $EMA(t_i, n)$ is the exponential moving average for n days. It can be calculated by the following recurrence relation and suitable initial value:

$$EMA(t_i, n) = \alpha R(t_i) + (1-\alpha) EMA(t_{i-1}, n), \quad \alpha = \frac{2}{n+1}.$$

   (c) Loan Adjustment

   The *financing frame* is a measure of how much leverage an investor can have from their working capital. If the financing frame is equal to one, it means that the maximum loan is equal to the working capital or collateral.

If the financing frame is equal to 0.5, it means that the maximum loan is half of the working capital.

$$RM(t) = \frac{\text{(reserve money)}}{\text{(total loans)}}$$

$$\text{financing frame} = \begin{cases} 1, & (RM(t) \geq 0.7) \\ 0, & (RM(t) \leq 0.1) \\ \frac{10}{6}(RM(t) - 0.1), & \text{(otherwise)} \end{cases}$$

It is essential to adjust the frame when a bubble occurs, which happens when the price movement follows a pattern that is similar to a power-log distribution. Restricting the loan in a heating market is beneficial for decreasing liquidity in the market. If a bubble is detected, the bank can restrict the average investor loan based on Y, as defined in equation 2.2 and maintain a profitable investor leverage. That is, the previous financing frame is replaced by

$$\text{financing frame} = \begin{cases} 1, & (g(f(v)) = \text{profitable}) \\ \frac{1}{2}(y_2 - y_1), & (g(f(v)) = \text{surviving and } y_1 \geq y_3) \\ 1 - \frac{1}{2}(y_2 - y_3), & (g(f(v)) = \text{surviving and } y_1 < y_3) \\ 0, & (g(f(v)) = \text{bankrupt}) \end{cases}$$

Here $f(v) = (y_1, y_2, y_3)$.

3 Classification Methods

In this section, we present a concise summary of the fundamental theory of each of the four methods that we used to create our credit score. These methods are all commonly used in current credit-scoring research [20]. One of these is a statistical method (multiple discriminant analysis) and the other three methods are from the field of artificial intelligence (the C4.5 algorithm, RPNN and support vector machines).

3.1 Discriminant Analysis

Multiple discriminant analysis is an extension of linear discriminant analysis (LDA), which was invented by Ronald A. Fisher in 1936 [13] for classifying data into more than two classes. LDA assumes a standard distribution of classes or that the classes have equal covariance and it searches for the linear combination of variables that best separates the classes. Fisher solved this problem by finding a linear function that maximizes the distance between the means of the various classes but minimizes the variance of each class. The result of Fisher's LDA is equal to that of a least-squares problem or a linear regression classification [38]. It was also shown by Duda et al. [11].

In 1968, Edward I. Altman discovered a formula that uses Fisher's LDA to predict corporate bankruptcy. His work was developed from William Beaver's research on bankruptcy prediction, which used univariate analysis of an accounting ratio. Instead of using the t-test to evaluate each ratio, Altman applied discriminant analysis to multiple variables concurrently [2]. He chooses five ratios, each from a different category: liquidity, solvency, profitability, leverage and activity; this combination was shown to be able to predict bankruptcy with statistical significance. The five ratios that were chosen as predictors are X_1 : (working capital)/(total assets); X_2: (retained earnings)/(total assets); X_3: (earnings before interest and taxes)/(total assets); X_4: (market value of equity)/(book value of total liabilities); and X_5: (sales)/(total assets). The Z-score formula is $Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.009X_5$. A score above 3.0 means that it is unlikely that the company will go bankrupt and a score below 1.8 means that it is likely to do so. Although the initial test showed that the accuracy is around 72% for the predicting bankruptcy within two years, Altman's Z-score is the leading model. In 1999, further research by Altman considered more firms and used more recent data and the accuracy was shown to have increased to approximately 80%-90%. The improvement of the Z-score formula has resulted in its use as a bankruptcy prediction tool in other business sectors, such as private firms, non-manufacturers and emerging markets [3].

Altman's Z-score cannot be used for lending decisions for margin trading because it is difficult to calculate the Z-score for each investor; in particular, it is difficult to calculate X_4, the (market value)/(total liabilities). If the total liability is zero, then X_4 will be undefined and if the total liability is much smaller than the stock market value, X_4 will be excessively large and will overwhelm all of the other information. Moreover, for individuals, the variables X_1, X_2 and X_3 measure almost the same thing, namely, profit per total asset. Although it can be calculated, the Z-score is not valid for making predictions. However, its principle still can be implemented to create a credit score for margin trading. Bankruptcy can be predicted by assessing financial ratios which have significant correlation with the outcome.

Our Z-score function is defined by a linear form of eight financial ratios $v_1, \ldots, v_8$ as follows:

$$Z = \langle \alpha, v \rangle = \alpha_1 v_1 + \alpha_2 v_2 + \cdots + \alpha_8 v_8,$$

where $v = (v_1, v_2, \ldots, v_8)^\intercal$ and $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_8)^\intercal$. We classify samples into three classes those are bankrupt, surviving and profitable. Then the coefficients α for each class are determined by using Fisher's LDA. Let μ_i be the mean and σ_i the standard deviation for each class. The Z-score for each class can be interpreted to the probability density of investor status as follows:

$$N_i(Z) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(Z-\mu_i)^2}{2\sigma_i^2}\right).$$

Hence, we can translate the Z-score function into the AI function $f(v)$.

