An Agent-based System for Issuing Stock Trading Signals

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Abstract: Simulation-based models are becoming a promising research tool in financial markets. A general Complex Adaptive System can be tailored to different application scenarios. This paper describes an application of a Complex Adaptive System-based agent model in stock trades signalling. The model has been evaluated using historical movement of Bank of America stock. Agents in the system are initialized using random decision rules. Genetic algorithms and machine learning methods are utilized to reduce the sample space and improve the decision rules. Final rules are generated via Monte Carlo simulation and modified with a market momentum estimate. By following the advice suggested by the model. The hypothetical investors have outperformed the S&P 500 index and buy-and-hold investors. Compared with benchmark agents with buy-and-hold strategy on stock and index respectively, the model achieved higher return even in periods of stock's poor performance. The stock trade-signalling model is implemented using the Netlogo framework.

1 INTRODUCTION

Picking winning stocks is hard, sometimes impossible, as both endogenous and exogenous events influence the value of shares in any given moment. However, this has not stopped many investors to try to either time the market or establish strategies that would provide them with long-term gains. Consequently, there are day trading, technical trading, value trading, fundamental trading, and contrarian trading among many other strategies that have been advanced over the years as potential winning strategies in the stock market.

With the advent of computers and sophisticated analytical techniques, many of the previously mentioned approaches have been automated using information technology tools, (Subramanian, 2007, Saad, 1998, Teixeira, 2010) although with limited success. In recent years, complex adaptive systems – inspired methods, primarily using agent-based modelling techniques, have been tried as a way to simulate traders' behavior and capture the intricacies of stock trading (Kodia, Said and Ghedira, 2010). This paper introduces an agent-based model for signalling the opportune times for stock trading. The system has been evaluated in the context of Bank of America in the period from 1987 – 2014. The model outperformed S&P 500 and buy-and-hold strategy.

2 BACKGROUND

Besides the ordinary active and passive investment strategies, a simple momentum and relative-strength strategy could outperform the buy-and-hold strategy 70% of the time tracing back to 1920s (Faber, 2010). There will be another improvement for the performance after adding a simple trend before taking positions. Abovementioned methods are not effective at the level of individual agents who are making decisions in real time. They simply provide a way to retroactively simulate market movements. Agent-based modelling techniques offer the opportunity to simulate rational trading individuals taking into consideration their interactions. The Zero Intelligence model (Farmer, 2005) shows that agent-based models can produce a high fit to the real stock market. The Complex Adaptive Systems (CAS) framework and agent-based modelling (ABM) implementation offer a natural approach to capturing interactions between agents in the market place. There was a successful implementation of ABMs in simulating the NASDAQ market using a single stock (Darley and Outkin 2007). In the NASDAQ market simulation model, Darley and Outkin present a new paradigm for the financial market. Their markets were treated as complex systems whose behaviour emerges as a result of the interactions among different agents. It shows an overall picture of the market but not the issue of

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trading signals. In our model, we created a trading environment to train agents. In the training stage, agents will keep learning all the historical data. Then in the testing stage, agents will issue the stock trading signals that maximize profits based on their prior learnt knowledge.

3 COMPLEX ADAPTIVE SYSTEMS APPROACH TO SIGNALING STOCK TRADES

Complex Adaptive System tools offer another option to model nonlinear systems due to their ability to capture the essence of distributed, self-organizing social and natural phenomena characterized by system's component interactions and feedback loops.

Financial markets are complex systems (Johnson, 2003) with micro behaviors, interaction patterns, and global regularities (Cappiello, 2006). ABMs can model financial markets as a dynamic system of agents. There already have been successful implementations of ABM models in fields as diverse as economics, government, military, sociology, healthcare, architecture, city planning, policy, and biology (Tesfatsion, 2006, Johnson, 2013, Dreau, 2009, Hadzikadic 2010, Su and Hadzikadic, 2014). In financial market simulations, a large number of agents engage repeatedly in local interactions, giving rise to global markets (Raberto, 2001, Bonabeau, 2002).

In this paper we describe an ABM system that issues a stock trading signal (buy, sell, or hold) for a stock (Bank of America in our example). Agents trade stocks based on the publicly available data from January 2, 1987 to December 31, 2014. In addition, agents will have the knowledge of the current status of the stock market, be it bull or bear, based on the recession data available from the National Bureau of Economic Research (NBER). Here bull market indicates a financial market of a group of securities in which prices are rising or expected to rise. Bear market denotes the opposite in financial market terms. Agents use this information to select their trading rules.

