

Is Genetic Programming “Human-Competitive”? The Case of Experimental Double Auction Markets

Chen Shu-Heng and Shih Kuo-Chuan

AIECON research center, Department of Economics, National Chengchi University,
Taipei, Taiwan
`{chen.shuheng,melvinshih}@gmail.com`

Abstract. In this paper, the performance of human subjects is compared with genetic programming in trading. Within a kind of double auction market, we compare the learning performance between human subjects and autonomous agents whose trading behavior is driven by genetic programming (GP). To this end, a learning index based upon the optimal solution to a double auction market problem, characterized as integer programming, is developed, and criteria tailor-made for humans are proposed to evaluate the performance of both human subjects and software agents. It is found that GP robots generally fail to discover the best strategy, which is a two-stage procrastination strategy, but some human subjects are able to do so. An analysis from the point of view of cognitive psychology further shows that the minority who were able to find this best strategy tend to have higher working memory capacities than the majority who failed to do so. Therefore, even though GP can outperform most human subjects, it is not “human-competitive” from a higher standard.

Keywords: Experimental Markets, Double Auctions, Genetic Programming, Human-Competitiveness, Working Memory Capacity.

1 Introduction and Motivation

The Double Auction market (DA) has a long history in experimental economics [1]. It serves as an important foundation for public policy and market mechanism designs [2]. It also plays an important role in the understanding of the strategic behavior of individual agents [3] [4] [5] [6]. Recently, it has been studied from a psychology viewpoint to observe the effects of cognitive capacity on traders’ and the market’s performance [7] [8]. It has been intensively simulated by agent-based models using software agents [9].

Chen and Yu [9] proposed a series of agent-based simulations on the double auction markets, using one kind of machine learning, namely, genetic programming (GP), in their simulation. It was found that GP agents are smart in terms of market timing. Specifically, they attempted to postpone their participation in the market transaction so as to avoid early competition and become a *monopsonist* at a later stage. This strategy is then called the *theory of optimal procrastination* to signify the best way to trade under a specific market environment. As explained in Koza *et al.*

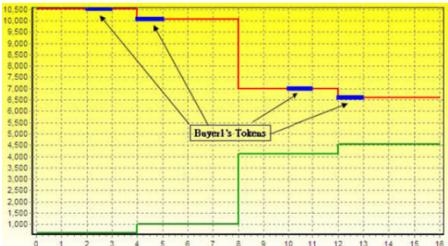
[10], eight criteria have been described in the field of artificial intelligence, machine learning, and GP; based on those criteria, GP in 36 instances are shown to be human-competitive. In this vein, we ask the question: can we have an additional instance of showing the human-competitiveness of GP? In other words, is GP human-competitive in the double auction markets?

To rigorously compare GP agents with human subjects, we need to observe whether the agent has learned the theory of optimal procrastination and when. In addition, if the agent failed to learn the theory, we need to know how far he is away from there. Only after we can answer these questions, can a comparison of the performance of human subjects and software agents be meaningfully conducted. The earning that the agent obtained in an experiment can certainly tell us something about whether the agent has learned, but it is not precise enough to indicate when he learned and how far away he was if he did not learn. In this paper, we therefore present a learning index which is able to dynamically characterize the agent’s learning status.

The rest of the paper is organized as follows. Section 2 describes the design of the double auction market experiments. Section 3 is the main contribution of the paper. The work here is divided into three parts. Section 3.1 first transforms the double auction experiments into an integer programming problem, and the optimal solution to the problem serves as the benchmark on which the performance comparisons of GP and human subjects are based. Section 3.2 then develops a learning index to evaluate the learning performance of human subjects during the experiments. The essence of this proposed learning index is to separate very different learning dynamics of human subjects. Section 3.3 further develops the accident-tolerance criteria, which are tailor-made for humans. Using these criteria, we are able to identify whether the human subjects have learned and when. Section 4 applies these criteria to classify the human subjects into two groups, the group that learned and the group that did not, and then study the contribution of cognitive capacity to this difference. Section 5 presents the concluding remarks.

