Bank Lending Strategy in The Stock Market

Dissertation

Bank Lending Strategy in The Stock Market

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Abstract

Margin trading is stocks trading using loan leverage from a financial institution; in here we call a bank. It is beneficial for improving liquidity in the market and creating smooth price formation of the stock. However, margin trading has a tendency to escalate the price. As the price of the stocks increases drastically, the authority then raises the minimum margin or minimum collateral to mitigate the risk. Theoretically it will slow down the price movement. Unfortunately, the market reaction result is different. Most of them sell their stocks, so the price then collapses. It was what happen in US great depression in 1929 and lost decade in Japan 1990.

For bank or lender, increasing margin requirements is an effective tool to mitigate the risk. However, good investors usually also being filtered out by it, as margin requirement only keep investors who have good working capital but, unfortunately, are incompetent to predict good performance investor.

A new method to predict investor bankruptcy in margin trading for the banking industry is successfully developed. In comparison to the margin requirement that screens investors merely by their capital and collateral, the scope of credit scoring can be extended to include the character, capacity and condition of the trader. Some artificial intelligences to create credit scoring for granting player loan proposals are implemented by comparing multiple discriminant analysis, neural network, decision tree and support vector machine performance then choose the most suitable one. The impact of credit scoring on price movement then is studied to control bubble price movement. Our method can predict investor as bankrupt, surviving and profitable. By classifying the investor into three groups, the bank can manage their loan absorption to profitable and surviving investor.

A new bank strategy for taming the bubble is developed using three methods; these are AI credit scoring, bubble detection and loan adjustment. The loan is delivered base on investor prediction. When the reserve's money is running out or bubble condition is detected, bank adjusts the loan parameter so called financing frame. As loan is restricted, the price movement then slightly decreases. After bubble condition or run-out reserve money disappear. The bank can relax the loan.

Various bank's reserve strategies also are analyzed to find their influence to the price movement. We performed some simulations to compare a smart bank with a non-smart bank and with static and dynamic reserves. A non-smart bank with a static reserve strategy and dynamic reserve

strategy will cause a price collapse because the non-smart bank cannot predict investor status so they unable to request early payment to bankrupt investor. Limiting the amount of cash by static reserve will also have a tendency to cause a collapse. When the reserves are gone, the bank is in a dangerous position.

The non-smart bank with dynamic reserve money will generate money creation and on the way building it up the price is collapsed. When the reserves are unlimited, it depends on the total value of the stock market. It is called the money creation as bank print new money to increase the reserve and deliver the money when an investor sells their stock. The dynamic reserve will nurture the development of the price. However, the non-smart bank cannot predict investor status, so they risk to collapsing increase. The impact of the bubble bursting with dynamic reserve money is severer as money creation leads the price to a new level and incompetent non-smart bank explode the bubble.

A smart bank can prevent the collapsing price either using static reserve or dynamic reserve. 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.

The smart bank can prevent the bursting price although the reserve is unlimited. Increasing price with smart bank is grounded from good investor financial status. By ability to detect the bubble and predict investor status, the smart bank is able to deliver the loan to profitable and good surviving investor on the right time. Loan will be restricted if investor status is bad or bubble detection is occurred. When condition is safe, bank can relax the loan so market liquidity increases and the price also increases again. Price will move to the new level if investor has good financial status to support it. Thus, smart bank can control money creation to nurture financial development.

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

Contents

Chapter 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 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 [34]. 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 [39]. 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 study, 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. [24, 26] and Zhu [43]. 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, 21, 23, 28, 35, 42]. However, Wang [38] 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 [25]. 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 [36] 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.

Various bank's reserve strategies also are analyzed to find their influence to the price movement. We performed some simulations to compare a smart bank with a non-smart bank and with static and dynamic reserves. A non-smart bank with a static reserve strategy and dynamic reserve strategy will cause a price collapse because the non-smart bank cannot predict investor status so they unable to request early payment to bankrupt investor. Limiting the amount of cash by static reserve will also have a tendency to cause a collapse. When the reserves are gone, the bank is in a dangerous position.

The non-smart bank with dynamic reserve money will generate money creation and on the way building it up the price is collapsed. When the reserves are unlimited, it depends on the total value of the stock market. It is called the money creation as bank print new money to increase the reserve and deliver the money when an investor sells their stock. The dynamic reserve will nurture the development of the price. However, the non-smart bank cannot predict investor status, so they risk to collapsing increase. The impact of the bubble bursting with dynamic reserve money is severer as money creation leads the price to a new level and incompetent non-smart bank explode the bubble.

A smart bank can prevent the collapsing price either using static reserve or dynamic reserve. 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.

The smart bank can prevent the bursting price although the reserve is unlimited. Increasing price with smart bank is grounded from good investor financial status. Ability to detect the bubble and predict investor status makes smart bank able deliver the loan to profitable and good surviving investor on the right time. Loan will be restricted if investor status is bad or bubble detection is occurred. When condition is safe, bank can relax the loan so market liquidity increases and the price also increases again. Price will move to the new level if investor has good financial status to support it. Thus, smart bank can control money creation to nurture financial development.

The rest of this dissertation is organized as follows. In Chapter 1, we briefly describe the background and the purpose of the research. In Chapter 2, we present mathematical finance that is used in the research. In Chapter 3, we describe the real world stock market system while, in Chapter 4, we explain about how our market simulation work. Moreover, we present artificial intelligence algorithms that are used to develop credit scoring in Chapter 5. The main part, our results are thoroughly discussed in Chapter 6 for credit scoring and Chapter 7 for taming the bubble. Finally, we provide remark and conclusion in Chapter 8.

Chapter 2

Mathematics of Finance

The essential idea of credit appraisal is comparing similar characteristic between previously recorded customer behaviour with the new one. If the new proposal has a tendency same with bad group attribute value that default their loan, the proposal should be rejected. If the proposal element same with good customer group, then, the loan can be granted. There are two techniques that usually used, these are loan officer judgmental analysis or credit scoring technique [1].

The judgmental technique depends on the expertise and experience of the evaluator. The more expert evaluator can judge not only from the quantitative value of the proposal but also the qualitative value of the person. However, standardizing the evaluator is difficult. Their judgemental method is inconsistent, subjective and unquantified. These are some weak reasons of this technique. On the other hand, credit scoring provides a quantitative approach for classifying proposal using historical data. Credit scoring can classify with less information being provided. Only highly correlated data to repayment performance that is needed by credit scoring. The other advantage of this method is replicable easily. Another evaluator can use the same reliable credit scoring method to evaluate other credit proposals with the same performance. The main problem of the credit scoring method is the weakness of the quantitative approach itself. The quantitative approach that can be used are vary from traditional methods such as univariate analysis [23], regression analysis [7] discriminant analysis [2, 7, 23], logistic regression [28] into advanced methods such as neural network [28], genetic programming [7], decision tree [7, 28] and support vector machine [1, 7, 21, 28].

The simplest credit scoring assessment is univariate analysis. It explores each variable and choose one variable that has the strongest correlation with the target. Miller [23] use total liability to total asset to show that probability to default increase as liability increase. Altman [2] uses discriminant analysis to predict bankruptcy using multiple variables. His work is well known and widely used in financial industry as his result give good reasoning in approving credit proposal since the variables he used are the firm accounting ratios. We will use discriminant analysis, neural netwrok, decision tree and support vector machine to build credit scoring. Neural network, decision tree and support vector machine will be discussed in chapter 5 and discriminant analysis will be explained later after we discuss the following financial ratio section.

2.1 Financial Ratio

Every company produces the financial statement to describe their financial performance. Investors use this financial statement to evaluate and justify their investing decision on this company. However, financial statement consists of many items that intercorrelated. Some ratios are developed to make data more meaningful. These ratios are very useful to show the relationship between financial statement data. Not only for analyzing the same company over time but also very helpful to compare among firms performance.

There are many financial ratios to describe the firm financial performance. Altman [2] identified 22 potential ratios that have ability to predict bankruptcy. His further study found that only five ratios that have significant correlation to predict bankruptcy. These ratios are working capital/total assets, retained earnings/total assets, earning before interest and taxes/total assets, market value of equity/book value of total liabilities and sales/total assets [2].

1. (working capital) / (total assets)
   Working capital = current assets - current debt. The companies that continuously have operating losses will slice their working capital as their asset is used to cover the losses. The firms that have positive working capital mean that they can pay their short-term obligation.

2. (retained earnings) / (total assets)
   Retained earnings = beginning retain earnings + net income or net loss - dividends paid. The ratio determines the maturity of capital firms. The younger firms have a higher tendency to bankrupt than the older firms. Thus, the younger firms will have a low ratio as they have not had the time to accumulate their profit.

3. (earning before interest and taxes) / (total assets)
   Fundamentally, this ratio assesses the firms earning power using their assets. It will detect insolvency when the firms cannot utilise their liabilities.

4. (market value of equity) / (book value of total liabilities)
   This ratio calculates how much the firm's asset value can decrease as the market value of equity decline before their debt exceed the asset and the companies become insolvent.

5. (sales) / (total assets)
   This ratio measures the assets turnover to generate revenues or sales using their assets. It shows efficiency of the company to utilise their assets to the sales.

As margin trading simulation that is being studied is for individual investor, these financial ratios cannot be used. Using the same analogy, investor should has individual financial performance.

However, The simulation program also do not populate individual investor characteristics like job, wage, address, age, job duration etc. The simulation program only record investor performance from four variables, cash, stocks market value, debt and profit. Two important factors to develop financial ratios to evaluate investor are ratio is not hindering other ratio and the ratio can be calculated without being violate computational calculation such as divided by zero. There are eight ratios we propose

1. (market value) / (total assets)
2. (profit or loss) / (total assets)
3. (liabilities) / (working capital)
4. (cash) / (working capital)
5. (market value) / (working capital)
6. (profit or loss) / (working capital)
7. (liabilities) / (total assets)
8. (cash) / (total assets)

2.2 Discriminant Analysis

The multiple discriminant analysis is extended version of linear discriminant analysis (LDA) invented by Ronald A. Fisher in 1936 [13] to classify data into more than two classes. LDA works with assumption standard distribution classes or equal classes covariance to search a linear combination of variables that best separates two classes. Let Z be a function with linear combination of variables $X = \{X_1, X_2, \ldots, X_n\}$ and coefficients $\tilde{\alpha} = \{\tilde{\alpha}_1, \tilde{\alpha}_2, \ldots, \tilde{\alpha}_n\}$ as follows:

$$Z = \tilde{\alpha}_1 X_1 + \tilde{\alpha}_2 X_2 + \cdots + \tilde{\alpha}_n X_n.$$

Assume that we have N samples $\{x_1, x_2, \ldots, x_N\}$ by observation, N_1 of which belong to group 1 and N_2 to group 2. One noticeable measure to classify the samples is how different are the mean values of Z for the two different groups. Fisher solved it by proposing the followings score function:

$$\begin{aligned} S(\alpha) &= \frac{\text{(Variance of } Z \text{ between Groups)}}{\text{(Variance of } Z \text{ within Groups)}} \\ &= \frac{(\alpha\mu_1 - \alpha\mu_2)^2}{\alpha^T C \alpha} \\ &= \frac{(\alpha\,(\mu_1 - \mu_2))^2}{\alpha^T C \alpha}. \end{aligned}$$

C is a pooled covariance matrix, while C_1, C_2 and μ_1, μ_2 are covariances and means vectors of group 1 and group 2. Given the score function, the objective is to estimate the linear model coefficient α that maximize the score that can be solved by

$$\begin{aligned}\alpha &= C^{-1}(\mu_1 - \mu_2)\\ C &= \frac{n_1 C_1 + n_2 C_2}{n_1 + n_2}.\end{aligned}$$

A new point X is categorized by projecting it onto the maximally separating direction and classifying it as group 1 if

$$\alpha^T = \left(X - \frac{\mu_1 + \mu_2}{2}\right) > \log \frac{p(G_1)}{p(G_2)},$$

where $p(G_1)$ and $p(G_2)$ are the probability of group G_1 and G_2. The result of Fisher's LDA is equal to least square problems or linear regression classification [41]. It also had been shown by [11].

