

Socially Embedded Multi Agent Based Simulation of Financial Market

Kiyoshi Izumi
DHRC, AIST
2-41-6 Aomi, Koto-ku
Tokyo 135-0064, JAPAN
kiyoshi@ni.aist.go.jp

Hiroki Matsui
ITRI, AIST
Central 2, 1-1-1 Umezono,
Ibaraki 305-8568, JAPAN
hiroki.matsui@aist.go.jp

Yutaka Matsuo
ITRI, AIST
1-18-13 Sotokanda,
Chiyoda-ku,
Tokyo 101-0021, JAPAN
y.matsuo@aist.go.jp

ABSTRACT

This paper proposed a new approach that integrated an artificial market simulation and text-mining with real information. In this approach, economic trends were extracted from text data circulating in the real world. Then, the trends were inputted into the market simulation. The simulation could support users' action to the actual market. This approach was used for the decision of exchange rate policy and suggested that the operation by intervention was effective for the stabilization of the yen-dollar rate in 1995. Our simulation revealed that the action rule proposed by our system could reduce over 70% of rate fluctuation. This approach can offer a useful social simulation as a tool to users.

Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence—*Muliagent systems*; H.4.2 [Information Systems Applications]: Types of Systems—*Decision support*

Keywords

Artificial market, multi-agent simulation, text-mining, decision support system

1. INTRODUCTION

In recent years, artificial market studies have obtained some success in market analysis. Many of them were however too simple and abstract to be a useful model of actual markets. One major purpose of multi-agent simulation of social phenomena is to build models of actual social phenomena on computers, and to use them for supporting actual action. For that purpose, a model must reflect the real world so that its simulation results are reliable. This paper proposes a new approach SEMAS (Socially Embedded Multi Agent based Simulation). This approach integrates an artificial market simulation and text mining, and takes

real information into the simulation. The SEMAS approach consists of the two stages. First, economic trends are extracted from text data using text-mining technique. Next, the extracted trend is inputted into a multi-agent model of a foreign exchange market, and its computer simulation is carried out. Based on the simulation results, our proposed system can support a user in determining his/her behavior in the market.

2. EXTRACTION OF THE INFORMATION FROM THE REAL WORLD

For the economic trend analysis, we used market reports which JCIF (Japan Center for International Finance) distributed every week to its members such as professional dealers. Each document was first divided into the smallest meaningful units using ChaSen [1], and these units were classified into 183 keywords such as “yen”, “rise”, and “large”. The feature of each document was evaluated by tf-idf (term frequency inverse document frequency) values of the 183 keywords. The tf-idf value was calculated by dividing the term frequency by the document frequency. The tf-idf values of the 183 keywords are inputted into decision trees, and economic trends of week t are estimated with respect to 14 kinds of categories in Table 1. The economic trends are represented in $\{0, \pm 1, \pm 2, \pm 3\}$ about each category. A positive (negative) value of the coding data means a trend for stronger (weaker) yen. The decision trees were determined by J4.8 using the feature vectors and training data hand-coded about the preceding 3 years. J4.8 is implementation of C4.5 algorithm in data-mining software WEKA [3,4]. We tested the decision trees acquired by J4.8 using percentages of correctly estimated documents. As shown in Table 1, the decision trees correctly estimated economic trends of 92.2% of the 156 documents in estimation of the training data, and 71.9 % in 10-fold cross-validation test¹.

3. MULTI-AGENT MODEL OF FINANCIAL MARKET

As the second stage of SEMAS, a multi-agent simulation is performed using the economic trends extracted from the real world in the first stage. This section describes a multi-agent model of a foreign exchange-rate market, AGEDASI

¹In this test, 9/10 of data is used for learning and 1/10 is for the test.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

AAMAS'07 May 14–18 2007, Honolulu, Hawai'i, USA.
Copyright 2007 IFAAMAS.

Table 1: Evaluation of decision trees (Number of documents N= 156). % of correct classification.

