Dumb Software Agents on an Experimental Asset Market

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In this paper a simulation is presented, where programmed traders compete on a market implemented by a double auction market institution. To this end, we added a XML-interface to an Iowa-style asset market system and implemented a collection of programmed traders with pure and simple strategies. The implementation and the simple simulation presented in this paper represent the starting point to investigate whether software agents change the strategies of human subjects in a follow-up study.

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1. INTRODUCTION

As electronic media and computer networks made their appearance in the world of finance, traders began to use software programs that could help them exploit the possibility of market gains that are generally forgone by humans. This is either due to the rapidity with which the transaction must be executed or to the great amount of data that has to be processed in order to perform these transactions. Such software programs - also known as programmed traders - are being utilized for different transactions and, consequently, differ greatly in complexity, ranging from very simple to complicated programs which require statistical analysis.

One of the possible future applications of agents is the field of electronic commerce. In this particular context a commercial interaction is composed of at least three distinct steps. First, there is a "searching moment" in which buyers and sellers look and find one another; then the two parties negotiate the terms of exchange; finally there is a settlement and the exchange of the good [Guttmann et al. 1998, Wurman, Walsh, and Wellman 1998]. Aim of this paper is to study the negotiation procedure of artificial agents acting on electronic markets that incorporate a centralized auctioneer process. Although our investigation seems to be more suited for business-to-business electronic commerce,

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where a “variable-price model” is well established, this model may be also applied to the consumer side: in fact there are strong signals in this context - such as online auctions - that the “fixed-price model” may not be the only scenario in retail electronic commerce.

To be more specific, the paper analyzes the impact of agents and their trading strategies on an experimental electronic asset market. For this purpose, we added an XML-interface to an existing electronic market and introduced artificial agents which act as elements of disturbance in the trading process. These artificial traders apply simple and constant strategies which may sometimes appear “rational” or random to the eyes of other traders. We then stepped back and recorded the reaction of the electronic market.

The research emphasis lies not in finding the agent which applies the best strategy: other papers have dealt with this problem in much greater detail [Rust et al. 1993]. Rather the emphasis lies with the “market” and with questions such as: “How does the market react to agents?” Far from being obvious, this question is far more complicated than intuition would prompt to think. There has been a discussion on the lower bound of traders’ intelligence to act similarly to human traders in a market institution. Gode and Sunder [1993], for example, introduce “zero-intelligence” traders that act randomly and, nevertheless, converge to the theoretical equilibrium price within a continuous double auction (CDA) framework, suggesting that price is determined more by market structure rather than by the intelligence of the traders. On the other hand, Cliff and Bruten [1998] present criticism to this point of view, arguing that these results are an artifact of the experimental regime chosen by Gode and Sunder and introduce “zero-intelligence plus” traders, which seem to have some more “intelligence” by employing a modified adaptive version of the random agent.

This paper is organized as follows: In the next Section we discuss the technical implementation of the market-agent interface. Section 3 gives an overview on the set of the implemented trading strategies. Next comes the presentation of the results of the simulation experiment in Section 4. We then defer a discussion of related work to Section 5 in order to be able to better place our work in the context of related efforts. Open research questions for further exploration and concluding remarks are given in Section 6.

2. MARKET-AGENT INTERFACE

In this Section we first present a short description of the electronic market, whereas the market itself is regarded as a black box. We then focus on the information available to the programmed traders and on the communication between them and the market.

2.1 Market rules

Our market is an artificial stock market infrastructure that has been used for several sports and election markets.[1] So far, human traders invest their own funds and buy/sell contracts, based on their expectations about the outcome of some kind of event. The experiments that have been run with human traders are in the tradition of experimental economics [Smith 1976] in that participants are paid according to their results. The design of the market follows closely the Iowa Electronic Markets, who have pioneered political stock markets [Forsythe et al. 1992].

