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Using Intelligent Multi-Agents to Simulate Investor Behaviors in a Stock Market

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Abstract

Stock markets are comprised of complex systems which are characterized by a large yet dynamic investing population. In order to deal with this complexity, we propose an intelligent multi-agent system which models a set of investors trading with others within a virtual stock market. Each investor is represented by an intelligent agent who learns the investor's behavior pattern from historical investment data. A virtual stock market framework also permits intelligent agents to trade with others. This research presents a novel method to simulate the stock market. Experimental results indicate that the proposed model can simulate actual stock market and investor's behaviors well with intelligent agents and data mining methods.

Keywords and Phrases: Intelligent agent, Investor's behavior, Data mining.

1. Introduction

The information explosion of stocks has helped investors to make better trading decisions. However, this tremendous amount of information has also caused the phenomenon of information overload. In order to alleviate this problem, several working projects have been developed to predict the tendencies of stocks. There are three approaches identified as quantitative technical data analysis [4][6], artificial intelligent technology [5][11], and investor behavior analysis [3][9][10].

Quantitative technical data includes macroeconomic variables and technical analysis variables. Artificial intelligence technology has been applied to predict the tendencies of stocks. Environmental analysis and historical transaction data have been applied to predict investor's behaviors and decisions.

Investor supply and demand determine stock price, including the TWSP (Taiwan weighted stock price index). The investor is an entity of the stock market, and an investor's investment decision can be simulated in a virtual stock market, which can be used to predict the trend of the stock price.

In this study, an intelligent multi-agent is applied to simulate and learn the investor's behaviors according to the investor's historical data. Then, agents will develop rules for the investor's behaviors and these rules help agents to make decisions. A virtual stock market is then constructed, in which multi-agent can commit their transactions. If the process of investor's decision-makings can be learned with high probability, the weighted stock prices can be predicted.

Information regarding the stocks affects stock prices and significantly influences investor behaviors. Investors in the stock market behave in various manners, depending on their individual preferences, expectations, decision environment, strategy, and individual characteristics [7].

Because stock prices are determined by supply and demand and it is also formed by the mutual behavior of investors. News affects the investors first, and then the investors' behavior affects the stock price. An investor may try to anticipate the trend of all investors' trading in the stock market and follow the tendency to invest. This tendency is the foundation of stock price [7].

The news and information that affect the stock market actually affect individual investor or institutional investors. In this research, the investors' decision-makings are simulated according to how investors are influenced by financial news.

The factors affecting investors can be classified as follows.

(i) Economics: economic factors include the exchange rate, interest rate, inflation, money supply, international economics, and internal economics. The fluctuation of exchange rate has obvious influence [1]. For example, in 1997, the Thailand's currency dropped by 80% in one day, starting the Asian financial crisis. Stock prices fell drastically and the foreign investments flew out. Those factors triggered the start of the financial crisis [15]. In reaction, the government diminished the interest rate to increase the money supply, and investors were encouraged to invest their money in the stock market. Thus, both international and the internal economics influence investor behaviors.

(ii) Politics: political factors include war, Cross-Strait relationships and the political situations. In October of 1998, the TAIEX plummeted, with the weighted index dropping by almost one half from its high of 10,200 points to an all-time low of 5,421 points. This could have been caused by missile threats by mainland Chinese authorities, a ripple effect of the Asian financial crisis, or a long-time effect of over-speculated stock valuations [7]. Thus, some emergency political situations will also influence the stock market [12].

(iii) Corporate risks: those include technical analysis, economic conditions, financial structure, cash flow, debt paying ability, buying on margin, short sales, and others.

(iv) Others: those include earthquake and other unexpected factors. An earthquake influences stock prices because it will cause much damage to the electronics industry.

Investor behaviors may change due to the related messages, technical analysis, fundamental analysis, etc. Investors might actually not make decisions from the information they collected, but they would follow the herd. Herding means that a group of investors together trade in the same way in the some period.

Feedback trade is a relation between the herding and lag return, and there are two type of feedback trading.

(i) Positive feedback trade strategy: the decision threshold is the average performance in the pass. If a stock's performance is higher than the threshold, its purchase can be highly recommended; whereas if its performance is lower than the threshold, it should be sold.

(ii) Negative feedback trade strategy: this is a negative strategy to the positive feedback trade strategy. The stock is recommended to purchase if the performance of the stock is lower than the threshold performance, otherwise it is recommended to be sold.

The investors follow the same messages to form the herding. The individual investor sells a stock on which he earned small profits, but a loser will hold a stock for a long time [8].

In this study, an intelligent multi-agent is applied to simulate investor behaviors. The individual investor may be influenced by news, individual preferences and wealth structure. The intelligent agents receive news about stock transaction records, including stock market rumors, speculation the operating situations of companies, and other information.

Due to individual preferences, the intelligent agents make individual decisions. There is also different influence on stock market because of individual wealth structure, so that each intelligent agent may make different investment decisions.

2. Literature Review

This chapter reviews works related to this study, including LLS model, virtual stock market technology, artificial neural network and document classification.

2.1 The Levy, Levy and Solomon model (LLS model)

LLS model can be applied for wide perspective and extensions to achieve a precise and detailed dialogue with actual stock market data.

