# Does Cognitive Capacity Matter When Learning Using Genetic Programming in Double Auction Markets?

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**Abstract.** The relationship between human subjects' cognitive capacity and their economic performances has been noticed in recent years due to the evidence found in a series of cognitive economic experiments. However, there are few agent-based models aiming to characterize such relationship. This paper attempts to bridge this gap and serve as an agent-based model with a focus on agents' cognitive capacity. To capture the heterogeneity of human cognitive capacity, this paper employs genetic programming as the algorithm of the learning agents, and then uses population size as a proxy parameter of individual cognitive capacity. By modeling agents in this way, we demonstrate a nearly positive relationship between cognitive abilities and economic performance.

## 1 Introduction

Information and cognitive capacity are the two sources of bounded rationality of human decision makers. While economists, either theorists or experimentalists, have mainly emphasized the importance of information, the significance of cognitive capacity has been lost but started to regain its position in economic experiments in recent years. We term experimental studies which discuss the implications of the heterogeneous cognitive capacity of human decision makers as ***cognitive economic experiments*** to highlight their emphasis on *human decision makers'* cognitive capability.

Some of the earliest experimental ideas concerning cognitive capacity came from Herbert Simon, who was the initiator of bounded rationality and was awarded the Nobel Memorial Prize in Economics. In problems such as the "concept formation" experiment and the arithmetic problem, Simon pointed out that the problem was strenuous or even difficult to solve, not because human subjects did not know how to solve the problem, but mainly because such tasks could easily overload human subjects' "working memory capacity" and influence their performance when decision supports such as paper and pencil were lacking [1].

More concrete evidence comes from the economic laboratories. Devetag and Warglien (2003) found a significant and positive correlation between subjects'

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short-term memory scores and conformity to standard game-theoretic prescriptions in the games [2]. Devetag and Warglien (2008) pointed out that subjects construct representations of games of different relational complexity and will play the games according to these representations. It is shown that both the differences in the ability to correctly represent the games and the heterogeneity of the depth of iterated thinking in games appear to be correlated with short term-memory capacity [3]. These cognitive economic experiments, together with other emerging ones such as Segal and Hershberger (1999), Casari, Ham, and Kagel (2007), and Jones (2008), demonstrate the economic significance of human decision makers' cognitive capacity at both the individual level and the aggregate level [4][5][6].

While more and more evidence is discovered by experimental economists in various game and market settings, most agent-based economic models, as a complementary research tool to human experiments, do not take cognitive capacity and its heterogeneity into account in a corresponding way[1]. This creates a discrepancy between human experiments and agent simulations in economic research, whereas there is a tendency to integrate these two fields to advance our understanding of economic systems.

This paper aims to make an effort to eliminate this gap. To achieve this goal, an operable method to characterize the cognitive capacity of autonomous agents should be proposed. In this paper, Genetic Programming (GP) is employed as the agents' learning algorithms in double auction markets. GP is employed to model agents because it can develop efficient strategies autonomously based on relatively little background knowledge. Furthermore, the parameter of population size will be regarded as the proxy variable for traders' cognitive ability. In so doing, we have a chance to advance our understanding of the hypothetical link between cognitive capacity and economic performance, similar to Simon's ideas of "Studying human intelligence by creating artificial intelligence." [1]. A series of simulations will be reported, and the results will be compared with what we have known about cognitive capacity from psychological studies.

The remainder of this paper is organized as follows: Research questions will be elaborated in Section 2. Section 3 depicts the experimental design, including the market mechanism, trading strategies, and experiment settings. The results, evaluations, and analysis of the experiments are presented in Section 4. Section 5 provides the conclusion.

[1] There are indeed agent-based systems where agents are endowed with different degrees of "cognitive capacity". For example, Takashina and Watanabe (1996) model the entropy of the sensor output of agents in a quasi-ecosystem [7], and Savit, Manuca, and Riolo (1999) model the length of memory of decision makers in a minority game [8]. However, a real challenge is how to characterize the cognitive capacity of autonomous agents, whose strategies can change and adapt to the environment. As far as we know, [9] is the only study that explicitly models the cognitive capacity of autonomous agents in economic models.