3.2 Resilient Propagation Neural Network

Recently, artificial neural networks have become a practical technology for financial industries [1]. Many financial applications can exploit the strength of neural networks; these include determining credit card fraud, evaluating mortgage applications, predicting bankruptcy and option pricing [14]. We developed a neural network which consists of three layers: an eight-node input layer, a five-node hidden layer and a three-node output layer (the three output nodes represent the three classes). A sigmoid transfer function is used for each node. Because of its fast performance, we used the resilient propagation neural network (RProp) as the learning algorithm; it was created by Martin Riedmiller and Heinrich Braun in 1992 [30]. RProp uses batch updates to obtain the gradient of each weight. The sign of the gradient is then used to estimate the direction in which the weight is updated. The update value, delta, is not fixed. The changing sign of the gradient is used to adjust delta so that the speed of the training can increase [18].

The initial step size was 0.1, the coefficients for changing Δ were $\eta^+ = 1.2$ and $\eta^- = 1.2$ and the boundaries on delta were $\Delta_{\max} = 50$ and $\Delta_{\min} = 10^{-6}$.

3.3 C4.5

A *decision tree* is a graph-like structure which consists of nodes as test variables and branches as test results; a leaf node is a class label [21]. The first node is called the root. A decision tree is a nonlinear discrimination method which uses a set of independent properties to split data into progressively smaller subgroups [8]. Decision trees are popular classification algorithms because they can be intuitively explained [27]. In this study, we used only C4.5, because it is free and it performs well, as shown in a comparative study [27]. C4.5 was invented by Ross Quinlan [29] for generating decision trees using a divide-and-conquer technique. In order to divide and conquer the data, C4.5 uses the concept of information entropy; this entropy is used to quantify how informative a variable is when it is used to separate the data. The gain principle is used to select which attribute is to be split at any given node. However, when this criterion is used to determine the node splits, the algorithm tends to create leafs for attributes with many distinct values. In order to rectify this, the C4.5 normalizes the data and uses a gain-ratio criterion. To reduce the error, the tree continues to grow bigger and this can lead to overfitting. To reduce overfitting, pruning is used. *Pruning* is a technique for removing a leaf for which the power to classify has only a small significance. The threshold for pruning is called the *confidence factor* and its value is between 0 and 1. Lowering the threshold results in more pruning and a more general tree. We used a confidence factor of 0.25 in this study.

3.4 Support Vector Machine

The support vector machine (SVM) was invented by Boser, Guyon and Vapnik in 1992 [5]. They combined the margin hyperplane and the kernel method for discriminating between two groups in the data. The margin hyperplane is used as a linear classifier when nonlinear data are treated by a kernel trick to manipulate the domain function into a higher-dimensional space. The essence of the SVM is to find the best hyperplane as a classifier of two classes in the input space, for example, the surviving class $(+1)$ and the bankrupt class (-1). The best hyperplane between those classes can be computed by finding their maximum margin hyperplane. The margin is the closest distance between two classes. In some cases, it is hard to use a hyperplane to separate samples completely. The samples must be transformed into a higher feature space by a kernel function $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ [17]. There are several types of kernel functions, including linear, polynomial, sigmoid functions, exponential radial basis functions and Gaussian radial basis function. We use a Gaussian radial basis function kernel, $K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\gamma \|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2\right)$, to implement our SVM credit scoring method, because the data are not linear and the classification problem has three classes (bankrupt, surviving and profitable). We used the LIBSVM library created by Chang and Lin [7], with the default parameter settings and $\gamma = 1/8$.

4 Credit Scoring

To avoid making risky loans, a bank must be able to identify appropriate investors. We propose a credit-scoring method that filters out risky investors. We compare credit-scoring methods to find the best average performance. We then use the best method to prevent bubbles from bursting. In this first part of the experiment, we implemented the four methods (MDA, RPNN, C4.5 and SVM) to create a credit score. These methods were then tested with several market conditions.

Let us assume we are assessing a credit proposal. The result of our evaluation can be positive (approved) or negative (rejected). We will say that a correct prediction is true and an incorrect one is false. An enhanced credit score should maximize the true cases and screen out the false ones [32]. We will use confusion matrix Table 1 to assess the performance of our credit score:

We introduce basic terminology of confusion matrix as follows:

Table 1: Confusion Matrix [32]

		Survive Investor	Bankrupt Investor
Loan Approval	Approved	True Positive (TP)	False Positive (FP)
	Rejected	False Negative (FN)	True Negative (TN)
		Sensitivity = TP / (TP+FN)	Specificity = TN / (TN+FP)

True positive : number of investors correctly approved.

True negative : number of investors correctly rejected.

False positive : number of investors incorrectly approved.

False negative : number of investors incorrectly rejected.

Misclassified : number of investors assigned to wrong class; false positive + false negative.

Sensitivity or recall : probability of being correctly approved, given that it is a good financial investor [28]; (true positive)/(true positive + false negative).

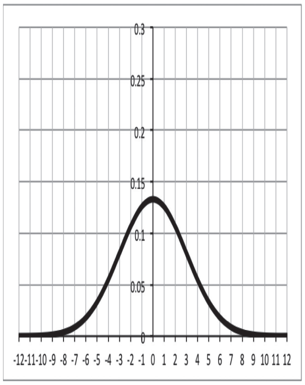
Specificity : probability of being correctly rejected, given that it is a poor financial investor [28]; (true negative)/(true negative + false positive).

Accuracy : probability of being correctly predicted [28]; (true positive + true negative)/population.

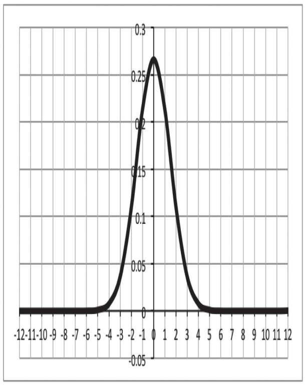
Precision : proportion of correctly approved to total approved [28]; (true positive)/ (true positive + false positive).

F-Score : it combines positive predictive value with the rate of true positives [28]; 2 (precision $\times$ recall) / (precision + recall).