The microscopic elements in LLS represent the individual investors. Those elements trade the stocks and the bonds as their interactions [13]. If the stocks are assumed to be risky assets, the bonds are assumed to be a safe asset. In the original LLS, the investors are allowed to revise their portfolios synchronously at given time slots. The LLS model has already been studied and shown to be adequate [13].

2.2 Virtual stock market technology review

An architecture “SCHOOL” has been proposed to simulate stock markets [14]. In “SCHOOL”, the genotype is designed to map the phenotype. This is an agent-based model, that is considered as an evolving population by single population.

An agent represents a trader (who can be also an investor). Traders learn investment strategies in "SCHOOL" and apply these strategies in a virtual stock market. In the model, each individual investor is simulated as an agent. In this study, a virtual stock market is built as "SCHOOL" in which an agent can make investment decisions.

2.3 Artificial neural network and document classification

ANN and document classification techniques are always combined to deal with news [2], and news is classified into several fixed categories by a key table. The price index of Taiwan Weighted Stock Price Index (TWSPI) is computed on a daily basis. The Chinese historical news has been transformed into quantitative data and used as an input of ANN. Finally, the degree of news influence has been computed by ANN. The main process is shown in Figure 1, and the news classification mechanism of hierarchical clustering is shown in Figure 2.

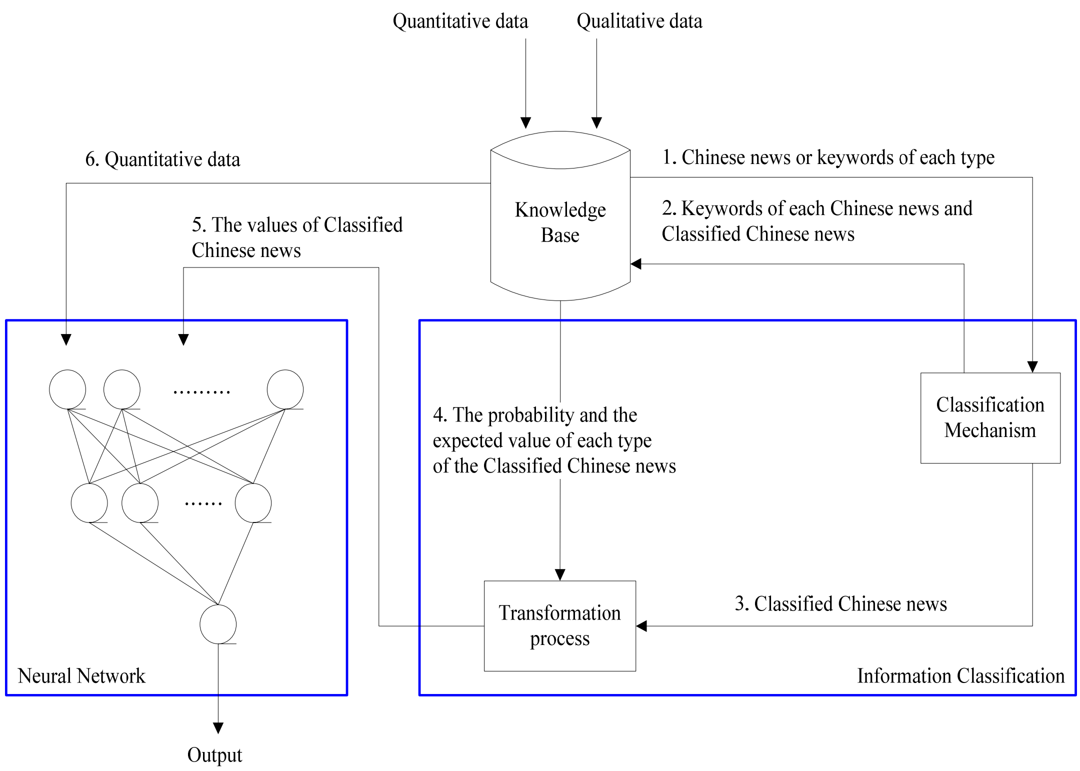

Figure 1. Main process of ANN and document classification method

First, the classification mechanism saves and outputs some keywords. Secondly, clustering methods are applied to deal with each category. This method would group the similar Chinese history news into the same type for each category. In this framework, hierarchical clustering is applied to group similar news into the same type. Then, raising or falling rate of each historical news is applied to compute an average raising rate and occurrence frequency. Finally, ANN-document classification is applied to deal with news and try to find the news that influences investors.