## 2 Cognitive Capacity, Learning, and Economic Performance in Double Auction Markets

In this paper, we choose the double auction (DA) market as the environment in which to study cognitively heterogeneous agents. An important reason why the DA market is chosen is that the DA market has been intensively studied both in experimental economics and in agent-based computational economics. Therefore, the DA market can serve as a good starting point to narrow the gap between these two fields.

The double auction market experiment is probably the oldest and the most intensively conducted experiment in experimental economics. However, most conventional studies are concerned with only the aggregate outcomes. Rust, Miller, and Palmer (1993, 1994) are the only few exceptions, and study the DA market from the individual perspective [10] [11].

Rust, Miller, and Palmer (1993, 1994) conducted double auction tournaments with software trading strategies in the Sante Fe Institute. They raised 30 trading algorithms and categorized them according to whether they were simple or complex, adaptive or nonadaptive, predictive or nonpredictive, stochastic or nonstochastic, and optimizing or nonoptimizing. The result is rather surprising: the winning strategy is simple, nonstochastic, nonpredictive, nonoptimizing, and most importantly nonadaptive. In spite of this, other strategies possessing the same characteristics may have performed poorly. Based on their findings, does it really mean that decisions in double auction markets do not require much cognitive capacity? To answer this question, we can test the relationship between agents' cognitive capacities and their performances.

Cognitive capacity is a general concept used in psychology to describe human's cognitive flexibility, verbal learning capacity, learning strategies, intellectual ability, etc [12]. Although cognitive capacity is a very general concept and can be measured from different aspects with different tests, concrete concepts such as intelligence quotient(IQ) and working memory capacity are considered highly representative of this notion.

Two additional questions are also worthy of investigation. First, in a series of human-agent competition studies, researchers found that human subjects did learn, but most people were defeated by software trading programs, and only few of them performed comparably to software agents [13] [14] [15]. This leaves us a question: How much cognitive capacity should a learning agent have to defeat other well-designed software trading strategies?

Second, as the psychological literature points out, high intelligence does not always contribute to high performance–the significance of intelligence in performance is more salient when the problems are more complex. In addition, it appears that intelligence exhibits a decreasing marginal contribution in terms of performances[2]. Can our model generate phenomena consistent with these observations?

[2] [16] demonstrates that the correlation between intelligence and performance increases when the tasks are made more complex. As to the decreasing marginal value of intelligence, please see [17] and [18].

Finally, an important issue here concerns which aspect of cognitive capacity to consider while cognitive capacity can be expressed or measured in different ways. Although *intelligence quotient* may be an intuitive candidate, it is not easy to model since intelligence is multi-dimensional and is used to describe many related abilities. In this regard, we model agents' cognitive capacity via the concept of *working memory capacity*. Working memory is the mental resources used in our decision-making processes and is highly related to *general intelligence* [19]. In this paper, GP agents' cognitive capacity is measured in terms of the number of strategies in their population–a counterpart of the working memory capacity of human traders[3].

In the next section, we will introduce an agent-based double auction market where GP's population size is treated as the proxy variable for cognitive capacity (working memory). By doing so, we can try to answer the questions mentioned above.

## 3 Experimental Design

Experiments in this paper were conducted on the AIE-DA (Artificial Intelligence in Economics - Double Auction) platform which is an agent-based discrete double auction simulator with built-in software agents.

### 3.1 Market Mechanism

AIE-DA is inspired by the Santa Fe double auction tournament held in 1990, and in this study we have adopted the same token generation process as in Rust et al.'s design [11]. Our experimental markets consist of four buyers and four sellers. Each of the traders can be assigned a specific strategy–either a designed trading strategy or a GP agent.

During the transactions, traders' identities are fixed so that they cannot switch between buyers and sellers. Each trader has four units of commodities to buy or to sell, and can submit only once for one unit of commodity at each step in a trading day. Every simulation lasts 7,000 trading days, and each trading day consists of 25 trading steps. AIE-DA is a discrete double auction market and adopts AURORA trading rules such that at most one pair of traders is allowed to make a transaction at each trading step. The transaction price is set to be the average of the winning buyer's bid and the winning seller's ask.