2 Human Experiments

Based on the experiment settings of Chen and Yu [9], four experimental double auction markets are designed. Each market is characterized by a supply-demand curve which indicates the value of tokens assigned to 4 buyers and 4 sellers. This assigned token value controls the buyer’s highest willingness to pay and the seller’s minimum acceptable price. An example (Market IV) is given in Figure 1. In order to make deals, buyers and sellers can submit bids or asks at each step; however, only the buyer with the highest bid (current bid) and the seller with the lowest ask (current ask) are qualified to engage in transactions. If there are two or more qualified buyers or sellers, one of them will be determined randomly. Of course, a transaction can be made only if the current bid is greater than or equal to the current ask, and in this case the transaction price will be the average of the two. The gain from the trade is then simply the difference between the transaction price and the value of the respective token. The process lasts for 25 steps unless all possible deals are finished earlier. To give human subjects the opportunity to learn from their experience, a duration of 30 periods is set for each experiment.



	Token1	Token2	Token3	Token4
Buyer1	10518	10073	6984	6593
Buyer2	10519	10072	6981	6593
Buyer3	10516	10071	6985	6589
Buyer4	10521	10071	6987	6590
Seller1	622	1013	4102	4547
Seller2	622	1010	4101	4548
Seller3	618	1014	4100	4545
Seller4	619	1016	4100	4550

Fig. 1. The Supply-Demand Curve for Market IV

In our experiments, one human subject is matched with seven software agents. All human subjects are assigned the same role, specifically, Buyer One. Other buyers and sellers are taken up by software agents that are designed using the truth-teller strategy, which is to bid and ask at the given token value. This design is equivalent to Chen and Yu [9] except that Buyer One in their markets is a GP robot rather than a human subject. The fixed design makes it easier to trace and analyze the performance of either the human subject or the software agent.

A series of DA experiments was conducted in the year 2010. All subjects were college or graduate students of universities in Taipei. Furthermore, they had formerly taken part in another series of DA experiments [8] and were recruited from the experimental subject database of the AIECON Research Center. Moreover, the experiment's environment was developed using JAVA programs. Each human subject participated in the DA experiments in a computer laboratory. Before the experiments, a 90-minute tutorial was given to ensure that all subjects fully understand how the programs and the market mechanisms operated. However, they were not told that their opponents (the software agents) were truth tellers. To entice the subjects to do their best, the subjects were paid a fixed attendance fee and, depending on their market performance, some additional amounts. A total of 165 subjects participated in these experiments.

3 Performance Measurement

3.1 The DA Market as a Combinatorial Optimization Problem

The experimental design can be modeled as a *constrained combinatorial optimization problem* [11] or an integer programming problem, i.e., to maximize Buyer One's consumer's surplus or transaction gains (Equation (1)) subject to the 20 constraints (Equations (2) to (21)). Notations of the variables in these equations are given in Table 1. Many of the variables are Boolean. Basically, we use these Boolean variables and the inequalities and predicates derived to represent the trading mechanism (time flow, transaction schedule, trading sequence of tokens, correlations among bids, asks and transactions) associated with the double auction market in general and the market specifically comprised of truth tellers. Many of the constraints are applied to buyers and sellers symmetrically. To save space, we combine these symmetries into one constraint, but use the symbol \parallel to separate them.