3.1 Agents

A collection of agents constitutes the "trading world" in this ABM simulation. Agents are given a certain amount of money at the model initialization stage. Agents' transactions are triggered by their decision rules and the amount of capital they have. As they are aware of the current market status, agents at each time step choose between two sets of trading rules: bull and bear market trading rules. Table 1 describes the trading rules assigned to individual agents. The long position in financial market is the action of buying a security while the short position is the selling of a security.

Table 1: Trading rules assigned to individual agents.

Buy-Threshold	Minimum price change required for taking a long position
Buy-Period	Time window agents observe before evaluating the Buy-Threshold
Sell-Threshold	Minimum price change required for taking a short position
Sell-period	Time window agents observe before evaluating the Sell-Threshold

The Table 2 describes agents' decision rules in detail.

For instance, if the values for buy-threshold and buy-period for an agent are 0.2 and 30 respectively, then the agent will take the following buying strategy: IF the stock price goes up 20% in the past 30 trading days, THEN take a long position on this stock. Similarly, if the values for sell-threshold and sell-period are 0.1 and 50 respectively, then the agent will take the following selling strategy: IF the stock price goes up less than 10% in the last 50 trading days, THEN agent will take a short position. Also, short selling is allowed at any point. An agent can short sell any amount of stock up to their available cash amount. IF none of these conditions are met, THEN agents will keep the status quo, that is, a hold strategy applies.

Market momentum is also an important factor that will impact the agents' decision rules. The more agents are buying stocks, the higher bidding price.

The more agents are selling stocks; the stock prices will tend to be low as agents are trying to liquidate their inventories. In the model, agents will issue trading signals based on the current market momentum, thus making the trading signals more consistent with the contemporary market status.

Agents will have access to current market latent transaction information. As a result, the bandwagon effect produces a significant impact on agent transactions. The bandwagon effect simply means that agent behaviors and beliefs, as well as their consequences, spread around. Consequently, agents will adjust their thresholds for both long and short positions. In another words, if there is a huge number of agents who are going to take a long position on stocks, then they will increase their buy-

Table 2: Agents' Trading Rules.

- Basic trading rules: rational + momentum
- Buy Rule:
  - X > Y * (1 - self-confidence * *momentum of buying*) in past Z
  - Agents will buy
- Sell Rule:
  - X < Y * (1 – self-confidence * *momentum of selling*) in past Z
  - Agents will sell
- Momentum ranges in [0, 1]
  - Count how many people intend to buy/sell
  - If no one is *buying/selling*, *momentum of buying/selling* will be 0
  - If everyone is *buying/selling*, *momentum* of *buying/selling* will be 0
- X – Change in Stock Price
- Y – Buy/Sell Threshold
- Z – Buy/Sell Period

threshold. At the same time, if the majority of agents are interested in taking a short position on stocks, then a substantial number of agents will correspondingly decrease their sell-threshold as they try to liquidate their assets as soon as possible. In order to control the impact of market information, as well as the momentum, agents are assigned a local variable called self-confidence, which is randomly assigned at the setup stage of the simulation. Self-confidence controls how much each agent trusts other agents, and how much it believes that the agents around are accurate in their estimates. If an agent is totally self-confident (self-confidence = 1.0), the agent only follows its own trading rules and ignores the information provided by other agents in the market.

In this model, the world is represented in 2 dimensions. Both X-axis and Y-axis range from -10 to +10. In this 20 x 20 world, agents have a local variable named radius to define the distance within which agents can reach out to other agents for learning. This results in a trading decision rules optimization. Each agent has a different value for its radius in order to create a diversified trading environment. At the same time, the radius reduces the impact of unification among the agents by differentiating their learning preferences.

3.2 Implementation

This stock position advising CAS model wasimplemented using the Netlogo 5.1.0 programmable modeling environment (Wilensky 2009). Netlogo offers a user-defined grid and the possibility of defining agents, normally called turtles in NetLogo.

In this model, the exploration space for all possible trading strategy combination is measured in trillions. As the combination is extreme large, it has huge impact on the computing speed of the simulation. If all the combinations initialized in the beginning of simulation, to provide a trade-off between the computing speed and the space exploration, we set the agent number to 1,000. All transaction decision rules described in Table 1 are randomized within the [-0.4,0.4] range for required returns and within [0,100] range for the trading periods. Self-confidence and aggressiveness at set to 0.3 and 0.001, respectively. However, in order to maintain the possibility of exploring the whole search space, a mutation mechanism is added, allowing a subset of agents to mutate from [-0.4,0.4] to [-1,1] for required returns and from [1,100] to [1,1000] for trading periods. Agents are assigned the initial capital in the amount of $50,000. The transaction cost is fixed at $10 per transaction, thus forcing agents to trade off for the opportunity costs. The mutation rate is fixed at 0.1, which allows 10% of all agents to get buy/sell threshold and buy/sell period generated in [-1,1] and [1,1000] respectively. Also, interest will be distributed at the end of each tick based on the amount cash hold on hand.

