How to Investigate the Decision Making Behavior of Investors in Financial Markets by means of Software Agents

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Abstract: Financial markets are an example of complex systems where relevant behavior happens to be a synthesis of independent and singular decisions taken by individual entities operating in them. Such is the case of financial markets where several investors autonomously decide what investment decisions to undertake. In our work, in particular, we focus our attention to the following research question: can a software agent simulation reproduce the behaviour of a significant financial market time serie by concentrating on many simple interactions among investors-agents. 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 or a whole simplified economy [Bruun, , Canzian, 2009, Fagiolo and Dosi, 2002, Neri, 2005, Tesfatsion, 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.

In [Arthur et al., 1997], an artificial market, the SFI Artificial Stock Market, is used to empirically test hypothesis about how investors adapt their expectations about how the other traders will act and operates on the markets accordingly. Hypothesis about the traders' behavior are continuously generated and discarded if observed different from the way the aggregate market behave.

Our research aims to find the simplest computational model able to simulate a financial market behavior in a meaningful way. In particular we started our work taking a purely computational perspective and exploring if and how by a greed and fear factor could determine the investment decision process of each individual operating in the stock market. Ideally the simulation of all the individual decisions will result in an emerging behavior able to approximate the overall rise or decline of the market as a whole.

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 index or stock index is a (usually) market capitalization weighted index of stocks traded in a specific stock exchange. This means that an index is build by first selecting a set of stocks in the market, maybe 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 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 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 our research is to realize a computation tool able to study how the emerging market behavior, as synthesized by a market index time serie, is affected by the investment decisions made by the individual investors. 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 a real market, many investors make up each of the above classes, so in our financial simulator many investing (software) agents are used to simulate 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%. This percentage are given and not object of the experimentation. They approximate the real world proportion of such class of investor according to the author.

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.

There are many ways to determine the Sentiment about the economy outlook some more qualitative other more quantitative. In the next section, we will explore two of the possible ways to determine the Sentiment values both from the qualitative and quantitative perspective.

5 Experimental findings on a Qualitative Sentiment function

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.

In the first set of experiment, we have calculated the Sentiment time serie in a qualitative and then subjective way, but then converted it into a numerical value, buy browsing through the headlines of major Italian financial newspaper (Il Sole 24 ore) and the economic sections of a well known Italian newspaper (Corriere della Sera) for the whole 2008 year. Essentially we would like to reproduce by the Sentiment variable the economic feeling for the future of financial market by informed Italian investors who based their buy/hold/sell decisions on major titles from the press.

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

As a consequence an intriguing hypothesis about the real world market 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. If so, investment decisions where only based on fears or hopes about the economy and were not based on fundamental or economic analysis of the stocks composing the markets.

6 Findings on a quantitatively determined Sentiment function

Some readers with a scientific background may feel uneasy about using a qualitative approach to estimate the Sentiment value. Some considerations addressing these issues are therefore needed. One must observe that in finance or economy experts play by different rules than in the hard sciences because of the different nature of the economy subject of their studies. In fact, while branches of finance are dedicated to fundamental analysis of companies and markets trying to explain in terms of qualitative and partially quantitative theory why and how the financial markets behave as they do. Other branches of finances, behavioral finance for instance, try to explain observed economic behavior only in terms of the psychology of the actors operating in the markets. And, anyway, there is also a body of finance trying to address the analysis of stocks and companies in terms of numbers and mathemathical functions. Some of the most well known are based on combining moving averages, maximum or minimum of stock price and the likes of simple, mathematically speaking, functions. Behind the use of such functions, however, rest a sometimes untold qualita-

tive economic theory of how the markets should behave.

Coming to our work, in this new set of experiments, we decide to take a purely quantitative approach to estimate the Sentiment of the market. We have therefore decided to calculate the Sentiment time serie at a given time t, on the base of values from other economic variable having a timestamp lesser or equal to t-1. So we will not bias our simulation by using future values (i.e. having timestamp equal or greater than t) to estimate the future value of the market index.

Now the idea on which we will base the calculation of the Sentiment values for this new set of experiments is that we can extimate the mood of the investors by comparing how the market behaved, on average, in the last days with how the market behaved the last observed day. So we are aiming to use the prime derivate, in a sense, of the market for the last day to assess if the current mood is bullish or bearish.

