Using Software Agents to Simulate How Investors' Greed and Fear Emotions Explain the Behavior of a Financial Market

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Abstract: Understanding and reproducing the behavior of stock markets is both an interesting and difficult topic. In fact stock markets are an example of complex systems where the emergent behavior, coming from the aggregate effect of the action performed by independently acting investors, has a direct and important impact on our dayly lives. In our study, we want to explore if a computational simulation technique based on software agents could be used to model a stock market. Also we would like to investigate if a simple modelisation of the complexity underlying stock market operations could result in a good-enough estimate of the future market behaviour. A case study where we use our software agent based simulation to track the S&P500 index is described and discussed.

Key–Words: Software agents, financial markets, simulation of complex systems, simplification oriented modelling of complex systems.

1 Introduction and State of the Art

Software agents can be a flexible methodology to be used when realizing simulations of complex systems such as, for instance, consumer markets [Neri, 2005]. We will describe here how the software agent paradigm can be a powerful and versatile simulation tool to model and study complex systems such as financial markets.

Some researchers have investigated stock market behaviour by using multi agent systems and either neural networks or genetic algorithms to deal with large amount of parameters, such as a few n-days moving averages, oscillators, a few n-days relative strength, etc., used to define the financial market behavior [Kendall and Su, 2003]. The overall objective of the research seems to prove that the agents in the systems operate by using different investing strategies and do well depending on the market conditions. Quite interesting they do not compare their simulation runs with a real stock or index time serie so there is no way to know how good is their system in estimating or tracking the market.

Other researchers [Schulenburg et al., 2000], instead, use multi agent systems based on learning classifiers to assess they ability to outperform simple investing strategies such as "buy and hold" or "keeping the money in a saving account". No focus is given to predicting market behavior, in term of tracking a stock or index, but instead their aim is to develop investing strategies for the individual investor. Example of investing rules found by the systems are reported but, as normal with learning systems, they do not show how their recommendations are linked with financial or economic theory. Consequently no real world investor would trust this kind of rule and one may wonder about their general validity on data not present in the learning set.

Another research approach uses agent based simulators, where agents behave accordingly to well defined types of investment strategies, to understand how an hypothetical market would evolve depending on the investors' decisions. [Takahashi and Takano, 2007]. In particular, in the cited work, the researchers focus their attention of what happen in a market when over confident investors abund and how the market value gets influenced by their investment decisions.

In [Hoffmann et al., 2006], a social simulation based on software agents is described where two main investment strategies are used by the individual investors. The two investment strategy are one based on trend expectation of the stocks and the other on basic fundamental analysis of the stock. Another interesting point addressed by the work is how to deal with excess demand or offer and how to deal with the consequent variation of the stock price.

Our simulation approach goes in the direction of simplifying the computational model to be used to simulate a financial market behavior by possibly using only the greed and fear factor to capture the implicit elements that influence individual investors decision making. And, thus, the emerging behavior of the market as a whole.

In addition, we also aim to model or trace the market behaviour by trying to predict its future value on the base of the greed and fear factor dynamics.

2 Financial markets and market indexes

The most relevant concepts used to describe financial markets will be explained in this section.

A stock market, or financial market in the following, is an electronic or physical place where financial titles (stocks, bonds, options, etc.), quoted on that market, are traded between buyers and sellers.

A market or stock index is a (usually) market capitalization weighted index of stocks traded in a specific stock exchange. That is an index is build by first selecting a set of stocks in the market, may be the biggest n stocks in term of their market capitalization, and then calculating a weighted average of the selected stock prices in term of their capitalization. The importance of stock indexes in current financial markets is that they synthesize in a single value at a given time instant how the market is doing with respect to the type of stocks included in the index. Therefore indexes and their time series are measures of the aggregate market behavior over a period of time.

For instance the S&P500 is a well known market index calculated over stocks traded in the New York Stock Exchange which represent the first 500 companies in term of market capitalization.

