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Abstract

Objective: The objective of this study was to examine and determine future directions in regard to future machine learning techniques based on the review of the current literature.

Methodology: A systematic review has been used to review the current trends from the peer-reviewed journal articles in the past twenty years. For this study, four categories have been categorized, the use of neural networks, support vector machines, the use of a genetic algorithm, and the combination of hybrid techniques. Studies in each of these categorize have been evaluated.

Finding: Firstly, there is a strong link between machine learning methods and the prediction problems they are associated with. The second conclusion that we can conclude from this review is that past studies need to improve its generalizability results. Most of the studies that have been reviewed in this analysis has only used the machine learning systems through the use of one market or during only a one time period without taking into consideration whether the system would be adaptable in other situations and conditions. Limitations, future trends, as well as policy implications have been defined.

Keywords: *Machine learning, genetic algorithm, stock market prediction, stock market valuations, artificial intelligence, neural networks*

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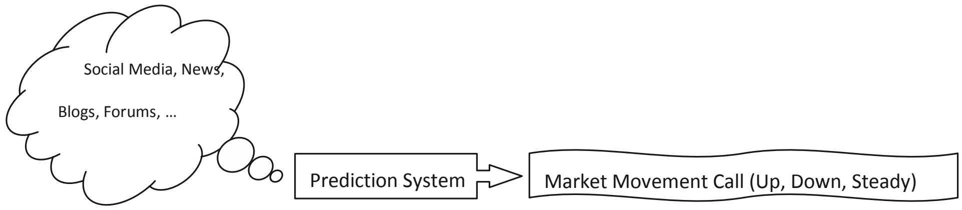
Introduction

The stock market investment techniques are often complex and rely, and in most cases, it does involve the evaluation of a large set of data. A recent development in machine learning has led to the re-examination of techniques used in predicting stock market valuations. The use of machine learning algorithms has proved to be more efficient and reliable as compared to the traditional stock market analysis. By large, modern societies depend on the market economies for their welfare. Financial markets lie at the heart of the market economy, with supply and demand factors affecting market equilibrium (Greenwald & Stiglitz, 1993). Thus, it is imperative to study the market to better adapt and learn about its movements. Understanding of the market primarily facilitates one with the ability to predict future market movements (Mosavie et al. 2018). The ability of individuals to predict the market changes can be equated to wealth creation as it can reduce market losses and, on the other hand, can ensure financial gains. Despite this, the ability to predict markets is such an extremely difficult endeavor. Generally, the prediction of the market forces can be divided into technical and fundamental analyses. The difference between the two is their input data and their historical market data (Patel et al. 2015). Traditionally, investors have been relying on their personal experience, knowledge, and instinct to identify the shifts in market patterns and trends today, and this is not a feasible method of analysis because the market size and the speed at which investments and innovations are being executed. The use of simple statistical analysis of the financial data does provide insights into the market trends (Pound, 2019). In recent years, however, companies have turned various forms of artificial intelligence systems such as: limited memory, self-awareness, and reactive machines, to look at patterns of market trends using real-time equity and economic data ((Marr, 2017). Such artificial intelligence systems support human decision-making and have been used in predicting market trends over the last few years (Donepudi, 2017).

Figure 1.1 Machine learning research taxonomy

This figure represent the machine learning research taxonomy of four categories. The current stock market prediction models suffer from low accuracy in the prediction and classification of data. The low accuracy involved in the classification affects the reality and the reliability of the stock market predictors, such as the use of the statistical figures and the financial reports, which explains the returns from the existing stock market (Ou & Wang, 2009). Machine learning techniques involve enabling computers to read and simulate raw data and act on the data to optimize the performance criteria through the machine experience or through the example data (Qian & Rasheed, 2007). The goal of using machine learning is to develop methods and patterns which has the ability to detect patterns in raw data automatically and then use this to these trends to uncover patterns that would enable prediction of future data (Donepudi, 2016).



Objective

The objective and purpose of this study was to identify the possible directions of future machine learning in predicting stock market behavior based on the existing literature.