The market is a centralized information hub in which all the transactions are explicitly regulated via predefined and fixed rules and the agents interact via the market system. The artificial stock market uses the continuous double auction (CDA), i.e. an auction in which sellers and buyers may submit bids and asks simultaneously and asynchronously: sellers

[1]Soccer world championships 1998, http://wm.wiwi.hu-berlin.de, State elections Berlin 1999, http://www.wahlboerse-berlin.de (Hansen et al., 2001), European soccer championships 2000, http://www.ribaldo7.de (Schmidt et al., 2001).

and buyers are free to accept bids or asks at any time. The CDA is very popular among financial markets, both real and virtual, and is thought to have the remarkable quality of being fast and efficient [Friedman 1984, 1993]. In contrast to markets where the emission of contracts is organized by an initial public offering, the emission on this market is implemented via a bundle mechanism. The bundle consists of a standardized unit-portfolio of one piece of each contract at a fixed price: this can be bought from or sold to the bank at any time and any quantity.

The market allows three valid operations: (1) posting market orders (bids implement buy orders and asks sell orders), (2) deleting own market orders, and (3) buying/selling bundles at the bank.

For the simulation in Section 4 we have used a winner-takes-all (WTA) payoff scheme, where at the end of the market one contract pays off the price of a bundle, and all other contracts pay off zero. Compared to vote share payoffs, where each contract pays off a fixed percentage of the total bundle, WTA markets are considered a risky environment: when the agent's portfolio does not contain the winning contract the invested money is lost completely. We used a WTA market for the experiment, because of the nice property, that contract prices relate directly to the probability of a contract paying off [Hanson 1995], and human trader often prefer them over vote contract markets.

2.2 Information

In order to apply a strategy the agents require information about the market. One of the design goals of the market-agent interface was to give the same information that so far was available to human traders now to artificial agents. For this purpose we analyzed the information available to human traders in former experiments and categorized the information into the following macro-categories:

(1) Public Rule Information

- basic bundle composition
- bundle price (bought/sold to the bank)
- payoff rules at the end of the market
- start and stop time of the market

(2) Public Market Information

- last traded price of each contract
- current bids and asks of each contract
- order book: top 5 bids and asks including prices and quantities of each contract
- server time

(3) Private Information

- portfolio of the trader
    - type of contracts
    - quantity of contracts
- liquid money

(4) Transaction Status Information

- validity of transaction
- success of transaction

Out of the above categories we designed the framework for the market-agent interface. Extensible Markup Language (XML) was chosen as high level data exchange format.

Two Document Type Definitions (DTD) incorporating the above information categories were developed: the first consists of rule, market, and personal information; the second returns the result status when an agent is performing one of the three legal market transactions. [2]

2.3 Agent-Market Communication

The implemented communication between the agent and the market may be broken down into several steps (Figure 1): (1) the agent makes a request to the electronic market via HTTP to obtain private and public information, (2) the electronic market replies by supplying the relevant market information as an XML document, (3) based on the information contained in the XML file the agent applies its strategy and decides whether it should perform one of the three legal actions or do nothing. In step (4) the agent might perform one of the three valid market transactions (posting market orders, deleting own market orders, buying or selling bundles at the bank) and (5) receives an XML document with the status of the transaction. Now the agents continue with step (1) in order to get new market information.

Figure 1: Time sequence diagram: communication between agent and market

3. AGENTS AND STRATEGIES

Considering the game theoretical point of view we can define strategy as a player's complete plan of action for all possible occurrences in the game. From the computer science point of view, strategy is the execution of a fixed algorithm. The two definitions are, of course, not mutually exclusive and indeed we need both of them.[3] However, because we will describe the actions of the agents we have implemented, we will stick to the latter interpretation of the strategies. We have chosen to design agents inspired by strategies employed by human traders in artificial stock markets. This compilation may not be complete nor is it designed to uncover a successful strategy. In the following, we first describe the general idea behind each strategy, then the reason for which we have created such a strategy (the "real world analogy"), and finally we describe, in words, the algorithm (the instance).[4] Table 1 provides a quick reference for the market transactions triggered by the different agents.

Table I. Agents and parameter values

3.1 The fundamentalist (patriot style)

Strategy description: A "fundamental strategy" is one in which a trader buys a contract and waits for the final event to happen, trusting his/her analysis of the fundamental data regarding the entity (company, soccer team, etc.) whose contract is bought.