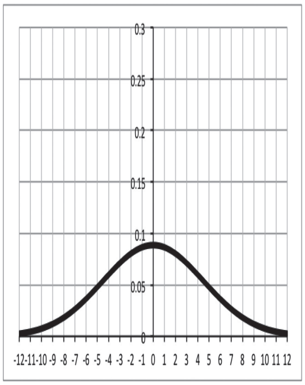
Experiment 1 (Credit scoring performance with various random normal settings)**.** *After creating our credit-scoring methods, it is necessary to test their robustness in various market conditions. Six scenarios were considered. Each scenario consists of 100 simulations; each of these was populated by 100 bankrupt investors, 100 surviving investors and 100 profitable investors. Ten-fold cross-validation was used for each credit scoring method in each simulation. All investors have 3 million JPY as their initial working capital. The basic assumption is that the scenarios are in a free market in which many players are able to trade. Thus, any one action by a player has no impact on the equilibrium price. All decisions to buy, sell, or hold and their order volumes are based on a normal distribution.*



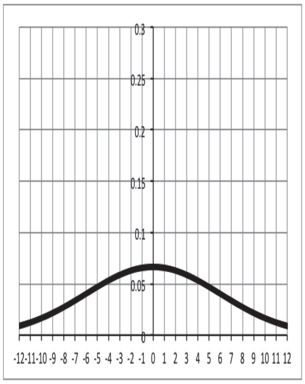
(a) $\mu = 0$, $\sigma = 3$ million JPY



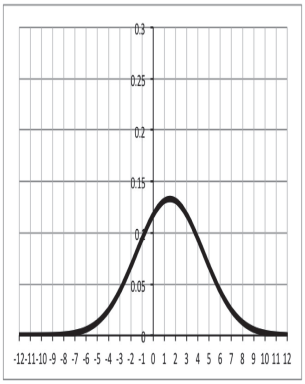
(b) $\mu = 0$, $\sigma = 1.5$ million JPY



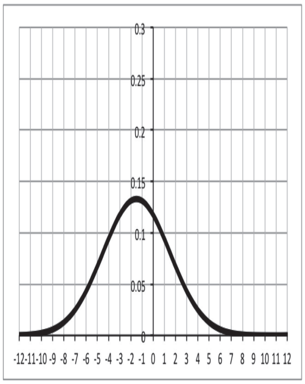
(c) $\mu = 0$, $\sigma = 4.5$ million JPY



(d) $\mu = 0$, $\sigma = 6$ million JPY



(e) $\mu = 1.5$ million JPY, $\sigma = 3$ million JPY



(f) $\mu = -1.5$ million JPY, $\sigma = 3$ million JPY

Figure 2: Probability density function of order value for six different market behaviors

Figure 2 presents six different player behaviors and shows the probability density functions (pdf) of the order values for each player in each scenario. Positive values are buying orders and negative ones are selling orders. Both are shown in units of one million JPY. The maximum purchase order is cash multiplied by leverage and the maximum sell order is the amount of stock that the player owns. A hold occurs if the absolute value of the order is less than 100 times the current stock price.

Figure 2a shows an example pdf for a player order decision with mean 0 and standard deviation 3 million JPY. This means that approximately 70% of the order value is less than 3 million. The purchase order is greater than the leverage multiplied by their cash and it is set to buy the maximum possible for the given cash and leverage. Note that a sell order that exceeded the stock value results in the sale of all the stocks. Figure 2b shows the behavior of a player in a stressful market condition, so the order *is placed very carefully. The order is expressed as half a standard deviation of the working capital and in this example, that is 1.5 million JPY. This means that 95% of this order will not exceed their working capital. Figures 2c and 2d show a situation in which a player fully uses a loan and sells all their stocks, respectively. Around 70% of the transactions would be less than 4.5 million for Figure 2c and 6 million for Figure 2d. Figure 2e shows a player who tends to buy, while Figure 2f shows a player who tends to sell.*

Tables 2 and 3 show the average of each of the six scenarios. The results demonstrate that the artificial intelligence methods perform better than the statistical method and among the artificial intelligence methods, there are only slight performance differences. The SVM had the highest accuracy, which exceeded that of the C.45 decision tree by only by 0.148% in accuracy and 0.005 for the F-score. However, the C4.5 decision tree had the most success in predicting profit; it had an average accuracy 69.547%, while the profit accuracy of the SVM was 67.707%.

Table 2: Average Prediction Result for Normal Distribution

	Predicted \ Actual	Bankrupt	Surviving	Profitable	Accuracy
MDA	Bankrupt	96.988%	0.027%	2.980%	73.270%
	Surviving	1.523%	72.643%	25.833%	
	Profitable	15.560%	34.263%	50.177%	
C4.5	Bankrupt	98.912%	0.740%	0.348%	80.506%
	Surviving	0.0%	73.060%	26.940%	
	Profitable	0.0 %	30.453%	69.547%	
RPNN	Bankrupt	99.438%	0.182%	0.380%	79.950%
	Surviving	0.018%	72.878%	27.120%	
	Profitable	0.200%	32.267%	67.533%	
SVM	Bankrupt	100%	0%	0.0%	80.654%
	Surviving	2.703%	75.133%	22.163%	
	Profitable	0.942%	31.352%	67.707%	

Table 3: Average Performance of Credit Scoring with Normal Distribution

	Sensitivity	Specificity	Precision	FScore
MDA	0.733	0.866	0.727	0.719
C4.5	0.805	0.902	0.816	0.801
RPNN	0.800	0.900	0.802	0.799
SVM	0.810	0.905	0.811	0.806

Experiment 2 (Credit scoring performance with uniform probability random behavior)**.** *In order to evaluate the robustness of the credit scoring methods, we tested them in a market situation in which the investors trade randomly. We performed 300 simulations, each of which was populated by 100 bankrupt investors, 100 surviving investors and 100 profitable investors. Each simulation was evaluated using ten-fold cross-validation. Using fewer investor and running only 300 simulations gave a more reliable result. All of the decisions in this experiment were randomly selected from a uniform probability distribution.*