We then decided to calculate the Sentiment time serie by applying the following formulas:

S&P500MINRangeValue = 800
    (input parameter for scaling purposes)

ScaledS&P500Value(t-1) =
    (S&P500(t-1) - S&P500MINRangeValue) /
    (MAVG(S&P500(t-20),S&P500(t-1))*1.2 -
    S&P500MINRangeValue)

Sentiment(t) =
    MIN(0.6, MAX(ScaledS&P500Value(t-1) ,0.2))

In words, we decide to consider the Sentiment timeserie as a scaled ratio of how the last available value of the market index, at time t-1, is doing with respect to the 20 days moving average of the index itself. The MAVG(a(t-k),a(t-1)) function, moving average, is simply the arithmetic average function calculated from a values going from time t-k till time t-1.

The other formulas and constant values are simply use for rescaling purposes as we want to pass from to a value in the interval 0.2 and 0.6 for our Sentiment timeserie. Of course constant values occurring above could be furtherly tuned to reduce the prediction error but this was not the point of our study.

In figure 1, we can see both how our simulator has been able to track the S&P500 market index, left scale, and also how the Sentiment time serie calculated by using the formulas just described is behaving, on the right scale. It can be noted that the Sentiment time serie is much more stable than the Sentiment time series used in the previous set of experiments, for the first three quarters of the year and then it starts oscil-

lating more wildly than in the previous set of experiments for the last quarter of the year.

In figure 2, the tracking error of the simulation is reported as well. We can see that the simulation higher errors correspond to those situations where the market change abruptly as the simulation cannot, by design, track such quick variations. Yet the error stays in the -100,+100 range for most of the period.

From this novel set of experiments we believe that we can confirm the findings about the simulation and about market behavior that we made in the previous section. In summary, the real market time serie seems to have been determined by the fear and greed of the investors during the period more than by a well sounded economic analysis of the financial stocks. If it were not so, a simulation of the market based on one single parameter aiming to reproduce in a single value the dayly mood of the market would have result in a predicted time series strongly diverging from the real one. Instead the experimental results proved that the predicted outcome tend to stay in a well defined range of the real market index for the whole period.

In addition we believe that the two sets of experiments, when taken togheter, show the robustness of our market model. Consider how different are the Sentiment time series in the first and second set of experiments. Yet the simulator or, said in another way, the simplyfied architecture of the interactions occurring among the investors and their decision making process proved to produced stable results from the point of view of the market index time serie.

7   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.

We presented a case study involving the estimation of the S&P500 index over the year 2008 and we enriched the modelization activity by describing a simple decision making process for the investors and by introducing the notion of market/economy future outlook in term of the economic sentiment that is spread across the economic community by, for instance, the daily financial news.

Finally we hope that this research could support a broad research perspective about the flexibility of the software agent paradigm when tackling the modeling of complex systems.
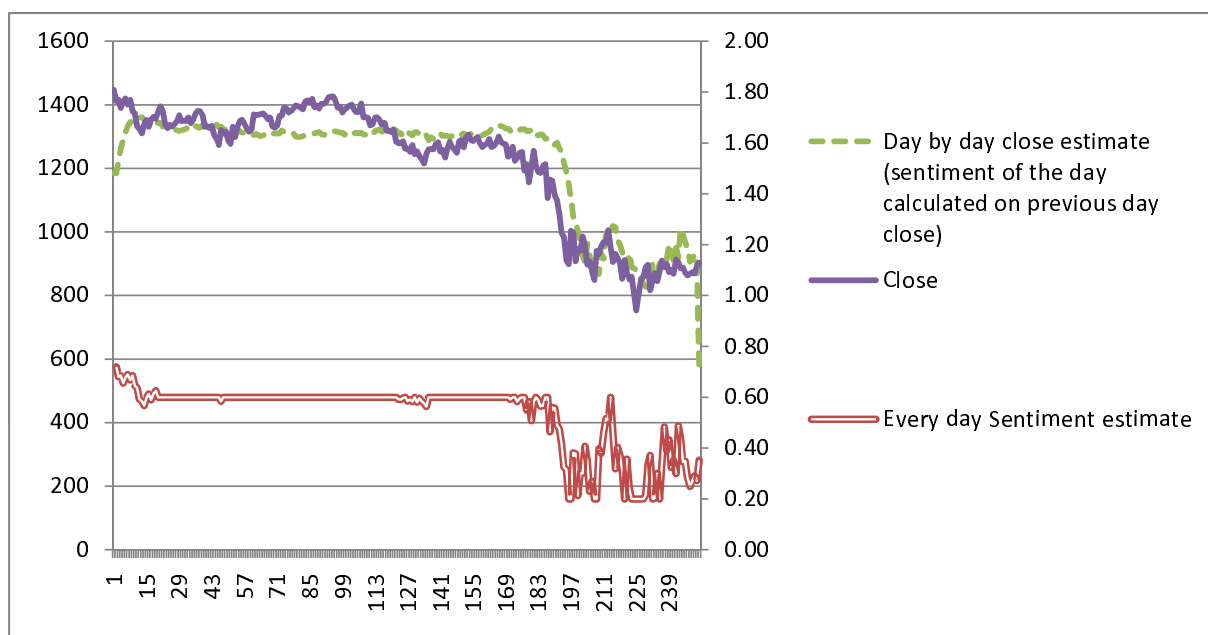
Figure 1: Time series of the S&P500 close value, of the Estimated value of the S&P500 index as produced by the simulator, of the Sentiment time series estimated using a quantitative method.