In 1968, Edward I. Altman discovered a formula that used 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 investigated financial data from 66 firms and found 22 potential variables or ratios for predicting from the literature. The variables were grouped into five categories: liquidity, solvency, profitability, leverage and activity. Afterward, those variables were assessed by examining statistical significance impact of each independent variable and inter-correlations among variables. Prediction accuracy then evaluated before formulated the result. From 22 ratios, 5 ratios were chosen as predictors. The five ratios 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 to that outcome.

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

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

where $v = (v_1, v_2, \dots, v_8)^\intercal$ and $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_8)^\intercal$. 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 $f(v)$ which will be discussed at Chapter 6.1.1.

Chapter 3

Stock Market

The stock market is a venue where share prices for listed stocks are discovered [33] and ownership of shares are exchanged [31]. The stock market shall provide timely and accurate information on past transactions and current buy and sell order so investors can justified a proper price when entering the market. Another main requirement is the market also should provide liquidity, the ability to buy or sell a stock quickly at a known price. A good market is whether the market could provide no lag in time and price with low transaction cost.

There are two types of stock market, these are primary market and secondary market [31]. Companies are acquiring new capital by issuing new stocks and sell it in the primary market. The outstanding stocks then sell in the secondary market. The new stock can be from initial public offering (IPO) or seasoned equity issues. The firm sells their stocks to the public for the first time through IPO while the firm that already has outstanding stocks sells their stock through seasoned equity issues.

The stock market has stricted and complex regulations to ensure transparency and accountability. Because of that, the members of the stocks exchange are limited. Individual investors who want to do the transaction in the stock market have to join a securities company that already a member of the stock market. The securities company will ask few fees for their services. If investor joins to securities company that is not a member of the stock market, the securities company will put the order to other securities company that has a membership.

3.1 Order Mechanism

The stock market has two major trading systems usually used. It can be one of them or their combination. First is a pure auction market and the other is a dealer market [31]. The pure auction market or an order driven market, is a market that bid and ask or buy and sell orders are matched by an agent that does not have the stocks in a centralized manner. The pure auction market system is also referred to as price driven since spot price is determined by the highest bid price and the lowest ask price.

The dealer market systems or also referred to as quote driven market is a market with at least one individual dealer for one stock provides liquidity for the investors by purchasing and selling the shares for themselves. Ideally, there should be numerous dealer or market maker that will compete against each other to create a fair spot price. They will compete to form the highest bid price when we want to sell and provide the lowest ask price when we want to buy. Thus, the dealer market system is a decentralized trading system.

Based on the operation of the stock exchange, in terms of how and when the share is traded, stocks market is divided into two categories, call market and continuous market [31]. Call market is a batch market system by matching ask and bid price to a single spot price that execute as much as possible the quantity of demand and supply. Usually, call market is used in an opening market. The opening fair price is determined from a queue of order after the market is closed. The continuous market order executes at any time when the market is open either by auction or by dealers. The continuous market operation matches the order from the price and time arrival.

The Tokyo Stock Exchange (TSE) is a double auction continuous market system mixed with the call market system. In the opening market, the TSE uses call market so call itayose method and after the market open, the TSE uses double auction continuous operation so called zaraba method [37]. In Itayose method, the price is defined using these three necessities

1. All market orders must be executed. Market order is buy or sell order with spot price.
2. All limit orders to offer at prices lower than spot price must be executed and bid orders at prices higher than spot price also must be executed. Limit order is buy or sell order by specifying the price.
3. At the spot price, either all buy or all sell orders must be executed completely.

The following table 3.1 illustrates an order book. We will use itayose method to determine the opening price. Aggregated offers start from market order then lowest price to the highest price while aggregated bids start from market order then highest price to the lowest price. The 3 requirements are set to determine the fair price that balances out between aggregated bids and offers.

After the market open, the order transaction now uses double auctions continuous mechanism or zaraba method. It is called double because the price formations are auction on buy and sell orders. Zaraba method is the process to match incoming order with the highest priority order that already in the order book. The order priority is determined by price and time. Market order is the highest priority. Moreover, The highest price in bids and the lowest in offers have higher priority over the other. In the same price, priority is decided by arrival time, the earliest has the highest priority. The table 3.2 shows how the order is executed after the market open.

Table 3.1: The Itayose Method

Offer (sell)		**Price**		**Bid (buy)**
Aggregate	**Quantity**		**Quantity**	**Aggregate**
	600	Market Order	500	
5300	700	752	100	600
4600	1500	751	500	1100
3100	2000	750	1500	2600
1100	300	749	800	3400
800	200	748	2500	5900

Offer (sell)	**Price**	**Bid (buy)**
600	Market Order	500
700	752	100
1500	751	500
2000	**750**	1500
300	749	800
200	748	2500

According requirement (1), market order should be executed first, 500 shares buy orders are matched with 500 shares sell orders at market price leaving 100 shares sell orders

Offer (sell)	**Price**	**Bid (buy)**
100	Market Order	
700	752	100
1500	751	500
2000	**750**	1500
300	749	800
200	748	2500

All market orders, bid orders above spot price and offer orders below spot price are matched, fulfil requirement (1) and (2)

Offer (sell)	**Price**	**Bid (buy)**
	Market Order	
700	752	100
1500	751	
2000	**750**	1500
	749	800
	748	2500

At spot price, All amount of buy orders, 1500 shares at 750 JPY is matched with 1500 shares sell orders. Leaving 500 shares sell orders.

Offer (sell)	**Price**	**Bid (buy)**
	Market Order	
700	752	
1500	751	
500	**750**	
	749	800
	748	2500

Finally, All the requirements are fulfilled. The opening price is 750 JPY and the order book now look like this.

Table 3.2: The Zaraba Method

Offer (sell)	Price	Bid (buy)
1000	Market Order	
800	752	
1000	751	
500	**750**	
	749	**2000**
	748	3000

Currently, the best bid is 2000 shares at 749 JPY and the best offer is 500 shares at 750. The market price now is 750 JPY. A market sell order arrives at the book for 1000 shares.

Offer (sell)	Price	Bid (buy)
	Market Order	
800	752	
1000	751	
500	750	
	749	1000
	748	3000

This new sell market order is matched with the bid highest priority, 2000 shares at 749 JPY. Leaving 1000 shares bid order at 749 JPY. The market price is now 749 JPY.

Offer (sell)	Price	Bid (buy)
	Market Order	
800	752	
1000	751	1000
500	**750**	
	749	1000
	748	3000

After that, 1000 shares bid order arrives at 751 JPY. It will be matched with the offer highest priority 500 shares at 750 JPY. Thus, the market price increases to 750 JPY.

Offer (sell)	Price	Bid (buy)
	Market Order	
800	752	
500	**751**	
	750	
	749	1000
	748	3000

The outstanding 500 shares are now matched with 1000 shares offer at 751 JPY. The market price then increases to 751 JPY. Leaving 500 shares at 751 JPY. The transaction continuously run this way during the trading hours.

3.2 Margin Trading

Fundamentally, margin transaction is a credit transaction where the investor only pays some portion of the cost and the financial institution will pay the remaining [8]. Margin trading useful for increasing liquidity and fair price smooth formation as margin trading will attract more investor to trade by the help of securities financial firms money. Financial brokerage uses the shares as collateral for the loan. So, when the investor sells their stock they have to pay their loan plus interest. People can leverage their capital to gain bigger profit by buying in the margin. However, it is a double-edged sword that also increases the risk of loss. Minimum margin for TSE market is 30% of transaction value or 300,000 JPY whichever is greater while New York Stock Exchange (NYSE) is 50% of transaction value. Furthermore, maintain margin to be preserved, as fluctuation of the price is at least 20% for TSE and 30% for NYSE.

Currently, The TSE in Japan implements two types of margin trading; the first is standardized margin trading and the other is negotiation based margin trading [18]. The standardized margin trading governs by specific regulation set by the TSE. The TSE defines which share that eligible to trade in margin trading base on their liquidity with particular terms. On the other side, large financial companies usually perform the negotiation margin trading. They freely negotiate the fees and the terms.

Standardized margin trading in Japan was firstly implemented in 1951. Specialized securities financial companies were appointed to provide credit and borrowed shares to stabilize and expand Japan's securities market within the doubtful period after World War II [18]. As individual investors are less creditworthy, the system tries to offer investing leverage for more individual investors to borrow stocks and funds from securities finance companies easily. This process is identified as a security loan transaction so call taishaku torihiki in Japanese. The standardized margin trading work as follows: investor sends margin order to broker. The broker then checks their order list and stocks portfolio to match the order with other orders for the same stock from other investors. When brokers stocks inventory and the matching process cannot fulfill the margin order from the investor, the broker then contact the securities finance company to fill the gap.

The ordinary loan transaction regulation was relaxed since Japanese the financial big bang in December 1998 [18]. Investors and brokers can negotiate the loan rate and repayment period at will. Thus, negotiation based margin trading then started. However, mostly the players of negotiation based margin trading are institutions rather than the individuals because institutions are more creditworthy to negotiate the contract than the individual. Not only the player, but also capitalization value.