At the beginning of each simulation, each trader will be randomly assigned a trading strategy or as a GP agent. Traders' tokens (reservation prices) are also randomly generated with random seed 6453. Therefore, each simulation starts with a new combination of traders and a new demand and supply schedule[4].

[3] Such kind of analogy has been applied to autonomous agents modeled by Genetic Algorithms, see [9] for a concrete example.

[4] Considering the vast number of combinations and permutations of traders, we did not try out all possible trader combinations. Instead, 300 random match-ups were created for each series of experiment.

### 3.2 Trading Strategies

In order to test the capability of GP agents, we developed several trading strategies from the double auction literature as GP agents' competitors. They are: **Kaplan**, **Ringuette**, and **Skeleton** modified from Rust et al.'s tournament [11]; **ZIC** from Gode and Sunder [20]; **ZIP** from Cliff and Bruten [21]; **Markup** from Zhan and Friedman [22]; **Gjerstad-Dickhaut** (**GD**) from Gjerstad and Dickhaut [23]; **BGAN** from Friedman [24]; **Easley-Ledyard** (**EL**) from Easley and Ledyard [25]; and the **Empirical** strategy which was inspired by Chan et al. [26], and works in the same way as Friedman's BGAN but develops its belief by constructing histograms from opponents' past shouted prices[5].

Although most of the strategies were created for the purpose of studying price formation processes, we still sent them to the "battlefield" because they can represent, to a certain degree, various types of trading strategies which can be observed in financial market studies.

### 3.3 GP Agents

In this paper, GP is employed as the learning algorithm of the autonomous agents, whose goal is to maximize their profits for each trading day. Each GP trader is endowed with a very fundamental terminal set, which consists of the average, maximum, and minimum prices/bids/asks as well as some public information concerning the time. The function set used to develop strategies is also quite simple, which means that GP traders have to build up their strategies from scratch[6].

Each GP trader has a number of strategies in his/her mind. In this paper, we regard the population size of each GP trader's strategies as the proxy parameter of his/her cognitive capacity. The reason why population size can be a proper parameter of cognitive capacity is straightforward: since we tackle the issue of cognitive capacity via the concept of working memory, the largest number of *chunks* stored in each agent's mind becomes a natural measurement of the agent's cognitive capacity. A chunk is a unit of information, which may be as simple as a digit or as complex as a formal concept stored in a human's short-term memory [27]. Similarly, the strategies of a GP agent can be represented by parse trees which may comprise a single terminal element or a tree with many levels. As a result, we can analogize a strategy tree of a GP agent as a chunk stored in a human's short-term memory[7].

[5] Named by or after their original designers, these strategies were modified to accommodate our discrete double auction mechanism in various ways. They were modified according to their original design concepts as well as we possibly could. As a result, they might not be 100% the same as they originally were.

[6] The elements of the function set are plus, minus, multiplication, division, abs, log, exp, sin, cos, max, min, if-then-else, if-bigger-than-else, and bigger.

[7] To put it in another way, working memory capacity matters to human decision makers because they will operate different numbers of chunks in their minds–even if they have the same source of information and knowledge. Similarly, every GP trader has the same terminal and function set, but what really matters is how many operable concepts each agent develops out of these primitives.

GP agents in this study adopt only standard crossover and mutation operations, by which is meant that no election [28], automatically defined functions (ADFs) or other mechanisms are implemented. At the beginning of every trading day, each GP trader randomly picks a strategy from his/her population of strategies and uses it throughout the day. The performance of each selected strategy is recorded, and if a specific strategy is selected more than once, a weighted average will be taken to emphasize later experiences.

GP traders' strategies are updated–with selection, crossover, and mutation–every $N$ days, where $N$ is called the "select number." To avoid the flaw that a strategy is deserted simply because it was not selected, we set $N$ as twice the size of the population so that theoretically each strategy has the chance of being selected twice. Tournament selection is implemented and the size of the tournament is 5, however big the size of the population is. We also preserve the elite for the next generation, and the size of the elite is 1. The mutation rate is 5%, in which 90% of this operation is tree mutation.

