Multi-Agent Simulation of a Fruit Market

Arguing Agents group 01 – Final report

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Abstract

Individual variations in actors can affect the outcome of the economic dynamic system in which they participate. This report analyzes the effects of price elasticity and patience in a model where agents make autonomous decisions about which other agent to negotiate and trade with. Price elasticity has a significant negative correlation with the financial performance of an agent, whereas patience does not show a significant correlation.

1 Introduction

In *agent-based computational economics* (ACE), the dynamics of decentralized markets are analyzed by using autonomous agents[1]. These markets and agents can be effectively modeled in frameworks such as agent-based models. Continued improvements in computational power have benefited ACE by allowing more complex models to be carried out in less time. The use of agent-based models has resulted in new insights in how macroeconomics (the study of major economical systems) and microeconomics (the study of small-scale economical markets) influence each other in a real-time feedback system. This two-way feedback system has been studied before agent-based models were used[4], but modeling explicit constraints and variables into the agents can present new findings about how variations on an individual level can affect the system at large. These findings can be used by governments, international agencies and other economic stakeholders to research the effects of financial and economic regulations and market restriction policies.

However, a major limitation of ACE is that although groups can display fairly predictable behavior, individuals often do not. Modeling realistic individual actors in a dynamic economical system presents some specific challenges. Firstly, all actors are different, which means that the agents must be different as well in order to accurately reflect the real economic system. It is not clear, however, how to identify these differences, how many differences there are and how to assess their relevancy to the outcome of the system. Secondly, actors are irrational[2] and forgetful and often base decisions on emotional judgment rather than rational analysis. It is not clear how to realistically model these crucial psychological factors into accurate economical systems.

In this report, two simple factors that are related to the rationality of financial trading are analyzed by using a simulation of a decentralized market. On this market, agents can trade fruits and negotiate on the trade price. The agents have two parameters that reflect influence of irrational judgments during negotiation. The first of these parameters is patience. Patience defines how for how many time steps an agent is willing to negotiate prices for a particular trade before it declines and moves on. This parameter both models the real-world irrational tendency for short-term gratification as well as the capricious nature of trading partners. The second parameter is price elasticity. This parameter defines how much an agent is willing to move toward the other agent's price. This models the fact that in the real world, actors are not all equally skilled in negotiation, and do not have the same strategic bargaining power.

This research will analyze if and how these parameters affect the financial success of the agents. Since in the real world not all goods are equally distributed, the agents will be initialized with random amounts of different fruits. The performance of an agent is defined as the total increase of the sum of its money and the value of its fruits over the course of the simulation. The research question is thus: "do the patience and the price elasticity of an agent affect its final performance?"

The hypothesis for the patience parameter is that a higher patience is correlated with a higher performance, since this will presumably result in more successful trades. Furthermore, the hypothesis for the price elasticity is that a moderate price elasticity will lead to the highest performance, since a low elasticity likely leads to many declined trades, and a high elasticity leads to many bad trades, especially when the trading partner has a low elasticity.

2 Method

2.1 Simulation model

2.1.1 System and environment

As the environment of our system we used an own implementation of a market place simulation. The virtual market is represented as a grid of width w and height h with $w * h \geq |agents|$, since no more than one agent can exist on a tile at once. The market is fully decentralized, so each agent that exists in it is considered a peer of the other agents.

The goods that are traded in the market are different kinds of fruit, namely mangoes, oranges, apples, bananas, strawberries, blueberries, tomatoes, papayas, pineapples, grapes and lemons. All agents initially have a number of each of these fruits, but will trade with each other in order to buy more fruits to which they assign a high value or sell fruits to which they assign a lower value. The evaluation of an agent of every kind of fruit is determined by multiple factors, among which a global price of the fruit.

The global price contains an 'objective' overview of the actual values of the fruits that are traded. It is used to help the agents to determine their individual valuation of all goods. Further explanation on the global price and how the agents use it can be found in Section 2.1.3.

2.1.2 Agent design

States The agents in the simulation are entities that are self-contained. Based on their internal decision making process, they will display behavior by changing their "state". These states are used in the model to distinguish between different modes of behavior and display them visually by means of color mapping.