Figure 3.1 describes the margin trading system in the TSE. Just like ordinary stock transaction, customer should join a securities company to be able do a transaction. For margin trading, customer opens a special account transaction so call margin account. Margin account is used to manage stock transaction, loan and client's collateral. Securities company acts as brokerage for investor to help transaction in stock exchange, manage stock settlement with clearinghouse and deal with financial institution like bank or other securities finance firm to provide loan to

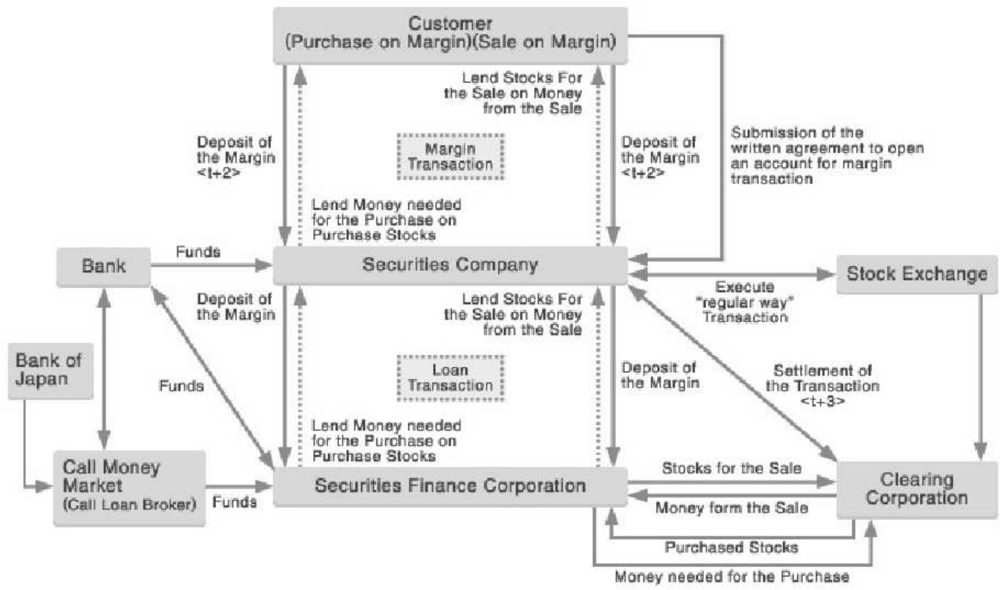


Figure 3.1: Margin Trading System in Tokyo Stock Exchange [20]

investor. So, in here, securities company hinders all complicated work from investor. Investors only know one door to do all the transaction just by open a margin account.

Chapter 4

Stock Market Simulation

Figure 4.1: Stock Market Simulation

The stock market simulation is developed base on Nakatani [24] and Zhu [43] work. There are three main agent, Investors, stock market server and bank. Investors and bank agent are developed using Java programming language and stock market server using C programming language. Moreover, multiple investors can connect to stock market server to trade. The three of them communicate using TCP/IP. This communication does not allow any loss of data. Any one bit of error will lead one message fail to interpret. We use the followings message format to transmit and receive data.

Data ID: 32 bit signed Integer
Data: Depends on the message

The stock market simulation server applies a simplified Tokyo stock exchange rules. At Tokyo stock exchange, the order is accepted on between 8:00 -11: 00 and 12:05 - 15: 00. The market opens at 9:00 - 11: 00 (morning session) and 12:30 - 15:00 (afternoon session). At 8:00 - 9:00 and 12:05 - 12:30, the orders are accepted and processed by itayose method. In the morning session and afternoon session, the order is processed by zaraba method. We only implements

1. Double auction continuous trading mechanism or zaraba method, so the closing price will become the opening price in the following day.
2. There are two types of order, market order (highest priority) and limit order (lower priority). Limit order can be bid or offer order.

3. The tick price is 5 JPY.
4. There are 300 turns time in one day.
5. There is only one type of the stock.
6. The trading unit is 1 share.
7. In one day, there is only one trading session.

We divide the stock market simulation operation into 11 processes, there are login process, order process, order cancellation process, loan process, logout process, order execution process, board information, bank process, loan with credit scoring process and time update.

1. Login process
   Every time client connects to the stock market server, server gives the client ID and identifies the client using this ID for any process. The table 4.1 shows the detail of the login process.

Table 4.1: Login Process

Client		Server	
Message	Description	Action	Description
Login request	Request for client ID	Login Registration	Send Client ID
Market size inquiry	Ask how many stock name that will be traded	Send market size	Send a number of stock name that will be traded
Collateral rate inquiry	Ask rate of leverage	Send collateral rate	Send collateral rate or financing frame
Stock price inquiry	Ask the initial price	Send stock price	Send the initial stock price
Send cash	Send initial cash	Set the client cash	Record the client initial cash
Server time inquiry	Ask server current time	Send server time	Send server current time

2. Order process
   The investor initiates order. Investor sends an order to the server then the server register the order to the board list. The table 4.2 describe the message passing.

3. All order cancellation process
   If player send an instruction to cancel all of his order, server will search all his order and cancel it from the board list. Server will send notification to the investor for each order being cancelled. The table 4.3 illustrates the communication.

Table 4.2: Order Process

Client		Server	
Message	Description	Action	Description
Send an order	Submit an order	Order registration	Received order is registered to the board

Table 4.3: All Order Cancellation Process

Client		Server	
Message	Description	Action	Description
Request all order cancellation	Ask for cancellation of all order	Order cancellation notice	Send the notice for each order being cancel to investor who request cancellation

4. Loan process
   Investors send loan request to the bank. They send their loan amount proposal and their working capital. Bank checks their remaining loan and loan proposal. If adequate, the loan granted. The table 4.4 describe the process.

Table 4.4: Loan Process

Client		Bank	
Message	Description	Action	Description
Loan request	Send loan amount proposal and working capital	Financing submitted	Compare the loan proposal and remaining loan of that investor. If sufficient, send the financing. If not, send zero financing notification.

5. Logout process
   If a player send request to logout, Server will cancel all his order and detach him from the server. The table reftab:logout shows the message passing.

6. Order execution process
   Order execution is based on double auction continuous method. If there is an execution, the owner of the order will be notified by a message describes on the table 4.6. If number of buy order and sell order are the same, both of them are cleared from the board. If not the same, then there is a remaining order on the board.

Table 4.5: Logout Process

Client		Server	
Message	Description	Action	Description
Logout request	Send instruction to logout	All order cancellation notice	Send notices of all order being cancelled and detach the client from the server.

Table 4.6: Order Execution Process

Server		Client	
Message	Description	Action	Description
Send execution order information	Send number of shares being executed and the execution price to the owner of the order.	Update client's portfolio	Client update his stock, cash and order number.

7. Board information
   On every turn, the server broadcast information of the board, total remaining loan available and the current time of the server. The table 4.7 shows the message.

Table 4.7: Board Information

Server		Client	
Message	Description	Action	Description
Send board information	Send all the quantity of the order and the spot price.	Update board information	Client update their information base on current board data
Send bank information	Send total available loan.	Update account	Client update his account
Send server time	Send current time of the server.	Update time	Client time synchronize with server

8. Bank process
   On every turn, bank will send request of repayment to the investor who has due date and bankrupt notification to particular investor. The table 4.8 describes the message.

9. Loan with credit scoring process
   If bank credit scoring is activated, when the investor request for loan, the bank will cal-

Table 4.8: Bank Process

Bank		Client	
Message	Description	Action	Description
Send repayment request	After due date and the total loan amount exceeds the total amount available for lending, bank send repayment request to all clients who received the loan.	Repay	Clients repay the loan with their cash if not adequate they sell their stocks at market price
Send bankruptcy notification	If investor cannot pay the loan after the repayment instruction, bank send bankruptcy notification and force the client to logout.	Liquidated and detach	Client sell their stocks at the market price, cancel all order and detach from the program

culate investor credit scoring and judge the credit appraisal from this credit scoring. The table 4.9 illustrates the message.

10. Time update
    Client and server program are synchronized by server time. On every turn, server sends its current time. The table 4.10 shows the message.

Table 4.9: Loan Process with Credit Scoring

Client		Bank	
Message	Description	Action	Description
Loan request	Send loan amount proposal, shares market value, cash, debt and profit	Financing submitted	Compare the loan proposal and remaining loan of that investor. If sufficient, bank calculates investor credit scoring, if the score eligible for the loan then bank send financing. If not, send zero financing notification.

Table 4.10: Time Update

Server		Client	
Message	Description	Action	Description
Time update	Notification for next turn.	Next turn	Client send their current portfolio information to the server and increment their time

Chapter 5

Artificial Intelligence

5.1 Artificial Neural Network

The artificial neural network is a cellular system that can learn, store and recall its knowledge. It is constructing by modelling the structure of the human brain. The human brain consists of millions of interconnected neurons that using biochemistry reaction on receiving, processing and transmitting the signal. Information is received by dendrites from the external environment or neighbor neurons. It is then collected and transmitted through axon and dendrites (if over the threshold) to other neurons. Among dendrites, there is a synapse, which can reduce or strengthen the information. On the other hand, the artificial neural network receives information from n inputs. Each input has relative weight than others just like a synapse. The information then is summed and transmitted through processing element called transfer function [10]. The transfer function is a formula to convert the input into output. There are also many types of transfer functions. Examples of various basic of transfer functions are listed below

1. Hard limit
   There are two types of hard limit transfer function, binary and bipolar. Binary hard limit transfer function provides output 0 or 1 and the bipolar hard limit produce 1 if input less than 0 or -1 if input greater or equal 0.

2. Linear
   Unlike the hard limit transfer function that only provide two output, linear transfer function can provide unlimited output. Linear transfer function is calculate by $y = f(x) = \alpha x$. If output equal with input, the function is called an identity function.

3. Linear piecewise
   This function only produces linear output between 1 and -1. Otherwise, 1 if input greater than 1 and -1 if input less than -1.

4. Sigmoid
   The sigmoid transfer function can have any value input x between minus infinity and plus infinity and squashes the output into the range 0 to 1.

The Figure 5.6 shows the transfer functions and their equation.

The artificial neural network can be consisted of one or multi-layer neurons. There are four basic neural network architectures: feed forward, recurrent, symmetrical and asymmetrical [10].