In the model, we created two benchmark agents. Benchmark agent 1 (BA1) always tracks and replicates the action of the best performer in the model. Benchmark agent 2 (BA2) tracks, weighs, and replicates the top 10% best performers in the whole system. For BA2, if the majority of the agents in the 10% top performers have a preference to buy, then BA2 will take a long position. A short position represents the opposite case. If the number of buy and sell agents is equal, then hold strategy will be applied.

The complete simulation timeframe is divided into 2 stages. Stage 1 is training phase in which agents learn best individual trading strategies. Stage 2 is a test stage. At the beginning of this stage Agents' capital is reset to the initial value, while agents retain all the rules they learned in the training phase. Agents trade based on the strategies learned in Stage 1, while attempting to maximize their profits.

Learning from other agents is disabled in the first 1,000 ticks, which leaves enough time for agents to evaluate their initial trading strategies. After that, agents learn throughout the rest of the simulation. This mechanism allows agents sufficient time to optimize their strategies throughout the volatilities of the market, i.e. financial crises or huge price volatility periods.

We used a genetic algorithm for regenerating or eliminating agents (Holland, 1975). A hatch and die concepts of NetLogo were used to introduce new agents or eliminating underperforming ones. Agents who lose all their money are eliminated from the environment. At the same time, new agents are initialized and placed into the environment, thus keeping the number of agents constant. This mechanism makes sure that a robust simulation environment and active trading among agents are maintained.

4 RESULTS

In the stock trading signalling model, S&P 500 and Bank of America (BAC) buy-and-hold strategies were used as performance benchmarks. As the timeframe of the data is from 01/02/1987 to 12/31/2014, different settings of training/test experiments were conducted during the simulation. Table 3 shows three typical experiments.

Table 3: Experiment Setups.

Experiment 1	Training	From	01/02/1987
		To	12/31/2014
	Test	From	N/A
		To	N/A
Experiment 2	Training	From	01/02/1987
		To	12/31/2004
	Test	From	01/02/2005
		To	12/31/2014
Experiment 3	Training	From	01/02/1987
		To	12/31/2011
	Test	From	01/02/2012
		To	12/31/2014

In experiment 1, agents are trading all the time from 1987 to 2014. There is no test period, as agents' capital is not reset during experiment. It indicates how well agents perform in the maximum timeframe.

In experiment 2, the whole timeframe is divided into 75% training and 25% testing tranches. In other words, training stage is from 1987 to 2004, while the test stage starts in 2005 and ends in 2014. This cut is inspired by best practice in supervised learning.

As the underlying stock in the model is Bank of America, which is in financial sector that was the major cause of recent financial crisis, experiment 3 creates a bull market period for the testing stage in order to test how well the model performs in a bull market with less volatility in stock prices. As a result, the training period is from 1987 to 2011, and the testing period is from 2012 to 2014.

The results of the experiments are shown as below in Table 4

Table 4: Experiment Profits in %.

Experiment 1	Benchmark	S&P 500 Buy & Hold	735.42%
		BAC Buy & Hold	664.53%
	Benchmark Agents	BA1	358.33%
		BA2	581.12%
	Model	Best Performer	1,189.71%
		Top 10% Best Performers	718.44%
Experiment 2	Benchmark	S&P 500 Buy & Hold	73.3 %
		BAC Buy & Hold	- 50.4%
	Benchmark Agents	BA1	37.16%
		BA2	71.29%
	Model	Best Performer	540.46%
		Top 10% Best Performers	88.89%
Experiment 3	Benchmark	S&P 500 Buy & Hold	61.88%
		BAC Buy & Hold	28.61%
	Benchmark Agents	BA1	71.85%
		BA2	61.51%
	Model	Best Performer	374.02%
		Top 10% Best Performers	105.34%

It is obvious that the performance of the stock trading signalling model is much better than a buy-and-hold strategy on Bank of America stock. It even outperforms the S&P 500, which shows an ascending trend in the long term. As the Bank of America stock has not recovered from the downfall of the last financial crisis, it is a good test for evaluating the performance of a simulation model, especially when compared to S&P 500 index. Figures 1 through 3 show the comparisons between the model's performance and the buy-and-hold (BAH) strategy on BAC and S&P 500 in a more intuitive way.