Objective Function.

$$\max \sum_j^{np} \sum_k^{nt} [(btv_{1,k} - DV_j) * BW_{1,k,j}] \quad (1)$$

Constraints.

$$\forall b, j, k \ BW_{b,k,j} \leq BT_{b,k,j} \quad \parallel \quad \forall s, j, k \ SW_{s,k,j} \leq AT_{s,k,j} \quad (2)$$

$$\forall j \ \sum_s^{ns} \sum_k^{nt} SW_{s,k,j} = \sum_b^{nb} \sum_k^{nt} BW_{b,k,j} \quad (3)$$

$$\forall j \ \sum_b^{nb} \sum_k^{nt} BW_{b,k,j} \leq 1 \quad \parallel \quad \forall j \ \sum_s^{ns} \sum_k^{nt} SW_{s,k,j} \leq 1 \quad (4)$$

$$\forall b, k \ \sum_j^{np} BW_{b,k,j} \leq 1 \quad \parallel \quad \forall s, k \ \sum_j^{np} SW_{s,k,j} \leq 1 \quad (5)$$

$$\forall b \ \sum_j^{np} \sum_k^{nt} BW_{b,k,j} \leq nt \quad \parallel \quad \forall s \ \sum_j^{np} \sum_k^{nt} SW_{s,k,j} \leq nt \quad (6)$$

$$\forall b \in 2..4, j \ BV_{b,j} = \sum_k^{nt} (BT_{b,k,j} * btv_{b,k}) \quad (7)$$

$$\forall s, j \ AV_{s,j} = \sum_k^{nt} (AT_{s,k,j} * stv_{s,k}) \quad (8)$$

$$\forall b, j \ \sum_k^{nt} BT_{b,k,j} \leq 1 \quad \parallel \quad \forall s, j \ \sum_k^{nt} AT_{s,k,j} \leq 1 \quad (9)$$

$$\forall b \ BT_{b,1,1} = 1 \quad \parallel \quad \forall s \ AT_{s,1,1} = 1 \quad (10)$$

$$\forall b, j \in 2..np \ BT_{b,1,j} = BT_{b,1,j-1} - BW_{b,1,j-1} \quad \parallel$$

$$\forall s, j \in 2..np \ AT_{s,1,j} = AT_{s,1,j-1} - SW_{s,1,j-1} \quad (11)$$

$$\forall b, k \in 2..nt, j \in 2..np \ BT_{b,k,j} = BT_{s,k,j-1} + BW_{s,k-1,j-1} \quad \parallel$$

$$\forall s, k \in 2..nt, j \in 2..np \ AT_{s,k,j} = AT_{s,k,j-1} + SW_{s,k-1,j-1} \quad (12)$$

$$\forall s \ \sum_j^{np} SW_{s,nt+1,j} = 0 \quad (13)$$

$$\forall j \ \sum_b^{nb} BB_{b,j} = 1 \quad \parallel \quad \forall j \ \sum_s^{ns} BS_{s,j} = 1 \quad (14)$$

$$\forall b, j \ BB_{b,j} \geq \sum_k^{nt} BW_{b,k,j} \quad \parallel \quad \forall s, j \ BS_{s,j} \geq \sum_k^{nt} SW_{s,k,j} \quad (15)$$

$$\forall j \ BBV_j = \sum_b^{nb} (BB_{b,j} \times BV_{b,j}) \quad \parallel \quad \forall j \ BAV_j = \sum_s^{ns} (BS_{s,j} \times AV_{s,j}) \quad (16)$$

$$\forall b, j \ BBV_j \geq BV_{b,j} \quad \parallel \quad \forall s, j \ BAV_j \leq AV_{s,j} \quad (17)$$

