TOWARDS COOPERATION AMONG COMPETITIVE TRADER AGENTS

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Abstract: In order to manage their portfolios in stock markets, i.e., to determine buy and sell signals, human traders use a set of algorithms created by economists, which are based on stock prices series. These algorithms are usually referred as technical analysis. However, traders prefer to use a combination of several algorithms as indicators, rather than choosing a single one. The several signals provided are used to determine the trader order to buy or sell some stocks, or even to decide to not submit any order. In the last years, some researchers have tried to create new algorithms with learning skills in order to produce autonomous automatic traders, some of them using AI techniques. Inspired by the human traders´ decision processes, our architectural approach composes heterogeneous autonomous trader agents in a competitive multiagent system. This architecture allows the use of several algorithms, based on different technical analysis indexes to manage portfolios. We have implemented this architecture and we have performed a set of simulation experiments using real-data from NASDAQ stock market. The experimental results were compared to the performance of single agents playing alone, and a better global performance was observed when traders compete with each other for resources. These preliminary results indicate that competition among agents, as proposed here, may reach very good results, even among agents created to act alone in this kind of market.

1 INTRODUCTION

In this paper, we propose an architecture based on autonomous agents to model the behavior of autonomous stock trading. The architecture uses several trader agents, each one with its own independent strategy. These agents are permanently assessed and resources may be transferred to agents with better performance. This approach allows adaptation in the agent society behavior, because agents with more allocated resources have a greater influence on the overall system performance.

2 RELATED WORK

Stock prices prediction or autonomous stock trading management is a common problem and there is a lot of work in the literature about it. This work may be basically divided in two big groups: using a single autonomous agent, which may be based on many approaches like neural networks, reinforcement learning, fuzzy sets, bayes networks, etc or using a multiagent system, where specialized agents perform the multiple tasks that compose the decision process in stock trading.

In the first group, agents usually trade with a specific stock and use a simple decision process (Sherstov and Stone, 2004) (Kearns and Ortiz, 2003). Agents strategies are based on well known techniques from the financial market, like MACD (Appel, 2005) or use some AI techniques, as reinforcement learning (Sherstov and Stone, 2004; Yu and Stone, 2000). Some interesting work of this class are performed within PLAT (Penn-Lehman Automated Trading) project(Kearns and Ortiz, 2003) (Subramanian et al., 2006), which consists of an investigation of algorithms and strategies for automated trading in financial markets. This project uses an exchange system simulator called PXS that delivers real data from Nasdaq exchange at real time to trader agents.

It is important to note that managing many stocks with one agent for each stock, without either information exchange among agents or a global vision is not considered as a good idea: domain experts point out that using the natural complementarity among stocks is a good way to reduce risks and achieve more predictable results. In other words, the cooperation among (specific) traders is really important and common for humans traders. In the second group (multiagent systems), most of the work (that we know) in multiagent systems for automated trading (Decker et al., 1997) (Yuan Luo and Davis, 2002) use predetermined roles for each agent in the system. These roles are based on specialized tasks, such as technical analysis, decision making, fundamental analysis, communication, etc. In this approach, the adaptation in buying/selling strategy becomes harder and possibly slow down the decision making process, because all (or almost) agents are involved in each decision.

Our approach differs from the first group because it is based on multiagent systems and differs from the second group, because it uses a set of trader agents that (in contrast to the first group) are able to redistribute money and stocks among themselves in order to achieve better global performance. This approach is built over a flexible architecture that can use independent work based on autonomous agents and incorporate them in a competitive multiagent society, without serious changes in the deliberation mechanism of such agents.

The rest of the paper is organized as follows. In section 3, we briefly describe important indexes used in stock market. We present our architecture in section 4. We show some simulation results in section 5. Finally in section 6, we present our conclusions and suggestions for future work.

3 STOCK MARKET ANALYSIS TECHNIQUES

In this section, we present some different technical analysis techniques that are used by human operators when deciding about actions in stock markets. These techniques, briefly outlined here, will be used by the agents of our architecture, described in section 4.

- Relative Strength Index (RSI): it was created in 1978 by J. Welles Wilder and became the most known and popular oscillator used by stock market. The RSI is calculated using the positive and negative variations of price.