1. Feed Forward
   In feed forward neural network, there is no loop node interconnection. It provides a quick response to input.
   (a) Single layer feed forward network
       In this layered neural network, the neurons are organized in the form of Layers. In this simplest form of a layered network, we have an input layer of source nodes those projects on to an output layer of neurons, but not vice-Versa. In other words, this network is strictly a feed forward or acyclic type. Figure 5.7 illustrates the architecture [10].
   (b) Multi layer feed forward neural network
       Multilayer feeds forward networks: The second class of the feed forward neural network distinguishes itself by one or more hidden layers. The computation nodes that are correspondingly in the hidden unit are called neurons or units. The function of hidden neurons is intervened between the external input and the network input in some useful manner. The ability of hidden neurons is to extract higher-order statistics is particularly valuable when the size of the input layer is large. The input vectors are feed forward to 1st hidden layer and this pass to the second hidden layer and so on until the last layer i.e. output layer, which gives actual network response. Figure 5.8 shows the multi layer feed forward neural network architecture [10].
2. Recurrent
   A recurrent network differentiates itself from feed forward neural network, in that it has least one feed forward loop. As shown in Figure 5.9 output of the neurons is fed back into its inputs is referred as self-feedback [10]. A recurrent network may have a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons or multi-layer network so the network may have hidden layers or not.
3. Symmetrical
   In symmetrical neural network, multiplication result of output of node i with weight i to j is the same with multiplication result of output of node j with weight j to i. Figure 5.11 shows the symmetrical network architecture [10].
4. Asymmetrical
   In asymmetrical neural network, multiplication result of output of node i with weight i to j is not the same with multiplication result of output of node j with weight j to i. Figure 5.12 shows the asymmetrical network architecture [10].

$$y = f(x) = \begin{cases} 0, & \text{if (x < 0)} \\ 1, & \text{if (x} \geq \text{0)} \end{cases}$$

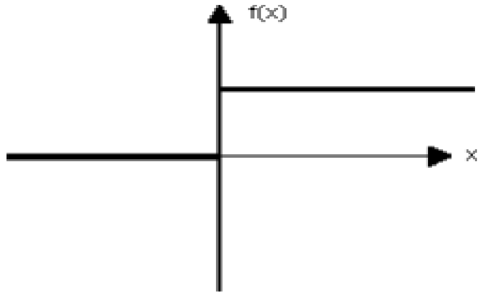


Figure 5.1: hard limit binary function

$$y = f(x) = \begin{cases} -1, & \text{if (x < 0)} \\ 1, & \text{if (x} \geq \text{0)} \end{cases}$$

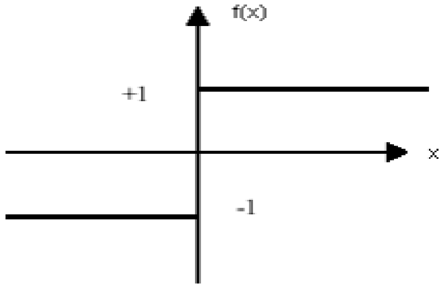


Figure 5.2: hard limit bipolar function

$$y = f(x) = \alpha x$$

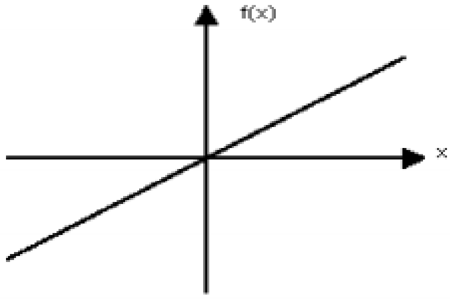


Figure 5.3: linear function

$$y = f(x) = \begin{cases} -1, & \text{if (x < -1)} \\ x, & \text{if (-1} \leq \text{x} \leq \text{1)} \\ 1, & \text{if (x > 1)} \end{cases}$$

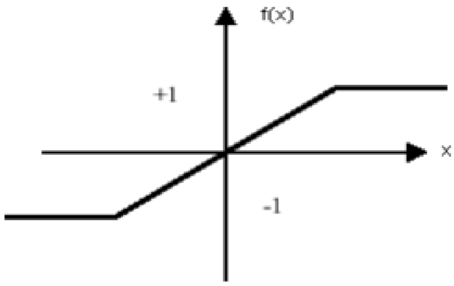


Figure 5.4: linear piecewise function

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

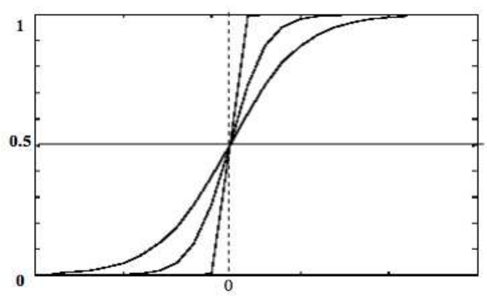


Figure 5.5: sigmoid function

Figure 5.6: Transfer Function

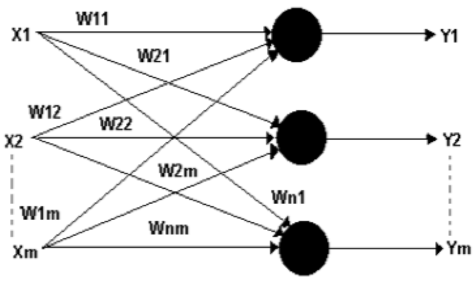


Figure 5.7: Single Layer Feed Forward Network

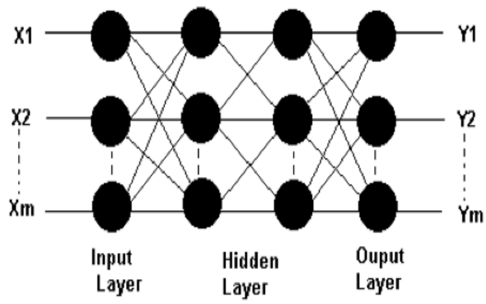


Figure 5.8: Multi Layer Feed Forward Network

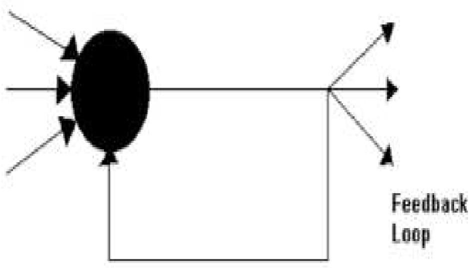


Figure 5.9: Single Recurent Network

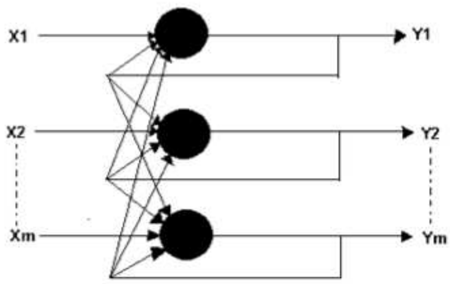


Figure 5.10: Multi Recurrent Network

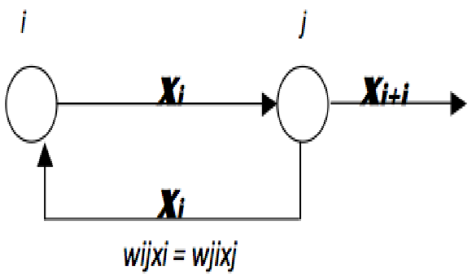


Figure 5.11: Symmetrical Network

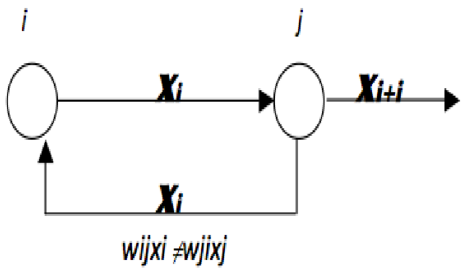


Figure 5.12: Asymmetrical Network

Figure 5.13: Neural Network Architecture [10]

Artificial neural network (ANN) consists of three layers, input layer, hidden layer and output layer. In the experiment we use eight nodes input layer, five nodes hidden layer and three nodes output layer representing each class, bankrupt, survive and profit. Sigmoid transfer function is used in each node. Each hidden unit computes the weighted sum of its inputs to get a scalar net activation or we call net. net_j is a net activation of hidden layer j. It is the inner product of weight of hidden unit and the inputs.

$$net_j = \sum_{i=1}^{d} x_i w_{ji} + w_{j0} = \sum_{i=0}^{d} x_i w_{ji} \equiv \boldsymbol{w}_j^t \boldsymbol{x},$$

where i is index unit of input node, j is index unit for hidden layer, d is number of input unit and w_{j0} is bias unit. w_{ji} is weights at hidden layer j that connect to input layer node x_i. Each hidden unit produce an output (y_j) as its activation function.

$$y_{j=f(net_j)}.$$

Similarly, each output node also calculate its net activation based on hidden unit result.

$$net_k = \sum_{j=1}^{h} y_j w_{kj} + w_{k0} = \sum_{j=0}^{h} y_j w_{kj} \equiv \boldsymbol{w}_k^t \boldsymbol{y},$$

where k denotes the index of the output node in output layer, h is number of hidden unit and w_{k0} is bias unit. Each output node calculate the transfer function with the data from hidden unit result.

$$z_k = f(net_k).$$

A chosen output class is the node with highest score.

$$\max\ z_k.$$

The fundamental concept of neural networks is that such parameters, weight or bias, can be adjusted so that the neural network exhibits some desired or interesting behavior. Thus, the network can be trained to do a particular job by changing these parameters. One of the learning algorithms that known from its fast performance is resilient propagation. Resilient propagation neural network (RProp) was created by Martin Riedmiller and Heinrich Braun in 1992 [32]. RProp is classified as supervised learning rule for feed forward artificial neural network. RProp uses batch updates to obtain the gradient of each weight. Sign of gradient is used to estimate the direction of weight update. The following is general algorithm of RProp where $E(t) = E(w,t)$ is an error function at time t and w_{ij} is weight of neuron ij.

1. Evaluate error after a batch of training examples.
2. Discover the gradient's direction by identifying sign of gradient of error function $\left(\frac{\partial E(t)}{\partial w_{ij}}\right)$ and $\left(\frac{\partial E(t-1)}{\partial w_{ij}}\right)$.

3. Take a greater step $(\eta^{+}\Delta_{ij}(t-1))$ than last epoch if sign is the same as the last epoch.
4. If it is different sign as last epoch, it means optimal weight has passed over. Step back and take a smaller step $(\eta^{-}\Delta_{ij}(t-1))$ for next epoch.

Furthermore, different weights need different value of step sizes for update. A step update value $\Delta_{ij}(t)$ at time t is calculated according to the following recurrence formula:

$$\Delta_{ij}(t) = \begin{cases} \eta^{+}\Delta_{ij}(t-1), & \left(\text{if } \dfrac{\partial E(t-1)}{\partial w_{ij}}\dfrac{\partial E(t)}{\partial w_{ij}} > 0\right) \\ \eta^{-}\Delta_{ij}(t-1), & \left(\text{if } \dfrac{\partial E(t-1)}{\partial w_{ij}}\dfrac{\partial E(t)}{\partial w_{ij}} < 0\right) \\ \Delta_{ij}(t-1), & (\text{otherwise}), \end{cases}$$

where

$$0 < \eta^{-} < 1 < \eta^{+}.$$

Weight update $(\Delta w_{ij}(t))$ then decrease as much update value ($\Delta_{ij}(t-1)$) if gradient weight is positive (increasing error). On the other hand, weight update $(\Delta w_{ij}(t))$ is increasing as much update value ($\Delta_{ij}(t-1)$) if gradient weight is negative (decreasing error).

$$\Delta w_{ij}(t) = \begin{cases} -\Delta_{ij}(t-1), & \left(\text{if } \dfrac{\partial E}{\partial w_{ij}}(t) > 0\right) \\ +\Delta_{ij}(t-1), & \left(\text{if } \dfrac{\partial E}{\partial w_{ij}}(t) < 0\right) \\ 0, & (\text{otherwise}). \end{cases}$$

From the empirical research, the best result is achieved by initial step sizes of 0.1, $\eta^{+} = 1.2$, $\eta^{-} = 1.2$, $\eta_{\max} = 50$ and $\Delta_{\min} = 10^{-6}$.

