Analysis of Micro-Behavior and Bounded Rationality in Double Auction Markets Using Co-evolutionary GP

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ABSTRACT

We investigate the dynamics of trader behaviors using a co-evolutionary genetic programming system to simulate a double-auction market. The objective of this study is two-fold. First, we seek to evaluate how, if any, the difference in trader rationality/intelligence influences trading behavior. Second, besides rationality, we also analyze how, if any, the co-evolution between two learnable traders impacts their trading behaviors. We have found that traders with different degrees of rationality may exhibit different behavior depending on the type of market they are in. When the market has a profit zone to explore, the more intelligent trader demonstrate more intelligent behaviors. Also, when the market has two learnable buyers, their co-evolution produced more profitable transactions than when there was only one learnable buyer in the market. We have analyzed the learnable traders' strategies and found their behavior are very similar to humans in decision making. We will conduct human subject experiments to validate these results in the near future.

Categories and Subject Descriptors: H.4 [Information Systems Applications]: Miscellaneous

General Terms: Economics, Experimentation, Algorithm.

Keywords: Bounded rationality, co-evolution, double-auction.

1. INTRODUCTION

> It is not from the benevolence of the butcher, the brewer, or the baker that we expect our dinner, but from their regard to their own interest.
>
> Adam Smith, The Wealth of Nations,1776

In the classic *An Inquiry into the Natures and Causes of the Wealth of Nations*, the great economist Adam Smith demonstrated that an individual pursuing his own self-interest also promotes the good of his community as a whole, through a principle that he referred to as "invisible hand". Since then, the study of individual behaviors in a market economy has evolved into the field of *microeconomics*.

In a standard market, buyers and sellers interact to determine the price of a commodity or service. During the trading process, individuals maximize their own profits by adopting different strategies based on their experiences, familiarity with the commodity and the information they acquired. These differences in individual qualities in decision making can also be explained by the concept of *bounded rationality* introduced by Herbert Simon [7], who pointed out that perfectly rational decisions are often not feasible in practice due to the finite computational resources available for making them. As a result, humans employ heuristics to make decisions rather than a strict rigid rule of optimization. The difference in human qualities in decision making is referred to as *the degree of rationality or intelligence*.

In a market which is composed of multiple self-interest traders, each of whom has a different degree of rationality, many unexpected behaviors may emerge. Our interest in studying the dynamics of these behaviors is motivated by the increasing popularity of Internet auction markets, such as *eBay* and *Amazon*. When designing an auction e-market, in addition to the maximization of macro market efficiency, the auction rules also have to consider the dynamics of auctioneers' behaviors. In particular, would a rule create the opportunity for an auctioneer to engage in unfair bidding practices? If so, how can we prevent them from happening?

This type of preventive study is not new in the Internet auction market business. For example, to prevent "sniping" (the act of submitting a slightly higher bid than the current one at the last-minute), *eBay* has incorporated software agents in the Internet bidding process. There, each auctioneer is asked to provide his/her highest bid to an assigned agent, who then carries out the auction on his/her behalf. By contrast, *Amazon* adopts a different approach by extending the auction period for 10 more minutes if a sniper appears at the end of an auction [6]. This type of preventive study is important in order to design fair and successful auction markets.

This research analyzes the behavior of traders with different degrees of rationality using a co-evolutionary GP system [2] to simulate an artificial double-auction (DA) market. This approach is different from that of experimental economics [8] in that instead of conducting experiments using human subjects, software agents are used to represent traders and to conduct market simulations under controlled settings. This paradigm of agent-based computational economics complements experimental economics to advance our knowledge of the dynamics of micro market behaviors.

2. PREVIOUS WORK

Previously, we have adopted GP to implement bounded rationality to study the co-evolution dynamics of traders behaviors in artificial DA markets [3] [4]. In those studies, the market has two types of traders: GP traders who have the ability to learn and improve their trading strategies and

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naive (no-learning ability) truth-telling traders who always present the assigned prices during an auction. To distinguish the cognitive abilities of GP traders, different population sizes were assigned to these traders.