These are the four agent states:

1. Random walk state
2. Walk-to-agent state
3. Wait-for-response state
4. Negotiation state

The random walk state is the default state of the agents, and also the simplest. Agents in this state will wander across the grid in random directions. Every time step, the agent moves up, down, left or right. If it is enclosed by other agents, however, it will not move. This state is meant to prevent the agents from agglomerating in one dense cluster.

Agents in the walk-to-agent state will approach another agent on the grid. They will use breadth-first search to find the path with the shortest Manhattan distance. This state includes a "goal action", which is the action that the agent will perform once it reaches its target. This goal action is a decision whether to buy or sell a particular fruit, as decided by the agent's inference model (see Section 2.1.3).

The wait-for-response state is activated for a single turn when an agent sends a negotiation request to another agent (see Section 2.1.4). This state is meant to stop the agent's movement and reject all incoming requests until it has received a response from the other agent. If for some reason the agent does not receive a response —for instance, if the other agent has accepted another request in the same turn—then this state will automatically change to the random walk state.

The last possible state is the negotiation state. Agents in this state are actively negotiating with another agent, and are unavailable for any trade requests. Agents can remain in this state for a considerable number of time steps, and will not move.

Variables Next to agent states, agents require a number of variables in order to function correctly. One of these is the amount of money they have. This is a non-negative number that is initialized at 500. They also have a collection of various fruits, initialized randomly between 0 and 10 each, which they can buy or sell. Most importantly, agents have two parameters, *patience* and *price elasticity*, that affect their behavior during negotiation. These fixed parameters are initialized randomly as a floating-point value between 0 and 1.

2.1.3 Decision making process

The decision making process (DMP) functions like a support system to an agent. An agent can ask its support system to make a decision on its behalf about the following two questions:

- "What do I need to do next?"
- "With whom do I need to do this?"

The first question indicates whether to buy, to sell or to do nothing. If the agent chooses to buy or sell, then it should decide on which entity (i.e., type of fruit). The second question indicates which other agent this agent should buy from or sell to. The combination of these two definition allows the agent to formulate conclusions (decisions):

- Buy(E_i, A_i). This means that the decision for the asking agent is to go and buy entity E_i from agent A_i
- Sell(E_i, A_i). This means that the decision for the asking agent is to go and sell entity E_i to agent A_i.
- None, which means that the DMP cannot make a decision.

The DMP can be seen as an activity aimed toward constructing all possible conclusions (decisions) and then to choose the best among them. In order to implement the DMP, we start by stating following the preferences for the DMP:

- If price is going down, then you buy.
- If price is going up, then you sell.

The DMP starts by forming all possible decisions for the asking agent. If there are k entities and n agents, then there will be $2 \times k \times (n-1)$ possible conclusions for the agent, because the agent can buy or sell any entity from any agent other than itself.
Next, the DMP asks the following **critical questions** to validate or invalidate each conclusion:

- Is the conclusion valid with respect to **price trend**?
  - The price trend is the record of GAP$(E_i)_t$, for last n time-steps, where GAP$(E_i)_t$ is the global average price of entity E_i at time step t.

$$\text{PriceTrend}(E_i) = \{\text{GAP}(E_i)_{t_1}, \text{GAP}(E_i)_{t_2}, \ \ldots\ , \text{GAP}(E_i)_{t_n}\} \tag{1}$$

  - If action is to *buy*, the conclusion will be valid if either price is going down continuously from last n times or if the system cannot tell anything about it.
  - If action is to *sell*, the conclusion will be valid if either price is going up continuously from last n times or if the system cannot make any conclusion about it.
- Is the agent free?
  - If the agent A_i is not free, then this conclusion becomes invalid. An agent is free if it is in a random walk state.
- Is the agent reachable?
  - If the Manhattan distance MD(A_i, A_j) between the goal agent A_i and the asking agent A_j is greater than the time left for the market to close, then this conclusion will become invalid.

- Is the agent interested in entity?
  - If action is to sell, then A_i should be interested in the E_i.
  - If action is to buy, then the asking agent A_j should be interested in E_i.
  - Otherwise, this conclusion becomes invalid.
- Does the agent have this entity?
  - If action is to buy, then A_i should have E_i.
  - If action is to sell, then asking agent should have E_i.
  - Otherwise, this conclusion becomes invalid.
- Does the agent have the required money for this entity?
  - If the action is to buy, then the asking agent A_j should have money greater than its maximum buying price for E_i.