The average percentages of the predictions are shown in Table 4. The C4.5 decision tree had the highest score for accuracy (79.478%), followed by the SVM, the RPNN and last, the MDA (78.645%, 76.499% and 71.874%, respectively). The harmonic mean of the true positive and true negative rates for the credit scoring methods are shown in Table 5 and these are not significantly different from the results of the first

Table 4: Prediction Result from 300 Simulations of Uniform Probability Random Behavior

	Predicted \ Actual	Bankrupt	Surviving	Profitable	Accuracy
MDA	Bankrupt	99.567%	0.107%	0.327%	71.874%
	Surviving	0.897%	55.673%	43.433%	
	Profitable	0.183%	39.433%	60.383%	
C4.5	Bankrupt	98.973%	0.767%	0.26%	79.478%
	Surviving	0.0%	59.423%	40.577	
	Profitable	0.0	19.963%	80.036	
RPNN	Bankrupt	99.753%	0.143%	0.103%	76.499%
	Surviving	0.046%	59.953%	40.0%	
	Profitable	0.003%	30.206%	69.79%	
SVM	Bankrupt	99.16%	0.84%	0.0%	78.645%
	Surviving	0.453%	55.183%	44.363%	
	Profitable	0.036%	18.37%	81.593%	

Table 5: Average Performance of Credit Scoring with Uniform Probability

	Sensitivity	Specificity	Precision	FScore
MDA	0.719	0.859	0.720	0.716
C4.5	0.795	0.897	0.812	0.789
RPNN	0.765	0.882	0.769	0.763
SVM	0.786	0.893	0.799	0.782

experiment. The machine learning methods outperform the statistical MDA method. The decision tree performed better in every aspect that was being measured: accuracy, sensitivity, specificity, precision and F-score. The decision tree showed human-like reasoning, as did the MDA, while the RPNN and SVM worked like black boxes.

5 Taming the Bubble

Bubble prices burst because some players with significant market wealth go bankrupt. The market is then flooded. As other players ask for lower prices, prices sink to lower levels. To show the impact of bubble prices when credit scoring in not used, we constructed a simulation to demonstrate this event. We populated the simulation with ten AI players, each of whom owned 10,000 shares, had 10 million JPY in cash and was able to take out a loan. We also populated it with 100 random players, each of whom owned 1000 shares, had 1 million JPY in cash and was not able to take out a loan. Note that these settings were also used in Experiment 4 and 5.

Figure 5a illustrates a bursting bubble. In this simulation, nine of ten AI players go bankrupt since they cannot repay their loans on their due dates. Since they have accumulated most of the market wealth, their bankruptcy bursts the price. As can be seen in Figure 6a, the total market value drops from 250 million JPY to 3 million JPY. This simulation is based on Nakatani's work [23], in which the bank agent checks only the ratio of debt to the working capital; that is, if an investor's debt is greater than their working capital, they are bankrupt and are liquidated from the stock market.

Regulators create a minimum margin in order to mitigate the risk, since the collateral value will drop as the price collapses. However, setting a minimum price also creates a barrier for liquidity and maintaining the price, because some good investors will have already stepped out of the market. We evaluate the effectiveness of this minimum margin in Experiment 3. In Experiment 4, we analyze a simulation of margin trading that uses credit scoring and in Experiment 5, we create a bank strategy for taming bursting bubbles. Again, ten AI players were used and they had the same capitalization as the 100 random players. Because they can each receive a loan, the capitalization of the AI players is double that of the random players. The bankruptcy of an AI player will have a significant impact on the price movement.

Experiment 3 (Minimum margin evaluation)**.** *We investigated the consequences of adjusting the minimum margin in the market. We wanted to determine how many investors would survive but be forced to liquidate. We simulated margin trading by using n investors with random behaviors for the period $[0,T]$ and defined the position of i-th investor at $t = T$ with respect to minimum margin as follows:*

$$position = \begin{cases} bankrupt, & (w_i(T) \leq \beta w_i(0)) \\ profitable, & (w_i(T) > \beta w_i(0) \ and \ \ w_i(T) \geq 1.4 w_i(T-22)) \\ surviving, & (otherwise) \end{cases}$$

where $w_i(t)$ is the working capital of i-th investor at time t, the parameter β signifies minimum margin ratio. The investor position and status coincide if $\beta = 0$. We increased the parameter and counted positions of investors.

Put $T = 300$ days and $n = 6347$. Table 6 shows the number of investors that go bankrupt or other positions with various minimum margins. We also calculated the differences, which is called misclassification, between investor position and status. When the minimum margin increases, misclassification also grows. In the USA, the margin trading market has the minimum margin set at 50% and in Japan, the Tokyo Stock Exchange (TSE) market is set at 30%. In this experiment, 314 surviving investors and 215 profitable investors were misclassified as bankrupt when the minimum margin was set at 30%. On the other hand, 603 profiting investors and 660 surviving investors were misclassified as bankrupt. By setting the minimum margin at 50%, the system already screens out 20% of the investors. It is almost half of the investors who likely gain profit more than 40% within a month. Of the total population, 9.5% was misjudged as bankrupt and it is equal to 38.97% of the profitable investors.

Table 6: Number of Investor Position when Minimum Margin is Adjusted

β	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8
Bankrupt	2400	2402	2417	2929	3329	3663	3847	3994	4098
Surviving	2400	2398	2385	2086	1944	1740	1625	1542	1479
Profitable	1547	1547	1545	1332	1074	944	875	811	770
Misclassification	0	2	17	529	929	1263	1447	1594	1698

For comparison, we developed a credit scoring and predicted investor condition. Table 7 shows the prediction accuracy of each of the four methods. Ten-fold cross-validation was used to measure the accuracy.

