Computational Finance

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Abstract. **Advances in hardware and software enable research in finance and economics that was not possible before. Some of this research challenges the fundamentals of economics. Others attempt to gain an insight into financial markets, or to explore business opportunities. This paper briefly outlines the scope and agenda of computational finance research.**

1. Introduction

Advances in computing have changed the society. Its implications to finance and economics are immense. Never before have we had the amount of financial data available for analysis today. Never before have we had the processing power to analyze such data. Processing power also enables us to simulate complex models, which opens new routes for studying finance and economic systems. Advances in algorithms, such as evolutionary computation, enable us to analyze data more efficiently than ever. Advances in computing give rise to a whole new area of research in finance and economics, which is the subject of this paper. From an academic point of view, some of this research challenges fundamental concepts in economics. Some researchers attempt to gain better insight into the behavior of financial markets. From a commercial point of view, effective exploitation of new computation methods will help institutes to make better decisions and improve their competitive edge.

What exactly is studied in computational finance? Like many young disciplines, computational finance means different things to different people. But for the health of a discipline, it is useful to have a working definition. Consensus on the definition avoids unnecessary debate and helps focus on important research issues. Boundaries of most young disciplines move over time (artificial intelligence is a good example). This paper is not meant to be a full survey of the topic - a full survey demands more space. Rather it is an attempt to define the scope and agenda of computational finance research. Examples of research so far are used to outline the scope of this young field.

2. Challenging the Fundamentals in Economics and Finance

2.1. What is Rationality?

One of the most fundamental concepts in economics is *rationality*. Individuals, which researchers often refer to as *agents*, are assumed to be rational. For example, from a purely economic point of view, when one is given two prices to purchase exactly the same commodity, one is expected to take the lower price. In a more complex situation, making rational decisions may involve more reasoning; for example solving an *assignment problem* in Operations Research. This is within the capacity of an agent with the right training. However, some agents may be able to solve larger problems more quickly than others. To push computational limit even further, making rational decisions may involve solving combinatorial optimization problems where no known NP algorithms are available; e.g. solving the traveling salesman problem with thousands of cities. Whether *rational agents* exist is therefore questionable; the best that one can do (in general cases) is to find approximations. Given a limited amount of time, some algorithms will be able to find better approximations than others. Given the same algorithm, the faster a computer is the more potential that it can find better solutions. Therefore, when serious computation is involved, how 'rational' an agent is depends on what algorithms it uses, and what computing power it has access to.

Computational complexity is not the only reason why the rationality assumption is challenged. Challenges also come from cognitive reasoning (Anderson 1991). How optimal human beings are is being questioned. A more realistic notion of rationality is *bounded rationality* defined by Simon (Simon 1957), that property of an agent that behaves in a manner that is nearly as optimal with respect to its goals as its resources will allow. Here ‘resources’ include processing power, algorithm and time available to the agent. Some of these resources are not always easy to quantify. Therefore, any mathematical models that assume rationality are subject to the definition of resources available. By using faster computers and better algorithms within a given time limit, an agent can become ‘more rational’.

2.2. The Efficient Market Hypothesis

Rationality is one of the major assumptions behind many economic theories. Here we shall examine the efficient market hypothesis (EMH), which is behind most economic analysis of financial markets. The proposal of the EMH can be traced back to Bachelier’s theoretical contribution (Bachlier 1964) and Cowles’ empirical work (Cowles 1933). In conventional economics, markets are assumed efficient if all available information is fully reflected in current market prices (Fama 1965).

Depending on the information set *available*, there are different forms of the EMH. Here we focus on the *Weak form of EMH* (Malkiel 1992). It suggests that the information set includes only the history of prices or returns themselves. If the weak form of EMH holds in a market, abnormal profits cannot be acquired from analysis of historical stock prices or volume. In other words, analyzing charts of past price and/or trading volume movements, is a waste of time; i.e. technical analysis is futile.

The weak form of EMH is associated with the term *Random Walk Hypothesis* (Cootner 1964). Random walk hypothesis suggests that investment returns are serially independent. That means the next period's return is not a function of previous returns. Prices only changes as a result of new information, such as the company has new, significant personnel changes, being made available

A large number of empirical tests have been conducted to test the weak form of EMH, e.g. see Levy 1996. Recent work illustrated many anomalies, which are events or patterns that may offer investors opportunities to earn abnormal return. Those anomalies could not be explained by the weak form of EMH. To explain the empirical anomalies, many believe that new theories for explaining market efficiency remain to be discovered.