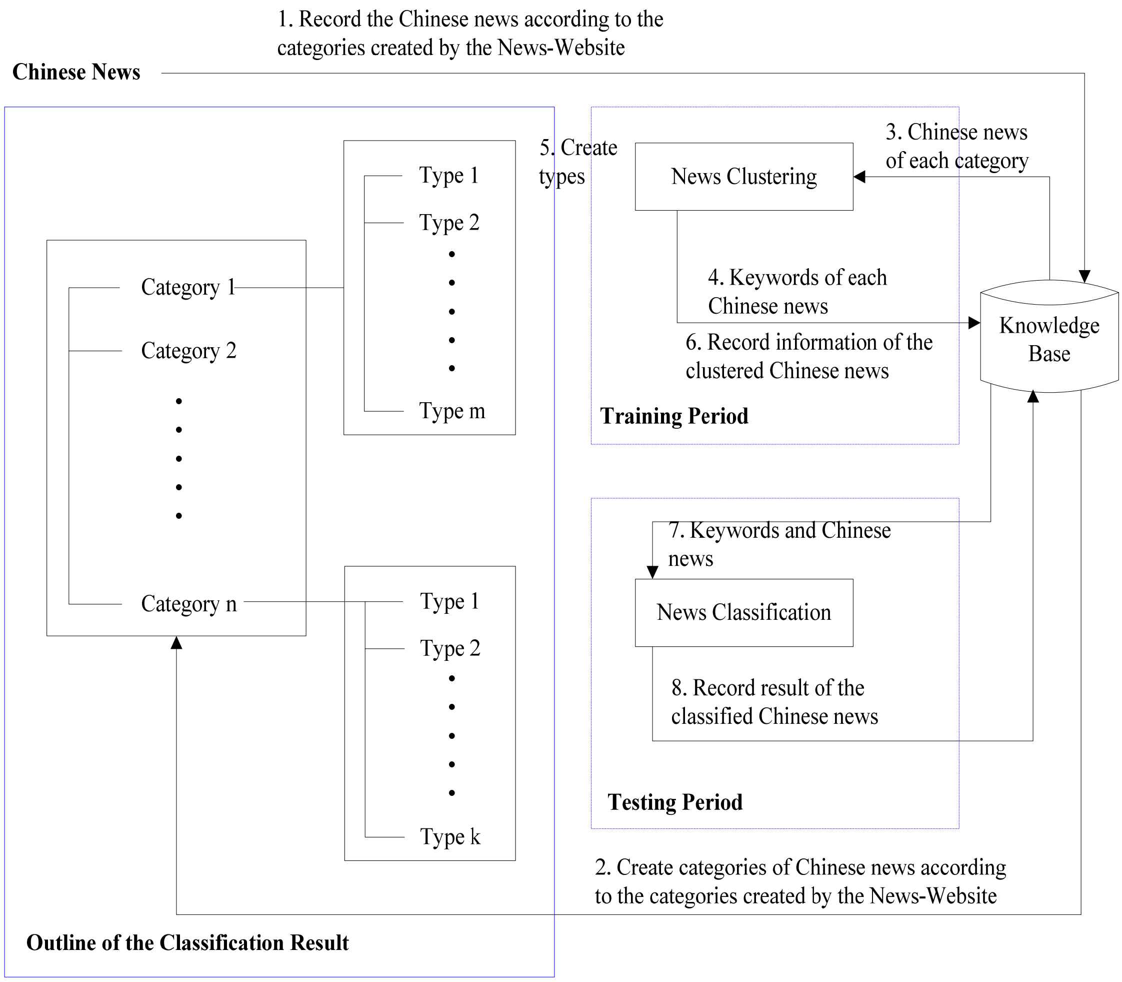

Figure 2. News classification mechanism

3. Methodology

This chapter includes two parts, architecture of the proposed model and framework of the agent's decision discussed as follows:

3.1 Architecture of the proposed model

In this study, agents are used to simulate real investor behaviors and each agent represents an individual investor. Agents have to trade stocks in the virtual stock market, and stock prices in the virtual market are decided by those transactions. The weighted stock price index is composed of stock prices in the virtual stock market, as shown in Figure 3.

The simulated agents would learn from individual investor's historical data. The simulated architecture includes two parts, agent learning cycle and learning framework for the agent.

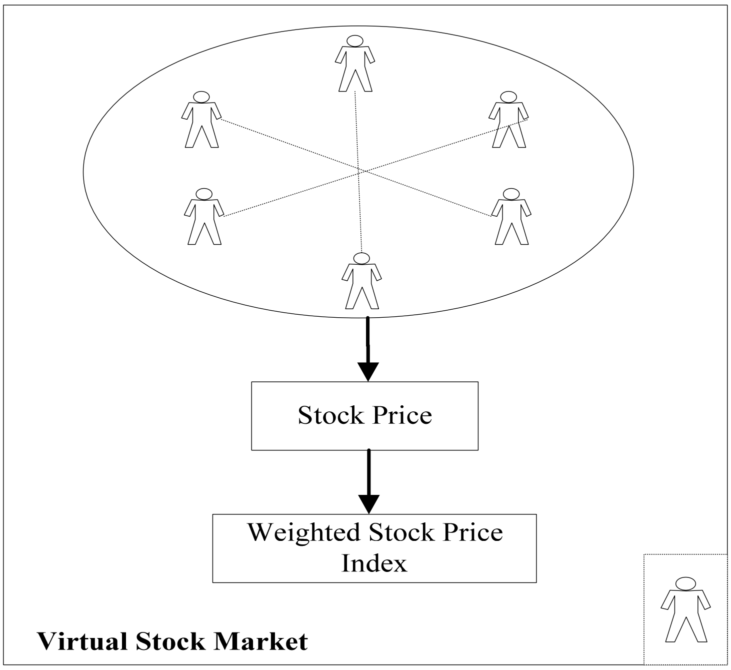

Figure 3. Agent's investments in virtual stock market

3.1.1 Agent learning cycle

An agent's learning model consists of following elements.