From Table 8, it can be seen that the SVM outperformed the other methods for profit and bankrupt predictions by 0.005 and 0.019, respectively (compared to the lowest). Unfortunately, it was the worst at predicting surviving investors. The MDA was the best at predicting surviving investors (by 0.034 over the lowest performance), but did not perform well when predicting bankrupt and profitable investors. There are only slight differences among the predictions of the MDA, C4.5, RPNN and SVM when it came to predicting bankruptcy in these experiments.

When credit scoring is used, there are fewer misclassification of profiting investors; the fewest misclassifications occurred with C4.5 and the SVM, with misclassification

Table 7: Predictions when using Credit Scoring

	Actual / Predicted	Bankrupt	Surviving	Profitable	Accuracy
MDA	Bankrupt	2047	353	0	81.9442%
	Surviving	761	1634	5	
	Profitable	13	14	1520	
C4.5	Bankrupt	2152	248	0	82.2751%
	Surviving	854	1543	3	
	Profitable	4	16	1527	
RPNN	Bankrupt	2213	187	0	81.9757%
	Surviving	928	1471	1	
	Profitable	13	15	1519	
SVM	Bankrupt	2047	110	0	82.023%
	Surviving	1013	1387	5	
	Profitable	0	18	1529	

Table 8: Benchmarking Credit Scoring

		Sensitivity	Specificity	Precision	FScore
MDA	Bankrupt	0.853	0.891	0.726	0.784
	Surviving	0.681	0.909	0.817	0.743
	Profitable	0.983	0.911	0.997	0.989
C4.5	Bankrupt	0.897	0.783	0.715	0.796
	Surviving	0.643	0.933	0.854	0.734
	Profitable	0.987	0.999	0.998	0.993
RPNN	Bankrupt	0.922	0.762	0.702	0.797
	Surviving	0.613	0.949	0.879	0.722
	Profitable	0.982	0.999	0.999	0.991
SVM	Bankrupt	0.954	0.743	0.693	0.803
	Surviving	0.578	0.968	0.916	0.709
	Profitable	0.988	1	1	0.994

of only 20 and 18 investors, respectively. By adjusting the minimum margin, misclassification of 20 investors are between 20% and 30%. However, the error predictions for bankrupt and surviving players varied quite significantly. The best performance was that of the SVM, which misclassified 110 bankrupt and 1013 surviving players. If we combine the minimum margin regulation with credit scoring, we obtain a condition where the minimum margin can be set to a minimal value, but the surviving and prof-

itable investors are able to maintain the prices even in a bubble-bursting condition. To test the effectiveness of the credit scoring method, we executed a simulation of margin trading with credit scoring as Experiment 4.

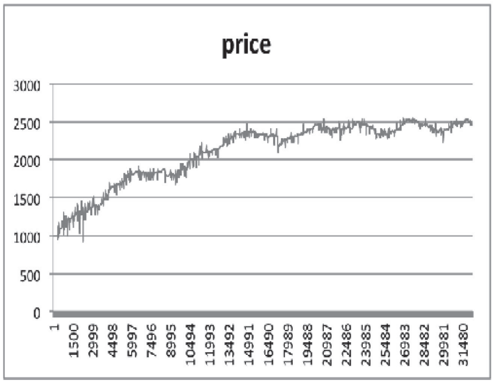
Experiment 4 (Margin trading with credit scoring)**.** *To investigate the effectiveness of our credit-scoring method for controlling a bubble, we carried out a simulation in which our credit-scoring method was implemented by a bank agent. We created ten AI players who each had 10,000 shares, 10 million JPY in cash and the ability to receive a loan. We also created 100 random players who each had 1000 shares, 1 million JPY in cash and did not have the ability to receive a loan. We assessed the impact on the price movement of credit scoring the loan applications. Credit scoring evaluate investors by considering their working capital, their debts and their profit performance. This screens out risky players and seeks repayment from them at an earlier time so they will not cause the market to collapse; at the same time, it gives leverage to healthy profitable investors. Figure 3 shows the results of some simulations using various methods of credit scoring.*

The results shown in Figure 3 confirm that all of our credit-scoring methods had similar accuracy. The least accurate method (MDA) failed to recognize one profiting investor, and so its price movement is slightly lower than that of the other methods. The RPNN, SVM and C4.5 had almost identical price movements.

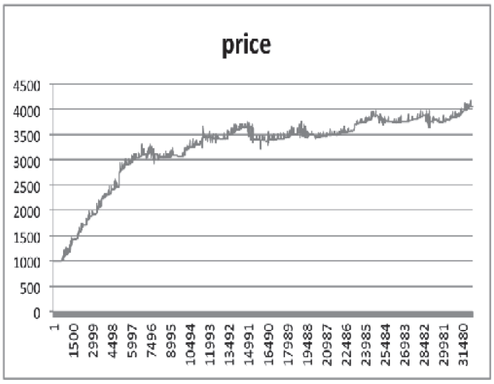
Credit scoring also resulted in good credit absorption for the bank's main business, as shown in Figure 4. However, on some timelines, the reserve value exposed the bank to a lack of cash for financing the players. The bank had negative cash at times 896 and 13,896. When there are inadequate reserves, banks can obtain loans from other banks and they can reject all new loans; they can also adjust the financing frame to limit the total debt owed to the players. The financing frame will be explained in the next experiment.