Real world analogy: Fundamentalist actions are quite common among traders in real world markets. Traders, for example, buy contracts relying on financial information regarding the firm (fundamental data) and keep them regardless of short-run price fluctuations of the contracts. In the context of a market on a sports event the fundamentalist strategy may be seen as a sort of patriotic behavior, in which the trader buys the contracts of his home team.

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[2] The DTD's and a sample XML file can be downloaded from `http://www.wiwi.hu-berlin.de/~jensg/etrade`.

[3] Different would be the case of a market that does not use software agents. In this case the game theoretical interpretation would be sufficient

[4] The agents and their strategies have been implemented as a stand-alone Java-client (JavaSoft 1997), that can be used on any standard personal computer. The source code is available at `http://www.wiwi.hu-berlin.de/~jensg/etrade`. The following requirements are needed in order to run the agents: JDK 1.1.8 or later (including the Java 2 SDK), JAXP - JAVA API for XML Parsing, `http://java.sun.com/xml`.

Instances: We implemented one fundamentalist agent. It basically concentrates its efforts only on one entity and buys the contracts only of that entity from the market. For simplification this agents posts only bids: the price at which the contracts are bought is the last paid price on the market or, if possibly, lower.

3.2 The follower

Strategy description: A "follower strategy" is one in which a trader echoes the actions of the other subjects of the market based on a pre-defined signal. In our case, the agent reacts to the price of a contract (the signal), buying when the price of the contract is high or low. The underlying assumption is that the price of a contract is a signal regarding the quality of the entity (e.g. a firm): if the contract's price is high, this means that many traders are asking for this contract and therefore we may presume that the contract is very valuable. On the other hand, if the price of the contract is very low, we may come to the conclusion that the entity whose contract is traded is not very valuable.

Real world analogy: Follower actions are quite common. Many traders rely only on the trend of the price of the contract, sometimes acting as if the contract had its own life and did not relate to a real world entity. Chart analysis, analysis based on historical data of the contract's price, is nowadays a "science" to which many traders subscribe.

Instances: We implemented two follower agents:

1. The follower high buys the contract with the highest price and does it as long as there is enough money. To put it differently, this strategy prompts to follow the mass: if the expectations about the final value of the contract are high, everyone will be willing to buy the contract. Thus, its price will be very high. This agent "adapts" its expectations to the others.
2. The follower low buys the contract with the lowest price and does it as long as there is enough money. It is basically the opposite of the first one. The trader buys the contracts which are discarded by all other traders. The price of the contract, again, reflects the expectation about the final value of the contract: the entity whose contract is bought is thought of being a sure looser. With a high probability the trader is going to incur a loss. Nevertheless, if, at the final event, the contracts bought are the paying-off ones, the agents will benefit considerably.

3.3 The stochastic

Strategy description: A "stochastic strategy" is one in which a trader buys contracts at a random price. In our case the agent does not choose a completely random price in the set of all possible numbers, rather a price which floats in a fixed range or in a range around a given value. We have implemented two kind of variations, one that uses the market rule information and one that uses the public market information to calculate the given value.

Real world analogy: Traders have different degrees of information, and traders who dispose of more information may appear to act random in the market to the eyes of poorly informed traders. A typical example may be an "inside trader" that handles contracts in a rational manner, but whose actions may appear "stochastic" to the eyes of non informed traders.

Instances: We implemented four stochastic agents. All of them continuously and randomly chose the contracts they bought and sold.

1. The *stochastic generates* its stochastic price bid/ask based on the following formula: "the stochastic price is an equally distributed value which lies between 0 and 1.5*bundle-price/number of contracts"
2. The *static stochastic* generates its stochastic price bid/ask based on a fixed predetermined parameter, so the prices of its orders will be randomly distributed around a given value. The formula states "the stochastic price lies in the range of ±

100*RV around a given value", where the random value (RV) is normally distributed between –1 and +1.