$$\forall j \ \sum_b^{nb} \sum_k^{nt} BW_{b,k,j} = D_j \quad (18)$$

$$\forall j \ (BBV_j - BAV_j) \times D_j \geq 0 \quad (19)$$

$$\forall j \ (BBV_j - BAV_j) < D_j \times bm \quad (20)$$

$$\forall j \ 2 \times DV_j = (BBV_j + BAV_j) \quad (21)$$

Table 1. Description of Variables

b	Index for buyers	nb	number of buyers
s	Index for sellers	ns	number of sellers
j	Index for steps	np	number of steps
k	Index for tokens	nt	number of tokens
$b_{tv_{b,k}}$	value of token k for buyer b	$stv_{s,k}$	value of token k for seller s
bm	A very big number		
$BW_{b,k,j}$	The judgment of the for buyer b for token k at step j [0,1]	$SW_{s,k,j}$	The judgment of the winner for seller s for token k at step j [0,1]
$BT_{b,k,j}$	The judgment of the bidden token for buyer b for token k at step j [0,1]	$AT_{s,k,j}$	The judgment of the asked token for seller s for token k at step j [0,1]
$BV_{b,j}$	The bidden value of buyer b at step j	$AV_{s,j}$	The asked value of seller s at step j
$BB_{b,j}$	The judgment of the best buyer for buyer b at step j [0,1]	$BS_{s,j}$	The judgment of the best seller for seller s at step j [0,1]
BBV_j	The best bid value at step j	BAV_j	The best ask value at step j
D_j	The judgment of whether a deal is made at step j [0,1]	DV_j	The deal value at step j

The best trading strategy as a solution for the problem (1)-(21) can be obtained by applying the branch-and-bound method to solve the formulated integer programming problem. Taking Market IV as an example, we solve the constrained combinatorial optimization problem and present the unique optimal strategy in the right panel of Figure 2. The last column of the panel articulates the best market timing. The time to enter the market is denoted by “Yes”. The bid is shown in the second column of this panel. A value of “-1” means “to pass” (no action). As we can now read from this example, the optimal time to enter the market is at step 7, 8, 15, and 16 with a bid of 6,988, 6,988, 4,548, and 4,550 respectively. In this way, Buyer One can earn a maximum profit of 17,067. According to the Chen and Yu [9], this optimal strategy can be understood as a *two-stage procrastination strategy*: Buyer One holds his first two bids up to step 7 and the last two bids up to step 15. The intuition behind this two-stage procrastination is that, as shown in Figure 1, there is a sharp fall in the market demand curve accompanied by the sharp rise in the supply curve. This large-change topology suggests dividing the sequence of actions into two, one before the change and one after the change.

Using this optimal solution as a baseline, other solutions either found by software agents or human agents can then be compared. Chen and Yu [9] applied GP to solve the same problem, and the most commonly found solution is shown in the left-panel of Figure 2. Both the market timing and the bids are in sharp contrast to the benchmark. Basically, instead of using the two-stage procrastination strategy, the rule found by GP is a kind of one-stage procrastination strategy, which can be imagined as a local optimum trapped in a rugged landscape. However, with the presence of the discontinuity topology of Market IV, a single procrastination fails to lead to the maximum profit. In the same way, we will examine the solutions found by human subjects, possibly by their heuristics or gut feeling during the experiments, and evaluate their performance in relation to GP.

GP simulation			Optimization		
Step	Bid value	deal?	Step	Bid value	deal?
1	-1		1	-1	
2	618		2	-1	
3	619		3	-1	
4	622		4	-1	
5	622		5	-1	
6	1010		6	-1	
7	1013		7	6988	Yes
8	1014		8	6988	Yes
9	1016		9	-1	
10	4100		10	-1	
11	4100		11	-1	
12	4101		12	-1	
13	4102		13	-1	
14	4545	Yes	14	-1	
15	4545		15	4548	Yes
16	4547	Yes	16	4550	Yes
17	4547		17	-1	
18	4548	Yes	18	-1	
19	4548		19	-1	
20	4550	Yes	20	-1	
21	-1		21	-1	
22	-1		22	-1	
23	-1		23	-1	
24	-1		24	-1	
25	-1		25	-1	

Fig. 2. Trading Strategy: GP [9] (Left Panel) and the Benchmark (Right Panel)

3.2 Learning Index

Observing the learning behavior of the human subjects can sometimes be a very perplexing task. Humans are emotional beings with physical limits and are not fault free. Their behavior in the laboratory may be difficult to replicate by any software agent, which generally does not share the human nature. This fundamental difference may call for a tailor-made evaluation design for humans, if we do not want to blindly treat humans as mechanical beings. In this subsection, we are going to develop a learning index, which can help us to better answer the questions with regard to the learning behavior of human subjects, in particular, whether they learned and when. We attempt to have a scoring system which can separate or self-classify very different types of learning behavior. As a concrete example, what is proposed in this section is a learning index built upon three criteria, namely, *the maximum earning*, *precise moment*, and *minimum effort*. These three provide some related but not redundant information about the learning behavior of human subjects. The first two criteria inform us of the global and local behavior of subjects, whereas the last one tells us about the trial-and-error effort made by the subject.