Categories	Training data	Cross-validation
1 Economic activity	88.9	62.9
2 Price	94.1	75.9
3 Interest rate	81.1	57.1
4 Money supply	97.4	97.4
5 Trade balance	96.7	85.0
6 Employment	90.9	66.2
7 Personal consumption	91.5	90.9
8 Intervention	95.4	66.8
9 VIP announcement	87.6	45.4
10 European trend	88.3	41.5
11 Goods market	99.3	99.3
12 Political condition	92.2	69.4
13 Stock market	93.5	75.3
14 Bond market	94.1	74.0
Average	92.2	71.9

TOF (A Genetic-algorithmic Double Auction Simulation in TOkyo Foreign exchange market). AGEDASI TOF is an artificial market with 100 agents (Fig. 1). Each agent is a virtual dealer which has dollar and yen assets and changes positions in the currencies for the purpose of making profits. Each week of the model consists of the five steps: (1) Each agent receives coding data of the 14 economic trends that created by the text-mining and 3 chart trends² (*Perception step*), (2) predicts the future rate using the weighted average of the trend data with its own weights (*Prediction step*), and (3) determines her trading strategy (to buy or sell dollars) in order to maximize its utility function (*Strategy Making step*) every week. Then, (4) the equilibrium rate is determined from the supply and demand in the market (*Rate Determination step*). Finally, (5) each agent improves its weights by copying from the other successful agents using GA operators [2] (*Adaptation step*). After the *Adaptation Step*, our model proceeds to the next week's *Perception Step*.

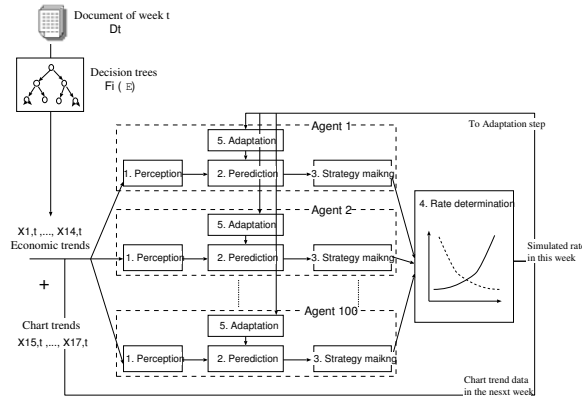


Figure 1: Framework of multi-agent model

²Short-term Trend 1 (Change in the last week), Short-term Trend 2 (Change of short-term Trend 1), and Long-term Trend (Change through five weeks).

4. SUPPORT OF USERS' ACTION TO THE REAL WORLD

Our artificial market model can support its users such as central bank staffs, policy makers, and authorities in deciding exchange rate policies. In this section our model is used for users to estimate the impact of users' own action to the market. The users try to find the best IF-THEN rule of their action for the stabilization of yen-dollar rate in 1995 using data from 1992 to 1994. The condition part of the rule consists of economic trends and/or chart trends. The action part of the rule is how to operate three *control factors* (interest rates, intervention, and announcement) during 1995.

First, based on simulation results using data from 1992 to 1994, the users select several *condition factors* from the 17 factors. The condition factors are the factors to which many agents attached large weights. The users will operate the control factors according to the trends of the condition factors. Second, seven candidates of the users' action were prepared according to the kind of the control factors to operate. These candidates were estimated by standard deviations of rate changes of the simulation in 1994, and the best action option was suggested.

4.1 Selection of condition factors

First, we trained the 100 agents in the artificial market using sample data from 1992 to 1994 by the following procedure. The initial population included a hundred agents whose weights were generated randomly and the position of each agent is square. Then we trained our model using data of the 17 factors and the actual rates from 1992 to 1994. During the training we skipped the rate determination step, and in the adaptation step, the fitness in GA was the cumulative value of differences between the forecast means of each agent and the actual rates.

As a result, *bond market*, *money supply*, *European trend*, *rate change in one week*, and *change of rate change* factors got the biggest weights from the agents on the average of the 100 simulation runs. That is, the artificial market was sensitive to these five condition factors in this period. Therefore, if there is a large change of the five factors' trends, the artificial market tends to become unstable.

4.2 Decision of the best action option

Second, seven candidates of the users' action (a)-(g) were prepared according to the kind of control factor to operate: **IF** there is a change of the condition factors' trends, (a) **THEN** make a value of the *interest rate* factor to +3 or -3 against the trend; (b) operate a value of the *intervention* factor similarly; (c) operate a value of the *announcement* factor; (d) the *interest rate* and *intervention* factor; (e) the *interest rate* and *announcement* factor; (f) the *intervention* and *announcement* factor; (g) the *interest rate*, *intervention*, and *announcement* factor.

Each exchange policy options was input into the artificial market simulation and results were compared. We generated 100 simulation paths for each option by repeating the following procedure a hundred times. Initialization and training methods are the same as mentioned using data from 1992 to 1993 this time. Then we conducted the extrapolation simulations in 1994. In the test period, our model forecasted the rates in the rate determination step using only the 14 economic trend data. Each option was used as input data.