In order to examine the validity of using population sizes as GP traders' cognitive capacity, a series of experiments were conducted, in which GP traders' population sizes were set at 5, 20, 30, 40, 50, 60, 70, 80, 90, and 100, respectively. Such a sampling enables us to scrutinize the issues posted in Section 2.

## 4 Results and Discussion

In this section, we evaluate the traders' performances with an efficiency point of view. Profitability is measured in terms of *individual efficiencies*[8].

### 4.1 Learning Capabilities of GP Agents

In investigating the GP traders' learning capability, we simply compare GP agents with designed strategies collected from the literature. We are interested in the following questions: (1) Can GP traders defeat other strategies? (2) How many resources are required for GP traders to defeat other strategies?

GP traders with population sizes of 5, 50, and 100 are sampled to answer these questions[9]. Figure 1 is the result of this experiment. Here we represent GP traders of population sizes 5, 50, and 100 with P5, P50, and P100 respectively.

[8] In order to compare the performance across simulations, we adopted the notion of *individual efficiency*. Individual efficiency is calculated as the ratio of one's actual profits to one's theoretical surplus. For example, if a buyer has only one token whose value is 10, and the theoretical equilibrium price is 6 (acquired in the intersection of the demand and supply curves), then its theoretical surplus will be 4. If this trader makes a transaction and actually earns 3, the individual efficiency of this trader will be $3/4 = 75\%$.

[9] The corresponding $N$ (select number) were set at 10, 100, and 200, respectively. Briefly put, $N$ is the evaluation cycle for each GP generation.

Profits earned by these traders (both GP agents and designed strategies) are computed as the mean of the average profits in a specific generation across different simulations[10]. We have the following observations from Figure 1:

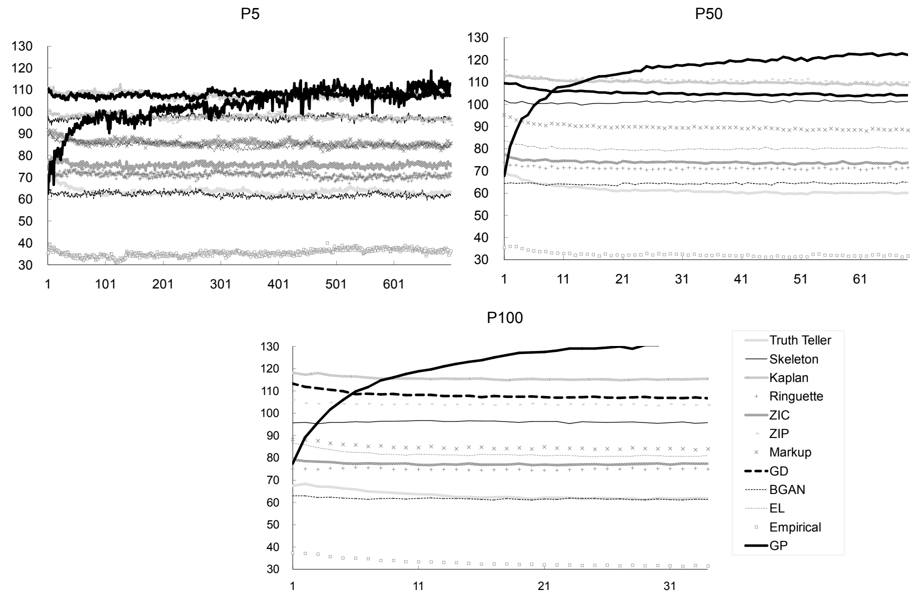


**Fig. 1.** Comparison of GP Traders with Designed Strategies. The horizontal axis denotes the generation, and the vertical axis denotes their performance in terms of individual efficiency (in percentages).

First, no matter how big the population is, GP traders can gradually improve and defeat other strategies. Second, GP traders can still improve themselves even under the extreme condition of a population of only 5[11]. In the case of P5, the average complexity almost equals 1 at the end of the experiments, meaning that GP traders could still gain superior advantages by constantly updating their strategy pools composed of very simple heuristics[12]. In contrast with P5, in the case of a bigger population, GP develops more complex strategies as time goes

[10] For example, "P100's profit in generation 10 is 106.56" indicates that the mean of the average profits in generation 10 across the 198 simulations where P100 traders took part equals 106.56. Here the average profit in generation 10 of a specific simulation is the mean of individual efficiencies achieved by a P100 GP trader during the 200 trading days in the 10th generation.