5.2 Decision Tree

Ross Quinlan invented C4.5 [30] to generate a decision tree using divide and conquer technique. In order to divide and conquer the data, C4.5 uses information entropy concept. Entropy is exploited to quantify how informative a variable to separate the data. The Entropy of sample S is calculated as follows:

$$\text{Entropy}(S) = -p_1 \log_2 p_1 - p_0 \log_2 p_0$$

where p_1 and p_0 are proportions of examples of class 1 or class 0 in sample S. Essentially, the entropy evaluates the order (or disorder) in the sample data S with respect to the classes. It generates 0 (maximal order, minimal disorder) when $p_1 = 0$ or $p_0 = 0$ and it generates 1 when $p_1 = p_0 = 0.5$ (maximal disorder, minimal order). Gain(S, X_i) is described as anticipated reduction in entropy as a result of splitting or sorting on attribute X_i

$$\text{Gain}\,(S, X_i) = \text{Entropy}\;(S) - \sum_{v \in \text{values}\,(X_i)} \frac{|S_v|}{|S|} \text{Entropy}\;(S_v)$$

where values (X_i) denote the set of all potential values of attribute X_i, S_v the subset of S where attribute X_i has value v and $|S_v|$ is the number of observations in S_v. The Gain principle was used select upon which attribute to split at a given node. However, when this criterion is applied to determine the node splits, the algorithm favors create leafs on attributes with many distinct values. In order to rectify this, C4.5 implemented normalization and uses the gain ratio criterion, which is described as follows:

$$\begin{aligned} \text{Gain ratio}\,(S, X_i) &= \frac{\text{Gain}\,(S, X_i)}{\text{Split Information}\,(S, X_i)} \\ \text{Split Information}\,(S, X_i) &= -\sum_{k \in \text{values}\,(X_i)} \frac{|S_k|}{|S|} \log_2 \frac{|S_k|}{|S|}. \end{aligned}$$

5.3 Support Vector Machine

Support vector machine (SVM) firstly invented by Boser, Guyon and Vapnik in 1992 [5] by combining margin hyperplane and kernel method for discriminate two groups data. Margin hyperplane is used as linear classifier while non-linear data is treated by kernel trick to manipulated domain function into higher dimensional space. The essence of SVM is finding the best hyperplane as a classifier of two classes in input space, for example, classes $+1$ and -1. Look at Figure 5.14, class -1 is on the left and class $+1$ is on the right. Classification problems can be translated as an endeavor to obtain hyperplane (line) that separate two groups. The best hyperplane between those classes can be computed by finding their maximum margin hyperplane. Margin is the closest distance between two classes pattern.

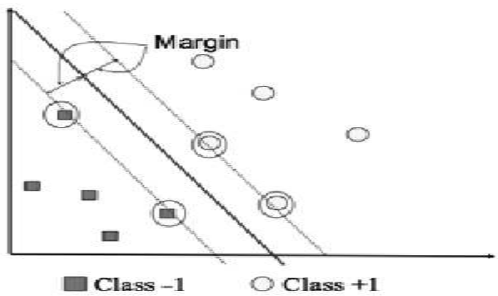


Figure 5.14: Margin Hyperplane

Training data are symbolized as $\boldsymbol{x}_i \in \mathbf{R}^d$ and class label for each data is noted by $y_i \in \{-1, +1\}$ for $i = 1, 2, 3, \ldots, l$, which l is number of data. Denote by $\boldsymbol{x} \cdot \boldsymbol{y}$ the dot product of two vectors. It is assumed that class -1 and $+1$ can be separately perfectly by a hyperplane in d-dimensional space $\mathbf{R}^d$ that is defined as follows:

$$\boldsymbol{w} \cdot \boldsymbol{x}_i + b = 0.$$

Furthermore, positive and negative instances of training data can be written as

$$\begin{array}{ll} \boldsymbol{w} \cdot \boldsymbol{x}_i + b \geq +1 & \text{for positive training data } \; y_i = +1, \\ \boldsymbol{w} \cdot \boldsymbol{x}_i + b \leq -1 & \text{for negative training data } \; y_i = -1. \end{array}$$

Consider two hyperplanes

$$H_1 = \{\boldsymbol{x} \in \mathbf{R}^d \mid \boldsymbol{w} \cdot \boldsymbol{x} + b = 1\} \quad \text{and} \quad H_{-1} = \{\boldsymbol{x} \in \mathbf{R}^d \mid \boldsymbol{w} \cdot \boldsymbol{x} + b = -1\}.$$

Then the distance between the two hyperplanes is given by

$$\operatorname{dis}(\boldsymbol{x}_0, H_{-1}) = \frac{|\boldsymbol{w} \cdot \boldsymbol{x}_0 + b + 1|}{\|\boldsymbol{w}\|} = \frac{|1+1|}{\|\boldsymbol{w}\|} = \frac{2}{\|\boldsymbol{w}\|},$$

where $\boldsymbol{x}_0 \in H_1$.

To gain the best hyperplane, we have to maximize the distance $2/\|\boldsymbol{w}\|$. The distance will be maximized if a function $\tau(\boldsymbol{w}) = \frac{1}{2}\|\boldsymbol{w}\|^2$ is minimized. The vector $\boldsymbol{w}$ and the scalar b can be found by minimizing equation (5.1) with equation constrain (5.2).

$$\min_{\boldsymbol{w}} \tau(\boldsymbol{w}) \tag{5.1}$$

$$y_i(\boldsymbol{x}_i \cdot \boldsymbol{w} + b) \geq 1, \qquad i = 1, \ldots, l, \; y_i \in \{-1, +1\}. \tag{5.2}$$

It is so-called quadratic programming problem. Lagrange multiplier then is used to solve this problem. We put $g_i(\boldsymbol{w}, b) = y_i(\boldsymbol{x}_i \cdot \boldsymbol{w} + b) - 1$ and construct corresponding Lagrangian as follows:

$$\begin{aligned} L(\boldsymbol{w}, b, \alpha) &= \tau(\boldsymbol{w}) - \sum_{i=1}^{l} \alpha_i g_i(\boldsymbol{w}, b) \\ &= \frac{1}{2}\|\boldsymbol{w}\|^2 - \sum_{i=1}^{l} \alpha_i (y_i(\boldsymbol{x}_i \cdot \boldsymbol{w} + b) - 1), \quad \alpha_i \geq 0, \forall i, \end{aligned} \tag{5.3}$$

where α_i is a Lagrange multiplier with positive value. Optimal value of equation (5.3) can be found by minimizing L by $\boldsymbol{w}$ and b and maximizing L by α_i. By finding partial derivative $L = 0$, we get

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^{l} \alpha_i y_i x_i = 0 \tag{5.4}$$

$$\frac{\partial L}{\partial b} = \sum_{i=1}^{l} \alpha_i y_i = 0. \tag{5.5}$$

By plugging equation (5.4) and (5.5) to equation (5.3), we will find an equation that remove dependence of $\boldsymbol{w}$ and b.

$$L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i\alpha_j y_i y_j (\boldsymbol{x}_i \cdot \boldsymbol{x}_j)$$

$$\text{subject to} \quad \alpha_i \geq 0, \ \sum_{i=1}^{l} \alpha_i y_i = 0. \tag{5.6}$$

Optimal value of L (5.6) now only depends on maximizing $L(\alpha)$ by α_i.

Kernel Trick

In some cases, it is hard to separate samples completely by a hyperplane. For example, separating data in the inner circle and outer circle. Over here, we need to use a transformation function Φ from linear into a polynomial. It is written as follows [17]:

$$\Phi : \mathbf{R}^2 \to \mathbf{R}^3, \qquad (x_1, x_2) \mapsto (x_1^2, \sqrt{2}x_1x_2, x_2^2).$$

Recalling equation (5.6) to optimize $L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i\alpha_j y_i y_j (\boldsymbol{x}_i \cdot \boldsymbol{x}_j)$. Now, by transforming into higher feature space by Φ, we have to calculate $\Phi(\boldsymbol{x}_i) \cdot \Phi(\boldsymbol{x}_j)$ rather than $\boldsymbol{x}_i \cdot \boldsymbol{x}_j$. However, this is higher cost computation. Luckily, there is a kernel function K that can be applied to avoid calculating Φ.

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \Phi(\boldsymbol{x}_i) \cdot \Phi(\boldsymbol{x}_j).$$

Equation (5.6) now become

$$L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i\alpha_j y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j),$$

subject to $\alpha_i \geq 0, \ \sum_{i=1}^{l} \alpha_i y_i = 0$, with decision function as follows:

$$f(x) = \sum_{i=1}^{l} \alpha_i K(\boldsymbol{x}_i, \boldsymbol{x}_j) + b.$$

There are some other kernel functions that can be applied to create non-linear feature map transformation [17].

$$\text{Polynomial kernel: } K(\boldsymbol{x}_i, \boldsymbol{x}_j) = (\boldsymbol{x}_i \cdot \boldsymbol{x}_j + 1)^d$$

$$\text{Gaussian radial basis function: } K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(\frac{-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{2\sigma^2}\right)$$

$$\text{Exponential radial basis function: } K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(\frac{-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|}{2\sigma^2}\right)$$

$$\text{Sigmoid or multi layer perceptron function: } K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \tanh(\kappa\boldsymbol{x}_i \cdot \boldsymbol{x}_j - \delta).$$

In this study, we use Gaussian radial basis function kernel to implement our SVM method in credit scoring artificial intelligence because the data is not linear and the problem is classifying into three classes bankrupt, survive and profit.

Chapter 6

Credit Scoring

6.1 Model

6.1.1 Simulation Model

There are three phases in the experiments, price discovery, credit scoring and taming the bubble.

1. Price Discovery
   Firstly, We develop and execute the stock market simulation and explore some trading behaviors. The stock market simulation program was developed by the simplifying system of Tokyo Stock Exchange. The simulation program market clearance works base on the double auction continuous method or so call, zaraba method in Japanese as explain on guide to TSE trading methodology [37]. Zaraba method works to find equilibrium price by matching market and limit order price base on time arrival and price order queue [16].

