# Modeling Social Heterogeneity with Genetic Programming in an Artificial Double Auction Market

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**Abstract.** Individual differences in intellectual abilities can be observed across time and everywhere in the world, and this fact has been well studied by psychologists for a long time. To capture the innate heterogeneity of human intellectual abilities, this paper employs genetic programming as the algorithm of the learning agents, and then proposes the possibility of using population size as a proxy parameter of individual intelligence. By modeling individual intelligence in this way, we demonstrate not only a nearly positive relation between individual intelligence and performance, but more interestingly the effect of decreasing marginal contribution of IQ to performance found in psychological literature.

## 1 Introduction

Inequality has long been an important issue in economics since Vilfredo Pareto's research in wealth distribution. Pareto probed into this issue and thought that one of the sources of the inequality comes from the heterogeneity in measured and unmeasured abilities and skills in the labor pool [1]. Pareto termed this fact "Social Heterogeneity," which constitutes an important part of his economic thinkings.

> "Human society is not homogenous; it is made up of elements which differ more or less, not only according to the very obvious characteristics such as sex, age, physical strength, health, etc., but also according to less observable, but no less important, characteristics such as intellectual qualities, morals, diligence, courage, etc. " (Pareto [2], Chapter II, 102)

Unfortunately, the significance of the heterogeneity in individual capabilities did not attract much attention from economists until late twentieth century.

In 1994, Herrnstein and Murray published their controversial book entitled *The Bell Curve: Intelligence and Class Structure in American Life*, which discusses group differences in IQ and their socioeconomic consequences [3]. Regardless of the sources of differences between IQ, *The Bell Curve* and subsequent research using sibling data has revealed the importance of intelligence on various socioeconomic performances [4] [5]. Ever since then, IQ has been employed to

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explain statistically the causes of the inequalities in income and wealth between nations [6] [7], or been explicitly put into the growth model as a proxy of human capital to model GDP growth [8] [9].

While IQ has been used to explain macroeconomic variables, not much attention was paid to model the influence of intelligence on individual behavior in economic literature.[1] However, we know from psychological literature that intelligence is crucial to people's learning capability [11], that brings about an important question: Are there proper ways to model individuals with heterogeneous intelligence?

This paper aims to serve as a preliminary effort to model heterogeneous-intelligence individuals in an agent-based double auction market. The purpose of Agent-based modeling is to construct heterogeneous-agent systems. In these models, algorithms from computational intelligence can be used to portray agents' learning behavior. Although agents could be endowed with "intelligence" to learn and adapt, however, to the best of our knowledge, none of the existing agent-based economic models takes into account the degree of intelligence as a factor of learning behavior.

In this paper, we employ Genetic Programming (GP) as agents' learning algorithms. Furthermore, we choose the parameter of population size as the proxy variable of IQ. A series of simulations will be reported, and the results will be compared to what we have known about IQ from psychological studies.

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

## 2 IQ, Learning, and Economic Performance

Intelligence is an important and widely investigated issue in psychological studies, and psychologists have developed various IQ tests and models to measure and explain human intelligence. One of the facts that interests us is the relation between intelligence and learning. Gottfredson defines intelligence as a term used to describe people's capability of learning:

> "Intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, *learn quickly* and *learn from experience*." (italics added, see [11])

As what can be seen from the definition, it suggests that a positive relation should exist between intelligence and the learning capability. As a model which

[1] Rydval and Ortmann's research is the closest one. They compared the influences of IQ and monetary incentives on human subjects' performances, and found that most of the differences in performances can be attributed to differences in IQ instead of the amount of monetary payoffs. See [10].

seeks to find the parameter representing individual's intelligence, there is no doubt that it should be able to exhibit such a positive relation.

Nevertheless, two additional questions are worthy of investigation in the quest of the parameter for intelligence. 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, only few of them performed comparably to software agents [12] [13] [14]. This leaves us a question: How much intelligence 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 performance is more salient when the problems are more complex. Also, it appears that intelligence exhibits decreasing marginal contribution in terms of performances.[2] Can our model generate phenomena consistent with these observations?