(i) Historical data: the investor's investment transactions will be saved as historical data every day, consisting of stock name, stock shares, times, and other investor investment information from the past. Historical data also concludes the difference between agent's decisions and real investor's decisions. Then the difference will be used to modify the agent's learning model.

(ii) Analytic information: historical data is applied to analyze investor's behaviors. The analytic information includes the frequency of an investor's trade, individual investor preference, day interval and rules regarding investor behaviors.

(iii) Investment portfolio: this is an investment list of stocks in which an agent may want to invest. Many events influence investor's behaviors. Therefore, analytic information and events are applied to find out agent's portfolio.

(iv) Decisions: an agent makes decisions by its portfolio obtained from the step three in virtual stock market.

(v) Events: events are the news or qualitative data that occur every day, and news may affect the investor behaviors. ANN-Document Classification is applied to deal with the events.

The agent's learning cycle is shown as in Figure 4.

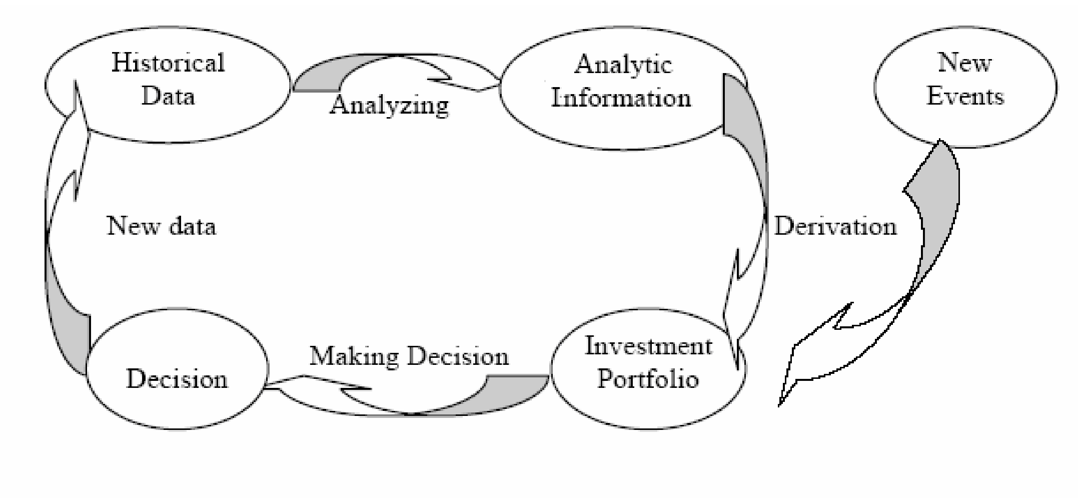

Figure 4. Intelligent agent's decision learning cycle

Finally, there may be differences between the agent's decisions and real investor's decisions. This difference and the real investor's decisions become the new data for next learning cycle. Then, the agent will learn the historical data and the new data in the next learning cycle.

3.1.2 Agent learning framework

A framework is constructed in which investor's behaviors are simulated. The framework is as shown in Figure 5.