3. The *dynamic stochastic (1)* generates its stochastic price bids/asks based on a constantly changing parameter, the last price on the market. The formula states: "the stochastic price lies in the range of ± 100*RV around the last paid price", where RV is a normally distributed random value between –1 and +1. Clearly, the *dynamic stochastic agent (1)* has a higher degree of adaptation to the sub events of the market than the static stochastic.
4. The *dynamic stochastic (2)* builds its strategy on the *dynamic stochastic (1)* agent, but adds a peculiarity: it additionally modulates the quantity. The rule is as follows: the lower the last market price the higher the quantity will be chosen for bids and asks.

3.4 The arbitrageur

Strategy description: An "arbitrageur strategy" tries to earn a profit without taking a risk. This is implemented by buying a standardized portfolio from the market and selling it back to the bank or the other way around. Differently stated, the agent exploits the difference between market price and bank price for the same bundle. This will lead to sure profit when the agent can perform the complete set of transactions.

Real world analogy: This is a more elegant strategy and probably the one which bears the greatest resemblance to real trade strategies. Arbitrage trading happens daily in the markets. These actions may be performed by expert traders who can simultaneously follow different markets, but, since these actions are quite tedious and need constant attention, they can be performed by software agents.

Instances: For the arbitrageur strategy we implemented one agent. The agent considers the contracts which form the bundle X, the bundle that the bank is always ready to buy and sell at any time at a fixed price. Then it looks for the outstanding bids/asks of the single contracts forming the bundle. If the overall ask of the bundle is lower than the bank price the agent will buy the bundle from the market and afterwards resell it to the bank. Otherwise, if the best buy offers (bid) on the market sum up to a higher bundle price than the price of the bank the agent will buy the bundle from the bank and resell it to the market.

3.5 The speculator

Strategy description: This agent applies a similar strategy to the arbitrageur, though with a small but relevant difference: it does not aim for a sure win by exploiting the difference between market price and bank price, rather it "raids on the wave of speculation", pushing the willingness to pay of the other traders. To put it differently, it gives them the contracts they want gambling on the fact that in a situation of collective excitement, traders will be ready to pay a little bit more in order to possess the "hot" contract.

Real world analogy: Speculative bubbles may be our best examples. People - both experts and non experts - buy contracts because of "voices" or because in recent times the contract's value has risen tremendously (possibly because others before bought them based on the same reasoning). The speculator hopes to make money not from the "dividend" of the contract, but from the difference between buying price and selling price, trusting that the price of the contract will continue to rise even more after the contract was bought.

Instances: We implemented one speculator agent. It looks at the market price of the contracts or, better said, of the bundle of contracts: if the market price of the bundle is overvalued, that is, if the sum of the ask is greater than the bundle price at the bank, the agent buys the bundle from the bank and tries to resell it to the market at the overvalued price plus a mark-up. The formula states: "buy stock from the bank and resell it in the market at the last-price + RV* given value", where the random value (RV) is between 0 and +1 the right half of a normal distribution. The “given value” is a parameter which gives the higher cap on the mark-up or, in other words, how much more the agent may ask at maximum.

4. SIMULATION RESULTS

To test the market-agent interface, we conducted a simple simulation experiment where the market design was taken from the previously running Euro2000 market [Schmidt and Werwatz 2001]: traders could buy and sell contracts of 16 countries participating in the European soccer championships with a payoff of 1.000 units[5] for the European Champion and a payoff of 0 for all other 15 teams. The agent experiment used the same rules, yet there were some changes: the a priori probability for each contract being the winner was 1/16, the market was open only for one hour, and during that time only market information was available to the agents. Each of the 11 agents started with an initial endowment of 500.000 and without any contracts. The exact parameters of the agents' strategies are described in Table 1. To give all agents an equal opportunity to trade on the market each instance of an agent was started on the same computer consuming the same amount of CPU time and memory. In a one hour trading period the average trading volume was 2.4 Mio and there was about one market transaction, where buy and sell offers were matched, every second.

During a market run, the first active traders are the non-adaptive agents: these are the ones which start posting offers and trade with each other. At the point where the market is over-/undervalued the arbitrageur starts trading. When prices for all contracts develop all other market-adaptive agents start to post offers. A very active trader in selling contracts is the speculator, whereas the follower low is the most active in buying contracts. Yet, the overall most active traders are the stochastic agents, which are doing both, buying and selling on the market. A more background-like strategy can be observed for the fundamentalists, which try to buy their specific contract at a reasonable price. An overview on some behavioral variables of the individual software agents can be found in Table 2.