For a given period of future time (days, weeks, months, etc.) financial analysts try to estimate the trading range of a stock price or of a market index. The trading range consists of a maximum and of a minimun values that the index can reach over the period of time unless extraordinary conditions may occur. The minimum and maximum values of the market index are linked to the expected or estimated future stock returns and to the future economic growth.

3 The architecture of the financial market simulator

Goal of the simulation is to realize a computation tool able to study how the emerging market behavior, as synthesized by a market index curve, is affected by the investing decisions made by the individual investor in the market. Most important we want to keep as simple as possible the architecture of the simulator in order to allow for a thorough understanding of the obtained findings from the simulation process.

Therefore some assumptions about the financial market's contextual conditions are necessary in order to realize a working computational simulator that is able to capture the market dynamics object of this study.

To begin we hypothesized a market where the main actors are: private investors, institutional investors (including banks), hedge funds (and speculators), and government related investors. These four classes of investors well represent the actors who operates on the market day by day. Note that as in the real market many investors make up each of the above classes so in our financial simulator many investing (software) agents are used to realize a given investor class.

The proportion of investors belonging to a given class with respect to the total investors in the simulation follows: private investors represents 40% of the total investors, institutional investors amount to 30%, hedge funds represent 20% of the investors and government related investors make up the remaining 10%.

Also we define as input a minimum a maximum value that the market index can reach during the simulated period of time, as well as the total amount of assets, in cash or not, available in the economy during the same period of time.

Depending then on the amount of assets invested in the market, the market index will have a proportionally related value. Roughly speaking, if all the assets available in the economy would be invested in the market then the market index would reach its maximum value for the period. To be precise, not all the assets in reality could be invested in the market as any investor will keep a part of them as liquidity or not invested in the market anyway. Our simulation will consider this peculiarity of the investors by allowing the definition of a minimum value of liquidity for each investor class.

Given the simulation perspective and in order to define completely each investor class, we have also decide: how many assets the class will have, their proportion actually invested in the market at the beginning of the simulation, the maximum proportion of assets that can be invested in the market (or the reverse, the minimum tolerable liquidity), and finally their bias in making an investment decision (the fear/greed factor).

In our investigation we want to understand if and how a variation of the fear/greed factor in investor may affect the market index. Note that the greed and fear factor, or GF for short, is not a novel concept but it is a well known component of the decision making process involving investment decision in real life situation.

For instance: should one invest her savings in Google stock for the next 10 years to build up an integrative pension hoping in an awesome return or is it better to play it safe and put her savings into governmental bonds which will not default for sure but will return a relatively modest income even after 10 years? In the end the investment decision is affected by how one's greed and fear emotions will bias the selection of a future favorable or unfavorable future economic scenario notwithstanding all the rationalization one can make about the future state of the economy.

To give an example of how the above discussed hypothesis concerning the market have been implemented in the simulator in a simple but effective form, we show here how the estimated value of the market index to be studied is calculated during the simulation process:

Cost of a Unit of the Market Index =
(Total Assets - Minimum Allowed Liquidity) /
Maximum Value of the Market Index

Estimated value of the Market Index (t) =
Invested Assets(t) /
Cost of a Unit of the Market Index

In particular, note that because we believe that the market index value depends on the percentage of total assets invested in the market, we start by determining the cost of a unit of the market index by dividing the total amount of assets that can be invested in the market by the maximum allowed value of the index (given as input). After determining the cost of a unit of the market index, than determining the current value of the market index is just a matter of dividing the value of the assets currently invested by the unit cost.

Let's move now to how a single investor has been modeled as a software agent. The abstract model of the decision making process, that we take as reference in our study, has been done by Bettman [Bettman, 1979] for studying consumers' buying behavior. Essentially a software agents is a piece of software able to perform decision about a specific task at hand [Neri, 2005], in this case investing. Therefore modeling an investor by means of a software agent consists in defining in a formal way the decision making process of the investor so that a suitable decision function can be coded.