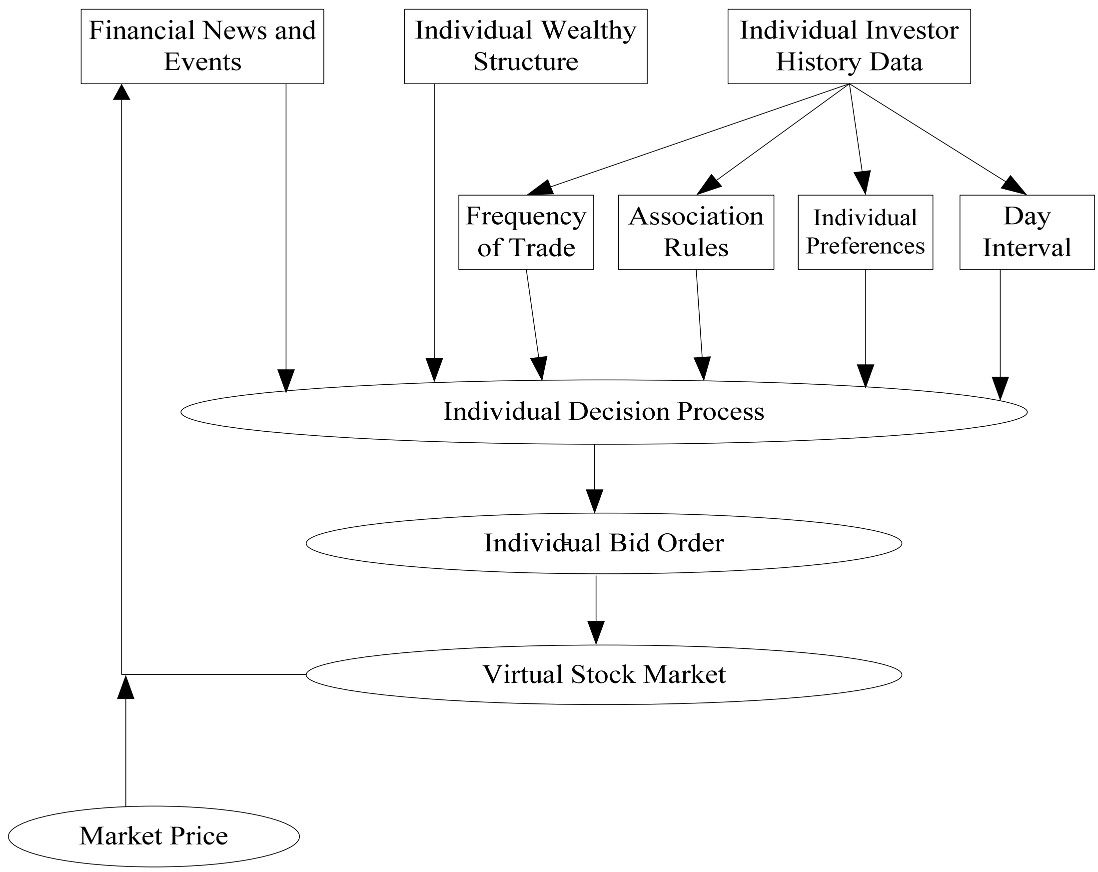

Figure 5. The framework of investment simulation

(i) *Individual wealth structure*：individual wealth structure means how much money an investor can invest in the stock market. An individual investor has his own individual wealth structure. The wealthy distributions of bonds, common fund, stocks and so on are recorded in individual wealth structure. The more ability to buy stocks that an agent has, the more influence on the stock market it has. An agent's wealth structure would change dynamically while an agent gains or loses from investments. It will leave from the virtual stock market if it loses all its money. An agent also can enter the market again if it has money afterwards. The wealth structure decides whether or not an agent is active in the virtual stock market.

(ii) *Individual investor historical data*: in this component, an investor's investment data is stored every day. The data includes stock transaction details and information of the investor's stocks margin sales.

(iii) *Individual decision process*: in an individual decision process, the data, including frequency of transaction, individual preference, association rules, and day interval, are applied to produce an individual bid order by an agent.

(iv) *Individual bid order*: an individual bid order is a trading list that an agent plans to trade next week. The intelligent agent will make decisions by its bid orders in the virtual stock market.

(v) *Virtual stock market*: a virtual stock market is constructed to simulate the real stock market in Taiwan. The virtual stock market includes the following three parts.

  (a) Taiwan Weighted Stock Price Index (TWSPI): the virtual stock can decide the TWSPI according to stock prices. The TWSPI can be predicted by using agent's supply and demand.

  (b) Model of price determination: the mechanism is to decide the stock price at which the agent trades, which is similar to the real Taiwan stock market. The agent can buy stocks by cash, margin sales, and short sales. In the virtual stock market, the stock price can be decided according to the agent's investment decisions on buying or selling the stock.

  (c) An intelligent agent: an intelligent agent represents an investor, and an agent can trade according to its bid order in the virtual stock market.

3.2 Framework of agent's decision

In this section, the technologies used in the framework and how to construct agent's decision framework are be introduced step by step. The framework is shown in Figure 6, including the following three elements:

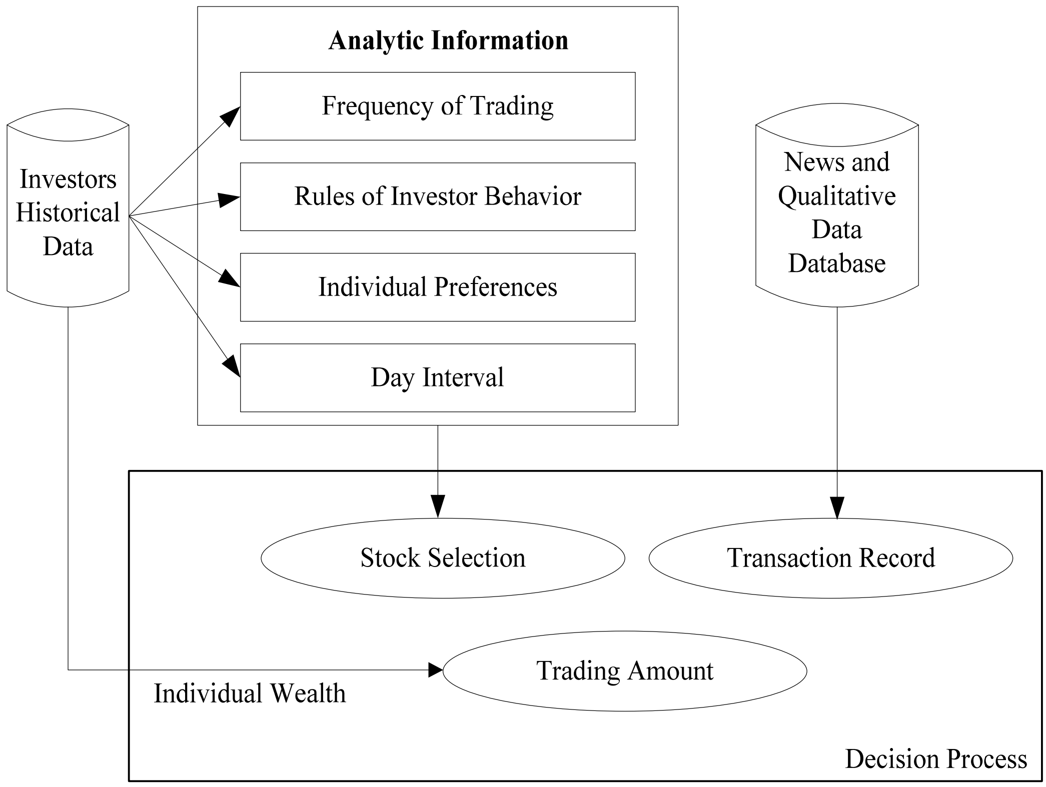

Figure 6. Agent's decision framework

(i) Transaction record: events to collect include news or qualitative data saved in the database and used to decide whether or not investors trade stocks. An ANN-document classification method is applied to deal with the data in database.