Experiment 5 (Bank's reserves)**.** *We examined the impact on the price movement when the bank's reserves are controlled. In the previous experiment, we confirmed that loans will increase the stock price. By controlling the reserves, the bank can adjust the liquidity of the market. We wanted to find out whether controlling the reserves would influence the price movement. We performed some simulations to compare a smart bank with a non-smart bank and with static and dynamic reserves.*

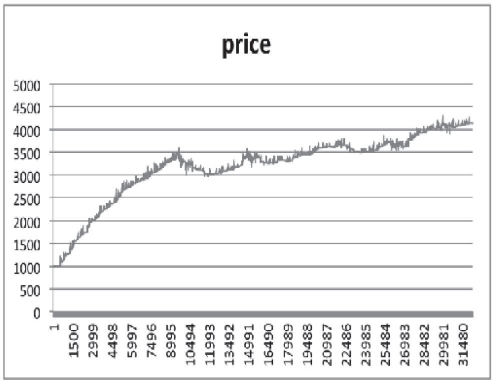
Figure 5 illustrates some price movements for various bank reserve strategies and Figure 6 shows the bank reserves during a transaction. A non-smart bank with a static reserve strategy will cause a price collapse and if it uses a dynamic strategy, the price will soar rapidly and then collapse. This shows that increasing either the cash invested in the market or the liquidity of the market will increase the price and create a bubble. Limiting the amount of cash will also have a tendency to cause a collapse. When the reserves are gone, the bank is in a dangerous position.



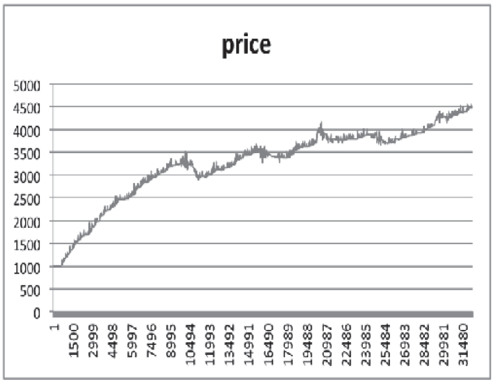
(a) MDA



(b) RPNN



(c) SVM



(d) C4.5 (Decision Tree)

Figure 3: Price Movement with Various Credit-Scoring Methods

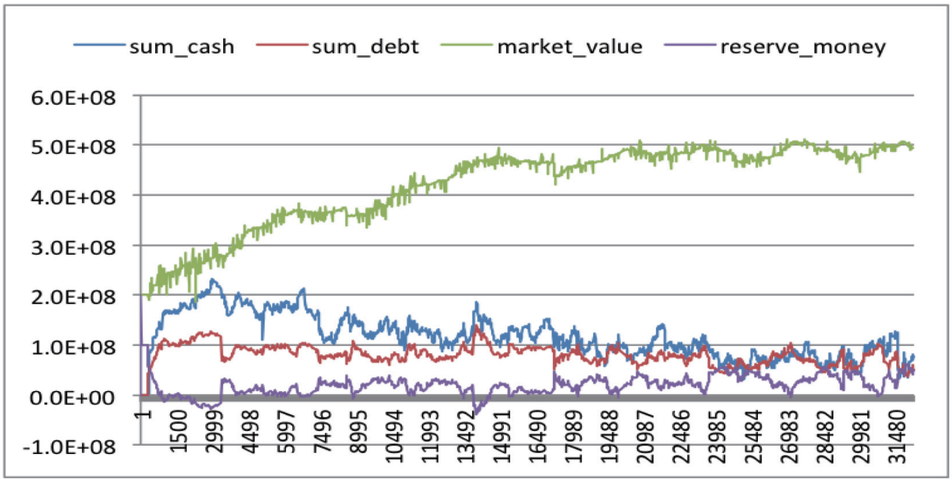
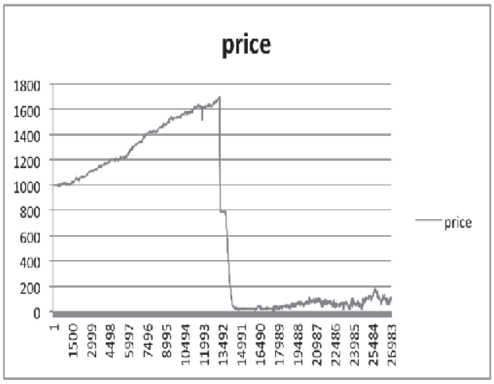
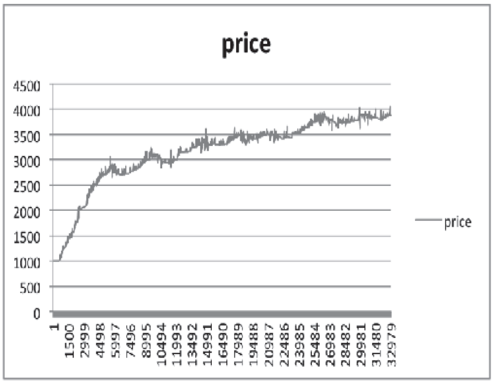


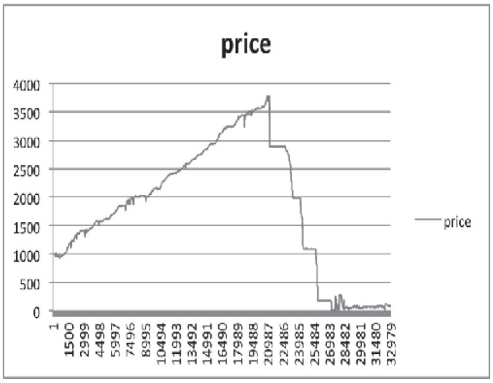
Figure 4: Credit absorbing using credit scoring