Experiment 1 indicates how well agents can perform in the maximized timeframe. Agents are trading based on their experience that accumulated overtime. There is no capital reset during the experiment 1, as we are trying to mimic the trading situation in real life and give out a sense of the maximum possibility of agents' profitability. At the same time, experiment 1 allows us to observe the full story that happened during the whole timeframe while

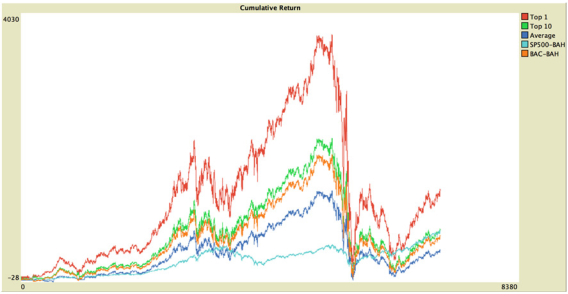

Figure 1: Experiment 1.

agents are trading. In Figure 1, the best performer achieved the profit of 3,450% in 2007, right before the beginning of the subprime mortgage crisis. All agents suffered huge losses during this crisis and they have not recovered even by the end of the simulation.

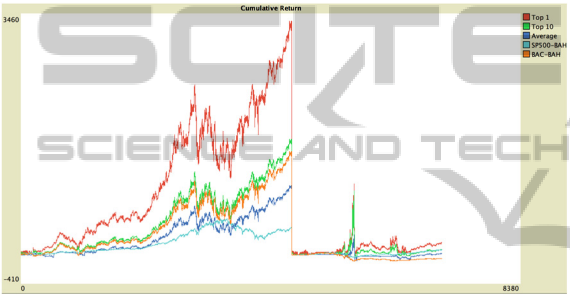

Figure 2: Experiment 2.

Experiment 2 resets agents' capital in the first trading day of 2005. Agents did well in the training stage. In the test phase, agents secured significant profits until the crisis happened. It took agents about 3 years to recover from the downfall incurred by the crisis.

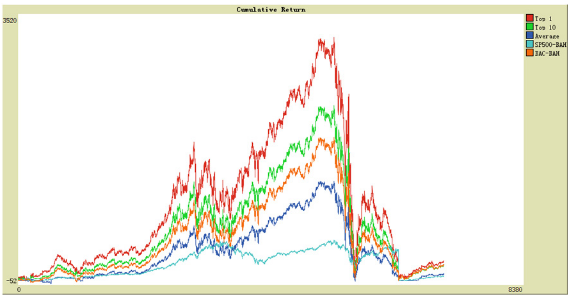

Figure 3: Experiment 3.

In the last experiment, agents' capital was reset at the beginning of 2012. In a pure bull market, the best agent gained around 374% profit, which was 13.34 times more than the simple buy-and-hold strategy on Bank of America stock.

However, it's interesting to see that benchmark agents (BA1 and BA2) underperformed their tracking targets, the best performer and top 10% best performers respectively. BA1 always replicates the current market best performer's action. BA2 mimics the top 10% best performers' action in the market. One possible explanation is that the trading frequency in bear market is much higher than that in the bull market, as the higher transaction frequency enables agents to secure the slight profit room in small price changes. Although this strategy comes with higher transaction costs, the extra profit can offset this drawback. Table 5 shows this phenomenon through the trading volumes.

Table 5: Trading Volumes in Shares.

Experiment 1	BA1	293,162
	Best Performer	12,686
Experiment 2	BA1	113,770
	Best Performer	6,851
Experiment 3	BA1	57,070
	Best Performer	4,802

Table 6 shows the best trading decision rule set derived from the experiments:

Table 6: Trading Rules for Best Performer.

For bull market:
- If the stock price goes down 37% in last 87 trading days, take a long position.
- If the stock price goes up less than 20% in last 71 trading days, take a short position.

For bear market:
- If the stock price goes down 20% in last 10 trading days, take a long position.
- If the stock price goes up less than 40% in last 61 trading days, take a short position.

The strategies above are the core decision rules for issuing stock trading signals. However, the market momentum turns the decision rules to actual transaction thresholds, which are then used to help agents make their moves.

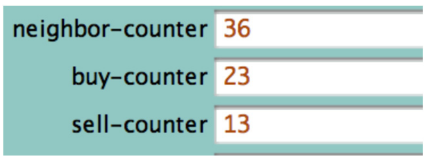

Figure 4: Agent's Built-in Variables for Momentum.

For example, the above figure (Figure 4) shows an agent's built-in variable for momentum. There are 36 agents around it. Out of these 36 agents, 23 want to buy and 13 want to sell. As the confidence is 0.3, Table 7 shows the actual decisions in that particular tick.