Table II. Descriptive agent results, values are the average of 30 market runs.

The time series of the market prices of the 16 contracts can be divided in two categories. The contracts the fundamentalist strategies are buying (0 and 5) on the one hand, and the rest of the contracts on the other hand. The private information of the fundamentalist, to buy contract 0 up to until 250 and contract 5 up to until 200, results in a concave rise of these contract prices, yet the information is not fully revealed (Figure 5, top left). The public information, that all contracts have a winning probability of 1/16, is revealed in the market by similar prices for the rest of the contracts. These contracts do not seem to follow a pattern, which not surprisingly suggests a random walk (Figure 5, top right). When we look at information efficiency, Fama [1970] distinguishes between markets with fully revealed private information and not revealed private information. Our market experiment revealed the private information partly, which goes in accordance with empirical market data.

Figure 5: Sample time series of traded prices of contract 5 (top left) with the corresponding trade volumes (bottom left) and contract 4 (top right and bottom right).

To our surprise the *arbitrageur* only yielded a tiny win on average and even lost money on occasions. It turned out that the agent could often not complete the whole set of trades to employ its arbitrage strategy. This is due to the market mechanism, which does not allow for atomic transaction for a set of trades in order to gain arbitrage. In the case of the

[5] Experimental currency unit

arbitrageur the result was an unbalanced portfolio, which is equal to engaging in a risk. The strategy may be improved by re-balancing the portfolio.

Given the set of implemented agents and the WTA market rule, the most successful strategy is the follower low, who attempts to buy a portfolio of low priced contracts. This agent starts his first market transaction late, waiting for the other agents to generate prices. At this point the strategy is very effective in conducting market transactions that implement a successful portfolio (see Table 2). Similar to the most successful strategy described by Rust et. al [1994] the agent can be described as "sit in the background". Yet, the follower low would not be as successful, if the fundamentalist would buy the paying-off contract, driving the prices of this contract up. Runner up is the static stochastic strategy, which also manages to get a diversified portfolio by posting rather constant prices on every contract. Not successful have been the specializing fundamentalists, who attempt to buy an extremely unbalanced portfolio. These strategies lost all their invested money in picking up a contract that did not pay off.

5. RELATED WORK

Much work has been done about automated agents in the context of electronic commerce. A good starting point on agent mediated electronic commerce can be found in Guttmann et al. [1998]. In the following, we will focus on related work that is concerned about automated negotiation. In particular we will review market based approaches, which provide a market institution and a set of rules to do the negotiation. In our context agents negotiate in a competitive environment, yet there are other approaches in the AI community, such as collaborative agents, that will not be reviewed here.

In experimental economics community work on strategies has been done by conducting tournaments [Abreu and Rubinstein 1988, Selten et al. 1997]. Rust et al. [1993, 1994] report on the Santa Fe Double Auction tournament, where researchers where invited to submit software agents that compete on a CDA market against one another. The focus was to find successful trading strategies out of the submitted set of agents. The most successful strategy in this tournament can be described as rather parasitic: sitting in the background and exploiting the strategies of other traders. In addition, they report about an evolutionary tournament, where the percentage of traders was adjusted in accordance to the success of a strategy over time. Parallel to the tournament there has been a discussion on the lower bound of traders' intelligence to act similarly to human traders in a market institution [Gode and Sunder 1993a&b, Cliff and Bruton 1998]. A recent overview on agent-based computational finance can be found in LeBaron [2000].

Applications for multi-agent systems using the CDA mechanism have been developed by the XeroX Palo Alto Research Center (Parc). This includes a system for controlling building environments, where cool air is auctioned in the Parc building [Clearwater and Huberman 1994, Huberman and Clearwater 1995]. In this application thermostat-agents buy and sell cool air with the help of a central auctioneering process. Other applications include, for example, computational resource allocation [Huberman and Hogg 1995, Clearwater XXX].