Now, the DMP has to infer the best choice from the multiple valid conclusion available. If no valid choice is available, then it will tell the asking agent to do nothing.

Argumentation Modeling

- **Conclusion**: Buy E_i from A_i
  - **Premises:** Either price of E_i is going down or cannot tell. A_i has entity E_i. A_i is reachable.
  - **Attacks:**
    * Less decrease in global average price of E_i.
    * A_i is far away.
    * More negative negotiation with A_i than positive in the past.
    * Less drop in price with respect to maximum buying price limit of agent.
- **Conclusion**: Sell E_i to A_i
  - **Premises:** Either price of E_i is going up or cannot tell. A_i has entity E_i. A_i is reachable.
  - **Attacks:**
    * Less increase in global average price of E_i.
    * A_i is far away.
    * More negative negotiation with A_i than positive in the past.
    * Less increase in price with respect to minimum selling price limit of agent.

Inference Model In order to infer the best conclusion, we assign a score to every conclusion. These scores are modeled in terms of weights of premises and attacks. The weights W of the above mentioned premises and attacks are defined as follows:

- **Premise**: Price is going up/down for entity
  If the price is either going up or going down, then we give the corresponding weight a constant value of 1. Otherwise, if we cannot tell, then we give the weight a constant value of 0.5.
  - In case of buying

$$W_P = \begin{cases} 1 & \text{if price is going down} \\ 0.5 & \text{if cannot tell about price going down} \end{cases} \tag{2}$$

  - In case of selling

$$W_P = \begin{cases} 1 & \text{if price is going up} \\ 0.5 & \text{if cannot tell about price going up} \end{cases} \tag{3}$$

- **Attack 1**: Less change in entity price trends

$$W_{A1} = \frac{\text{GAP}(E_i)_{tc} - \text{GAP}(E_i)_{ts}}{\text{GAP}(E_i)_{tc}} \tag{4}$$

  where t_c is the current time-step and t_s is time step in which E_i was traded first. If the conclusion is weighed with the action 'buy', then W_{A1} is multiplied by -1.

- **Attack 2**: Bad past experience with other agent

$$W_{A2} = \frac{\text{PN}_{ki} - \text{NN}_{ki}}{\text{TN}_{ki}} \tag{5}$$

  where PN_{ki} is the total number of positive negotiations between agent k and agent i. NN_{ki} is the total number of negative negotiations between agent k and agent i. TN_{ki} is the total number of negotiations between agent k and agent i. Here the asking agent is denoted as k.

- **Attack 3**: Less decrease/increase in price with respect to maximum buying / minimum selling price limit of agent, respectively.

  – In case of buying:

$$W_{A3} = \frac{\text{MaxBuy}(E_i) - \text{GAP}(E_i)_{tc})}{\text{MaxBuy}(E_i)} \tag{6}$$

  – In case of selling:

$$W_{A3} = \frac{\text{GAP}(E_i)_{tc} - \text{MinSell}(E_i)}{\text{MinSell}(E_i)} \tag{7}$$

- **Attack 4**: Agent is far away

$$W_{A4} = \text{MD}(A_k, A_i) \tag{8}$$

  Where $\text{MD}(A_k, A_i)$ is the Manhattan distance between agent k and agent i.

Score of conclusion

$$S_c = \frac{W_P + W_{A1} + W_{A2} + W_{A3}}{W_{A4}} \tag{9}$$

Where S_c is the score for conclusion c.
The conclusion with the maximum score is inferred by the decision making process.

2.1.4 Negotiation process

Requesting a negotiation When an agent has successfully approached one agent, it will send a negotiation request. Based on the inference model (see Section 2.1.3) the agent has decided which fruit to buy or sell. This request contains the following information: whether to buy or sell, the fruit type, the quantity and the price offer. Later during the same time step, the other agent will receive this request and formulate a response. It will answer positively if the request is to sell to the receiving agent. If the request is to buy from this agent, it will answer positively if and only if the agent has enough of the fruit. Then, the requesting agent will receive the response. If this response is negative, it will return to its default state of random walking. If it is positive, then both agents will enter a negotiation state.