The rationale of this design decision is based on the *learning from experience* analogy of [1]. In a DA market, a trader's strategies are influenced by two factors: the trader's original ideas of how to bid, and the experiences he/she learned during the auction process. In GP learning, the population is the brain that contains the possible strategies to be used for the next bid. It is therefore reasonable to argue that a GP trader with a bigger population size has a larger reservoir to store and process new strategies, and hence is more intelligent.

We have designed two settings to conduct the experiments. In the first setting, there was one GP buyer among a group of truth-telling traders. The experimental results showed that when assigned with a larger population size, the GP buyer was able to evolve a higher-profit strategy, which did not exist when the population size was smaller. The results suggest that when all other traders have no learning ability, more "intelligent" traders can make more profit.

In the second setting, the market had two GP buyers, who co-evolved their strategies to outdo each other and earned more profits. The experimental results showed that the competition between two GP buyers has produced more profitable transactions. To investigate the generality of these results, we have devised a less conventional market in this research to conduct our experiments. This market is described in the following section.

3. THE DA MARKET ENVIRONMENT

The artificial DA market has 4 buyers and 4 sellers, each of whom is assigned 4 private token values for trading. For buyers, these are the 4 highest prices that they are willing to pay to purchase 4 tokens and, for sellers, they are the 4 lowest prices that they are prepared to accept to sell these tokens. All sellers in the market are truth-tellers, who always gave the assigned true token value during an auction. For buyers, however, two setups were made: one with one GP buyer and one with two GP buyers. The first setting allows us to analyze GP buyers' learning behaviors under stable conditions and the second one is used to analyze the co-evolution dynamics of the two GP buyers.

Figure 1 gives the demand and supply curves of the studied market. This market is unique in that the four buyers have 4 identical token values and the four sellers have the same 4 token values (see Table 1). When all traders are truth-tellers, only 12 of 16 tokens will be traded. The remaining 4 tokens have their supply price (cost) higher than the demand prices, and hence no transaction can take place. Among the 12 traded tokens, only 4 transactions generate a profit while the other 8 do not, because the 8 tokens have the same demand and supply prices. Also, each of the 4 profitable transactions generates profit of 4, which is allocated equally to the buyer (profit 2) and the seller (profit 2). Since each trader has only 1 profitable transaction, they all have the same daily profit of 2.

However what would happen if one or two buyers were equipped with GP learning ability? Are they able to devise strategies that generate a daily profit that is > 2? The answer to this question will be given in Section 5.

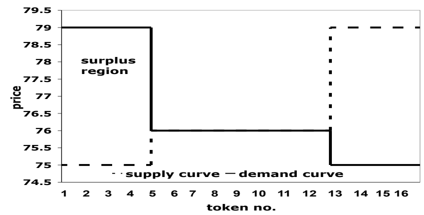

Figure 1: The Market Demand and Supply Curves.

Table 1: The Market Token Value Table

$buyer_1$	$buyer_2$	$buyer_3$	$buyer_4$	$seller_1$	$seller_2$	$seller_3$	$seller_4$
79	79	79	79	75	75	75	75
76	76	76	76	76	76	76	76
76	76	76	76	76	76	76	76
75	75	75	75	79	79	79	79

4. THE CO-EVOLUTIONARY GP SYSTEM

In the co-evolutionary GP system, each GP buyer evolves a population of strategies to use during an auction. The strategies are represented as rules. We provide 3 types of information for GP to construct these rules (see Table 2):

- Past experiences: terminals 1 – 9 and 16 – 17;
- Time information: terminals 10 – 11;
- Private information: terminals 12 – 14;

Table 2: Terminal Set

Index	*Terminal*	*Interpretation*
1	PMax	the highest transaction price OTPD[1]
2	PMin	the lowest transaction price OTPD
3	PAvg	the average transaction price OTPD
4	PMaxBid	the highest bidding price OTPD
5	PMinBid	the lowest bidding price OTPD
6	PAvgBid	the average bidding price OTPD
7	PMaxAsk	the highest asking price OTPD
8	PMinAsk	the lowest asking price OTPD
9	PAvgAsk	the average asking price OTPD
10	Time1	the number of auction rounds left for today
11	Time2	the number of auction rounds that have no transaction
12	HTV	the highest token value
13	NTV	the second highest token value
14	LTV	the lowest token value
15	Pass	pass the current auction round
16	CASK	the lowest asking price in the PAR[2]
17	CBID	the highest bidding price in the PAR
18	Constant	randomly generated constant number