The 3 chart trend data and the fitness in GA were calculated from the simulated rates in the rate determination step. Each option is evaluated using a standard deviation of rate change in 1994 on the average of 100 simulation runs.

As a result, the action based on the option b (*intervention operation*) could reduce the rate fluctuation the most (Fig. 2). The standard deviation of the simulated rate with this operation was 0.02310 on the average of 100 runs, and it reduced about 40% of the standard deviation of the actual rate in 1994 (0.03793). The operations including intervention (the options b, d, and f) could reduce over 30% of rate fluctuation. However, the effect of operation by all the three factors (the option g) was not so large, because its effect was too large. The above results showed that the following exchange policy option was effective for the stabilization of the yen-dollar rate. **IF** there is a change of the trends of *bond market*, *money supply*, *European trend*, *rate change in one week*, and *change of rate change factors*, **THEN** operate a value of the *intervention factor* against the trend.

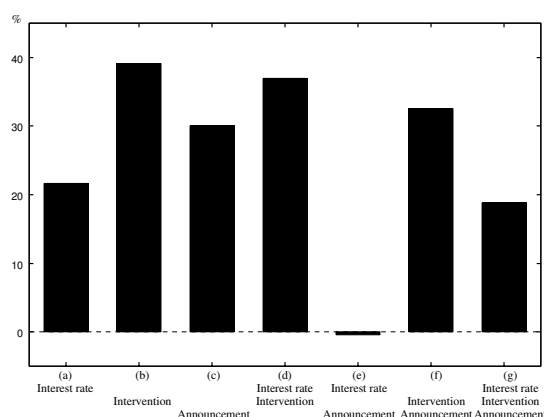


Figure 2: The reduction rates of rate fluctuation.

5. TEST OF THE BEST OPTION

We tested whether the best option obtained in the simulation using the data by 1994 could stabilize the rate in 1995. The agent was initialized like the above-mentioned and the training period was four years from 1992 to 1994. The extrapolation simulation in 1995 was performed 100 times using the weights acquired by training. Initialization and training methods are the same as mentioned above using data from 1992 to 1994. Then the extrapolation simulation is carried out about rates in 1995. In the simulation in 1995, the trend data of the control factors (interest rate, intervention, and announcement) were provided in two ways; the best action option and the actual action.

A solid line in Fig. 3 is the average path of 100 simulation results with the operation by intervention. A dashed line is the average path of 100 simulation results using the trend data that are hand-coded from the JCIF document about interest rate, intervention, and announcement. Although the width of change in the simulation path (the dashed line) with the actual action was smaller than the actual path (the dotted line), the whole tendencies such as the direction of

change were common. Compared with the simulation path with the actual action (the dashed line), in the simulation path with the best option (the solid line) was able to reduce the rate fluctuation in 1995 over 70% on the average of 100 runs. As compared with the actual path, the rate change was decreased no less than 80%. These results showed that the best action option obtained in the simulation was effective in the exchange rate stabilization in 1995.

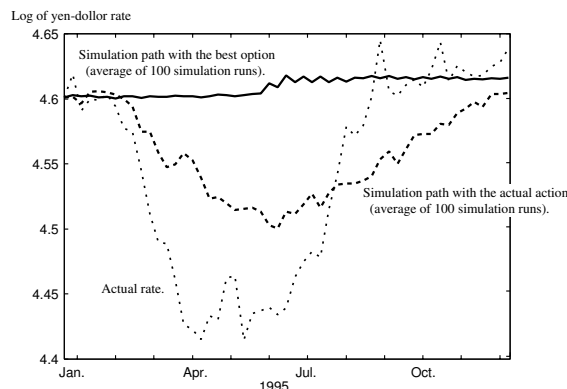


Figure 3: Comparison between simulated paths with the best option and those with the actual action.

6. CONCLUSION

The results of this paper showed the usefulness of the social simulation corresponding to the real world. If users act to the real world based on the simulation results, the action will affect the dynamics of the actual market. Then, it is extracted as the change of economic trends, and the artificial market model of SEMAS is updated. In such a feedback loop the SEMAS approach can offer a *useful* social simulation as a tool to users.

Acknowledgments.

This research was partially supported by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Scientific Research (B), no. 16300047.

7. REFERENCES

- [1] Chasen. <http://chasen.naist.jp/>, 2006.
- [2] D. Goldberg. *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley Publishing Company, 1989.
- [3] Weka. <http://www.cs.waikato.ac.nz/~ml/weka/>, 2006.
- [4] I. H. Witten and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann, second edition, June 2005.