Study on Artificial Intelligence and Investment Decision

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Abstract- **Computers play a role in many aspects of investing. Artificial intelligence is a technique of computing that is perpetually on the cutting edge of what can be done with computers. Artificial intelligence could apply to program trading, but also other aspects of investing. The techniques of artificial intelligence include knowledge- based, machine learning, and natural language processing techniques. The discipline of investing requires data identification, asset valuation, and risk management. Artificial intelligence techniques apply to many aspects of financial investing, and published work has shown an emphasis on the application of knowledge-based techniques for credit risk assessment and machine learning techniques for stock valuation. However, in the future, knowledge-based, machine learning, and natural language processing techniques will be integrated into systems that simultaneously address data identification, asset valuation, and risk management. AI has been widely adopted in such areas of risk management, compliance, and securities trading and monitoring, with an extension into customer relationship management (CRM). Tangible benefits of AI adoption include reduced risk of fraud, increased revenues from existing customers due to newer opportunities, avoidance of fines stemming from non-compliance and averted securities trade exceptions that could result in delayed settlement, if not detected.**

*Key words - **Artificial Intelligence (AI); Investment Decision-Making; Data Identification; Risk Assessment and Portfolio.***

I. INTRODUCTION

In the early days of computing, a typical task for a computer program was a numerical computation, such as computing the trajectory of a bullet. In modern days, a typical task for a computer program may involve supporting many people in important decisions, backed by a massive database across a global network. As the tasks that computers typically perform have become more complex and more closely intertwined with the daily decisions of people, the behavior of the computer programs increasingly assumes characteristics that people associate with intelligence. So this , a program earns the label of "artificial intelligence". The classic test for whether a program is intelligent is that a person would not be able to distinguish a response from an intelligent program from the response of a person. AI has found a home in financial services and is recognized as a valuable addition to numerous business applications. Sophisticated technologies encompassing neural networks and business rules along with AI-based techniques are yielding positive results in transaction-oriented scenarios for financial services.

II. MAIN USAGE OF ARTIFICIAL INTELLIGENCE IN INVESTMENT DECISION

While artificial intelligence (AI) could apply to many areas of investing, much of what happens in computer-supported investing comes from non-AI areas. For instance, computational techniques not considering primarily AI techniques include numerical analyses, operations research, and probabilistic analyses. These non-AI techniques are routinely used in investing.

The process of investing has three stages:

- Data identification.
- Asset valuation, and
- Risk management.

A range of computer programming techniques that are currently, popularly considered as artificial intelligence techniques include (Rada 2008):

- Knowledge-based techniques, such as in expert systems.
- Machine learning techniques, such as genetic algorithms and neural networks.
- Sensory or motor techniques, such as natural language processing and image processing.

These methods may apply to investing. For instance, expert systems have been used to predict whether a company will go bankrupt. Neural networks have been used to generate buy and sell decisions on stock exchange indices. Natural language processing programs have been used to analyze corporate news releases, and to suggest a buy or sell signal for the corporate stock.AI has been most often applied to asset valuation, but is also applicable to data identification and risk management.

Two, high-level types of data used in financial investing are technical data and fundamental data. The price of an asset across time is technical data, and lends itself to various computations, such as the moving average or the standard deviation (volatility). Fundamental data should support cause-and-effect relationships between an asset and its price. For instance, the quality of management of a company should influence the profitability of a company and thus, the price of its stock.

The universe of fundamental data is infinite. Many streams of data that might be relevant, such as corporate earnings or corporate debt, might also be related to one another. Various non-AI tools, such as linear regression analysis and principal components analysis, might be used in identifying what sets of data are more likely to be useful than what other sets. Such non-AI, computational techniques can be combined with AI techniques in experimenting with various combinations of data and choosing what data to use in asset valuation.AI has been most often applied to asset valuation, but is also applicable to data identification and risk management.