[11] The fact that the tournament size is also 5 means that strategies in the population might converge very quickly.

[12] In this paper, we measure GP agents' strategy complexity in terms of node complexity–the average number of terminal and function nodes of GP trees.

by. But even so, the average complexity of P100 is only around four[13]. Finally, what is worth noticing is that GP might need a period of time to evolve. The bigger the population, the fewer generations are needed to defeat other strategies. In any case, it takes hundreds to more than a thousand days to achieve good performances for GP traders.

The result of this experiment shows that learning GP traders can outperform other (adaptive) strategies, even if those strategies may have a more sophisticated design.

### 4.2 Cognitive Capacity and the Learning Speed

Psychologists tell us that the intelligence of human beings involves the ability to "learn quickly and learn from experiences" [29]. Figure 2 delineates GP traders' learning dynamics with a more complete sampling. Roughly speaking, we can see that the bigger the population size, the less time GP traders need to perform well. In other words, GP traders with higher cognitive capacity tend to learn faster and consequently gain more wealth.

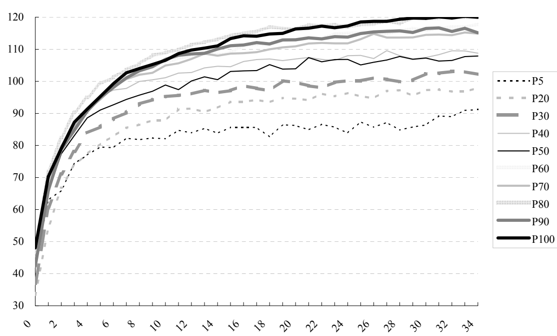


**Fig. 2.** GP traders' performances at different levels of cognitive capacity. The horizontal axis denotes the generation; the vertical axis denotes the individual efficiency (in percentages).

However, we may also notice that this relationship is not as monotone as we might have thought. It seems that there are three groups of learning dynamics in this figure. From P5 to P30, there exists a manifest positive relationship between "cognitive capacity" and performance. P40 and P50 forms the second group: they are not very distinguishable, but both of them are better than traders with lower "cognitive capacity". The most inexplainable part is P60 to P100. Although this group apparently outperforms traders with lower "cognitive capacity", the

[13] The best strategy of P100 traders in the 34th generation is a selling strategy–**Max(PMinBid, PAvg, PAvgAsk, LT)**, a simple rule which adjusts to the market situations by choosing whichever is bigger among several types of market and private information.

inner-group relationship between "cognitive capacity" and performance is quite obscure.

For a better understanding of this phenomenon, a series of nonparametric statistical tests were performed on these simulation results. The outcomes of these tests are presented in part A of Table 1. Pairwise Wilcoxon Rank Sum Tests show that when the "cognitive capacity" levels are low, small differences in cognitive capacity may result in significant differences in final performances. On the contrary, among those who have high cognitive capacity, differences in cognitive capacity do not seem to cause any significant discrepancy in performances.

**Table 1.** Wilcoxon Rank Sum Tests for GP traders' performances on individual efficiencies. " * " symbolizes significant results under the 10% significance level; " ** " symbolizes significant results under the 5% significance level.