- Stochastic Index: It is based on the hypothesis that one stock is in high trend, when its biggest

prices are observed in the end of an observation period. Similarly, the stock is in down trend, when its smallest prices happen in the end of the period.

- Moving Average (MA): It tries to identify trends in stock prices. The average is defined by an observation period, usually defined between 14 and 60 days, and a calculation method that can be simple average (sum of all prices and divide it by the number of values) or exponential average to give more relevance to newer quotation rather than older quotations. The moving average is interpreted using graphics with lines of moving average and prices. The moving average line is a resistance for high trends and down trends. When prices are in high trend (or down trend) and quotations line crosses the moving average line, it means a warning to trend reversal.

- Moving Average Convergence/Divergence (MACD): It is a trend following momentum indicator that shows the relationship between two moving averages of prices. The MACD is calculated by the difference between a 26-day and 12-day exponential moving average. A 9-day exponential moving average of the MACD, called the "signal" line is plotted on top of the MACD to show buy/sell signals (Appel, 2005).

- Price Oscillator: It is similar to the MACD, but the Price Oscillator can use any two user-specified moving averages. (The MACD always uses 12 and 26-day moving averages, and always expresses the difference in points). It is calculated by the difference between the moving averages divided by the shorter-term moving average and present usually as a percentage. There is a buy signal when the Price Oscillator rose above zero and sell signal when the indicator fell below zero.

4 ARCHITECTURE PROPOSAL

In the following subsections, we will briefly describe the general architectural guidelines, and the three kinds of agents that compose the proposed architecture: **trader**, **coach** and **conflict solver** agents. Finally, A short explanation about two assistance services used by agent society are presented.

4.1 General Guidelines

The main guidelines observed in the proposed architecture are the following: (i) adaptability: the architecture must allow high adaptability, (ii) simple trader agents: the traders must be as simple as possible to
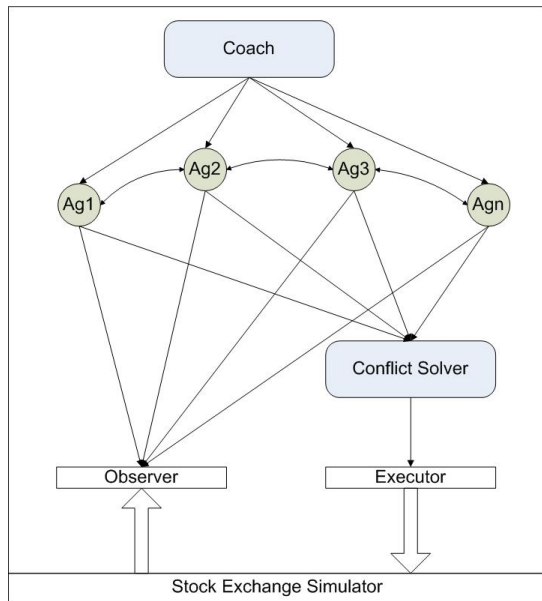
Figure 1: Architecture for Multiagent Stock Trading. Circles represent trader agents. The coach and conflict solver agents are represented by gray rectangles and white rectangles represent the assistance services.

facilitate their replacement and the incorporation of third part agents, (iii)autonomy: system must be able to trade without human intervention and (iv)dynamic society: at any moment it is possible to reallocate resources among agents in order to adapt society).

4.2 Kinds of Agents

The architecture is composed by a society of three kinds of agents: **coach**, **trader** and **conflict solver** agents, as shown in figure 1. The agents use two assistance services: one to transfer order to the exchange system, called **executor** and another, called **observer**, to monitor market quotations. We opted to implement these features as independent services to facilitate the migration to others systems, for example, others exchange systems simulators or even a real exchange system. We describe these three kinds of agents next.

4.3 Trader Agent

Trader agents are able to define buy and/or sell orders for an *specific stock*. Their goals are to obtain the best possible return and lower risks. Their decisions will be evaluated by the coach, who compares the return of each trader through its average revenue and its risks through standard deviation of trader portfolio value. Each trader agent works with some shares of one specific stock and some amount of money which are de-

fined in beginning of operation. These amounts are changed by buy/sell operation and by reallocation performed by coach agent. Moreover, each trader agents adopts a particular strategy to decide when to buy or sell their stocks, as described in section 3.