Sensors are used to access the state of affairs in the problem domain. In the trivial case, the sensors import relevant information into DSS. More advanced sensors need capabilities for locating, filtering and transforming relevant information, and generating alerts. With diminishing requirement of "switching media" when moving from decision-making to decision implementation, systems should enable implementation as well as monitoring of the results of decisions. Implementation primarily involves carrying out the decisions, but it may also entail planning and optimization activities, monitoring of execution, reviewing, and negotiating changes, if necessary. Conduct of these activities requires that the effectors have advanced capabilities. For example, production decisions may require purchase of items from sup- pliers with whom effectors could negotiate the purchase terms (Nissen 2000).

The examination of the basic capabilities of sensors and effectors reveals the fact that some of them are more "advanced" than the others. This insight leads to a dichotomous distinction between the "active" and "passive" capabilities of sensors and effectors. Table 1 summarizes passive vs. active capabilities of sensors and effectors

TABLE1 ACTIVEVS.PASSIVE CAPABILITIES OF SENSORS AND EFFECTORS

	Sensors		**Effectors**	
	Capabilities	**Supported functions**	**Capabilities**	**Supported Functions**
Passive	Connecting	Importing data	Connecting	Exporting data, carrying out actions
	Transforming	Filtering, pre-processing, noise reduction, etc.	Transforming	Converting decisions into actions
	Alerting	Drawing user's attention, signaling to effectors	Querying	Requesting information or authorization from user or sensors
Active	Adapting	Search for new sources, attuning transformational and alert generation logic	Adapting	Identifying alternative destinations, Adjusting transformation and alerting logic, bidding tac- tics, etc.
	Planning	Determining order of actions, scheduling sen- sory (monitoring) and adapting actions	Planning	Determining order and scheduling of actions

DECISION STATION

This section will describe an illustrative example of an agent-based investment Decision Station. The problem is in determining the portfolio of securities, monitoring its performance, and making modifications to the portfolio if necessary.

The sensors incorporate multiple agents that collect information from different sources. These include financial markets, historical information, analyst opinions, news articles, and other relevant sources. The sensors monitoring the markets collect information about overall market and specific industry performance indicators (S&P 500, DJIA, etc.), performance of individual securities from the user portfolio and the other securities on the "watch list".

The effectors are the means of executing the user's investment decisions. These can be linked to various online brokerage firms as alternative outlets for the ordering. The choice of the firm can be made inter- actively with the user on the basis of fees charged, reputation of the firm, past experiences, and other factors. The effectors support different types of order and can monitor execution of an order to see whether it had actually gone through or not. Active effectors can take charge of re-evaluating and resubmitting an order if necessary. Table 2 summarizes capabilities of sensors and effectors.

The DSS kernel incorporates the financial models for estimating portfolio risk and return, knowledge and formulas for conducting fundamental and technical analysis, and others. Manger decides when to update the local information, keeps track of performance of the models, translates user decisions into buy/sell signals for the effectors and may even authorize minor buying/selling decisions without user involvement within specified limits.

TABLE 2 CAPABILITIES OF SENSORS AND EFFECTORS IN AN INVESTMENT DECISION STATION

Sensors		**Effectors**	
Capabilities	**Key functions**	**Capabilities**	**Supported Functions**

Connecting	Accessing stock quotes, market indicators(DJIA, S&P500,NASDAQ) , news articles, firms financial data, historical data, etc.	Connecting	Placing buy/sell orders,transferrig funds between accounts
Transforming	Calculating moving averages, portfolio performances, speed of change in stock prices, market indexes, reconciling conflicting data, extracting keywords from news articles, etc.	Transforming	Calculating total amounts to be paid, placing special orders using pre-specified rules.
Alerting	Signaling a sharp change in stock prices, market conditions, notifying the user about key variables (price, P/E ratio, EPS) reaching pre-specified targets, signaling breaking news, etc.	Querying	Querying sensors about current prices to execute special orders, requesting for additional/missing information on order or seeking for confirmation of decision from the user, etc.
Adapting	Finding new sources of financial information, adjusting the thresholds for alert generation assessing the credibility and reliability of sources to improve assessment of conflicting information, etc.	Adapting	Adjusting the rules for placing special orders, adjusting planning capabilities (below)
Planning	Deciding how frequently to read the stock, firm and market data, when to search for new sources, when to adjust alert thresholds, etc.	Planning	Deciding when to query the sensors, when to execute orders, etc.