Table 7: Actual Decision Rules for Best Performer in a Particular Tick.

For bull market:

- If the stock price goes down 29% in last 87 trading days, take a long position.
- If the stock price goes up less than 18% in last 71 trading days, take a short position.

For bear market:

- If the stock price goes down 18% in last 10 trading days, take a long position.
- If the stock price goes up less than 34% in last 61 trading days, take a short position.

The following figure (Figure 5) is an example of the actual stock trading signalling over time. When the green line hits 1, the system advises a long position. When the red line hits -1, then the model advises a short position. If both lines stay at 0, then hold strategy is applied.

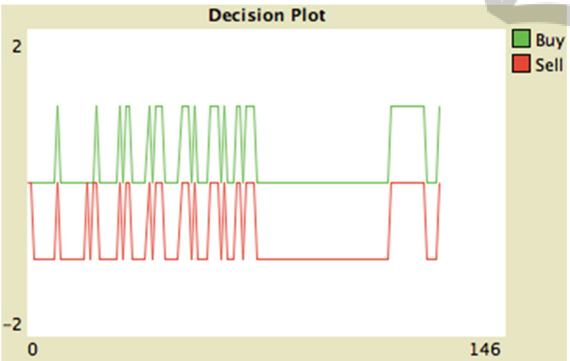

Figure 5: Decision Plot Overtime.

5 ISSUES

In the experiment, agents' learning too quickly was one of the key issues. There is a variable called aggressiveness which controls the degree of agents learn from the difference between its and the best agent's performance. The aggressiveness was set to 0.1 while we introduced the learning component. That is in each tick, each agent will learn the 10% of the difference of trading rules between it and the top performers in radius. As a result, uniformity spread throughout the simulation. The best trader's performance was much less than 500%. This result was way below the BAC buy-and-hold strategy.

Therefore, aggressive was decreased to eliminate the uniformity among agents. Since the whole simulation has only 7,053 ticks, if aggressiveness is set too low then learning is not that effective in changing agents' decision rules. After several hundred simulation runs aggressiveness was finally set to its more optimal value of 0.001, in order to reconcile the problem of diversity, learning speed, and limited learning time.

What's more, reducing aggressiveness increase the correlation of return distribution between stock trading signal issuing model and historical S&P 500. Table 8 shows the correlation in different settings of aggressiveness.

Table 8: Correlation of annual return between stock trading signal issuing model and historical S&P 500 data.

Aggressiveness	0.1	0.01	0.001
Correlation	0.43	0.46	0.54

6 DISCUSSION, CONCLUSIONS AND FUTURE WORKS

Computer simulations allow us to see the behind-the-scene actions of the agents, and then to generate the best stock transaction strategies based on the interaction of agents. Comparing the model performance with the buy-and-hold strategy of S&P 500 and BAC stock, the CAS stock-trading model shows a much higher return on a single stock trading in the same timeframe.

However, the momentum, a measure of the overall market sentiment (Scowcroft and Sefton, 2005), plays an important role in the CAS stock stock-trading model. All the rules are adjusted based on the market momentum in a specific time tick. With the benefit of momentum, the performance of the stock-trading model is far better than a simple buy-and-hold strategy for both S&P 500 and BAC. In for the current model, momentum is generated by the agents' desire to conduct transactions. Future refinements in the momentum component will lay a key component in improving the performance of the model.

We are currently working on several strategies for improving the computation of the momentum component. One is to extract the real time tweets from Tweeter and to run a sentiment analysis on those tweets. Then the signals from Twitter will be attached to the current momentum component. Another one is to use the transactions volume to deduce the historical drive in the market and plug it into the current momentum mechanism, leading to a more precise forecast about the upcoming market movements. In return, agents can anticipate the changes in the future investors' actions and adjust their transaction strategies to maximize profits.

The continuing refinement of the decision rules, will see a replacement of the single stock trading signaling mechanism with a multiple stock position advising one. As a result, this model will have practical values in the portfolio management as well. This improved CAS model can be very helpful with defining different parameters that best characterize agents' trading strategies, discovering and suggesting suitable positions for different stocks at different times, and discovering the factors affecting an optimal portfolio management strategy. Finally, agents in the future system will be categorized into individual investors and institutional investors, as the impact of their transactions differ in the real world.

Another version that allows agents to take historical data for the training stage is under development. By the end of the timeframe, agents will use real-time data to conduct potential transactions. We believe that agents will be able to influence the market as we create a portfolio that trade based on the agents' signals. In return, agents will change their trading behaviors corresponding to their feedback from the market.

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