(ii) Trading amount: how much money an individual investor invests in the stock market.

(iii) Stock selection: analytic information applied to select stocks for an individual investor to invest in the stock market. Analytic information can be found in the investor's historical data, and it includes rules of the investor's behavior, individual preferences, and frequency of trades. N-dimensional inter-transaction（*OP-Apirior*）and Apirior algorithm are applied to mine association rules. The frequency of trades is used as a scale for the sliding windows' dimensions. The day interval is the duration of two successive transactions for the same stock made by an investor.

3.2.1 Transaction record

Investors trade stocks by considering several factors, including news, data analysis, economic variables, EPS, etc. In this study, ANN-document classification is used to deal with factors that may influence investor's decisions. The process is as follows.

(i) Collecting inputs: ANN input includes the following elements.
   (a) Qualitative data: daily news reported in Taiwan, regarding internal politics, political situations, internal economic situations, international political situations, international economic situations, company situations, cross-Strait relationships, the general investment environment, and so on.
   (b) Macroeconomic variables: economic indicators including daily changes in exchange rate, daily changes in interest rate, monthly changes in unemployment rate, annual changes in economic growth rate, annual changes in consumer price index, annual changes in Gross Domestic Product (GDP), monthly changes in inflation rate, and monthly changes in money supply rate. Those data can be collected from several major countries, including America, Japan, Hong Kong, Singapore, Korea, England, France, and Germany.
   (c) Technological analysis variables: the Taiwan Weighted Stock Price Index (TWSPI) and several technological indicators, including Twenty-Four Days Moving Average (MV), Relative Strength Index (RSI), Bias, Moving Average Convergence/Divergence (MACD), Volume Moving Average, and Twenty-Four Days On Balance Volume (OBV).

   All of elements mentioned above should be saved in the news and qualitative data database shown in Figure 6.

(ii) Producing outputs: in the process of training the ANN-document classification model, the output of 1 means buying stocks and -1 means selling stocks.

(iii) Making predictions: the output is applied to predict possible stock transactions.

3.2.2 Trading amount

The formula for computing the trading amount is as below:

$$\text{Trading Amount} = \sum_{i=1}^{n} share_i * P_i \tag{1}$$

where:

Share_i : the share amount of a stock_i that an investor trades.

P_i : unit price of stock_i .

3.2.3 Stock selection

Analytic information applied to select stocks includes rules of an investor behavior, individual preferences, and day interval, as shown in Figure 7.

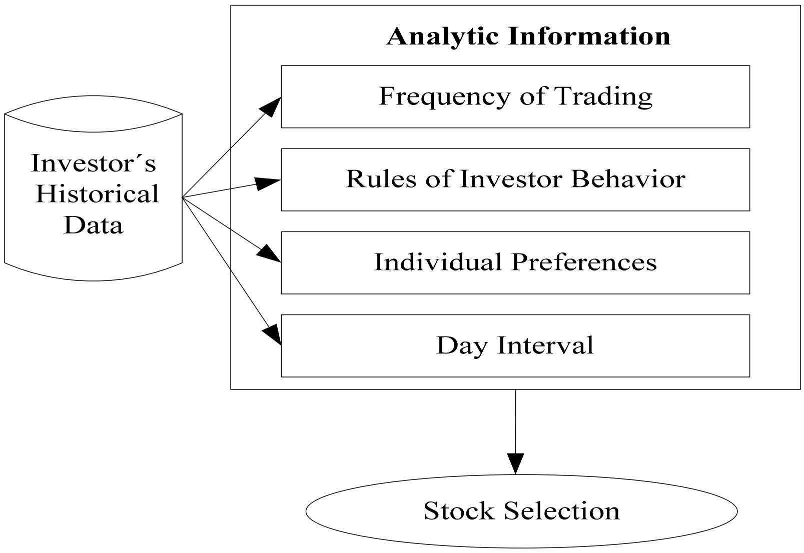

Figure 7. Data analysis from historical data

(i) Frequency of trading : from historical data, daily, weekly and monthly trading frequency can be computed. The formula is as below:

$$\text{Frequency of trade} = \sum_{n=2}^{N}(T_n - T_{n-1})/N-1 \qquad (2)$$

where:

T_n : Trading date that an investor invests the nth time.

$T_n - T_{n-1}$: the day interval between two consecutive transactions.

N : the total times of transactions.

(ii) Mining rules of investor's behaviors：OP-Apriori and Apriori algorithm are used to find rules of an investor's behavior using individual historical data. The steps to mine association rules are as fallows:

（a）Transforming to Star Schema: The individual historical data is transformed into star schema. As example, the original data is shown in Table 1, and the corresponding star schema is shown in Table 2.