The active interface adapts to the user preferences using direct and indirect input from the user. It displays the stock performance indicators and news articles that fit the user profile and interests. In an existing DSS prototype the system proactively generates four candidate portfolios (proposed by risky fundamental, risky technical, non-risky fundamental and non-risky technical analysis) for user's consideration. It also generates critique of the analyzed portfolios based on user profile. The described decision station will properly inform the investor about the situation, support his/her decision process, execute and monitor execution of the orders thus being an active situated system.

III. REVIEW OF LITERATURE

Kun Chang Lee, Namho Chung & Inwon Kang (2008) Today's financial firms are required to disclose a great deal of data—including investment support information—on their corporate web sites. Since web sites have become an integral part of financial information disclosures, and because the multimedia characteristics embedded in those web sites have been shown to affect investors' responses, our research examines the various factors influencing investors' intention to use financial web sites to search for information. The basic premise of this study is that the reactions of individual investors in such situations translate naturally to an intention to use financial web sites and, ultimately, to actual use of these sites. By using a technology acceptance model, we conducted a rigorous questionnaire survey, over an illustrative web site on which financial information is disclosed on a regular basis as a means of providing individual investors with decision support. Our principal findings showed that: (1) consistency and technical convenience influence perceived ease of use; (2) decision quality, investment information and information quality affect perceived usefulness; and (3) perceived usefulness to the individual investor is affected most by decision quality, while perceived ease of use is influenced equally by consistency and technical convenience.

M. Uther & H. Haley (2008) this study explored the issue of how web users understand how the back button works on a standard web browser. Sixty participants were divided into two groups: those who were taught the correct mental model (stack-based) vs. those who did not receive any mental model information. The participants were then given a scenario-based task in which they were required to predict which pages would be available with a back button and those which would not be. The participants were then required to perform a standardised web browsing task and the amount of page traverses and back button usages were measured. Results showed that there were significantly fewer page traverses as a result of the mental model condition, suggesting a more efficient web page browsing resulted from the mental model training. In addition, there were surprisingly few incorrect usages of the back button, possibly due to floor effects caused by demand characteristics. These data suggest that there is clearly an effect on web browsing navigation as a function of being taught the correct mental model.

Robert R. Trippi(2002) Artificial Intelligence is one of Wall Street's most promising new technologies. Used to assist investment decision-making, artificial intelligence systems can handle more information, react more quickly, and make more consistent decisions than a group of human experts. In this book the authors thoroughly can handle more information, react more quickly, and make more consistent decisions than a group of human experts. In this book the authors thoroughly explain how artificial intelligence systems can help to improve investment returns. Practical and filled with real-life examples, the book provides all the information financial professionals need to understand and evaluate an artificial intelligence system. For investors who want to stay on the cutting edge of technology, this book will be a must read. Highlights of Trippi & Lee's comprehensive guide include: overview of artificial intelligence in investment management; components of an artificial intelligence system; portfolio selection system issues; handling investment uncertainties; practice exercises with K-Folio, a typical artificial intelligence system.

Shun-Yao Tseng (2012) studied how individuals develop information searches under uncertainty. It is a crucial question attracting a number of studies on investment decision-making. Information on financial measures and advice seeking information are two usual studied variables in financial investment decision-making. This study extends the information search aspects to discuss heuristics reliance, a simplified information search method, on individual investment choices. We further examine the moderating effect of income on our extended information search model. 378 investors with investment experiment from financial holding companies were surveyed and the multiple-group structural equation modeling was employed. Reporting on two dimensions of stocks/options and mutual funds investment, the findings show that individuals with more risk aversion tend to seek more information. Heuristics have a strong positive influence on financial investment preferences. A mass of digital information through more advice-seeking information search and heuristics reliance can increase investors' interest in mutual fund investments. We clarify income differences in individual information searches in investment decision-making. The findings imply that (1) the movement to teach financial students to recognize investor psychology might be required to be more extensive, and (2) provision of financial information for different income groups may be needed, and meantime investor psychology is suggested to be taken into serious consideration.