   Subsequently, we simulated some trading conditions that could develop price movement into bubble conditions. It was started by buying and holding strategy, then increasing liquidity by taking the loan and then creating market competition between smart investors and random investors. These experiments tried to find factors to simulate bullish condition. Furthermore, we replicated bubble-bursting condition. Price drops that made most of the player going bankrupt.

2. Credit Scoring
   In the next step, we will formulate a credit-scoring schema to describe how credit scoring is developed and after that, 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 $[-1, 1]$.

$$Y \quad = \quad (y_1, y_2, y_3) = f(v_1, \ldots, v_8), \qquad -1 \leq y_i \leq 1 \ (i = 1, 2, 3). \tag{6.1}$$

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

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

3. 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 7.

(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 8. Figure 6.1 provides an overview of the simulation model.

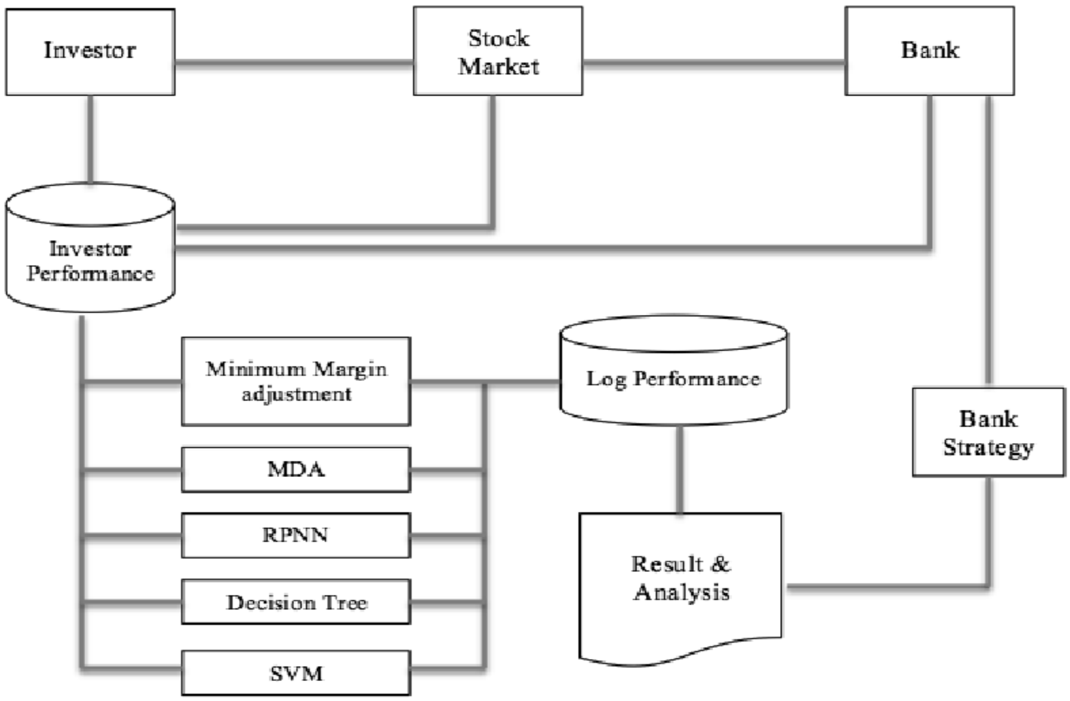


Figure 6.1: Overview the simulation model

4. 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 5 and 6; 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 7. 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 [36], 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 6.1 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 $f(v) = (y_1, y_2, y_3)$.

6.1.2 Player 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 [24] and Zhu [43]. 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:

$$f(x,\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{6.2}$$

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.

6.2 Price Discovery

In the first phase, we discovered some conditions that ignited increasing price or bullish condition. In microeconomic theory, The price is formed by supply and demand [27]. The price of the stock will be higher if demand is increasing and vice versa, decreasing when there is an excessive supply. Investor naturally trades a stock to get profit. They buy when the price is cheap and sell it when higher. However, because the price is fluctuating some investors are afraid to loose more. Thus, they release their stock. Price movements would follow Brownian motion.

$$dS_i = \tilde{\mu} S_i dt_i + \tilde{\sigma}_i S_i dx$$

where dx is standard Wiener process, S is the stock price, $\tilde{\mu}$ is the mean of price movement and $\tilde{\sigma}$ is standard deviation of the price movement [40]. We execute some various scenario simulations to explore some real world market behavior.

Experiment 1 (Increasing price)**.** In the first experiment, we want to prove that, by hold and buy strategy, the price change will increase. We need to explore this condition to create a bullish trend by random players. We constructed the simulation using 20 random players. The probability distribution for the order value, the random players follows the normal distribution with mean μ is zero and standard deviation σ equal to their working capital. Their initial working capital is 2 million JPY. 50% of their decision is to buy and hold. As 50% of sell decision is hold when

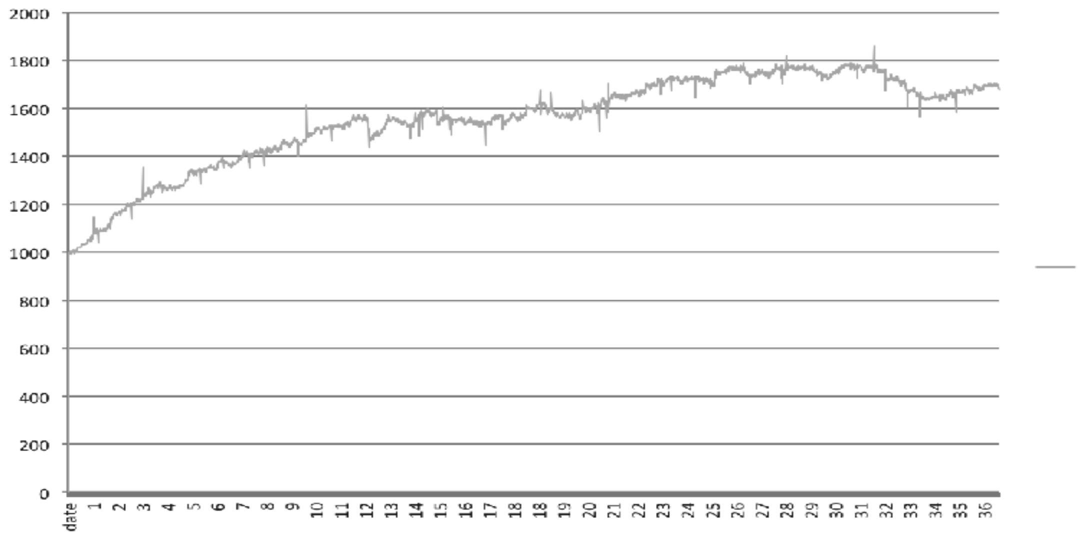


Figure 6.2: Half of trading decision is to buy and hold strategy

the price is lower than the previous price, the price movement has a tendency to an uptrend. Figure 6.2 shows that with 50% decision is to buy and hold the price is increasing.

Experiment 2 (Price move sideway)**.** In the second experiment, we want to construct price movement that move sideway. We need this condition to minimize influence from random players trading decision in price movement. By revealing factor that price move sideway, we can build a simulation to assess the impact of AI decision in price movement in creating bubble condition later. We can create this simulation by creating many random players with mean 0 and small variance decision. However, this action is inefficient as it will cost a lot. After several trial and error, we find that by using 25% of the decision is to buy and hold, Price movement will have a tendency to sideways. The players being populated was 20 random normal players with μ is zero and σ equal working capital and their initial working capital is 2 million JPY. We plot 10 data simulations to Figure 6.3 to explore this pattern.

Experiment 3 (The loan effect)**.** As our primary interest is margin trading, we want to discover what the impact of taking the loan in the price movement is. By knowing the consequence is, we can try to control or exploit it. We believe beside trading strategy, increasing the price also can occur from increasing liquidity. It can be from adding working capital or taking the loan to increase working capital. We executed ten simulations using 100 random investors that able to get the loan from a bank agent. Their initial wealth is 1000 stocks and 1000000 JPY cash. Their order value decisions are based on normal random with μ is zero and σ is equal to working capital. So, if the buy order value is exceeding their working capital, it means they take the loan to the bank. The maximum credit is equal to their working capital and their repayment due date is three days. Figure 6.4 demonstrates the escalating price by taking the loan. In the beginning,

Figure 6.3: A Quarter of trading decision is buy and hold strategy

price soaring rapidly, from tick time 0 to tick time 1200. One day consists of 300 tick times, so the simulation just run for four days. By using the equation (6.3), the drift $\tilde{\mu}$ is already 0.275 in 4 days.

$$S_i = S_0 e^{\tilde{\mu}T} \tag{6.3}$$

As players could take the loan to buy the stocks, their cash was more than their shares values. Increasing demand would raise the price. In Figure 6.4, the price increase three times from the initial price. After their average cash and average market value equal, the price tendency to move sideway after price touch 3500 JPY.

Experiment 4 (The competing price)**.** As the market is a mix, there are big and smart investors and there are also small zero intelligence investors. We want to discover their competition impact on price movement. We developed simulations using 10 AI players and 50 random players. AI players have 1000 stocks, 1000000 JPY cash and able to take the loan. On the other hand, casual players with each μ is zero and σ is equal to working capital, have 1000 stocks, 1000000 JPY cash and not able to take the loan. The result, the bullish trend also can be driven by the smart investor. Competition between the random player and the AI player force the price soaring into the new level. The smart investor with higher capital and knowledge lead the market and accumulate the wealth. Figure 6.5 presents the soaring price as the AI and the random player compete.