3. Understanding Financial Markets

Few researchers question that the market is efficient in the long run. The question of how market prices become efficient is being raised. Traditional theory was based on rationality: investors are all efficient, and therefore, when a new piece of information becomes available, they all come to the same conclusion on what the fair price should be to reflect the new information. Others seriously question whether investors are homogeneous and fully informed. If they are not, how does the market efficiency emerge through the interaction of these investors? Some of the research that attempts to gain a better understanding of the market will be elaborated in this section.

3.1. Agent-based Artificial Markets

One way to study properties of a market is to build artificial markets, whose dynamics are solely determined by computer programs that model various behaviors. Some of these programs may attempt to model naïve behavior, others may attempt to exhibit intelligence. Since the behavior of agents is completely under the designers' control, the experimenters have means to control various experimental factors and relate market behavior to observed phenomena.

The enormous degrees of freedom that one faces when one designs an agent-based market make the process very complex. Some of the most important lessons can be learned from LeBaron 2001b, Farmer et al 1999, Tesfatsion 2001 and Jefferies et al 2002. According to LeBaron 2001b, the main points to contemplate when designing agent based markets are: the agents, the trading mechanism, the securities, the evolution; benchmark and calibration and time. Each of these aspects has a non-trivial number of design possibilities.

The work by Arthur opened a new way of thinking about the use of artificial agents that behave like humans in financial markets simulations (Arthur 1994). The idea of bounded rationality wasn't new in those years, but to apply it in economics and in particular in financial markets was a turning point which gradually lead to the very influential work of the *Artificial Stock Market* (ASM) from the Santa Fe Institute (Arthur et al 1997, LeBaron et al 1999). The Santa Fe ASM was composed by several artificial agents who would decide to submit orders to buy or sell one risky asset in order to achieve their desired position of such asset and a risk-less asset, based on the market conditions.

The Santa Fe ASM opened new questions, which lead to other important work. LeBaron et al 1999 analyzed the time series properties of the endogenously generated returns. It was observed that the market replicated some of the empirical features (the so called "stylized facts") of the real markets. LeBaron 2001a further investigated other aspects of the market, the effects of the longitude of the traders' memory on the market. Farmer 2002 explored an artificial market with trend following traders and value investors using a price determination out of equilibrium. In his approach he tried to combine simplicity as well as realistic assumptions about the market, price formation and trading strategies.

Arifovic 1994 and 2001 explored the use of genetic algorithms in economic models, in particular in foreign exchange markets. Although the genetic algorithms had been used before in financial applications (e.g. see Bauer 1994), her approach was more complex, novel and entered fully in the economics field. The GA mechanism was used to evolve decision rules that were used to determine the composition of the agents' portfolios in a foreign exchange market. The returns and exchanges rates were generated endogenously. Unlike the Santa Fe Artificial Stock Market, Arifovic's Exchange Rate Market had no exogenous fundamental process influencing the exchange rate.

Two interesting phenomena to be analyzed in the study of financial markets are herd behavior and regime switching. Some different approaches have been developed and tested. In his seminal work, Kirman 1993 created a model that generates complex dynamics on the basis of simple behavior inspired on ants. In further work, Kirman et al 2001 developed an agent-based model to analyze the fish market in Marseille.

To explain the features of the stock market returns, Lux 1998 and Levy et al 1996, 2000 borrowed techniques developed in statistical mechanics. This work belongs to an emergent field known as *Econophysics*. The large number of papers testifies to the increasing importance of this research area. Farmer 1999 introduced the field and described some of the most important work. The main rationale behind these models is that the many interacting particles in physical systems obey universal laws (known as scaling laws) independent of the microscopic details of such systems. Such properties, the so called "stylized facts" (see Cont 2001), are shared across different markets (foreign exchange, stock markets), market indexes and stock returns.

Another important line of research surrounds the *Minority Game* (MG), which is a simplification of the problem first described in Arthur 1994. The Minority Game has been used extensively to model Financial Markets, e.g. see Caldarelli et al 1997 and Challet et al 2000. The aim behind the use of the MG in Financial markets is to have a simple enough mechanism that allows some analytical treatment and yet captures important aspects of the agents' individual behavior. In such models the authors represent different types of traders with differences in the memory length and observe the results of their interactions on the collective behavior.

3.2. Evolving Agents

Agent-based research plays an important role in understanding the market behavior. The design of the behavior of the agents that participate in an agent-based model is very important. The type of agents can vary from very simple agents to very sophisticated ones. The mechanisms by which the agents learn can be based on any of the artificial intelligence techniques like neural networks, genetic algorithms, learning classifier systems, genetic programming, etc. In this section we will present some important examples of different types of agents and learning mechanisms.