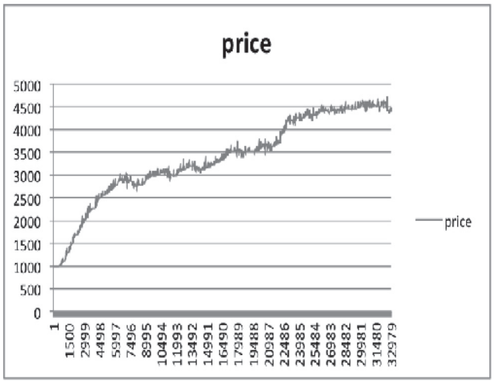
(a) Non-smart Bank with Static Reserves



(b) Smart Bank with Static Reserves



(c) Non-smart Bank with Dynamic Reserves

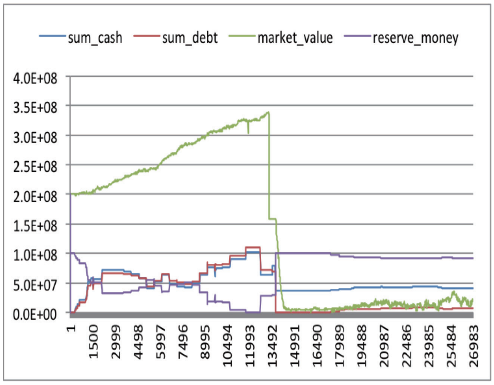


(d) Smart Bank with Dynamic Reserves

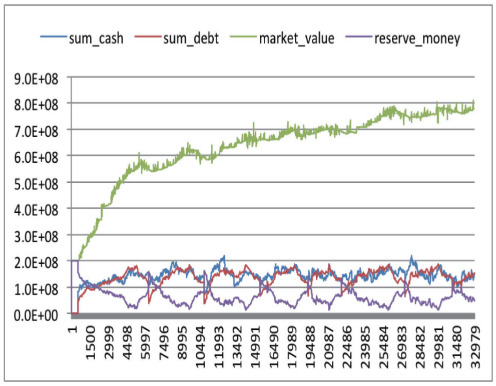
Figure 5: Comparison of Price Movement between Smart and Non-Smart Banks with Static and Dynamic Reserves

A smart bank can maintain the price movement. When the reserves are limited, the loans will be restricted. Thus, the prices will decrease slightly. After the reserves are refilled by credit repayments, the bank can relax the loans and the prices will increase. This runs in a continuous cycle. When the bank has large cash deposits, the prices increase steadily. The bank maintains market liquidity by assessing the credit scores of investors.

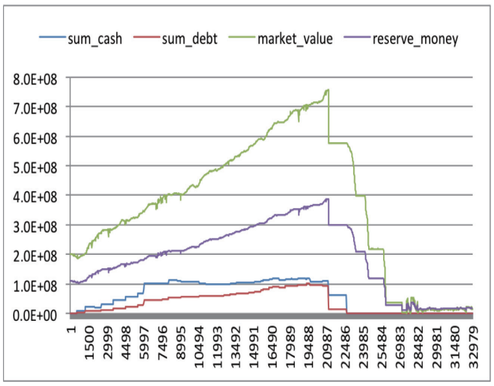
When the reserves are unlimited, it depends on the total value of the stock market. It is called the money creation. In this case, the smart bank can also predict the bubble phenomena and maintains market liquidity by assessing the credit scores of investors.



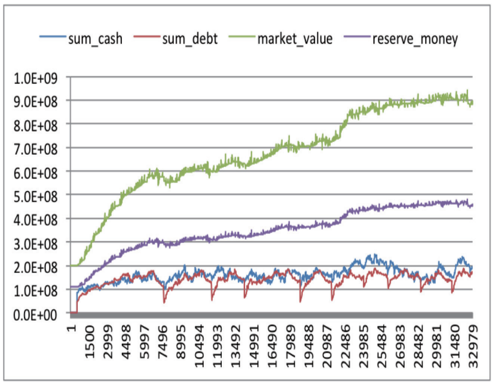
(a) Non-smart Bank with Static Reserves



(b) Smart Bank with Static Reserves



(c) Non-smart Bank with Dynamic Reserves



(d) Smart Bank with Dynamic Reserves

Figure 6: Comparison of Reserves between Smart and Non-Smart Banks with Static and Dynamic Reserves

6 Conclusion

We have developed a new method for filtering credit requests. The accuracies of the predictions are above 80% and thus our method for credit scoring for margin trading can be used to manage and quantify risk. We also implemented credit scoring in our simulation program. The results of the experiments show that credit scoring can prevent the market crashes by allowing good investors to maintain credit absorption. The financing frame can be adjusted to slow the rate of price increases, since it can be used to detect bubbles and to monitor the bank's reserves. In general, prices rise when there is growing demand and they drop when there is excess supply. Restricting the entire market heightens the effect of a crash, since the market needs capital in order to maintain the price. In this study, we investigated four methods for creating a credit score;

one of these methods was from statistics (discriminant method) and the other three were from the field of artificial intelligence. The accuracy of the artificial intelligence methods was better than that of the statistical method, but the statistical method gave more logical reasons for approving loans.

We have created a new strategy that banks can use to tame price bubbles. We investigated several strategies for managing reserves and we investigated how each of them influenced price movement. We found that a smart bank with a dynamic reserve policy can prevent a price collapse and maintain market liquidity.

Future research should aim at improving the accuracy of predicting good investors and quantifying the risk of bankrupt investors. Risk management by hedging potential defaulted loans is another potential area of study.

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References

[1] H. Abdou and J. Pointon, Credit Scoring Statistical Techniques and Evaluation Criteria: A Review of the Literature, Intelligent Systems in Accounting, Finance & Management **18.(2-3)** (2011), 59–88.

[2] E. I. Altman, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, The Journal of Finance **23-4** (1968), 589–609.

[3] E. I. Altman et.al., Predicting financial distress of companies: revisiting the Z-score and ZETA models, Working Paper, Stern School of Business, New York University, 2000.

[4] R. Anderson, *The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation*, Oxford University Press, 2007.