The decision making process for the individual investor, according to our perspective of the market, consists of the following components:
a) the initial investment situation of the customer in term of: its available total assets, the amount of them already invested, her acceptable minimum level of cash (liquidity), and her greed and fear factor (GF).
b) her investment decision function. The decision to invest is defined in term of a probability function declared as: buy if P(v<GF), sell if P(v>(GF+(1-GF)/2), otherwise do nothing. For any buy or sell transactions, an amount of stocks equal to 10% of the Total Assets of the investor is bought or sold.

Of course this is a simplyfied but precise view of the decision making function as the implemented program has to take into account some specific situations, such as what to do in the case of a buy signal but of no available cash to invest, and act accordingly.

Each investors is represented as a sofware agent that is instantiated by one of the investor types. Each investor starts from the given initial conditions and then autonomously decide if to invest or not in the stock index. This results in a different internal status for each agent during the simulation thus reproducing what happen in a real financial market where each investors has a distinguished investment position at any given instant of time.

As we have now described all the individual components, we can move to the overall architecture of the simulator.

The simulation process is then made up of a series of rounds, each one representing an atomic interval of time, which follows one another until the whole time period that one wishes to simulate is covered.

During each round, all the investors can decide if to buy, sell or do nothing with regard their assets. As each investor's decision is a stochastic function, each investor ends quickly in a state different from the initial one and from those of the other agents. The resulting emerging behavior of the system is thus unpredictable a priori but generated by simple and well defined rules governing each investors.

4 The economic sentiment and its influence on financial markets

If it is true that each investor tend to take investment decisions independently from the others, it is also true that the public knowledge about the economic outlook, created and diffused by, for instance, economic commentators, will influence the decision process of every one operating in the market.

As an instance, if the economic outlook looks negative, people will tend to sell some of their stocks and buy instead government bonds or physical gold to deal with a possible drop in stock prices due to reduced future profits.

We will call the widely spread, public knowledge base about the future of the economy, Sentiment. We will consider, in our study, the Sentiment expressed as a numerical variable ranging from 0.0 to 1.0, where 0.0 represent a doomsday outlook and 1.0 represent instead an ebullient or over heated economic future.

To take into account the Sentiment into our simulation, we will use a modified formula for determining an adjusted greed and fear factor, GF', which will be calculated as GF' = GF * Sentiment, where GF is the greed and fear factor typical of each investor and give a priori as discussed in the previous section. The Sentiment time serie is instead an input time series for our simulation expressing day by day the estimated outlook of the future economy.

5 Experimental findings

We will describe here some experimental findings when we used our simulator to estimate the S&P 500 market index. We used the dayly close of the S&P500 as reference. The period of time under our investigation start from January 1st, 2008 till December 31st, 2008. All the market data used are publicly available and have been downloaded from the Finance section of Yahoo.com.

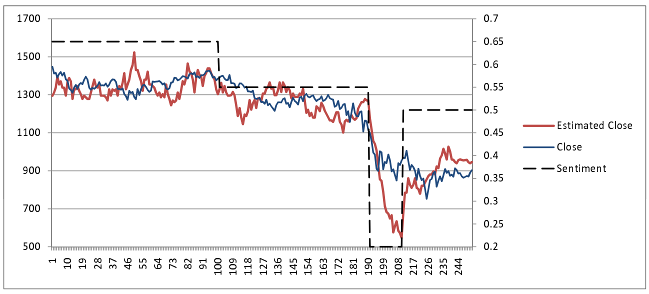

Figure 1: Time series of the S&P500 close value, of the Estimated value of the S&P500 index as produced by the simulator, of the Sentiment.

In figure 1, we can observe the real behavior of the dayly close values of the S&P500 index, over imposed it are the estimated values of the index as calculated from our simulator. Their respective values can be read on the left axis of the graph. The third time series represented by a broken line show the dayly values of the Sentiment variable during the whole simulated period. Note that the Sentiment line is intentionally showing either periods where the sentiment about the economy does not vary or periods where a brusque variation of the sentiment happens such as when critical news or bust/boom hinting headlines are published by the financial press.

