Project Outline

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"I can calculate the motion of heavenly bodies, but not the madness of people."

Sir Isaac Newton

1 Background

1.1 Agent-based modeling for economic science

Scientists can analyze human behavior, social interaction, and society in general with quantitative or qualitative methods. Quantitative methods often take the form of equation-based models, such as those which describe the behavior of gases, fluids, or solid bodies. While being easily applicable to the "hard" sciences, equations tend to be quite deterministic in nature, and as such are not easily adaptable to the social sciences in non-idealized scenarios [1]. A method better suited to socio-economic simulations is agent-based modeling (ABM). Depending on the subject of interest, agents may represent individuals, groups, companies, or countries; the main purpose is to simulate the interactions between these agents. Agent behavior can be formalized through equations, however they may be more generally specified by decision rules, implementing if-then logic and heuristics [1]. Agents can have any number of properties, which can be qualitative or quantitative in nature. For example, emotion, perception, sociability, risk-tolerance, etc, can all affect agent behavior (though each agent may be uniquely affected by changes in these parameters).

Previous work in the realm of applying ABM to financial markets provides fertile ground for potential research. In particular, the Santa Fe Artificial Stock Market is an exemplary starting point [2]. In this research, agents are given a choice between investing their money in a stock or leaving it in the bank, where it pays a fixed interest. Agents forecasted the future value of the stock individually, based on a unique strategy optimized by genetic algorithms. This forecast then determined whether they acted, and if so, whether they bought or sold. The rate at which the agents "explored" new hypotheses about the market was the exploration rate. The researchers found that the market can enter one of two regimes, one being a rational expectations equilibrium (more stable), and the other a complex, albeit realistic, regime featuring high trading volume, high volatility, with bubbles and crashes (less stable). Interestingly, the occurrence of the second regime is correlated to a higher exploration rate. At the boundary between the two regimes, the behavior of the market is determined by agent beliefs: if the agents believe in rational expectations, the market follows that belief, otherwise it develops into the second regime. This research employed the Swarm platform for agent-based modeling (www.swarm.org) and have published their code online, providing a good general framework for future research in this field.

One important aspect of note in such research is that the behavior of the agents being modelled is assumed to be rational. For example, the agents in the Santa Fe Artificial Stock Market were entirely technical traders, basing their decisions on the output of their models. In reality, while many traders operate in this fashion, many do not. Individuals who trade on their emotions, "intuition", the status quo, etc, can be described as "irrational". Because real markets are affected by the actions of irrational traders, there is room for improvement in this field by accounting for the behavior of such individuals.

1.2 Irrational agent-based financial models

A good illustration of such improvement can be found in a recent study (2016) which focused on the effects of financial news on an agent-based simulation [3]. In this study, irrationally acting agents receive financial news, which was either positive or negative, and the effect of their resultant behavior was analyzed. The researchers concluded that the behavior of the simulated market resembled that of a soliton, a self reinforcing solitary wave packet, which suggests how analysts' forecast errors could cause prices to adjust accordingly, demonstrating an irrational force.

While this is a step in the right direction, the opportunity remains to more fully model irrational agent behavior. Specifically, this simulation would account for individual propensities towards risk, crowding/herding, sentiment such as hope or fear, degree of greediness, etc. Of course, the main barrier towards such simulation is the daunting task of quantifying such unique and diverse emotions and experiences. Fortunately, the emerging field of neuroeconomics, which lies at the crossroads between neuroscience, behavioral economics, and psychology, can provide us with methods to answer such questions.

1.3 Neuroeconomics

Neuroeconomics combines methods and theories from neuroscience, psychology, sociology, and economics to study the human decision-making process. One such method is Functional Magnetic Resonance Imaging (fMRI), which has become the dominant technology for neuroscientific study. This method provides insight into the mechanisms within the brain which are present when different decisions are being made. For example, analytical and emotional thinking take place in different parts of the brain, and their activation during the decision-making process can affect the outcome (reflective vs. reflexive brain). This emotional/sentimental side of the brain, while the origin of irrational behavior, can be logically understood in terms of evolutionary adaptation.