| | | P5 | P20 | P30 | P40 | P50 | P60 | P70 | P80 | P90 | P100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A | P5 | X | | | | | | | | | |
| | P20 | 0.099* | X | | | | | | | | |
| | P30 | 0.010** | 0.328 | X | | | | | | | |
| | P40 | 0.002** | 0.103 | 0.488 | X | | | | | | |
| | P50 | 0.000** | 0.009** | 0.129 | 0.506 | X | | | | | |
| | P60 | 0.000** | 0.000** | 0.003** | 0.034** | 0.130 | X | | | | |
| | P70 | 0.000** | 0.000** | 0.015** | 0.121 | 0.355 | 0.536 | X | | | |
| | P80 | 0.000** | 0.000** | 0.003** | 0.036** | 0.131 | 1.000 | 0.558 | X | | |
| | P90 | 0.000** | 0.000** | 0.011** | 0.079* | 0.250 | 0.723 | 0.778 | 0.663 | X | |
| | P100 | 0.000** | 0.000** | 0.000** | 0.002** | 0.009** | 0.284 | 0.093* | 0.326 | 0.150 | X |
| B | P5 | X | | | | | | | | | |
| | P20 | 0.571 | X | | | | | | | | |
| | P30 | 0.589 | 0.288 | X | | | | | | | |
| | P40 | 0.170 | 0.060* | 0.442 | X | | | | | | |
| | P50 | 0.090* | 0.020** | 0.236 | 0.834 | X | | | | | |
| | P60 | 0.004** | 0.001** | 0.019** | 0.159 | 0.207 | X | | | | |
| | P70 | 0.066* | 0.015** | 0.191 | 0.671 | 0.848 | 0.280 | X | | | |
| | P80 | 0.016** | 0.003** | 0.062* | 0.333 | 0.422 | 0.656 | 0.577 | X | | |
| | P90 | 0.043** | 0.010** | 0.144 | 0.552 | 0.714 | 0.384 | 0.845 | 0.658 | X | |
| | P100 | 0.001** | 0.000** | 0.008** | 0.062* | 0.091* | 0.736 | 0.150 | 0.444 | 0.201 | X |

### 4.3 Can Diligence Make Up for Cognitive Capacity?

One interesting question about cognitive capacity and learning is that if we let those with lower cognitive capacity learn longer in financial markets, are they able to discover better strategies so that they can have as competent performances as those with high cognitive capacity?

To test this, we simply let GP traders with lower cognitive capacity evolve longer. Table 2 is the learning time for different types of GP traders. For example, traders with a population size of 5 have only 1/20 of the cognitive capacity of those whose population size is 100. Therefore, we let traders with a population of 5 evolve 20 times longer than traders with a population of 100.

Part B of Table 1 demonstrates the results of this experiment. We can observe that if the difference in cognitive capacity is not so large, it is possible to make up for the deficiency in endowed ability by hard work. However, diligence can only partially offset such a deficiency when the difference in cognitive capacity is large.

Taking GP traders with a population of 5 as an example, they can catch up with traders with a population of 40 if they work eight times longer. Nevertheless, when facing traders with a population of 100, they cannot reduce the gap even by working twenty times longer. This result seems to deny the hypothesis that traders with low cognitive capacity can fairly achieve appreciable performances just as smarter ones in double auction markets.

**Table 2.** Learning Span of GP traders

| Cognitive Capacity | Generations | Cognitive Capacity | Generations |
|---|---|---|---|
| 5 | 699 | 60 | 57 |
| 20 | 174 | 70 | 49 |
| 30 | 115 | 80 | 42 |
| 40 | 86 | 90 | 37 |
| 50 | 69 | 100 | 34 |

## 5 Conclusion

The purpose of this paper is to raise the issue of heterogeneity in individual cognitive capacity since most agent-based economic or financial models do not deal with it. In this paper, we propose a method to model individual cognitive capacity for autonomous agents in double auction markets. The autonomous agents are modeled with Genetic Programming, and their cognitive capacity is characterized by the population size of their strategies. A series of experiments were conducted to answer the questions raised by the experimental double auction literature. In general, there is a positive relationship between cognitive capacity and learning performance, and a decreasing marginal contribution of extra cognitive capacity. This exemplifies the significance of cognitive capacity in double auction markets. The results also show that the differences in agents' cognitive capacity cannot easily be compensated with extra efforts when the differences are large enough.

The results of this study also bring about issues such as the multi-dimensional properties of cognitive capacity, the classification of strategies developed by agents with different cognitive capacity, or the testing of cognitively heterogeneous agents in various environments to find the limiting behavior, etc. Such questions have already been studied in experiments with human agents, but are still new in agent-based economic simulations with autonomous agents. This suggests a closer collaboration between experimental economics and agent-based computational economics, and it is reasonable that psychological and even neural findings should also be consulted more properly in designing autonomous agents.

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