[5] B. E. Boser, I. M. Guyon and V. N. Vapnik, A training algorithm for optimal margin classifiers, Proceedings of the 5^{th} Annual Workshop on Computational Learning Theory, 144–152, ACM Press, 1992.

[6] M. K. Brunnermeier and M. Oehmke, *Bubbles, financial crises and systemic risk*, National Bureau of Economic Research, 2012.

[7] C. C. Chang and C. J. Lin, LIBSVM : A Library for Support Vector Machines, ACM Transactions on Intelligent Systems and Technology **2-3** (2011), 27:1–27:27

[8] M.Y. Chen, Bankruptcy prediction in firms with statistical and intelligent techniques and a comparison of evolutionary computation approaches, Computers and Mathematics with Applications **62-12** (2011), 4514–4524.

[9] J. P. Danthine, Taming the Financial Cycle, Swiss National Bank, 2012.

[10] H. Demuth, M. Beale and M. Hagan, *Neural network toolbox 6 User's guide*, The MathWorks Inc., 2008.

[11] R. O. Duda, P. E. Hart and D. G. Stork, *Pattern classification*, John Wiley & Sons, 2012.

[12] S. Finlay, *Credit Scoring, Response Modelling and Insurance Rating*, Palgrave Macmillan, 2010.

[13] R. A. Fisher, The use of multiple measurements in taxonomic problems, Annals of Eugenics **7-2** (1936), 179–188.

[14] E. Gately, *Neural Networks for Financial Forecasting: Top Techniques for Designing and Applying the Latest Trading Systems*, John Wiley & Sons, 1996.

[15] M. Glantz and J. Mun, *The Banker's Handbook on Credit Risk: Implementing Basel II*, Academic Press, 2008.

[16] Y. Hamao and J. Hasbrouck, Securities trading in the absence of dealers: Trades and quotes on the Tokyo Stock Exchange, Review of Financial Studies **8-3** (1995), 849–878.

[17] L. Hamel, *Knowledge Discovery with Support Vector Machines.*, John Wiley & Sons, 2009.

[18] J. Heaton, *Programming Neural Networks with Encog 2 in Java*, Heaton Research, Inc, 2010.

[19] Y. Ito, T. Kitamura, K. Nakamura and T. Nakazawa, New Financial Activity Indexes: Early Warning System for Financial Imbalances in Japan, Bank of Japan, 2014.

[20] J. Jayanthi, K. S. Joseph and J. Vaishnavi, Bankruptcy prediction using svm and hybrid svm survey, International Journal of Computer Applications **34-7** (2011).

[21] C. Kingsford and L. Salzberg, What are decision trees, Nat Biotechnol **26-9** (2008), 1011–1013.

[22] W. Miller, Comparing Models of Corporate Bankruptcy Prediction: Distance to Default vs. Z-Score, Available at SSRN: http://ssrn.com/abstract=1461704 or http://dx.doi.org/10.2139/ssrn.1461704 (2009).

[23] D. Nakatani, Search of Mathematical reduction and optimal investment behavior of the stock market by the simulation, Master Thesis, Kanazawa University, 2010. (in Japanese)

[24] K. Ohara, S. Omata and K. Kobayashi, Private Communications, 2011.

[25] K. Ohara, S. Omata and D. Nakatani, Short selling on virtual stock market, The Proceedings of The 59^{th} National Congress of Theoretical and Applied Mechanics, 281–282, 2010. (in Japanese)

[26] M. O'Hara and G. S. Oldfield, The Microeconomics of Market Making, The Journal of Financial and Quantitative Analysis **21-4** (1986), 361–376.

[27] D. L. Olson, D. Delen and Y. Meng, Comparative analysis of data mining methods for bankruptcy prediction, Decision Support Systems **52-2** (2012), 464–473.

[28] D. M. W. Powers, Evaluation: from Precision, Recall and F-measure to ROC, Informedness, Markedness and Correlation, Journal of Machine Learning Technologies **2-1** 2011, 37–63.

[29] J. R. Quinlan, *C4.5: Programs for Machine Learning*, Elsevier, 2014.

[30] M. Riedmiller and H. Braun, A direct adaptive method for faster backpropagation learning: the RPROP algorithm, IEEE International Conference on Neural Networks, 586–591, IEEE, 1993.

[31] A. Setzu and M. Marchesi, The effects of short-selling and margin trading: a simulation analysis, 1^{st} International Conference on Economic Sciences with Heterogeneous Interacting Agents (WEHIA 2006), 15–17, Citeseer, 2006.

[32] N. Siddiqi, *Credit risk scorecards: developing and implementing intelligent credit scoring*, John Wiley & Sons, 2006.

[33] D. Sornette and A. Johansen, Significance of log-periodic precursors to financial crashes, Quantitative Finance **1-4** (2001), 452–471.

[34] Tokyo Stock Exchange, Guide to TSE Trading Methodology, Tokyo Stock Exchange, 2012.

[35] S. Wang, Measuring Credit Risk for Securities Margin Trading and Securities Lending, International Journal of Innovative Management, Information & Production **4-2** (2013), 7–16.

[36] Y. Wang, Essays on Margin Requirements, Endogenous Illiquidity and Portfolio Choice, Ph.D. Thesis, Washington University, 2011.

[37] P. Wilmott, *Paul Wilmott introduces quantitative finance*, John Wiley & Sons, 2007.

[38] J. Ye, Least squares linear discriminant analysis, Proceedings of the 24th International Conference on Machine Learning - ICML '07, 1087–1093, ACM Press, 2007.

[39] L. Yu, S. Wang, K. K. Lai and L. Zhou, *Bio-inspired Credit Risk Analysis: computational intelligence with support vector machines*, Springer, 2008.

[40] Zhu Dandan, Short selling of shares using the neural network simulation, Master Thesis, Kanazawa University, 2012. (in Japanese)