Maximum Earning. Regardless of what the subject bid and when he bid, as long as he can earn the maximum trading profit, a substantial 1,000 points are granted to distinguish the subjects who may have found, or have the potential to find, the best strategy from those who simply have no clue yet.

Precise Moment. In our experiments, many subjects failed to earn the maximum profit, but they may still learn part of the structure. To characterize the degree of partial learning, 100 points will be given for any of their single bids which match well with one of the bids in the optimal strategy, by time and by value.

Minimum Effort. Minimum effort means that subjects will trade by minimizing the number of the bidding frequencies. Take Figure 2 as an example. As shown by the right panel, only four times are required to bid. Hence, additional frequencies of bids will be considered unnecessary. While these may do no harm to the accumulated profits of the subject, the unnecessary effort made to trade may signal the possibility that the subject is still in a trial-and-error process, even though he almost already has the best solution. Therefore, minus one point shall be given for each of these unnecessary trials to downwardly adjust his learning performance.

Index	Round																															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30		
-5	99	1098	1098	4	1096	196	1196	1297	1397	1299	1398	1399	1398	1398	6	1398	1298	1398	1398	1400	1398	1400	1397	1398	1297	1399	1298	1398	1398	1398		
step1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step3	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step4	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step5	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step6	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step7	-1	6988	6988	6988	-1	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988		
step8	-1	6986	6987	6987	6987	6987	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988		
step9	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step10	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step11	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step13	-1	-1	-1	-1	4545	4545	4545	4545	4545	-1	4548	-1	4548	-1	4548	4548	4548	4548	4548	4548	4548	-1	4548	-1	4548	4548	4548	4548	4548	4548	4548	
step14	4545	-1	-1	-1	4545	4545	4548	4547	4547	4548	-1	4548	4548	4548	4548	4550	4548	4548	4548	4548	4548	-1	4548	-1	4548	4548	4548	4548	4548	4548	4548	4548
step15	4545	4547	-1	-1	4547	4545	4545	4547	4547	4548	-1	4548	-1	4548	4548	4548	4548	4548	4548	4548	4548	4548	-1	4548	4548	4548	4548	4548	4548	4548	4548	4548
step16	4547	4748	4548	4548	4548	4548	4548	4548	4548	4550	4548	4548	4550	4548	4550	4550	4548	4548	4548	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550		
step17	4547	4749	4548	4548	4548	4548	4548	4548	4548	4548	4550	-1	4550	-1	4550	-1	4550	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548	
step18	4748	-1	4550	4550	4550	4550	4550	4550	4550	4550	-1	4551	-1	4551	-1	4551	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548	-1	4548
step19	4548	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step20	4550	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step21	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step22	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step23	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step24	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			
step25	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1			

Fig. 3. Learning Index Applied to Subject #1331

As an illustration, the proposed index applied to Subject #1331 is shown in Figure 3. The second row (the “Index” row) gives the sum of three scores for each of the three criteria. For example, the last column (period 30) shows that the subject did earn the maximum trading profits. In addition, the bids and bidding times are the same as the optimal solution. Hence, based on the first two criteria, a sum of 1,400 points (1000+4*100) is given to him. However, he also made two unnecessary early bids for the last two tokens; by the third criterion, he lost two points (-2). Therefore, his LI over the three criteria at period 30 is 1398 points. This, compared to the initial levels of “-5” (period 1) and “98” (period 2), shows a significant improvement. One, however, has to notice that LI, very typically, is not monotonically increasing in time. The LI of the subject falls sharply from a peak of “1,398” in period 15 to “-6” in period 16. This subtlety raises an issue with regard to the learning stability of humans and compels us to think harder as to whether and when the subject has learned the optimal strategy, an issue to which we now turn.