Evolutionary computation plays an important part in the study of financial markets. In particular, co-evolution is used to model competing agents. In the Santa Fe artificial stock market model (Arthur et al 1997), prices were determined by agents, which were modeled using genetic algorithms, more specifically, by a Learning Classifier System (LCS).

Before the arrival of the Bounded Rationality and Inductive Reasoning in the design of Artificial Agents, experimental studies were conducted with human beings. This well established field in Economics, known as "Experimental Economics" is a frequent source of inspiration for the more recent studies in Computational Finance, in particular in the simulation of Financial Markets. Chan et al 2001 made an interesting comparison between the two approaches.

Sunders (Gode et al 1993 and Sunders et al 2004) performed a series of experiments with humans and computational agents who take decisions in a random basis; they called them *zero intelligence* (ZI) agents. In their experiments, they obtained a remarkable allocative efficiency with these agents in a simulated double auction market. A key finding of these experiments was the fact that by simply applying a budget constraint to the zero intelligent agents, the allocative efficiency in such market is almost equal to the efficiency in markets with profit motivated humans. The results of these experiments challenge the neo-classical models regarding the utility maximization behavior of the economic agents.

Due to the flexibility of the agent-based paradigm, we do not have to assume the existence of fully rational optimizing agents with homogenous beliefs. We have the possibility of modeling markets with heterogeneous agents and with information asymmetry. The heterogeneity of beliefs is simulated in the work of Schulenburg et al 2002 by modeling classes of traders, rather than individual agents. The adaptive agents' decision process was driven by a learning classifier system. Although their model could not be considered a full scale Artificial Stock Market (the prices were not generated endogenously), its simplicity and the interesting findings deserve further attention.

3.3. Studying Market Microstructure

Another field that could benefit greatly from using advanced computation methods is the study of *Market Microstructure*. Sometimes it is desirable to compare different trading mechanisms; for example one may be interested in comparing the continuous double auction (as studied in Yang 2002) with the simple *Walrasian tatonnement* (as studied in Arthur et al 1997 and Arifovic 1994). We can stress the impact of these trading mechanisms in the price formation or the efficiency of different types of markets. We can analyze the role played by the market makers or the specialists on the price, or raise questions about the asymmetry of information among the agents. The number of research opportunities to explore is countless.

3.4. The Red Queen Thesis

In Santa Fe's experiments, change of behavior was exogenously imposed by the experimenter. Chen et al 1994 and 2001, proposed an endogenous scheme for retraining. In their experiments, prices in the artificial market are determined by artificial agents, which were modeled by genetic programs (Koza 1992). Chen and Yeh studied when and by how much agents (which are investors) retrain themselves. From the experimenters' point of view, retraining was endogenously motivated by 'peer pressure' and self-realization. They prescribed a way in which agents look for 'better' investment rules. To make an analogy to real world phenomena, they called this procedure 'Visiting the Business School'. Driven by differences in performance (as opposed to being determined by experimental parameters), agents co-evolve.

Like Chen and Yeh, Markose et al 2003 used genetic programs to represent trading strategies. If the artificial market resembles the real market, they expect wealth to follow the *power law distribution* - that a very small number of agents posses a large percentage of the total wealth, with the remaining of the population sharing the rest of the wealth. Agents are programmed to retrain themselves when their wealth fall below the median wealth of the population. Training is done using EDDIE, the genetic programming system for forecasting (Li 2001 and Tsang et al 1998, see Section 4). Markose et al's aim is to establish the *Red Queen's* condition, which require individuals to keep improving (through retraining) in order to maintain status quo in its performance in relation to the rest of population. This is encapsulated in Lewis Caroll's Red Queen (in Alice in Wonderland) who says "*in this place it takes all the running you can do, to keep in the same place*".

3.5. Computational Approaches to Game Theory

When one takes an agent-based approach and studies the market's microstructure, one has to focus on possible interaction between agents. Game theory describes the decisions of rational agents. One of the games most studied by computer scientists is the *iterative prisoners' dilemma* (Axelrod 1987), which payoff table is shown in Table 1. This is a dilemma because the equilibrium point is where both players choose to Defect, which give them each 1 in payoff, although they could have both achieved a payoff of 3 had they both chosen to cooperate.

Jin and Tsang applied genetic programming to find strategies for Rubinstein's model and confirmed that equilibriums can be approximated by genetic programming (Jin et al 2004). This gives opportunity to find approximate solutions to more complex situations for which theoretical solutions have yet to be found.