In this architecture, the society is composed by an arbitrary number of trader agents and this number may be changed along the operation. For instance, new trader agents may be included in society at any time and the coach may transfer all the resources from one trader to the others, what would be equivalent to exclude the former from society. Despite each trader is able to deal with just one stock, the system is able to deal with several stocks and to explore complementarity among stocks, due to the work of several trader agents and coach reallocations. The portfolio managed by the system is equivalent to the union of all stocks and money managed by each trader agent. The system result is a function of all traders results weighted by its resource allocation, therefore the reallocations performed by coach agent may change the system result.

4.4 Coach Agent

The goal of coach agent is to *evaluate each trader agent* and to *allocate more resources to the best traders in order to improve system performance*. These two processes are described next.

4.4.1 Evaluation

Evaluation of a stock trader performance is a common problem in financial analysis, which is naturally dealt with by evaluating the performance of human traders. Hence, there is no reason to create new ways of evaluation for software agents that trade stocks. Therefore, we decided to use well known methods of evaluation from financial analysis. Among several ways found in the field, one of the most used is the Sharpe index (Sharpe, 1994). Such indicator is a measure of performance adjusted to the risk and takes in account the average return and volatility associated to portfolio. The Sharpe index uses as reference the return of an asset free of risk. For simplicity, we will consider that this return is zero. For each trader A_i there is a R_i, that represents its return in a defined period. Therefore, we may calculate Sharpe index for an period of time from 1 to N as presented in equation 1:

$$SharpeIndex = \frac{\overline{R}}{\sigma} \qquad (1)$$

where:

$$\overline{R} = \frac{1}{N} * \sum_{i=1}^{N} R_i \qquad (2)$$

$$\sigma = \sqrt{\frac{1}{N-1} * \sum_{i=1}^{N}(R_i - \overline{R})^2} \qquad (3)$$

The performance of one trader agent (A_i) is based on its Sharpe index and defined as $P(A_i)$, as shown in equation 4:

$$P(A_i) = \frac{Sharpe(A_i) - Min\_Sharpe(A)}{Max\_Sharpe(A) - Min\_Sharpe(A)} \qquad (4)$$

This evaluation is a real number in the interval [0,1]. The expression Min_Sharpe(A) means the lowest Sharpe index among all trader agents (this number may be negative) and Max_Sharpe(A) is the biggest Sharpe index among all traders. Sharpe(A_i) means the Sharpe index of the target trader agent A_i for an given evaluation period. This period is less or equal to a quarantine period, described in section 4.4.2, to avoid distortion in evaluation by reallocations.

4.4.2 Reallocation

The reallocation is based on the evaluation of traders performance and its objective is to transfer resources from trader agents with poor evaluations to trader agents with better performance. One of the main issues in reallocation is that the process should be fast enough to adapt the systems to changes in stock market. On the other hand, when reallocation happens too often, the system may present oscillations or an inconsistent behavior. Another issue is to avoid that the reallocation interferes with the evaluation process. This may happen because coach evaluation is impacted by variation on assets, therefore a reallocation could interfere in evaluation. We avoid such problems by creating a *quarantine period*. After reallocation, the agents involved are put in a quarantine period. During such period, agent performance is evaluated but it does not participate of reallocation neither as source or destiny. Therefore, the quarantine period is defined as bigger or equal to evaluation period and it avoids interference in evaluation.

At each cycle, after agents evaluation, coach transfers resources from worst performance agent (A) to the best performance agent(B), except by those that are in quarantine. The money and share amount (resources) are proportional to difference between performance according to equation 5:

$$Reallocated\_Res = Res(A) * \lambda * \frac{P(B) - P(A)}{P(A)} \qquad (5)$$

When agents A and B trade with same stock, the coach reallocates not only money, but also an amount of shares defined by an equation similar to equation 5. The symbol λ is a calibration constant used to make the system faster or slower. The function P is the agent performance measured by the coach agent at the current moment, shown in equation 4.