In the next section, we will introduce an agent-based double auction market where GP's population size is taken as a proxy variable for intelligence. By doing so, we then try to answer the questions mentioned above.

## 3 Experimental Design

Experiments in this paper were conducted in AIE-DA (Artificial Intelligence in Economics - Double Auction) platform which is an agent-based discrete double auction simulator with build-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 adopted the same token generation process as Rust et al.'s design [18]. 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 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 25 trading steps. AIE-DA is a discrete double auction market and adopts AURORA trading rules such that at most one pair of traders are allowed to make 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

[2] [15] 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 [16] and [17].

randomly generated with random seed 6453. Therefore, each simulation starts with a new combination of traders and a new demand and supply schedule.[3]

### 3.2 Trading Strategies and GP Agents

In order to test the ability 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 [18]; **ZIC** from Gode and Sunder [19]; **ZIP** from Cliff and Bruten [20]; **Markup** from Zhan and Friedman [21]; **Gjerstad-Dickhaut** (**GD**) from Gjerstad and Dickhaut [22]; **BGAN** from Friedman [23]; **Easley-Ledyard** (**EL**) from Easley and Ledyard [24]; **Empirical** strategy is inspired by Chan et al. [25], and it works in the same way as Friedman's BGAN but develops its belief by constructing histograms from opponents' past shouted prices.[4]

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.

GP agents in this study adopt only standard crossover and mutation operations, by which it means no election, ADFs nor 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 through the whole 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 twice the size of the population so that theoretically each strategy has the chance to be 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 to 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' intelligence, a series of experiments were conducted, 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.

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[3] 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.

[4] 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 possible as we can. As a result, they might not be 100% the same as they originally are.

## 4 Results and Discussions

In this section, we evaluate traders' performances with a profit-variation point of view. Profit ability is measured in terms of individual efficiencies.[5] In addition to profits, a strategy's profit stability is also taken into account because in double auction markets, the variation of profits might be considered in human trading strategies, which are determined by human's risk attitudes [26]. Here we procure variations of strategies by calculating the standard deviation of each strategy's individual efficiencies.

### 4.1 Learning Capabilities of GP Agents

In investigating into 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 size of 5, 20, and 50 are sampled to answer these questions.[6] Figure 1 is the result of this experiment. Here we represent GP traders of population size 5, 20, and 50 with P5, P20, and P50 respectively. We have the following observations from Figure 1:

– No matter how big the population is, GP traders can gradually improve and defeat other strategies.
– GP traders can still improve themselves even under the extreme condition of a population of only 5.[7] Figure 2 shows the evolution of average complexity of GP strategies. In the case of P5, the average complexity almost equals to 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. In contrast with P5, in the case of bigger population, GP develops more complex strategies as time goes by.
– 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.

[5] In order to evaluate the performance of each strategy, we adopted the notion of *individual efficiency*. Considering the inequality in each agent's endowment due to random matching of strategies as well as random reservation prices, individual efficiency is calculated as the ratio of one's actual profits to his/her theoretical surplus, which is the sum of the differences between one's intramarginal reservation prices and the market equilibrium price.

[6] The corresponding select number were set at 10, 40, and 100 respectively. Briefly speaking, the number of selection is the evaluation cycle for each GP generation.