It is quite interesting to note that even by using a simplified model of the investors operating in the market, we could reach a quite good approximation of the market index in term of overall behavior across the whole simulated period. The only situation where there is a large prediction error, figures 1 and 2, happen when there is a large and quick variation of the real S&P500 index which also affect the common sentiment about the economy perspective.

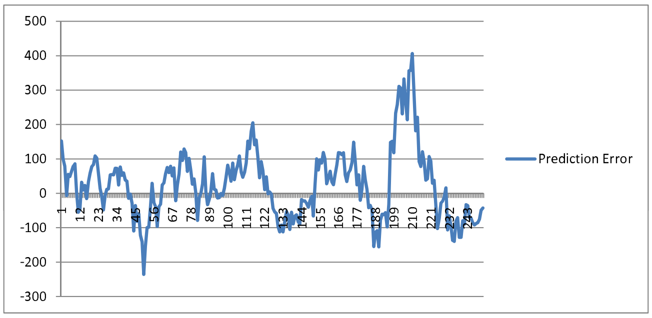

Figure 2: grafico 2.

When this happen, then, the simulator can adjust its prediction only after a number of rounds of simulation and therefore it cannot quickly catch up to the brusque variations of the tracked index.

The main findings however coming from the reported empirical simulation, which is an exemplar case of many run with the simulator, is that with a simple description of the investors operating in the market, given a priori and untouched during the simulatio, plus a rough measure of the overall outlook of the economy as expected by the economist, the Sentiment, we were able to observe a realistic behaving emerging behavior in our simulator which matches the shape of the curve representing the market index that we aimed to track.

Of course an interesting hypothesis about the real world that could be made after observing the experimental results, is that the financial markets have operated during the whole 2008 as places where investors reversed their emotions. Thus investment decisions where only based on fears or hopes about the economy and were not based on fundamental or economic analysis of the underlying stock returns.

6 Conclusions

In the paper, we described how a software agent based simulation could be developed to model a financial market, and a stock index in particular. Also we propose that a simple model of a financial market could be enough to obtain an estimate of the market index behavior close enough to the real performance of the market index.

Also we presented a case study involving the estimation of the S&P500 index over the year 2008 and the notion of market/economy future outlook in term of the economic sentiment spread across the economic community.

Finally we hope that this research could support the broad research perspective about the flexibility of the software agent paradigm when modeling complex systems.

References:

[Bettman, 1979] Bettman, J. (1979). *An information processing theory of consumer choice*. Addison Wesley, Reading, MA (USA).

[Hoffmann et al., 2006] Hoffmann, A. O. I., Delre, S. A., von Eije, J. H., and Jager, W. (2006). Artificial multi-agent stock markets: Simple strategies, complex outcomes. In *Advances in Artificial Economics, volume 584 of Lecture Notes in Economics and Mathematical Systems*, pages 167–176. Springer-Verlag.

[Kendall and Su, 2003] Kendall, G. and Su, Y. (2003). A multi-agent based simulated stock market - testing on different types of stocks. In *Congress on Evolutionary Computation (CEC03*, pages 2298–2305.

[Neri, 2005] Neri, F. (2005). Empirical investigation of word-of-mouth phenomena in markets: a software agent approach. *WSEAS Transaction on Computers*, 4(8):987–994.

[Schulenburg et al., 2000] Schulenburg, S., Ross, P., and Bridge, S. (2000). An adaptive agent based economic model. In *Learning Classifier Systems: From Foundations to Applications, volume 1813 of Lecture Notes in Artificial Intelligence*, pages 265–284. Springer-Verlag.

[Takahashi and Takano, 2007] Takahashi, H. and Takano, T. (2007). Analyzing the influence of overconfident investors on financial markets through agent-based model. In *Intelligent Data Engineering and Automated Learning - IDEAL 2007, volume 4881 of Lecture Notes in Computer Science*, pages 1042–1052. Springer-Verlag.