Table 1. Original historical data in database

Investor	Stock-Number	Buy-or-Sell	Price-Difference	Date
A	2806	sell	2	4/22
A	2409	sell	3	4/23
A	2409	buy	-2	4/24
A	2325	buy	-3	4/25
A	2806	buy	-1	4/26

Table 2. Star schema of historical data

Investor	Stock Number	Event	Buy or sell	Dimension one	Price Difference	Dimension Two	Date	Dimension Three
A	2806	a	Sell	2	2	4	4/22	1
A	2409	b	Sell	2	3	5	4/23	2
A	2409	b	Buy	1	-2	2	4/24	3
A	2325	c	Buy	1	-3	1	4/25	4
A	2806	a	Buy	1	-1	3	4/26	5

Dimension one: the field of buy_or_sell and its value can be either sell or buy. Then "buy" will be transformed to "1" and "sell" to "2".

Dimension two: the field of price_difference and its value can be -3, -2, –1, 2, or 3. Then we transform "-3" to "1", "-2" to "2", "-1" to "3", "2" to "4" and "3" to "5 ".

Dimension three: the field of date and its values are 4/22, 4/23, 4/24, 4/25, or 4/26. The scale of dimension three is 1 by applying Eq. (3), where "4/22" mapping to "1", "4/23" to "2", "4/24" to "3", "4/25" to "4" and "4/26" to "5".

$$\text{Frequency of trade} = \frac{(4/23 - 4/22) + (4/24 - 4/23) + (4/25 - 4/24) + (4/26 - 4/25)}{(5-1)} = 1 \quad (3)$$

(b) Scanning the database: OP-Apriori is applied to scan the investor's star schema. First, it scans each point in the N-dimensional database with sliding windows to find the base address. Secondly, it will infer the relative address according to the base address and it will move the sliding window to scan the n-dimension database. By using the data in Table 2, we can draw a 2-dimensional sliding window, as shown in Figure 8.

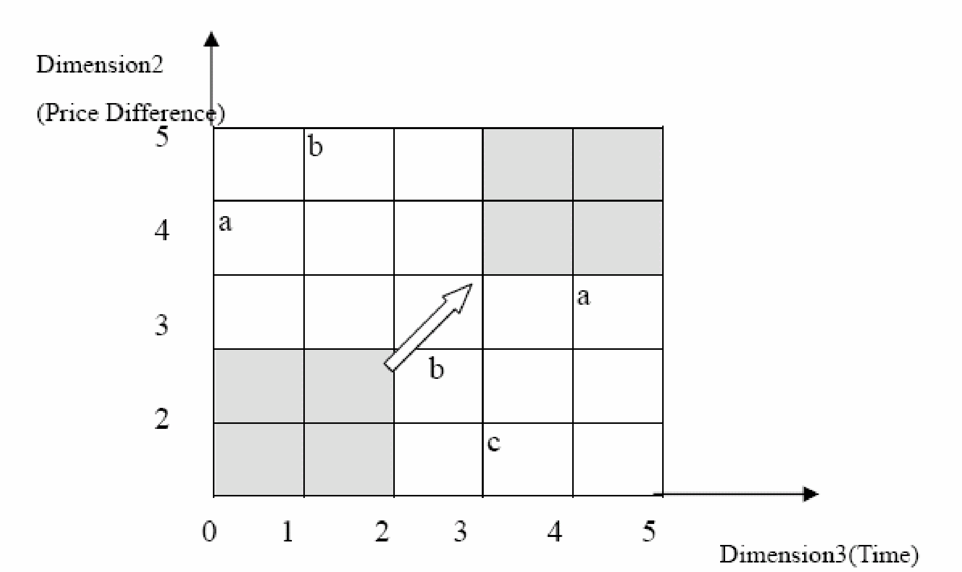

Figure 8. An example of a sliding window

(c) *Comparing the support values*: the support value is calculated and the threshold of support value is determined. If the support value of the item sets is over the threshold, association rules involving the itemset will be formed.

(d) *Saving the association rules*: the formed association rules are recorded in database. An agent can use those rules to select stocks.

(iii) Individual preferences：the investor may be familiar with certain kinds of industries, such as the electronics industry, and so prefer to invest in stocks of these familiar industries.

(iv) Day interval and density rate：the day interval is the difference between two consecutive stock transactions, and the density rate is the frequency that an investor invests in the same stock in a week. An example of investor data is shown in Table 3.

Table 3. An example of investor data

Auto_Number	Investor's Name	Stock Name	Date
1	Investor A	Stock A	2001/3/18
2	Investor A	Stock A	2001/3/19
3	Investor A	Stock A	2001/3/26
4	Investor A	Stock A	2001/3/28

The day intervals in the example are 0, 1, 7, and 2. The rule used to compute density is shown in Figure 9.

***Day Interval*= *Date*$_n$ - *Date*$_{n-1}$**
If *(Day_Interval > 0) and (Day_Interval < 7)*
   Count*=*Count* + *1
endif

Density Rate*= *Count /Sum of Trading Times

Figure 9. Day interval and density rate

In the example, two day intervals are between 0 and 7, while the density rate is fifty percent.