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

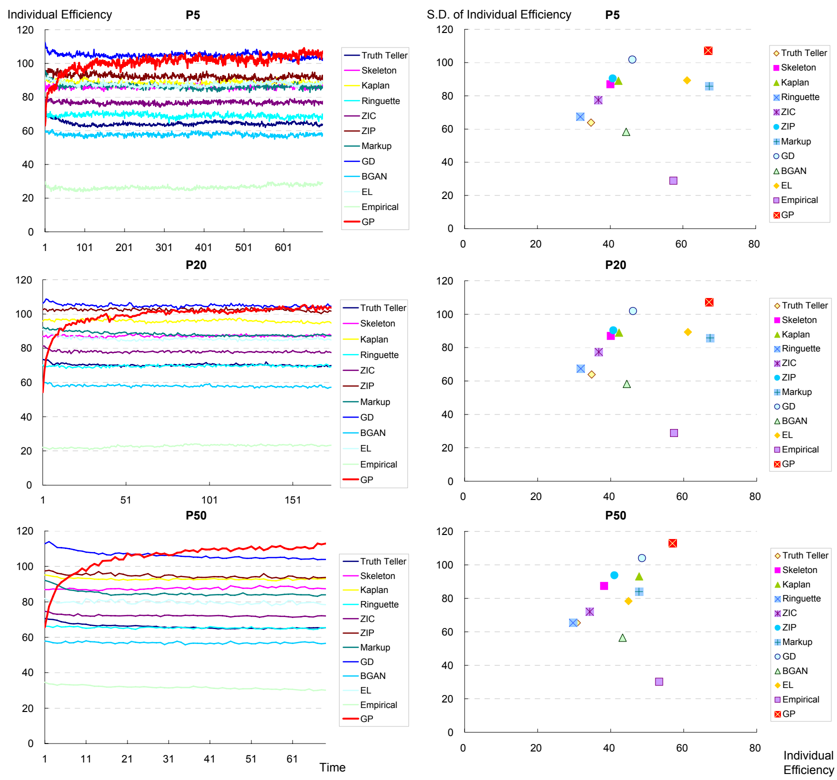


**Fig. 1.** Comparison of GP Traders with Designed Strategies. From the top to the bottom rows are comparisons when GP traders' population sizes are 5, 20, and 50 respectively. (a) The left panels of each row is the time series of individual efficiencies. (b) The right panels of each row is the profit-variation evaluation on the final trading day. The horizontal axis stands for their profitibility (individual efficiency), and the vertical axis stands for the standard deviation of their profits.

**Fig. 2.** Evolution of average GP complexity when the population sizes are 5, 20, and 50 respectively (from the left panel to the right panel)

– Figure 1 also shows the results in a profit-variation viewpoint. Other things being equal, a strategy with higher profit and less variation is preferred. Therefore, one can draw a frontier connecting the most efficient trading

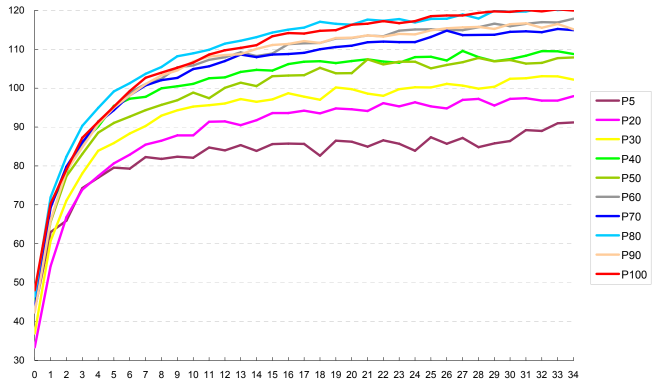


**Fig. 3.** GP traders' performances at different "intelligence" levels. The horizontal axis is generation; the vertical axis is the profit level attained by GP traders.

strategies. Figure 1 shows that GP traders, although with more variation in profits in the end, always occupy the ends of the frontier.

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 Intelligence and Learning Speed

Psychologists tell us that intelligence of human beings involves the ability to "learn quickly and learn from experiences" [11]. To investigate the influence of individual intelligence on learning speed, we think of a GP trader's population size as a proxy of his/her IQs. Is this parameter able to generate behavioral outcomes consistent with what psychological research tells us?

Figure 3 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 intelligence tend to learn faster and gain more wealth consequently.

However, if we are careful enough, we may also notice that this trend 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 manifest positive relation between "intelligence" and performance. P40 and P50 forms the second group: they are not very distinguishable, but both of them are better than traders with lower "intelligence". The most inexplainable part is P60 to P100. Although this group apparently outperform traders with lower "intelligence", the inner-group relation between "intelligence" and performance is quite obscure.