[1] OTPD stands for "on the previous day"
[2] PAR stands for "previous auction round"

The three types of information are combined using logical and mathematical operators to decide the bidding prices. Table 3 lists these operators. Each DA market simulation is carried out with a fixed number of GP generations (g), where each generation lasts n ($n = 2 \times pop\_size$) days. On each day, 4 new tokens are assigned to each of the buyers and sellers. The 8 traders then start the auction rounds to trade the 16 tokens. A buyer will start from the one with the highest price and then move to the lower priced ones while a seller will start from the one with the lowest price and then move to the higher priced ones. The day ends when either all 16 tokens have been successfully traded or the maximum number of 25 auction rounds is reached. Any un-traded tokens (due to no matching price) will be cleared at the end of each day. The following day will start with a new set of 16 tokens.

Table 3: Function Set

+	-	*	%	min
>	exp	abs	log	max
sin	cos	if-then-else	if-bigger-then-else	

On each day, a GP buyer will randomly select one strategy from its population and use it the entire day to decide the bidding prices. The strategy might be to *pass* the round without giving a bid. By contrast, a truth-telling trader never *passes* an auction. A truth-telling buyer bids with the highest value of the tokens it owns while a truth-telling seller asks for the lowest value of the token it has. The same 8 strategies will play for the day's 25 auction rounds, during which a GP trader may give a different bidding price if the auction strategy uses information from the previous round/day. The truth-teller, however, will always present the same bid/ask through out the 25 rounds.

In each auction round, after all 8 traders have presented their prices, the highest bid and the lowest ask will be selected. If there are multiple buyers giving the same highest bid or multiple sellers giving the same lowest ask, one of them will be selected based on their order, i.e. buyer (seller) 1 will be picked prior to buyer (seller) 2; buyer (seller) 2 will be picked before buyer (seller) 3 and so on. If the highest bid is equal to or more than the lowest ask, there is a match and the transaction takes place using the average of the bid and ask as the final price. The profit from the two strategies (the difference between the transaction and the given token values) is recorded. The fitness of the strategy F is the accumulated profit from the traded tokens during the day:

$F = \sum_{i=1}^{m} |TokenValue_i - TransactionPrice_i|$.

where m is the number of tokens traded using the strategy. Since one strategy is randomly selected each day to carry out the auction, after $n = 2 \times pop\_size$ days, each strategy in the GP population will most likely be selected at least once and will have a fitness value at the end of each generation. This fitness value decides how each strategy will be selected and alternated to generate the next generation of new strategies.

Table 4 gives the GP parameter values used to perform simulation runs. With 2 different population sizes (10, 50) and 2 different ways to assign GP buyers, the total number of setups is 4. For each setup, we made 90 runs. The number of simulation runs made is 360.

5. RESULTS AND ANALYSIS

To conduct our analysis, we collected all evolved strategies and their daily profit (F) generated during the last 10 generations of each run. We consider these strategies to be more "mature", and hence to better represent the GP buyers' trading patterns.

When the population size is 10, each generation is $2\times 10 =$ 20 days long. On each day, one strategy is picked randomly from the population to conduct the auction. The total number of strategies used during the last 10 generations is therefore $20 \times 10 = 200$. Since we made 90 runs for this setup, the number of strategies used to conduct our analysis is $200 \times 90 = 18,000$.

Table 4: GP Parameters

Parameter	*Value*	*Parameter*	*Value*
tournament size	5	elitism size	1
initialization method	grow	max tree depth	5
population size	10,50	no. of days	2×pop_size
crossover rate	100%	subtree mutation	0.5%
no. of generation	200	point mutation	0.45%
no. of runs per setup	90	no. of GP trader	1,2

When the population size is 50, each generation is $2\times 50 =$ 100 days long. The total number of auction days during the last 10 generations for all 90 runs is $100\times 10\times 90 = 90,000$. The following subsections present our analysis of these GP evolved strategies.