3.6. Research Opportunities and Challenges Ahead

Researches described above are just some of the more representative examples in computational finance. The variety of financial applications, the different types of learning mechanisms used in such applications and the different types of markets that one could simulate suggest a rich field of research. However, all this flexibility and freedom comes at a cost. One of the main criticisms to agent based markets is the large number of parameters and the tuning needed to get "realistic" price behavior. In some situations, small changes in the parameter settings could lead to significant changes in the market's behavior, both quantitatively and qualitatively. For any results to be creditable, changes in the parameters settings must not lead to significantly different results.

4. Forecasting in Computational Finance

4.1. Predicting the Future

The strong position of EMH amongst academics did not deter attempts to predict the future - understandably given to the potential return. Thanks to advances in memory technology and the reduction in hardware prices, large quantities of financial data are stored in data warehouses by Reuters and other companies. Financial data is more widely available to individual researchers. As a result, a significant amount of computing power is devoted to data analysis. Some of the researchers focus on forecasting - or to see whether the market is predictable. Some of the questions in forecasting are: (1) do patterns exist in past data? (2) if so, can they be found? and

Table 1: The Payoff Table of the Prisoners Dilemma

		Player B: Cooperate	Player B: Defect
Player A	Cooperate	Player B gets 3 Player A gets 3	Player B gets 5 Player A gets 0
Player A	Defect	Player B gets 0 Player A gets 5	Player B gets 1 Player A gets 1

(3) if patterns can be found, will they repeat themselves in the future?

Many technical analysts start with daily closing prices. This is partly because this data is most widely available. Figure 1 is a sample chart showing the daily closing prices of S&P 500.

4.2. Neural Networks in Forecasting

Neural networks play an important role in financial forecasting (Batchelor 2001, Dempster 2001 and Yao 2000). The choices of input and output are crucial to the success of financial forecasting. For example, in a network, one may choose to input the last 6 daily closing prices and output a prediction of the next day's price. Through supervised learning, the network may be trained to adjust its connection weights.

The performance of a trained network depends on whether a day's closing price could be predicted by the closing prices of the six preceding days. If such dependency does not hold, then the trained network is unlikely to produce accurate predictions. Therefore, the key is in the selection of the inputs. The six preceding days' closing prices are probably not as rich in information content as technical indicators such as moving average, break out rules, maximum and minimum prices in the n preceding days, or fundamental indicators such as dividends, interest rate and money supply.

4.3. Evolutionary Computation in Forecasting

Neural networks have sometimes been criticized by financial practitioners as being black boxes (a proposition which is debatable, e.g. see Benitez et al 1997). Some researchers turned to evolutionary computation. Bauer was one of the first researchers to use genetic algorithms to evolve investment strategies (Bauer 1994). Results were encouraging, though not conclusive. Mahfoud & Mani proposed a new genetic-algorithm-based system for predicting the future performances of individual stocks (Mahfoud et al 1997). Neeley et al 1997 and Oussaidene et al 1997 used genetic programming (Koza 1992) to test whether technical rules could be used to forecast foreign exchange prices. Hayward used genetic algorithms, in combination with artificial neural networks, for stock forecasting (Hayward 2004). Some success has been achieved, which at least suggests that the potential of technical trading should not be totally ignored.

It cannot be emphasized enough that the accuracy of a forecasting program is not only limited by the algorithm that it uses, but also by the quality of the data. EDDIE was developed as an interactive tool to help analysts to search the space of interactions and make financial decisions (Tsang et al 1998, 2004). Given a set of variables, EDDIE attempts to find interactions among variables and discover non-linear functions. FGP-2 is an implementation of EDDIE for financial forecasting (Li 2001). By using a constrained fitness function, FGP-2 provides the user with a handle for tuning the precision against the rate of missing opportunities (Li 2001). This allows the user to pick investment opportunities with greater confidence.

4.4. Using Data with Richer Information Content

Closing prices are the most widely available data in the public domain. It is reasonable to believe that the more information one uses, the more accurately one can predict. In addition to closing prices, one could use the opening prices, highest and lowest prices, volume, etc. as they are shown in Figure 1.

With more data available, financial expertise in what indicators to use and how to use them become more important. For example, some variables may be dominated by others; elimination of less relevant variables would enable the algorithm to search in a smaller space (hence likely to be more effective given the same amount of time). New independent variables that provide higher prediction power could be derived from original variables; e.g. Korczak & Lipinski 2004 dynamically generated a reduced set of (generated) variables for stock trading.