The caveat of CDA systems is that they will only be useful for spot markets, where homogenous goods can be described with a single price. Systems that handle goods with multi dimensional properties include Kasbah developed by MIT, a system where users can create autonomous agents that buy and sell goods on their behalf [Chavez and Maes 1996, Chavez et al. 1997]. This system uses a classified ad metaphor, where agents post their offers to the common blackboard and agents rely on one-to-one bargaining. A market based approach is the Michigan AuctionBot where human and artificial agents can engage in online auctions via Internet [Wurman et al.1998]. Other systems include the Fishmarket project [Rodriquez-Aguilar et al. 1998] and MAGNA [Tsvetovatyy et al. 1997], an integrated approach to an agent-based virtual market that should include all steps of a commercial interaction.

An introductory text for using economic principles in automated negotiation can be found in Binmore and Vulkan [1999]. Varian [1995] gives an introduction to economic mechanism design for computerized agents.

6. CONCLUSIONS AND OUTLOOK

We have extended an artificial stock market, used for experiments with human traders so far, with an automated agent interface. The application of a market institution resulted in a simple negotiation protocol which was implemented by using the eXtensible Markup Language (XML). For the first simulation experiment we employed a set of agents, that implemented pure and simple strategies on the ground of market rules and market information. These agents, some of which show random, others market adaptive behavior, can simulate human-like trading performance in the existence of a market institution.

Further work can compare strategies in different payoff regimes that impose different degrees of risk, e.g. vote-share markets compared to winner-takes-all markets. The analysis of the strategies should include a larger set of software agents that might be collected in a tournament, where traders might send in their own strategies. In addition, the fitness of successful strategies can be tested in an evolutionary experiment, where the population of strategies may converge towards more successful strategies. So far, the automated agents trade on behalf of rule and market information only. An extension could be to add an information source that provides a stream of news about the contracts.

The ultimate goal for further experiments is to inductively observe how agents change the strategies of human subjects operating in the electronic market. Now, the market-agent interface gives us the ability to explore this question in a laboratory environment, where human and artificial agents can participate alike.

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Table I. Agents and parameter values

#	Agent	Parameter	Value	Market transactions	Market-adaptive
1	*Fundamentalist (1)*	contract ID	0	market bid	yes
		limit price	250		
2	*Fundamentalist (2)*	contract ID	5	market bid	yes
		limit price	200		
3	*Follower High*	limit price	500	market bid	yes
4	*Follower Low*			market bid	yes
5	*Pure stochastic*			bank buy/sell, market bid/ask	no
6	*Static stochastic (1)*	mean price	65	bank buy/sell, market bid/ask	no
7	*Static stochastic (2)*	mean price	60	bank buy/sell, market bid/ask	no
8	*Dynamic stochastic (1)*			bank buy/sell, market bid/ask	yes
9	*Dynamic stochastic (2)*			bank buy/sell, market bid/ask	yes
10	*Arbitrageur*			bank buy/sell, market bid/ask	yes
11	*Speculator*	max. surplus	30	bank buy, market ask	yes

Table II. Descriptive agent results, values are the average of 30 market runs.

#	Agent	No of market trans-actions: buy	No of market trans-actions: sell	First trade after X market transactions	No of different shares in portfolio	Yield
1	*Fundamentalist (1)*	209	0	129	1	-40.9%
2	*Fundamentalist (2)*	161	0	88	1	-36.9%
3	*Follower High*	197	0	107	5.3	-45.1%
4	*Follower Low*	622	0	425	13	37.2%
5	*Pure stochastic*	570	961	8	15	11.6%
6	*Static stochastic (1)*	601	452	21	16	34.6%
7	*Static stochastic (2)*	567	474	6	15.6	30.9%
8	*Dynamic stochastic (1)*	222	151	34	16	9.3%
9	*Dynamic stochastic (2)*	191	141	32	16	10.2%
10	*Arbitrageur*	40	236	18	14.6	2.2%
11	*Speculator*	0	965	279	16	-13.1%

Figure 1: Time sequence diagram: communication between agent and market