5.1 One GP Buyer in the Market

When there is one GP buyer (with population size 10) in this market, the daily profit (F) generated by the 18,000 strategies is between -41 and 3.5. Among them, more than 95% of the strategies give a profit that is greater than 2, which is better than that produced by a naive truth-teller (see Section 3). This indicates that the GP buyer is more "intelligent" than the naive truth-telling buyers.

The strategies that generate a daily profit of 3.5 can be divided into two categories: `NTV` (the second highest token value) and those with length greater than or equal to 2. As shown in Table 5, `NTV` was used to conduct more than 83% of the auction, and we therefore decided to study how it generated the higher profit.

This strategy is actually quite smart: it bids with the second highest token value when all other truth-telling buyers bid the highest token price. During the first 3 auction rounds when at lease one truth-telling buyer bid the highest token value of 79, the GP buyer, who bid the second highest token value of 76, could not win the auction. However after the 3 truth-telling buyers purchased their first tokens and each earned a profit of 2, they moved to bid with the next highest token value of 76. Since buyer 1, the GP buyer, was preferred when there were multiple buyers giving the same highest bid (see Section 4), the GP buyer won the 4th auction round and performed the transaction using the average of the highest bid (76) and the lowest ask (75), which was 75.5. The token value that the GP buyer was purchasing was 79. So, the profit of this transaction for the GP buyer is $79 - 75.5 = 3.5$. In a market where all buyers have the same token values, this "waiting after all other buyers have purchased their tokens before winning the auction" is a more profitable strategy.

Did the more "intelligent" (population size 50) GP buyer devise a better strategy? We examined all 90,000 strategies but did not find one. Table 5 shows that the more "intelligent" GP buyer used profit-3.5 strategies slightly more often to conduct the auction (93% vs. 92%). Other than that, there was no significant difference between the behaviors of the GP buyers with population sizes of 10 and 50. This suggests that in a stable (all other traders are truth-tellers) market where all buyers have the same token values

Table 5: Profit 3.5 Strategies, by 1 GP buyer.

Population size	Strategy	Count	Ratio
P10	`Length` $\geq$ 2	1,653	0.0918
	`NTV`	14,957	0.8309
P50	`Length` $\geq$ 2	5,958	0.0661
	`NTV`	77,911	0.8657

Table 6: Strategies Used by 2 GP Buyers.

Population size	Buyer	Strategy	Profit	Count	Ratio
P10	buyer 1	`NTV`	4	16,414	0.9119
	buyer 2	`NTV`	3	16,265	0.9036
P50	buyer 1	`NTV`	4	83,283	0.9254
	buyer 2	`NTV`	3	82,996	0.9222

and all sellers have the same token values, a small degree of intelligence is sufficient to devise the optimal strategy (the one that generates daily profit of 3.5 is the optimal one in this market). Any increase in the traders' intelligence/rationality has no significant impact on their behaviors. In other words, the relationship between intelligence and performance is not visible.

5.2 Two GP Buyers in the Market

When both buyers 1 and 2 are equipped with GP learning ability, the trading behaviors become more complicated. Table 6 gives information about the 2 most used strategies by the 2 GP buyers under population sizes of 10 and 50.

It appeared that both GP buyers learned the `NTV` strategy. When they used this strategy to bid against each other, GP buyer 1 earned a daily profit of 4 while GP buyer 2 earned a daily profit of 3. How did this happen?

We traced the market daily transactions and found that the bias in the market setup gives GP buyer 1 an advantage over GP buyer 2 who also has an advantage over buyers 3 & 4. During the first 2 auction rounds, each of the two truth-telling buyers (who bid 79) won one auction round and made a profit of 2 by carrying out the transaction using a price of $(79 + 75)/2 = 77$. In round 3, all buyers bid the second highest token value of 76. However, buyer 1, a GP buyer, is selected, based on the market setup, to carry out the transaction using the price of $(76 + 75)/2 = 75.5$. The profit earned by buyer 1 is therefore $79 - 75.5 = 3.5$. In the next auction round, all buyers bid 76 again and buyer 1 is again selected to carry out the transaction using the price of 75.5. Since GP buyer 1 is purchasing the second token whose value is 76, the profit for this transaction is $76 - 75.5 = 0.5$. After that, GP buyer 1 did not make any profitable transaction and its total daily profit is 4.