Negotiation The negotiation process is a series of price offers and counter offers between a buying agent and a selling agent. This process is affected by the agents' patience and price elasticity parameters. The agent that sent the trade request offered an initial price P for this fruit entity E embedded in that request, given by Equation 10. This is how prices are set for initial buying offers, and depends on the maximum buying price MaxBuy and minimum selling price MinSell for an agent, which are fixed values. For all agents, it is the case that

$$P_{\text{buy}}(E) = \left\lfloor \text{Random}\left(\frac{\text{MaxBuy}(E)}{2}, \text{MaxBuy}(E)\right) \right\rfloor \tag{10}$$

$$P_{\text{sell}}(E) = \lfloor \text{Random}(\text{MinSell}(E), \text{MinSell}(E) \times 1.5) \rfloor \tag{11}$$

where Random(min, max) is a uniform random distribution between min and max.

This means that initial price offers are generally low (if buying) or high (if selling).

In defining the maximum buying price and minimum selling price for agents, it is the case that:

$$\forall_E \ \text{MaxBuy}(E) < \text{MinSell}(E)$$

Counter offers are affected by the price elasticity parameter, which is a randomly initialized value for each agent between 0 and 1. If the request is to sell, the receiving agent will offer to buy for counter price C_{buy} (see Equation 12). If the request is to buy, the counter price will be C_{sell} (see Equation 13).

$$C_{\text{buy}}(E) = \left\lfloor \text{MaxBuy}(E) \times \text{Random}\left(1 - \text{Elasticity}, 1 - \frac{\text{Elasticity}}{2}\right)\right\rfloor \tag{12}$$

$$C_{\text{sell}}(E) = \left\lfloor \text{MinSell}(E) \times \text{Random}\left(1 + \frac{\text{Elasticity}}{2}, 1 + \text{Elasticity}\right)\right\rfloor \tag{13}$$

After the initial price and counter offer are made, the agents will continually propose new buying prices P_{buy} and selling prices P_{sell} according to Equation 14 and Equation 15, respectively. It takes one time step t for both agents to offer their new prices.

$$P_{\text{buy}}(E,t) = T(P_{\text{buy}}(E,t-1), \text{MaxBuy}(E) \times (1 + \text{Elasticity}), P_{\text{buy}}(E,t-1)) \tag{14}$$

$$P_{\text{sell}}(E,t) = T(\text{MinSell}(E) \times (1 - \text{Elasticity}), P_{\text{sell}}(E,t-1), P_{\text{sell}}(E,t-1)) \tag{15}$$

where $T(min, max, mode)$ is a triangular distribution between min and max, inclusive, where the top of the triangle is at the $mode$ value.

Consequentially, both agents will move toward each other in price, where their price elasticity parameters will decide how much per turn.

The two agents will accept if their prices meet. That is, if $P_{\text{buy}}(E,t) \geq P_{\text{sell}}(E,t)$.

The agents will decline if for either agent the patience is not high enough:

$$t > \text{Patience} \times \frac{\text{Global time remaining}}{2} \quad \longrightarrow \text{Stop negotiating}$$

Agents will also decline if the price range has moved outside what the buying agent can afford.

After the trade is accepted or declined, both agents will make the transaction and return to a random walk state.

For example, if an agent A_b sends a buy request to agent A_s to buy 10 apples (this is decided by its inference model) for 20 money each. This initial price is calculated by Equation 10. Agent A_s will respond positively, because it has 10 apples in its inventory, and offer a counter price of 50 each. Agent A_b now offers 26 each, agent A_s offers 39 each, agent A_b offers 32 each, agent A_s offer 31 each, and the trade is accepted.

2.2 Experiment design

The experiments were performed by running the simulation multiple times and storing the data into a .csv file after each simulation. This data could then later be accessed in order to visualise it or perform statistical analysis on it.

The values of the parameters used in the experiments are shown in Table 1. These parameters were chosen by performing simple parameter sweeps with the goal of achieving a market that shows many interactions while keeping computational demands low.