4.5 Conflict Solver Agent

The conflict solver agent analyzes and eliminates inconsistent orders from trader agents. For instance, consider the case where trader agent A gives an order to sell 1000 shares of stock X, meanwhile trader agent B gives an order to buy 1000 shares of the same stock X. This may happen when agent A believes that price of stock X is going down, while B believes the opposite. The problem is that if both orders are sent to exchange, both agents would have to pay fees to exchange and brokers. These fees are eliminated by the conflict solver agent. This agent transfers 1000 shares of stock X from agent A to agent B and the amount of money equals to 1000*(Price of stock X in the market) from agent B to agent A and eliminates the sell order from A and the buy order from B. This allow both agents to follow their strategies and avoid unnecessary costs to the system.

5 SIMULATION EXPERIMENTS AND RESULTS

We have tested the proposed architecture by using a simulator. The main characteristics of this procedure, as well as the obtained results, are described next.

5.1 Simulation Characteristics

We have adopted a discrete time approach to simulate our architecture, using real data from NASDAQ exchange market. Each trader agent gives an order at every simulation cycle. In this work, one simulation cycle is equivalent to one day[1]. The trader agent order specifies the target stock, the operation type (buy or sell) and the amount of shares to transact. Orders with zero shares are acceptable and would be equivalent to an agent decision to not operate at the current cycle. Trader orders are executed at market price. Each trader agent may access quotation from all previous cycles, but never the current quotation. The simulation allocates for each trader agent an initial capital (usually 1 million dollars), that agents can use to buy shares. One trader agent is limited to its capital. It can not buy shares that worth more than his capital and it can not sell shares that it does not hold in the current

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[1]If necessary, it would be easy to change the simulation cycle duration.

cycle. For simplicity, we decide to not compute exchange or broker fees in agents transactions.

The sequence of action of agents and assistance services is cyclic and determined by simulation mechanism according to the following sequence: observer, coach, trader agents, conflict solver and executor.

5.2 Simulation Results

We have executed several simulations with real data from Nasdaq market exchange. We used the Nasdaq 100 Index (Exchange, 2007), which lists the top 100 stocks in Nasdaq, in order to select the papers. The data refers to history prices in the period from September 1986 to September 2006 obtained from Yahoo Finance (Yahoo, 2007). However, many companies listed on Nasdaq 100 Index are new companies and therefore don not have price information for the whole period. We arranged the companies listed in Nasdaq 100 index in four groups: 20 years (10 stocks), 15 years(40 stocks), 10 years (70 stocks) and 5 years (90 stocks), according with the price history available. The number of agents in society is defined by the product of the number of techniques by the number of stocks plus two, these latter corresponding to the coach and conflict solver agents.

We used trader agents that implemented the five technical analysis techniques described in section 3: Relative Strength Index (RSI), Stochastic Index, Moving Average (MA), Moving Average Convergence Divergence, (MACD, we used 10 and 30-day moving averages.) and Price Oscillator. In order to achieve complete flexibility, the MAS will have for each stock, five agents, one per each technique available. Additionally, each society has one Coach agent and one Conflict Solver.

We have performed some experiments using only three technical agents to analyze the impact of fewer agents in system performance 2. It is possible to realize that system performance improves when the number of stocks increases, since the best performance is obtained by 5 years groups, which deals the greatest number of stocks. In the experiment with five technical agents, the system performance was improved 3.These results show better MAS performance than when it was used only three techniques. This situation confirms our expectation about the use of more techniques. The society seems to present better performance when it has more options to do reallocation, or in another words, when it has more trader agents. In all experiments, we have adopted the values for the observation period and the calibration constant of resources λ respectively as 40% of total estimated time and 0.999.
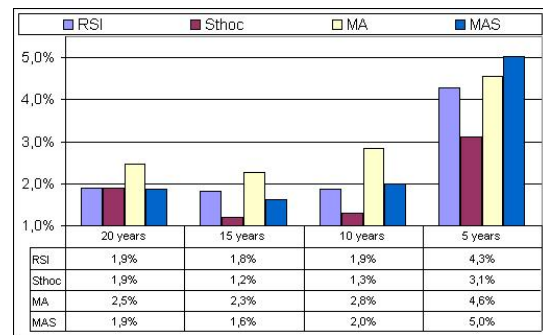

Figure 2: Sharpe Index obtained for agents groups of three specific techniques and a Multiagent System (MAS) built within the architecture proposed in this paper. Each column indicates the stock group managed by each group of agents.