IV. AI TRENDS BEHAVIOR INVESTMENT

A multiagent architecture for an integrated system that considers data identification, asset valuation, and risk management has been proposed by researchers at Carnegie Mellon University. The system is called WARREN, which refers to the first name of the famous investor Warren Buffet (Sycara, Decker, Pannu, Williamson, & Zeng, 1996). The WARREN system design includes components for collecting large amounts of real-time data, both numeric and textual. The data would be preprocessed and then fed to various asset valuation agents that would, in turn, feed their assessments to a portfolio management agent. The portfolio management agent would interact with clients of WARREN. Systems with various features of WARREN are available from commercial vendors, and are developed in-house by large investing companies, but more research is needed on how to develop integrated, AI systems that support investing.

Natural language processing systems may include large bodies of domain knowledge and parse free text, so as to make inferences about the content of the text. However, such natural language processing systems do not seem as popular in investing applications as much simpler natural language processing techniques. The natural language processing work that has been applied to the investing seems to be largely of the sort in which the distribution of word frequencies in a document is used to characterize the document. In this word-frequency way, Thomas (2003) has shown a potential value to processing news stories to help anticipate stock price changes.

V. FIELD OF ARTIFICIAL INTELLIGENCE- NEURAL NETWORK APPLICATIONS TO INVESTING

As one can see cycles in the value of financial assets, one can also see cycles in the frequency of publication of articles on certain topics. In the field of artificial intelligence, one might identify, roughly speaking, three phases, as follows (Rada, 2008):

1. Machine learning, which was then called perception and self-organizing systems research, was popular from 1955 to 1975,
2. knowledge-based, multiagent, or expert systems work was popular from 1975 to 1995, and
3. Machine learning research, now called neural networks or genetic algorithms research, returned to dominate the AI research scene from 1995 to the date of this article.

When AI research has been applied to investing, the AI technique used has tended to be the technique popular at the time. This leaves, unaddressed, the question of whether investing is more appropriately addressed with one AI technique or another.

The recent literature is rich with neural network applications to investing, but a new trend is the combining of knowledge-based techniques with neural network and genetic algorithm techniques. For instance, Tsakonas et al. (Tsakonas, Dounias, Doumpos, & Zopounidis, 2006) use "logic'' neural nets that can be directly understood by people (traditional neural nets are a "black box'' to humans). Genetic programming modifies the architecture of the logic neural net by adding or deleting nodes of the network in a way that preserves the meaning of the neural net to people and to the net itself. Bhattacharyya et al. (Bhattacharyya, Pictet, & Zumbach, 2002) have added knowledge-rich constraints to the genetic operators in their application for investing in foreign exchange markets.

A promising research direction is to combine the earlier knowledge-based work on financial accounting with the more recent work on machine learning for stock valuation. For instance, neural logic nets could represent some of the cause-effect knowledge from a bankruptcy system and become part of a learning system for predicting stock prices. Some of the bankruptcy variables are readily available online, such as a company's debt, cash flow, and capital assets.

VI. CONCLUSIONS

The financial markets are human markets that evolve over time as opportunities to make profits in this zero-sum game depend on the changing strategies of the opponent. Thus, among other things, what is important in the input may change over time. An AI system should be able to evolve its data selection, asset valuation, and portfolio management components. The future direction for AI in investing is to integrate the three major tools of AI (knowledge-based systems, machine learning, and natural language processing) into a system that simultaneously handles the three stages of investing (data collection, asset valuation, and portfolio management). Such systems will interact with humans so that humans can specify their preferences and make difficult decisions, but in some areas, such as program trading, these sophisticated AI systems could compete with one another.

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