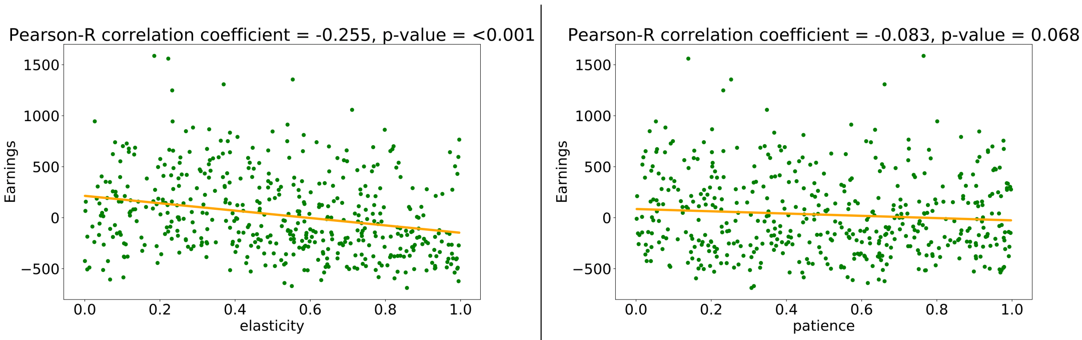
Running 25 simulations with 20 agents each yielded 500 data point of agent performance.

Table 1: Parameters used in the experiments

Parameter	**Value**
Number of agents	20
Grid width	25
Grid height	25
Time steps	1000
Patience	$(0, 1)$
Elasticity	$(0, 1)$
Starting money	500
Initial max buying price	$(25, 35)$
Initial min selling price	$(30, 50)$
Initial quantity of each fruit	$(0, 10)$
Number of repetitions	25

3 Results

The results are shown in the scatter plots in Figure 1. To test the correlation of both parameters to the earnings of an agent, a Pearson-R correlation test was performed. According to conventional standards ($\alpha = 0.05$), the elasticity of the agents shows a significant correlation with the earnings ($p < 0.001$) while the patience does not show a significant correlation ($p = 0.068$). Furthermore, the significant correlation showed a correlation coefficient of -0.255, which implies a weak negative linear relationship between an agent's elasticity and its earnings.



(a) The agents' earnings versus their price elasticity parameter.

(b) The agents' earnings versus their patience parameter.

Figure 1: Scatter plot showing the relation between the earnings (i.e., performance) of all agents and their price elasticity and patience.

4 Discussion

From the results in Figure 1, the effects of the parameters on the performance of the agents can be observed.

Figure 1a suggests a significant negative relationship between the price elasticity and the performance of the agent. It appears that on average, amenable agents have a lower performance than more obstinate agents. A possible reason for this correlation might be that a high price elasticity can lead to disadvantageous transactions—even one such transaction might lead to an insurmountable setback in agent value.

Figure 1b indicates no significant relationship between patience and agent performance. That means that this parameter can not independently predict how much value the agents will earn during the simulation.

The hypotheses about the parameters (i.e., "high patience correlates with high performance" and "moderate price elasticity correlates with high performance") are both rejected.

However, the experiment described in this report has some limitations that must be addressed in further research. Firstly, the randomly initialized values of the agents (fruit quantity, position and trade prices) might also have an effect on the final performance of the agent. In particular, the given quantity of fruits is hypothetically positively correlated with the earnings, as it provides more trading options for the agents. This leads to noise in the results. In this experiment, the high number of simulations offsets this noise, so the validity of the conclusions is not affected. However, it is good (albeit less realistic) to study the effect of patience and elasticity in a less noisy simulation. It might also be interesting to separately study the correlation of these initialization variables on the agent performance. Secondly, throughout this report there has been an implicit assumption of independence between the patience and the price elasticity parameters. However, it might be the case that these parameters depend on each other. For instance, patience might be correlated with performance in agents with a higher price elasticity. Thirdly, the significance value of the patience–performance correlation is scarcely larger than α. It is conceivable that additional testing with more simulations can change the conclusion about this parameter.

Additional research can address these limitations, as well as explore other ways in which individual variations can affect the outcome of the global system. For instance, the degree of variation between the final values of agents can be analyzed based on their initialization. This might lead to new insights on, for example, wealth inequality in society. Another factor that could be analyzed using these types of agent-based models is the influence of regulating factors in the dynamics of the market. This relates to monetary policy responses by economically authoritarian governments and the related field of Keynesian economic theory, given the assumption that the actors in the economic system are distinct, irrational and autonomous.

5 Task division

Task	**Done by**
Code: decision making process	Rohit
Code: grid visualization	Jits
Code: agents & negotiation	Werner
Code: other things and bugfixing	all of us
Report: introduction & abstract	Werner
Report: system and environment	Jits
Report: agent design	Werner
Report: decision making process	Rohit
Report: negotiation process	Werner
Report: experiment design	Jits
Report: results	Jits
Report: discussion	Werner

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