3.3 Learned or Not? An Accident-Tolerance Criterion

The next issue is to use the learning index (LI) developed above to decide whether the subject has actually learned the best strategy. This decision is more subtle than what one might think. Using the example above, can we consider a subject with a score of 1,400 to be a subject who has learned? The answer is *yes*, if he could repeatedly gain this score, but what happens if he does not. The idea to be discussed below is to allow for a kind of deviation which we shall call an *accident* and to develop an *accident-tolerance criterion* for determining whether the agent has learned.

To begin, let us consider the landscape of LI. The proposed LI maps the performance of subjects into several different plateaus. Both the first and the second criteria of the LI above contribute to the drifts. These drifts, therefore, help us to distinguish several different types of trading performances, and the one which concerns us most is the highest plateau, namely, the LI from 1,375 to 1,400.¹ Subjects who are able to obtain a score in this range are the ones who have already made the maximum profits, but did not minimize the number of bids. These additional bids (efforts) may be interpreted as a kind of *trembling* around the optimal value. This trembling may signify that the subjects have already learned the best strategy as long as they repeatedly behave in this way.

However, this is not a one-shot game. We, therefore, have to consider the case where the subject has learned the best strategy, but his LI may occasionally fall down to the other plateau (see Figure 3 for an illustration). These falls may occur for the following reasons. First, the subject was tired and made operational mistakes. Second, the subject did not know that he had already found the optimal strategy and attempted to explore further before realizing that nothing was there. Falls of these kinds can then be tolerated as long as they do not occur frequently. *Hence, a subject is considered to have learned the best strategy if he can stay on the highest plateau long enough to make any fall look like an accident.*

Criteria	Period	-6	-5	-4	-3	-2	-1	Current period
LI = 1400								
1400 > LI \geq 1395								
1400 > LI \geq 1390								
1400 > LI \geq 1380								
1400 > LI \geq 1375								

Fig. 4. Accident-tolerance Criteria for Deciding Whether the Subject Has Learned

The discussion above motivates the development of the accident-tolerance criteria. One example is the one given in Figure 4. Depending on the score that the subject has, we can accept different frequencies of fall. As suggested in the figure, it is sufficient to consider that the subject has learned the best strategy if he had the highest score (1,400) twice over the last three periods. In other words, if he has been

¹ Our design of the LI by following the three criteria does not allow any possible score to lie between 1,300 and 1,375. In other words, the plateau next to this highest one starts from 1,300 and below.

really good on two occasions, then missing once is accepted as an accident. In a similar vein, we also consider a subject to have learned if his scores are between 1,395 and 1,400 three times over the last four periods, or between 1,390 and 1,400 four times over the last five periods, and so on and so forth, or if his scores are between 1,375 and 1400 six times over the last seven periods. In sum, the higher the degree of the trembling, the longer that the stay in the plateau is required for the subject to be considered to have learned.

4 Learning Performance and Working Memory

The learning index (Section 3.2) and the accident-tolerance criteria (Section 3.3) are now applied to the 165 subjects. The results are shown in Figure 5. To avoid redundancies, we only show those subjects who have learned, at least once, in the sense of the accident-tolerance criteria (Figure 4). In other words, one of the five possibilities must apply for the subject at least once during the 30-period experiment; if that never happens, the subject simply did not learn the best strategy and is not shown here. In this way, the learning dynamics of 29 subjects are presented in Figure 5. The grayed cell means that one of the accident-tolerance criteria applies for the respective agent in the respective period. Close to 20% of the 165 subjects had been able to visit the best strategy. Some were able to do so in the very beginning, like subject #1165; some needed a longer time to do so, like subject #1384.