Table 2: A Sample Time Stamped Limit Order Book

French Stock 12062 at 02/03/04 11:00:03			
Ranking	Price	Quantity	# of orders
Lowest offer 3	18.49	8,156	1
Lowest offer 2	18.48	14,900	4
Lowest offer 1	18.47	6,531	2
Highest bid 1	18.46	179	1
Highest bid 2	18.45	3,153	5
Highest bid 3	18.44	8,480	3

4.5. Using High Frequency Data

Some traders make their profits by buying and selling within the same day. This is called intraday trading. To find patterns for automated intraday trading, daily closing prices are not terribly useful. A system must be trained with data that come in at a higher rate. For example, one could use tick by tick data - data that record the transactions as the take place in real time. These are called high frequency data. Dempster et al 2001 used intraday data for foreign exchange trading.

Transaction prices are not the only information that could help intraday trading. When the bids and offers are available, they should help to improve forecasting accuracy. Table 2 shows an example of a record that may be useful to a researcher. These records could be added to the transaction prices and volumes, which is not shown in Table 2 (transactions may not take place every minute or second).

The record shown in Table 2 was taken at a particular time point for the French stock 12062. Even if only one record is retained per minute, one could be presented hundreds of records per day. Each record here shows the three highest bids and three lowest offers (one could certainly include more bids and offers if one wants to), the volume in demand or supply and the number of traders that make those bids and offers. In the example shown, the best offer asked for a price of 18.47 Euro. This price was offered by two traders whose total demand was 6,531 shares. The highest bid was made by one trader, who

Figure 1 - The open, closing, maximum and minimum prices and volume of S&P 500

demanded 179 shares at the price 18.46 Euro. Data such as those shown in Table 2 provide the analysts with information that the transaction prices alone do not. For example, it shows that if more supplies are close to the trading price than the demands, this may suggest a pressure for the price to go down (though this does not necessarily happen).

4.6. Exploiting Arbitrage Opportunities

There are many other examples of business exploitation of computation finance. Markose et al 2002 and Tanaka-Yamawaki et al 2004 also used tick data for finding arbitrage opportunities. An arbitrage opportunity arises when the prices of the derivatives do not synchronize with each other. For example, when the option prices are too low in relation to the future prices of a stock, one can make risk-free profit by simultaneously buying options and selling futures. Theoretically, if the market is efficient, arbitrage opportunities should not occur; in other words, the derivatives should be priced in relation to each other to prevent risk-free profits. In reality, arbitrage opportunities were discovered (in hindsight) in real markets by these authors. For computational research in option pricing, see for example Los 2001.

4.7. Portfolio Selection

Every investor will attempt to maximize return and minimize risk. By investing in a portfolio, as opposed to putting all the investment in one stock, risk can be reduced. Each stock has its own expected return and risk (the calculation of risk itself is a major research topic in finance, see for example Dempster 2003). Therefore, the selection of a portfolio is a multi-objective optimization problem. A tremendous amount of research in multi-objective optimization has been conducted, which can be applied to portfolio selection; most recently, see Hanson et al 2002, Siokos et al 2002 and Streichert et al 2004. Work on non-computational methods for portfolio optimization is abundant, but beyond the scope of this paper.

5. Research Activities in Computational Finance

Advances in computing hardware and algorithms give rise to unprecedented opportunities in computational finance research. We are in a much better position to explore ways to forecast and to gain better understanding of the market. On the other hand, being an inter-disciplinary research area, computational finance involves hard work by its very nature. This is because researchers must gain sufficient knowledge in computing to know what their potential and limitations are. Researchers also have to know enough about finance to know where computing techniques can be applied.

To bring researchers from computing, finance and economics together, an increasing number of international conferences and workshops have been organized in recent years. Some of the most relevant and best attended conferences include:

- IEEE's International Conference on Computational Intelligence for Financial Engineering, which bridges between advanced computational methods and financial engineering
- Annual Workshop on Economics with Heterogeneous Interacting Agents (WEHIA), which attracts participants from agent-based economists;
- International Conference on Computing in Economics and Finance, which attracts a wide number of special interest groups including agent-based simulation, finance, econometrics, etc;
- International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS), which brings agent-based researchers (not limited to finance) together.

Tesfatsion's Agent-Based Computational Economics[1] and Chen's AI-ECON Research Center[2] provide excellent, up-to-date links to researchers and conferences.

Computational finance is establishing itself to be a major research subject. Clusters of communities are being formed. The potential impact of the community is immense. The maturity and potential of the community could benefit from more concerted organizations and activities, as it is the case in other young communities.

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[1] http://www.econ.iastate.edu/tesfatsi/ace.htm

[2] http://www.aiecon.org/

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