The second buyer, who also has GP learning ability, only gets to win the auction in round 5 when the first GP buyer has purchased two tokens. In round 5, GP buyer 1 bids its next highest token value of 75 (see Table 1) and all other buyers bid 76. Buyer 2, a GP buyer, is selected over buyer 3 and 4 to carry out the transaction using the price $(76 + 76)/2 = 76$ (note that all 4 sellers are trading their second lowest token with a value of 76 as each has sold its 75 token during the first 4 auction rounds). Since GP buyer 2 is purchasing its first token with value 79, the profit gained in this transaction is $79 - 76 = 3$. After that, no market transactions are profitable due to the increase in seller token prices and the decrease in buyer token prices. The second GP buyer earned a total daily profit of 3.

When the population size of both GP buyers is increased to 50, Table 6 shows that there is no significant difference in their behaviors. This might also be due to the market type, as explained previously.

6. CONCLUDING REMARKS

In the market we have studied, the co-evolution of two self-interested GP buyers has produced more profitable transactions than when there was only one GP buyer in the market. This phenomenon was also observed in our previous work [3] [4]. In other words, an individual pursuing his own self-interest also promotes the good of his community as a whole. Such behavior is similar to that of humans in real markets as demonstrated by Adam Smith. Although we have only studied the case where only buyers have GP learning ability, this result suggests that to some degree, the GP trader agents have similar qualities to humans in decision making. Meanwhile, the co-evolution dynamics in the devised artificial DA market resembles the dynamics of real markets. We will continue to investigating the market dynamics when both buyers and sellers have GP learning ability.

Our analysis of the GP-evolved strategies shows that GP buyers with different degrees of rationality did not exhibit different behavior. This is different from that reported in [3] [4]. There, the supply and demand prices in the market have room to exploit a higher profit and the more intelligent GP buyers have exhibited more intelligent behaviors, such as using higher-profit strategies more frequently or cooperating with each other to earn more profits. This suggests that the intelligent behavior of a GP trader becomes visible when the market has a profit zone to explore.

All of the observed individual traders' learning behavior make intuitive sense. Under the devised artificial DA market platform, GP agents demonstrate human-like rationality in decision making. We plan to conduct human subject experiments to validate these results in the near future.

7. REFERENCES

[1] W.B. Arthur. On designing economic agents that behave like human agents. *Journal of Evolutionary Economics*, 3:1–22, 1993.

[2] S.-H. Chen and C.-C. Tai. Trading restrictions, price dynamics and allocative efficiency in double auction markets: an analysis based on agent-based modeling and simulations. *Advances in Complex Systems*, 6(3):283 – 302, 2003.

[3] S.-H. Chen, R.-J. Zeng, and T. Yu. Co-evolving trading strategies to analyze bounded rationality in double auction markets. In R. Riolo, T. Soule and B. Worzel, editors, *Genetic Programming: Theory and Practice VI*, pages 195 – 213. Springer, 2009.

[4] S.-H. Chen, R.-J. Zeng, and T. Yu. Bounded Rationality and Market Micro-Behaviors: Case Studies Based on Agent-Based Double Auction Markets *submitted*, 2009.

[5] J. R. Koza. *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, MIT Press, , 1992.

[6] A. E. Roth and A. Ockenfels. Last-minute bidding and the rules for ending second-price auction: evidence from Ebay and Amazon auctions on the Internet. *American Economic Review*, 92:1093 – 1103, 2002.

[7] H. A. Simon. Behavioral economics and bounded rationality. In H. A. Simon, editor, *Models of Bounded Rationality*, pages 267 – 298. MIT Press, 1997.

[8] V. Smith. Experimental economics: induced value theory. *American Economic Review*, 66(2):274 – 279, 1976.