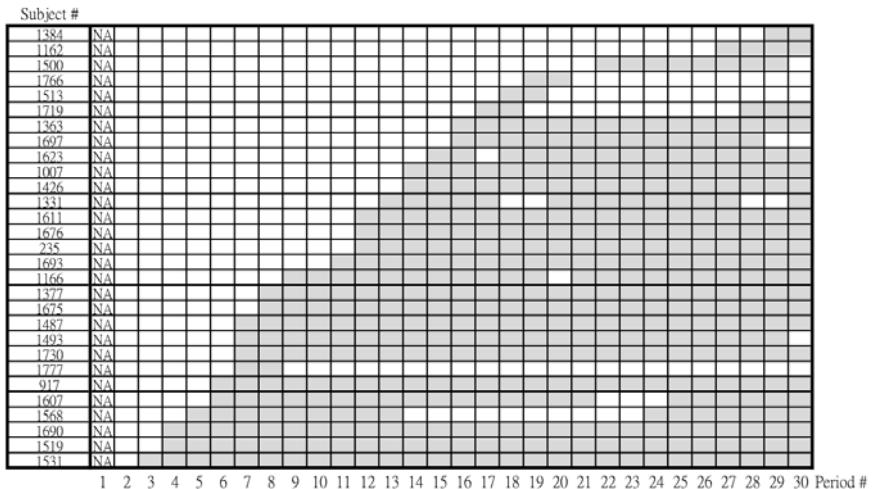


Fig. 5. Learning Performance

We further study the cognitive capacity of the subjects who learned and those who did not. The cognitive capacity of the subject is measured by a version of the working memory (WM) test [12]. Subjects are clustered into the groups: the performing group who learned (29 subjects) and the non-performing group who did not learn (136 subjects). It is found that the mean WM test score is 0.28036 for the performing

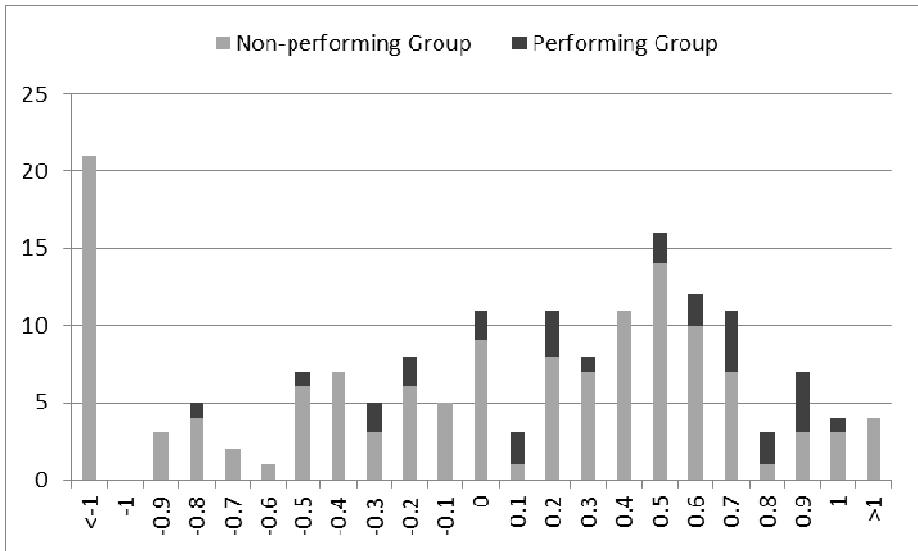


Fig. 6. Score Distribution of the Working Memory Test

group, but only -0.12648 for the non-performing group; the population average is -0.05004. This finding with regard to the significance of cognitive capacity is consistent with the one of Chen et al. [8]. Figure 6 gives the distribution of the WM Test Scores for the 165 subjects.