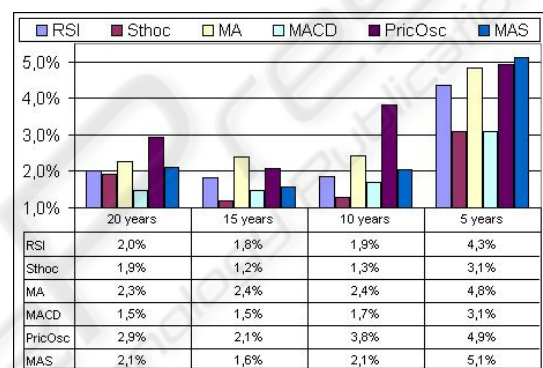|	20 years	15 years	10 years	5 years
RSI	1,9%	1,8%	1,9%	4,3%
Sthoc	1,9%	1,2%	1,3%	3,1%
MA	2,5%	2,3%	2,8%	4,6%
MAS	1,9%	1,6%	2,0%	5,0%

Figure 3: Sharpe Index obtained for agents groups of five specific techniques and a Multiagent System (MAS) built within the architecture proposed in this paper. Each column indicates the stock group managed by each group of agents.

	20 years	15 years	10 years	5 years
RSI	2,0%	1,8%	1,9%	4,3%
Sthoc	1,9%	1,2%	1,3%	3,1%
MA	2,3%	2,4%	2,4%	4,8%
MACD	1,5%	1,5%	1,7%	3,1%
PricOsc	2,9%	2,1%	3,8%	4,9%
MAS	2,1%	1,6%	2,1%	5,1%

5.3 Result Analysis

The obtained results show that a multiagent system built with the architecture proposed here achieved superior result according to Sharpe Index compared to all individual trader agents in the group of 90 stocks (5 years). In groups with fewer stocks, the results were in the average. This happens because with more options to choose, the coordination mechanism has more power to redistribute the resources among stocks. We realized that the better average return from RSI is obtained at cost of higher volatility (50% at RSI, and 34% at MAS).

By the graphs in figure 3, it is possible to realize that RSI and Price Oscillator (PricOsc) have very consistent Sharpe index compared to other agents. This situation leaves very low space for improvement to MAS, because there are few moments where these agents are outperformed by others. The MAS explores this moments to achieve better results than in-

dividual agents, but the difference obtained is not very significant. This limitation may be overcome with the introduction of new trader agents. As pointed in section 5.2, we achieved better results with higher number of techniques and higher number of stocks in simulation. Therefore, we believe that the design and implementation of new trader agents may improve the overall system performance when analyzed by Sharpe index.

Our architecture reduces the effort to design and implement such new trader agents. Even the implementation of techniques created by economists to be used by human analysts (like the five examples presented in the section 3) can be done quickly, because the designer does not need to care about communication with the exchange system or to achieve good performance in all market situation. These problems are treated by the assistance services and by the agents society.

The growth of the number of traders types causes a fast growth of the number of agents in the society, because each type is multiplied by the number of stocks. However despite the big number of agents (452) in the group of 90 stocks, the system was able to fulfill a complete cycle in less than 25 ms. This good performance and the discrete time approach allows the use of such systems in intra-day operations. Where, the interval between orders would not be one day, but some fraction of a second.

6 CONCLUSIONS AND FUTURE WORK

We presented here an architecture based on autonomous trader agents, each one with its own independent strategy. The trader agents are permanently assessed and resources may be transferred to agents with better performance. This approach allows adaptation in the agent society behavior, because agents with more allocated resources have greater influence on the overall system performance.

The proposed architecture may reach very good results, as shown by the simulation results presented in section 5.2. The improvement introduced is more relevant when there are more stock managed and more trader agents in the system. This is consistent with the common notion in financial market, that portfolio diversification is usually a good strategy. Furthermore, the architecture reduces the effort to design and implement new trader agents, even when their strategies were developed to be used by human beings. We intend to perform in the future some simulations with a larger number of techniques and stocks,

to achieve better performance. The competitive approach may be also used in another problems with similar characteristics: strategic games (the state is determined by action of all players and one agent does not know other agents strategies) and multiagent (several agents act at the same environment). We intend to study new applications for this approach in new domains with these properties.

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