The human brain has only changed by about 1% in the past 100,000 years, and is in many ways a living fossil [4]. It is designed to interface with a Stone Age world, where dangers and opportunities were immediate, and social interaction limited to the tribe or group to which an individual belonged. As a result, the human brain has retained, especially in the subconscious, a wide set of behaviors which, while seemingly irrational in the modern era, were entirely rational during the period in which they evolved. Examples are abundant, and include the flight or flight response, herding behavior, stereotyping, and impulsive judgements, just to name a few. These cognitive patterns are essential to understand, as 90% of decision-making processes take place subconsciously [4].

Much of the research in neuroeconomics attempts to understand these paleolithic holdovers, and their effects on human behavior. For example, one study sought to understand the relationship between investment decisions and the different regions of the brain [5]. To accomplish this, they took fMRI scans of traders as financial transactions took place. By analyzing these images, the researchers arrived at a several important conclusions. For example, their results showed that the trading strategy of a particular individual is heavily influenced by their previous experiences, and are by no means consistent across even professional traders. Additionally, they found that trading strategy varied between genders, suggesting the employment of different neuronal circuits. Ultimately, they concluded that financial decisions, and the strategies used to make those decisions, are highly subjective, and originate from various factors such as socioeconomic status, goals, personality, and learning ability.

Since different individuals can act in different ways in the same situation, it seems that neuroeconomics research points towards underlying inefficiencies in financial markets. These inefficiencies could potentially be identified through an agent-based model, where a combination of analytical/emotional thinking is accounted for. Once identified, such inefficiencies would provide a financial opportunity for the investor willing to provide market stability.

2 Objectives

2.1 Agent parameterization

Since the most fundamental unit of this research will be the individual, or agent, with market events (price increase/decrease, bubbles/crashes) being modeled as emergent phenomena, it is essential to properly parameterize them. For this research, parameters will take the form of either analytical or emotional, with each agent taking into account a mixture of both when formulating a decision. The degree to which either set is utilized will vary across the agent population.

2.1.1 Analytical parameters

The analytical parameters present in each agent will be designed to closely resemble the analytical process of humans. Fortunately, these parameters can be described by equations, such as the type which are used by analysts to forecast the performance of some stock. Whether or not these methods actually work is irrelevant, they must only mimic behavior which can reasonably be expected from "rational" investors.

For example, one such method would be the Dividend Discount Model, whereby an investor, or in this case, an agent, determines the "fundamental" value of a stock by analyzing its dividends, and then by comparing that fundamental value to the actual value, can decide whether to buy or sell.

These different types of analytical valuation will form a set of technical trading techniques, which will represent the methodologies used by "rational" investors. In this area, there is the opportunity for more advanced methods to be applied, such as genetic algorithms or artificial neural networks. However, due to computational constraints, it is infeasible to simulate such techniques for every agent.

2.1.2 Emotional parameters

Emotional parameters will represent "irrational" trader behavior. The following parameters will be instantiated for each agent with a different "weight", which will take the form of a point on a scale from 0 (not present in decision-making) to 1 (extremely present in decision making). The weights themselves will be dynamic, for example, if an agent with a high propensity for risk makes a series of disastrous investments, their tolerance for risk will decrease.

a) *Risk tolerance*, determines the degree to which the agent is willing to take risks

b) *Optimism*, determines agent's sentiment towards future performance (1 = very optimistic, 0=very pessimistic)

c) *Contrarianism*, the degree to which the agent follows or goes against the crowd (0=follows crowd closely, 1=very contrarian)

d) *Adaptability*, the degree to which the weights of emotional parameters are capable of changing (0=weights are constant, 1=weights can easily fluctuate)

e) *Regret*, the degree to which previous negative experiences (large losses or unrealized gains) affect decisions

f) *Preferred trading period*, the amount of time the agent would prefer to hold onto a stock before selling it (0=day trader, 1=holds onto stock for weeks)

g) *Reactionism*, the degree to which the agent's actions are determined by previous market events. High reactionism means the agent will buy if the price is increasing and sell if decreasing.