For a better understanding of this phenomenon, a series of nonparametric statistical tests were performed upon 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 "intelligence" levels are low, small differences in intelligence may result in significant differences in final performances. On the contrary, among those who have high intelligence, differences in intelligence do not seem to cause any significant discrepancy in performances.

### 4.3 Can Diligence Make UP for Intelligence?

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

To test this, we simply let GP traders with lower intelligence to evolve longer. Table 2 is the learning time for different intelligent GP traders. For example, traders with population size 5 have only 1/20 of the intelligence of those whose population size is 100, therefore, we let traders with IQ 5 evolve 20 times longer than traders with IQ 100.

Part B of Table 1 demonstrates the results of this experiments. We can observe that if the difference of intelligence is not so large, it is possible to make up for the deficiency of endowed ability by hard working. However, diligence can only partially offset such deficiency when the difference of intelligence is large. Take GP traders with IQ 5 as an example, they can catch up with traders with IQ 40 if they work eight times longer. Nevertheless, when facing traders with IQ 100, they cannot reduce the gap even by working twenty times longer. This result seems to deny the hypothesis that traders with low intelligence can fairly achieve appreciable performances as smarter ones in double auction markets.

### 4.4 A Test for Fluid Intelligence

In section 4.2, we've seen that GP with different IQs improve with different speed. However, we can also observe from Figure 3 that the learning dynamics of GP traders are quite similar, except for the magnitude of initial leaps. This may suggest that GP traders with higher IQs perform better than those with lower IQs simply because they can improve more at the begining, while they don't improve a lot in the rest of the simulations, just like those with lower IQs.

This brings us a question: according to psychological theory, *fluid intelligence* measures the ability to problem-solving and learning in new situations, so if GP traders with higher IQs can perform better in a fixed market environment, they should be able to do the same thing when facing constantly changing new environments. The next experimental result demonstrates GP traders' performances when the market demand and supply changes at the begining of every generation.[8]

Part C of Table 1 demonstrates the results of this experiments. We can see from the table that a similar pattern emerges as those in Part A and Part B.

[8] To be more specific, we reassigned market participants' reservation prices randomly at the begining of every generation.

**Table 1.** Wilcoxon Rank Sum Tests for GP traders' performances on individual efficiencies. "*" symbols significant results under 10% significance level; "**" symbols significant results under 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 |
| C | P5 | X | | | | | | | | | |
| | P20 | 0.085* | X | | | | | | | | |
| | P30 | 0.011** | 0.410 | X | | | | | | | |
| | P40 | 0.000** | 0.028** | 0.131 | X | | | | | | |
| | P50 | 0.001** | 0.093* | 0.379 | 0.620 | X | | | | | |
| | P60 | 0.000** | 0.013** | 0.096* | 0.799 | 0.460 | X | | | | |
| | P70 | 0.000** | 0.060* | 0.265 | 0.704 | 0.882 | 0.503 | X | | | |
| | P80 | 0.000** | 0.004** | 0.029** | 0.475 | 0.223 | 0.645 | 0.250 | X | | |
| | P90 | 0.000** | 0.007** | 0.050** | 0.663 | 0.357 | 0.851 | 0.376 | 0.745 | X | |
| | P100 | 0.000** | 0.000** | 0.000** | 0.022** | 0.005** | 0.038** | 0.004** | 0.101 | 0.053* | X |

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

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

This result therefore serves as a support for the suitability of modeling fluid intelligence with GP traders' population sizes.

## 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 intelligence in agent-based double auction markets. We then run a series of experiments to validate our results according to what psychological studies have shown to us.

Preliminary experimental results in this paper show that it is viable to use population size as a proxy of intelligence for GP traders. In general, the results are consistent with psychological findings–a positive relation between intelligence and learning performance, and a decreasing marginal contribution of extra intelligence. Our study therefore shows that, by employing Genetic Programming as the learning algorithm, it is possible to model both the individual learning behavior and the innate heterogeneity of individuals at the same time.

The results of this study remind us a possibility that there is another facet to connect human intelligence and artificial intelligence. Artificial intelligence not only can be used to model intellectual behavior individually, but is able to capture social heterogeneity through a proper parameterization as well.

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