(v) Stock selection：the steps to select stocks are as follows:

Step 1 Searching the association rule database. In this step, the algorithm used to search the association rule is as shown in Figure 10.

IF support value > threshold, **then**
association rules will be selected
IF the number of appropriate stocks>2, **then**
compare the stock of association rules, and find the popular stock then output the stock name
else output the stock name
else
Search the preference database and day interval database.

Figure 10. Rule selection algorithm

Step 2 Searching preference database and day interval database. An investor's preference is found from historical data, and the stocks transacted often are recorded as the buying preference data. The final n trading data are applied to find the day interval of those stocks. Agents will use the preference and the day interval as analytic information to select stocks in the virtual stock market.

4. Experiments

In this chapter, we introduce data preparation, experimental design, and experimental results.

4.1 Data preparation

For this experiments, 28 participants were chosen carefully. They were all highly educated, working in Hsinchu Science-Base Industrial Park, familiar with the electronics industry and all of them have investment experience in the Taiwan stock market. Participants were trained to invest stock through our simulation mechanism. The investment target was limited to the electronics industry due to the background knowledge of the participants. Historical trade data were recorded from 2002/3/1 to 2002/4/30. Validation data were recorded from 2002/5/1 to 2002/5/31.

4.2 Design

The design of the experiment was as follows :
Module one：the investor's preference is applied to predict which stocks the investor will trade next week for each agent.

Module two：the individual preference stocks and the day interval are combined to predict which stocks the investor will trade next week for each agent.
Module three：the individual preference stocks, the day interval, and association rules are applied to predict which stocks the investor will trade next week for each agent.

The formula for prediction rate is as follows:

$$\text{Prediction rate} = \frac{\text{Actual stocks that investor in a week}}{\text{The stocks an agent selects to trade in a week}} \tag{4}$$

4.3 Results

Table 4 summarizes the experiment results. Before module two was applied, the average prediction rate of module one was 36.7%, and the prediction rate increased to 43.6% after module two was applied. Then, the prediction rate increased to 46.9% after module three was applied. This observation implies that applying each feature can help the proposed model to increase the prediction accuracy.

There were 305 electronics companies listed in the Taiwan stock market during the experiment period. In the historical trade data, participants, in average, trade 5 companies per week and 12 companies in the entire experiment period. As the base line of the experiment when randomly selecting 5 companies from these 305 companies, the original possibility is extremely low, less then 0.001%. However, our proposed model can highly improve the prediction rate from the base line. The lowest prediction rate of our model is 36.7%. The highest prediction rate of proposed model is 46.9%. The average prediction rate of proposed model is 42.4%. The comparison is as shown in Table 5.

Table 4. Prediction rate of the experiment

Prediction Rate / Investors	Model one	Model two	Model three
01	20.0%	25.0%	35.0%
02	60.0%	80.0%	80.0%
03	35.0%	47.5%	47.5%
04	60.0%	60.0%	80.0%
05	20.0%	20.0%	40.0%
06	22.5%	22.5%	50.0%
07	50.0%	50.0%	50.0%
08	45.0%	70.0%	70.0%
09	25.0%	25.0%	25.0%
10	42.5%	70.0%	70.0%
11	20.0%	20.0%	22.5%
12	31.4%	38.5%	38.5%
13	45.0%	45.0%	45.0%
14	20.0%	20.0%	20.0%
15	35.0%	35.0%	35.0%
16	20.0%	20.0%	20.0%
17	60.0%	60.0%	60.0%
18	12.5%	12.5%	25.0%
19	65.0%	65.0%	65.0%
20	33.0%	33.0%	33.0%
21	10.0%	32.5%	32.5%
22	65.0%	65.0%	65.0%
23	40.0%	60.0%	60.0%
24	60.0%	60.0%	60.0%
25	25.0%	50.0%	50.0%
26	34.3%	48.6%	48.6%
27	12.5%	25.0%	25.0%
28	60.0%	60.0%	60.0%
Average rate	36.7%	43.6%	46.9%

Table 5. Comparison of the experiments

	Prediction rate
Base line (Random selection)	<0.0001%
Model one	36.7%
Model two	43.6%
Model three	46.9%

5. Conclusions

In this study, a multi-agent is applied to simulate an investor behavior according to historical investment data. An agent can find the analytic information including association rules and preferred stocks of an investor, and then predict the stock that the agent would trade next week.

The experimental results indicate that our simulation model can effectively represent the real stock market. The average prediction rate for which stock an investor would trade next week is greatly improved.

This work can be continued in the future to examine several aspects:

(i) Collecting data from Three Major Institutional Investors (TMII): in Taiwan stock market, TMII has huge capital and has strong influence. To improve accuracy of the prediction model, historical investment data from TMII is necessary.

(ii) Collecting long term data: to achieve higher accuracy in predicting an investor behavior and making the simulation results more reliable, long term data is definitely necessary.

(iii) Classifying the investors according to their intentions: investors can be classified in several types, each with its own characteristics. The classification techniques can classify investors' intentions. For example, to avoid risk, some investors will choose specific financial products, including bonds, mutual funds and treasury bills, etc. Base on these intentions, we can classify an investors to increase the accuracy of the proposed model.

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