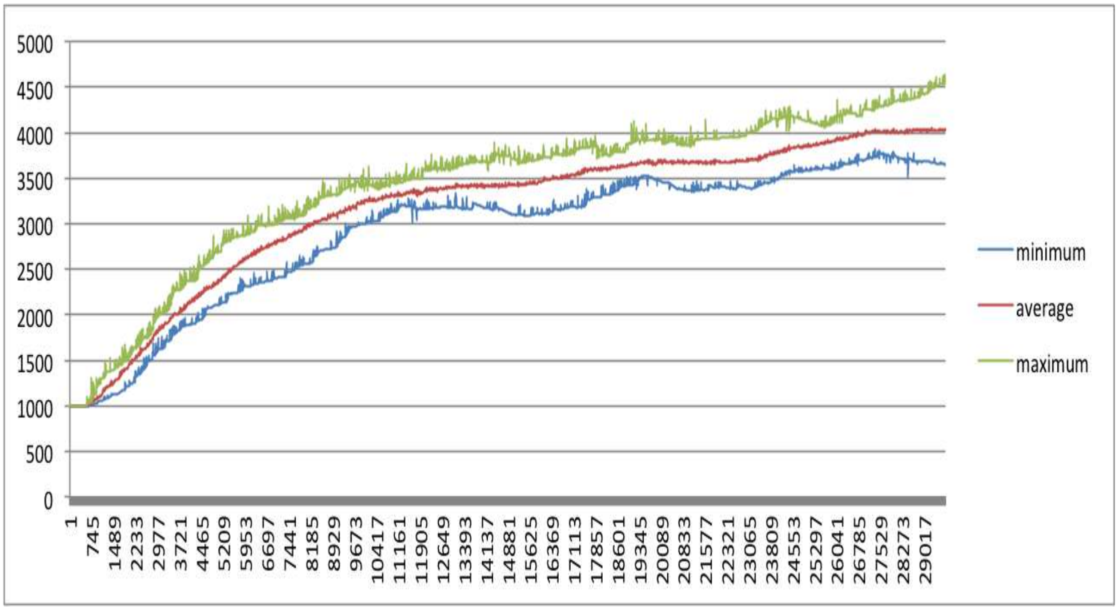


Figure 6.4: Price movement with loan enable

6.3 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. In the second phase, 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 [35]. We will use Table 6.1 to assess the performance of our credit score:

Table 6.1: Confusion Matrix [35]

		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)

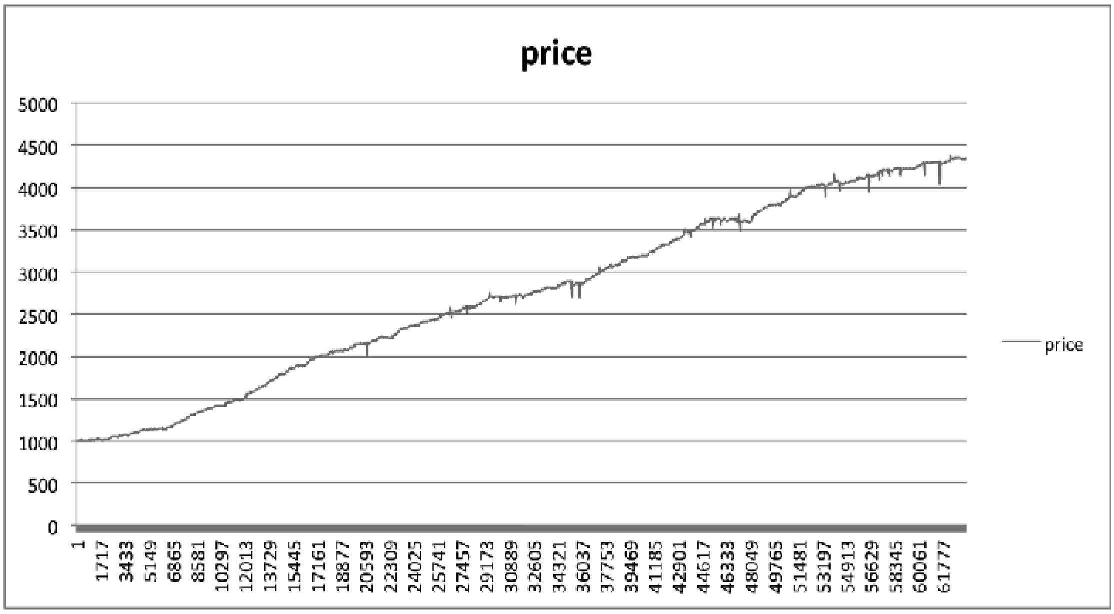


Figure 6.5: Price movement as competition AI and random player

We introduce basic terminology of confusion matrix as follows:

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 [29]; (true positive)/(true positive + false negative).

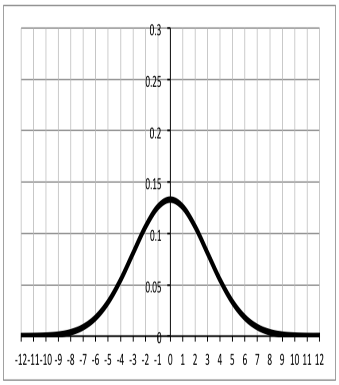
Specificity : probability of being correctly rejected, given that it is a poor financial investor [29]; (true negative)/(true negative + false positive).

Accuracy : probability of being correctly predicted [29]; (true positive + true negative)/population.

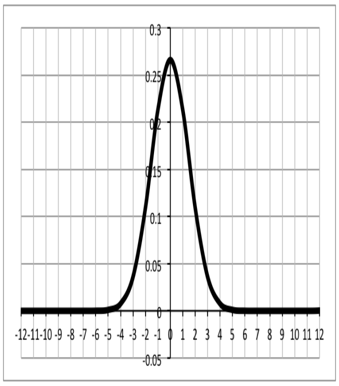
Precision : proportion of correctly approved to total approved [29]; (true positive)/(true positive + false positive).

F-Score : it combines positive predictive value with the rate of true positives [29]; 2 (precision $\times$ recall) / (precision + recall).

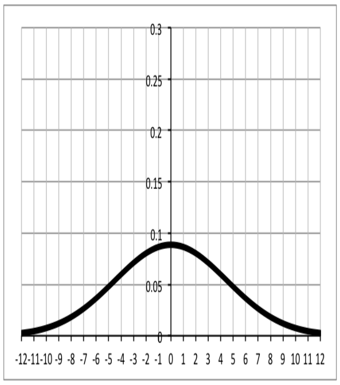
Experiment 5 (Credit scoring performance in various random normal settings)**.** After creating our credit-scoring methods, it is necessary to test their robustness in various market conditions. Six scenarios were considered. Each scenario consists of 100 simulations; each of these was populated by 100 bankrupt investors, 100 surviving investors and 100 profitable investors. Tenfold 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.



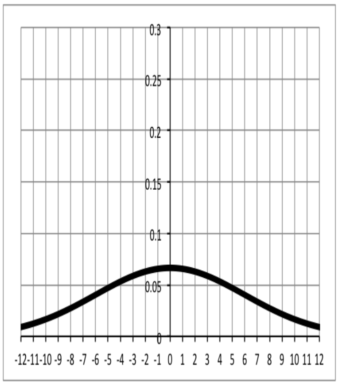
(a) $\mu = 0$, $\sigma = 3$ million JPY



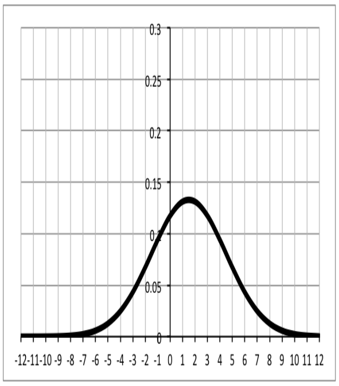
(b) $\mu = 0$, $\sigma = 1.5$ million JPY



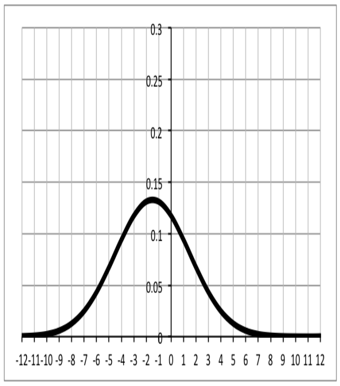
(c) $\mu = 0$, $\sigma = 4.5$ million JPY



(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 6.6: probability density function of order value from six different market behaviors

Figure 6.6 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 6.6a 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 6.6b 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 6.6c and 6.6d 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 6.6c and 6 million for Figure 6.6d. Figure 6.6e shows a player who tends to buy, while Figure 6.6f shows a player who tends to sell.

Tables 6.2 and 6.3 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%.

Experiment 6 (Credit scoring performance in 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 6.4. 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 6.5 and these are not significantly different from the results of the first 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.

Table 6.2: Average Prediction Result for Normal Distribution

	Actual / Predicted	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 6.3: 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

Table 6.4: Prediction Result from 300 Simulations of Uniform Probability Random Behavior

	Actual / Predicted	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 6.5: 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

Chapter 7

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 experiments 8 and 9.

Increasing the price increases wealth. However, there are some drawbacks, since some players will use loans to increase their portfolio, but at the same time, they are also increasing their risk. When big players are unable to repay their loans, the price collapses as their assets are sold by the bank at the market price in order to recover the loan. Figure 7.3a illustrates a bursting bubble. In this simulation, nine of ten AI players go bankrupt since they cannot a 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 7.4a, the total market value drops from 250 million JPY to 3 million JPY. This simulation is based on Nakatani's work [24], 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 7. In experiment 8, we analyze a simulation of margin trading that uses credit scoring and in experiment 9, 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.

Table 7.1: 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

Experiment 7 (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:

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

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 7.1 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.

For comparison, we developed a credit scoring and predicted investor condition. Table 7.2 shows the prediction accuracy of each of the four methods. Ten-fold cross-validation was used to measure the accuracy.

From Table 7.3, 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.

Table 7.2: 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	

When credit scoring is used, there are fewer misclassification of profiting investors; the fewest misclassifications occurred with C4.5 and the SVM, with misclassification 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 profitable 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 8.

Experiment 8 (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 7.1 shows the results of some simulations using various methods of credit scoring.

The results shown in Figure 7.1 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

Table 7.3: 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

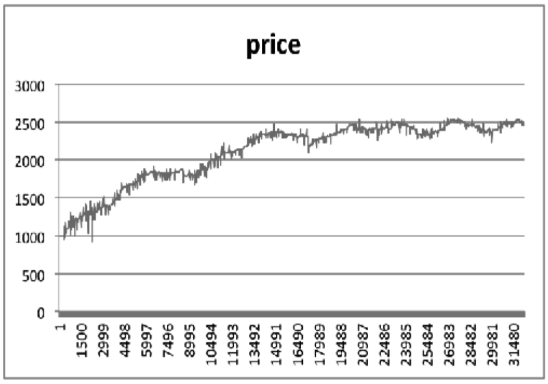
almost identical price movements.

Credit scoring also resulted in good credit absorption for the bank's main business, as shown in Figure 7.2. 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.

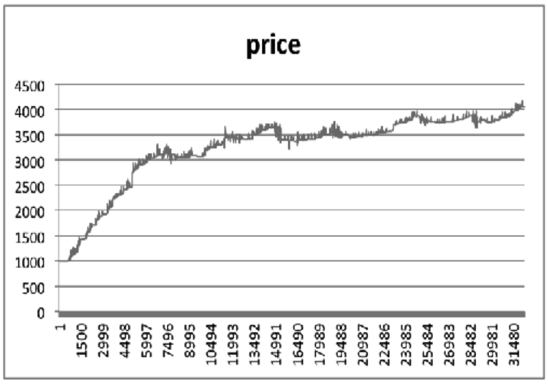
Experiment 9 (Bank's reserves)**.** We examined the impact on the price movement when the bank's reserves are controlled. In the previous experiment, we confirmed that loans will increase the stock price. By controlling the reserves, the bank can adjust the liquidity of the market. We wanted to find 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 7.3 illustrates some price movements for various bank reserve strategies and Figure 7.4 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.