2.2 Agent implementation

The implementation of the agents will take place in a Python environment, using the Mesa agent-based modeling framework (https://pypi.python.org/pypi/Mesa/). Once implemented, the agent populations can be generated, and their interactions simulated.

2.2.1 Agent behavior

Each day, the opening price of a simulated stock will be calculated from the previous day's actions (methodology in 2.2.2). Market variables, such as stock price, trading volume, volatility, dividends, etc, will be publicly available to all agents. These variables form the market conditions, which will be applied as input to the agents. Each agent will then make a simple decision: buy X shares at the current price, sell X shares at the current price, or hold (do nothing). The only limit to buying and selling is the amount of money or shares which the agent possesses. The way this decision is made will be determined uniquely by each agent, based on that agent's "personality" (the set of emotional parameters) and "history" (past experiences in the market).

2.2.2 Market response

To realistically model actual financial markets, the price of the stock will change every day in response to the transactions which take place between agents. Specifically, the change in price will be proportional to the excess supply or demand (excess supply causing the price to drop, excess demand causing a price increase). Supply and demand will also determine to what degree orders are filled; if there is a greater demand, all sell orders will be filled completely, with each buy order filled in proportion to the discrepancy between supply and demand, and vice versa. The total amount of shares in circulation will remain constant. These features are based on the market mechanics used in the Santa Fe Artificial Stock Market.

The dividend for this stock will be determined from a stochastic autoregressive process. When a specific population of agents is applied to real-world markets, this simulated dividend will be replaced with an actual dividend, as well as all of the various market variables. In this way, the real-world reaction to a specific set of market conditions can be simulated in advance, and forecasts about a real-world stock can be derived from the simulation. This is explored in more detail in section 2.4.

2.3 Population generation

Once agent and market mechanics have been implemented, a set of agent populations will be generated. These populations will vary greatly in agent personality. To assess the impact of these different makeups, each population will be simulated for several years, with market patterns analyzed afterwards. For example, population A may contain 70% high risk investors, and 30% low risk investors, with population B containing 30% high risk investors, and 70% low risk investors. Each population could be simulated, and each will likely exhibit unique features.

Populations are useful because they each behave differently, and each effect the market differently. The basic premise of this research is that market behavior can be modeled as the result of the sum of many individual agents and their interactions. If the future performance of a specific stock is to be predicted, an analyst could compare the past performance of that stock against the performance of a simulated stock under identical initial conditions with different populations. Whichever population most closely is able to reproduce the real past performance would likely provide the analyst with some insight into the real traders who are buying and selling the stock. Additionally, to predict the future value of the stock, the analyst could run the simulation using the current real market conditions as the initial simulated market conditions, and watch the previously mentioned population's effects on the stock price.

Of course, this model will assume that the population trading a specific stock remains constant, when in reality new players can enter the market at any time, and weary investors may drop out. Thus, no given population will be simulated for more than several years, as by that point it would stop relating to realistic scenarios.

2.3.1 Generating variations

For each emotional parameter, a set of agent populations will be generated, which vary only in regard to that specific parameter. By keeping all other parameters constant, the impact of varying one particular parameter can be assessed.

For more heterogenous population variations, a genetic algorithm could be developed. This genetic algorithm would take as input a specific real stock, and then attempt to generate a population of agents whose behavior, given the same market conditions as the real stock, would most closely mimic that of the real world trading population. If effective, this would provide a valuable tool for analysts wishing to forecast the performance of a stock, given only its past performance.

3. Project timeline

3.1 Agent parameterization

To parameterize each set of variables, analytical and emotional, will take about two weeks. This is because this step is the most important, as all market behavior is being modeled as emergent phenomena arising from agent to agent interaction.

3.2 Agent implementation

Agent implementation, due to its wide scope, will take roughly two months. This is simply because of the vast array of agent behaviors and interactions which will need to be coded.

3.3 Population generation

Population generation and assessment will take about one month. This is due to the many different agent populations which will need to be generated, simulated, and then subsequently analyzed.

4 References

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