5 Conclusions

While the human-competitiveness of GP has been shown in many recent studies [10], in the context of double auction market experiments, we found that a small group of human subjects can perform better than GP. Specifically, this group of human subjects with a working memory capacity higher than average can successfully learn to use the optimal procrastination strategy to trade, while GP rarely can find this solution. Our analysis of the learning behavior of human subjects, including the proposed LI and the accident-tolerance criteria, is tailor-made for humans. We hope that the approach proposed in this paper can advance a more delicate analysis of the learning perplexity of human behavior observed in the human-subject laboratory.

One thing which deserves a more careful treatment is a further look at the patterns within the performing group and those within the non-performing group, both from a dynamic viewpoint, since our proposed LI and accident-tolerance criteria may reveal many interesting hidden learning dynamics which are not easy to catch by eye-browsing. In addition, to see the usefulness of our proposed tailor-made approach for human subjects, it is necessary to apply it to more human subject experiments. This will be the focus of our next study.

Acknowledgments. The authors are grateful to two anonymous referees for their painstaking reviews. The paper has been rewritten substantially in light of their very constructive suggestions. NSC research grants no. 98-2410-H-004-045-MY3 and no. 99-2811-H-004-014 are gratefully acknowledged.

References

1. Smith, V.L.: An Experimental Study of Competitive Market Behavior. *Journal of Political Economy* 70(2), 111–137 (1962)
2. Furuhata, M., Perrussel, L., Thévenin, J.-M., Zhang, D.: Experimental Market Mechanism Design for Double Auction. In: Nicholson, A., Li, X. (eds.) *AI 2009. LNCS*, vol. 5866, pp. 1–10. Springer, Heidelberg (2009)
3. Gjerstad, S.: The Strategic Impact of Pace in Double Auction Bargaining. In: IEDAS, <http://129.3.20.41/eps/mic/papers/0304/0304001.pdf>
4. Deshmukh, K., Goldberg, A.V., Hartline, J.D., Karlin, A.R.: Truthful and Competitive Double Auctions. In: Möhring, R.H., Raman, R. (eds.) *ESA 2002. LNCS*, vol. European Symposium on Algorithms, p. 361. Springer, Heidelberg (2002)
5. Rust, J., Miller, J., Palmer, R.: Behavior of Trading Automata in a Computerized Double Auction Market. In: Friedman, D., Rust, J. (eds.) *Double Auction Markets: Theory, Institutions, and Laboratory Evidence*. Addison Wesley, Redwood City (1993)
6. Rust, J., Miller, J., Palmer, R.: Characterizing Effective Trading Strategies: Insights from a Computerized Double Auction Tournament. *Journal of Economic Dynamics and Control* 18, 61–96 (1994)
7. Ariely, D., Norton, M.I.: Psychology and Experimental Economics: A Gap in Abstraction. *Current Directions in Psychological Science* 16(6), 336–339 (2007)
8. Chen, S.H., Tai, C.C., Yang, L.X., Shih, K.C.: The Significance of Working Memory Capacity in Double Auction Markets: Modeling, Simulation and Experiments. In: The 2011 Allied Social Sciences Association Meetings, January 6-9. Denver, Colorado (2011)
9. Chen, S.H., Yu, T.: Agents Learned, but Do We? Knowledge Discovery Using the Agent-based Double Auction Markets. *Front. Electr. Electron. Eng.* 6(1), 159–170 (2011)
10. Koza, J.R., Keane, A.M., Streeter, M.J., Mydlowec, W., Yu, J., Lanza, G.: *Genetic Programming IV: Routine Human-Competitive Machine Intelligence*. Kluwer Academic Publishers, Dordrecht (2003)
11. Xia, M., Stallaert, J., Whinston, A.B.: Solving the Combinatorial Double Auction Problem. *European Journal of Operational Research* 164, 239–251 (2005)
12. Lewandowsky, S., Oberauer, K., Yang, L.-X., Ecker, U.K.H.: A Working Memory Test Battery for MatLab. *Behavior Research Methods* 42(2), 571–585 (2011)