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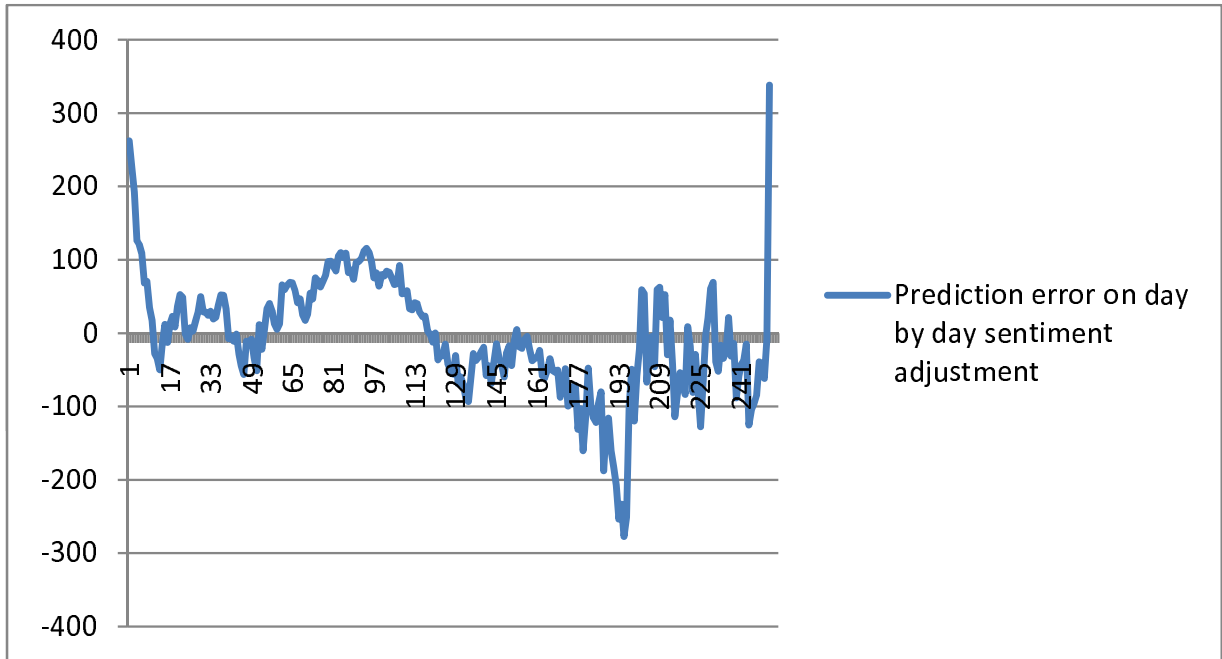
Figure 2: Prediction error measured over the estimate of the S&P500 close value as produced by the simulator by using a quantitative estimated Sentiment value.

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