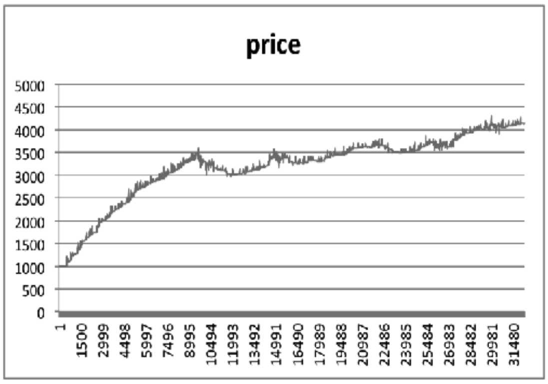
A smart bank can maintain the price movement. When the reserves are limited, the loans will be restricted. Thus, the prices will decrease slightly. After credit repayments refill the reserves, the bank can relax the loans and the prices will increase. This runs in a continuous cycle. When the bank has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



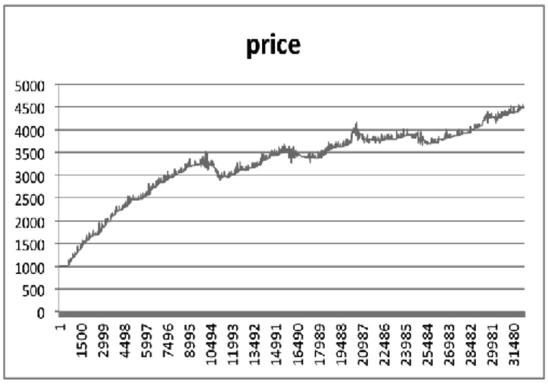
(a) MDA



(b) RPNN



(c) SVM



(d) C4.5 (Decision Tree)

Figure 7.1: Price Movement with Various Credit-Scoring Methods

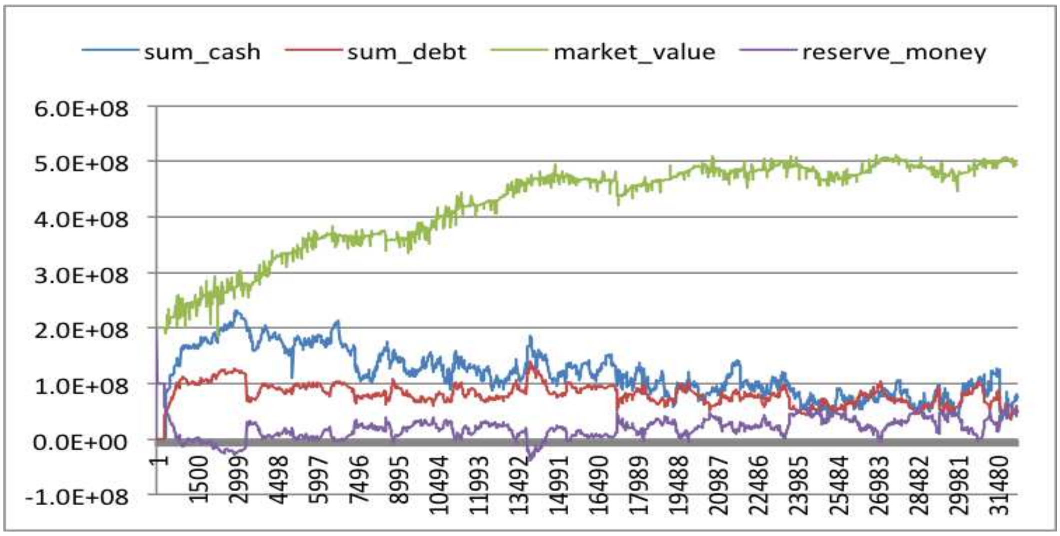


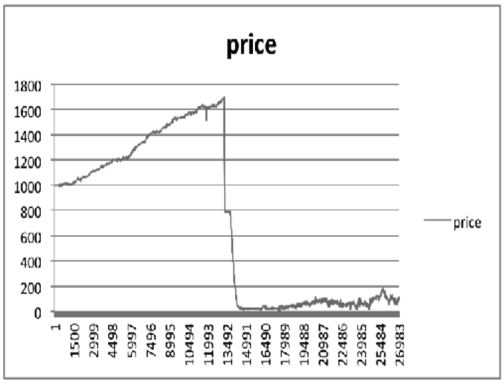
Figure 7.2: Credit absorbing using credit scoring

by assessing the credit scores of investors.

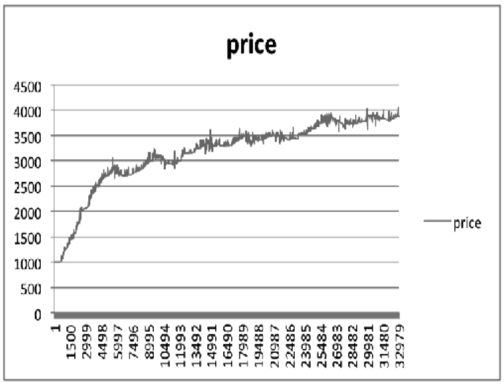
When the reserves are unlimited, it depends on the total value of the stock market. It is called the money creation. In this case, the smart bank can also predict the bubble phenomena and maintains market liquidity by assessing the credit scores of investors.

The non-smart bank with dynamic reserve money will generate money creation and on the way building it up the price is collapsed. When the reserves are unlimited, it depends on the total value of the stock market. It is called the money creation as bank print new money to increase the reserve and deliver the money when an investor sells their stock. The dynamic reserve will nurture the development of the price. However, the non-smart bank cannot predict investor status, so they risk to collapsing increase. The impact of the bubble bursting with dynamic reserve money is severer as money creation leads the price to a new level and incompetent non-smart bank explode the bubble.

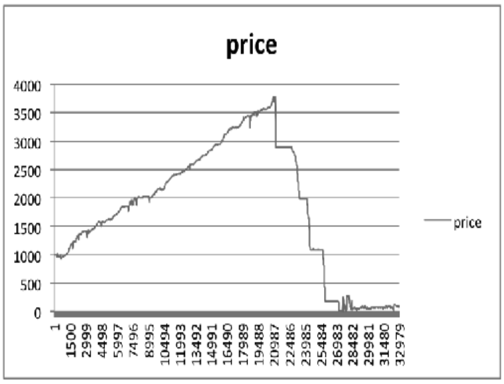
The smart bank can prevent the bursting price although the reserve is unlimited. Increasing price with smart bank grounded from good investor financial status. Ability to detect the bubble and predict investor status make smart bank able deliver the loan to profitable and good surviving investor on the right time. Loan will be restricted if investor status is bad or bubble detection is occurred. When condition is safe, bank can relax the loan so market liquidity increases and the price also increases again. Price will move to the new level if investor has good financial status to support it. Thus, smart bank can control money creation to nurture financial development.



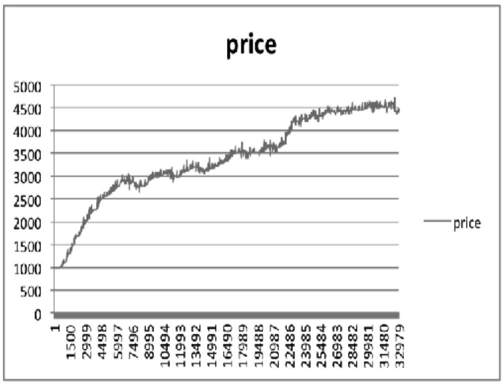
(a) Non-smart Bank with Static Reserves



(b) Smart Bank with Static Reserves

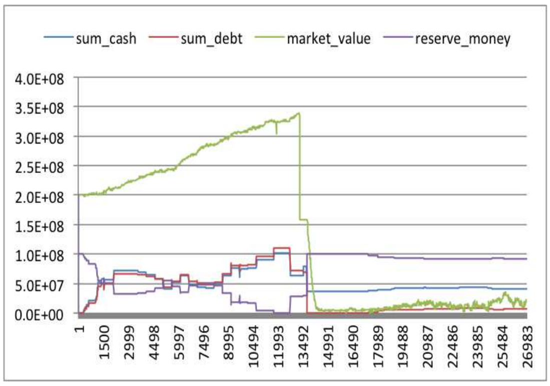


(c) Non-smart Bank with Dynamic Reserves

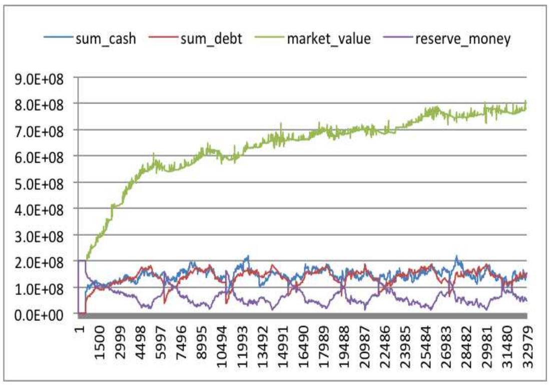


(d) Smart Bank with Dynamic Reserves

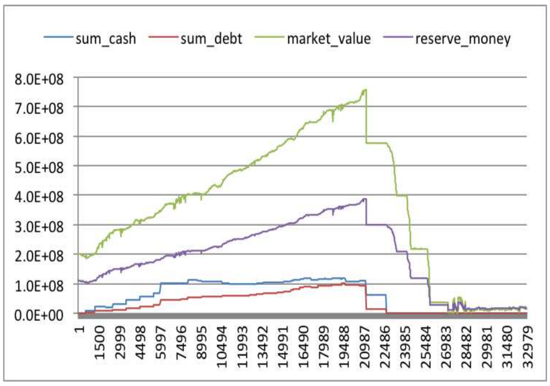
Figure 7.3: Comparison of Price Movement between Smart and Non-Smart Banks with Static and Dynamic Reserves



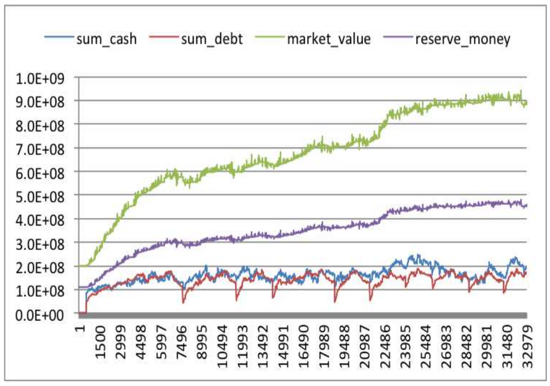
(a) Non-smart Bank with Static Reserves



(b) Smart Bank with Static Reserves



(c) Non-smart Bank with Dynamic Reserves



(d) Smart Bank with Dynamic Reserves

Figure 7.4: Comparison of Reserves between Smart and Non-Smart Banks with Static and Dynamic Reserves

Chapter 8

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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