Statement Problem

This study essentially targets the use and utilization of computational modeling and artificial intelligence in order to find a possible relationship between textual information and the economy. To do this, a systematic review of the methodology would be used to identify the relevant peer-reviewed journals collected and published over the last twenty years. These studies have been categorized into similar methods of study and context, and then the comparison of the studies in each category have been made to identify common finding, the unique findings, the study limitations and areas of further study for the investigation. The results of this study would be to provide artificial intelligence and finance researchers on the directions of the industry as well as the trends with the usage of machine learning techniques to be able to predict the stock market index values as well as its trends.

Literature Review

Efficient Market Hypothesis (EMH)

The idea and argument that the market is a completely random and not predictable phenomenon are rooted in the efficient market hypothesis (Malhotra, 2017), which asserts the fact that the financial market is an informational efficient and that in that consequence, an individual cannot consistently be able to achieve returns that are in excess of the average market returns based on a risk-adjusted basis with the given information during such a time that the investment has been made. This hypothesis is not correct, and in essence, Fama does revise its levels of efficiency to include the strong, semi-string, and weak efficiency levels. This statement does indicate that there exist many markets in which the predictability of data and trends is plausible, and the viability of such markets is often referred to as being weakly efficient (Wen et al. 2007). Market efficiency is correlated with the information that is available and whether the market is considered to be strongly efficient when all the information is provided within the market. This situation is really rare to occur. Hence, Fama (1965) considered his theory to be stronger in certain markets alone where the information is widely available and can be accessed instantly to all the participants in the markets and that that this assumption gets weaker when the assumption is cannot hold concretely.

Behavioral Economics

Both cognitive and behavioral economics look at the price as being a purely perceived value rather than it existing as a derivative of the production cost and other tariffs that exist in the market. The media not only report on the status of the market only but they also actively create an impact on market dynamics, which is based on the news that they release. The manner in which people interpret this information widely varies across many markets and depending on how people take in information (Zhang & Enke, 2019). Market participants have cognitive biases that include overconfidence, overreaction, representation of bias, information bias, and various other human errors and biases when reasoning out information (Wen et al. 2012). Behavioral finance and the investor sentiment theory does argue that the behavior of the behavior can be shaped largely if they feel optimistic about the market trends (bullish) or whether they are pessimistic (bearish) of the future market values and trends (Yeh, Huang & Lee, 2011).

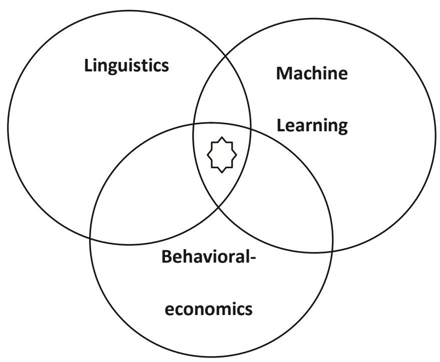


Fig. 2. Interdisciplinary between linguistics, machine-learning and behavioral economics, these three fields are interconnected. This figure provide the relationship between these three broad fields.

Markets Predictability

When stock markets are weakly efficient, then it is possible to predict their behavior or at least be able to determine the criteria with the predictive impact on them. The nature of the stock market is that that when market information is available, then they absorb this and adjust themselves and thus making the initial predictive criteria to be obsolete (Pound, 2019). Absorption of information in the new markets and reaching new equilibrium to occur in the new markets constantly, which has resulted in some researchers delving into modeling its dynamics and the parameters under special cases and circumstances (Kumar et al. 2011). Nevertheless, the existence of speculative economic bubbles does indicate the fact that in most cases, market participants operated in an irrational and often emotional assumption, thus, not paying attention to the actual underlying value. Wen et al. (2012), in their research, indicate that the predictability of Foreign exchange might not be efficiently sufficient.

Methodology

The researcher in this study conducted a search for peer-reviewed journal articles that featured the use of machine learning to predict stock market behavior and its related outcome.

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These articles were found and accessed through the use of Google Scholar, EBSCO, and EconLit. To identify the most relevant studies for this study, only studies published within the past 20 years have been categorized for analysis here in this study. Each of the studies evaluated in this analysis featured the use of the machine learning techniques in predicting the stock market behavior.

Table 1. List of Reviewed Machine Learning Stock Market Prediction Articles

Author(s) [publication year]	Machine Learning Method(s)	Primary Market(s) Studied and Data Time Period (Years)
Jasic and Wood [2004]	Artificial neural network	S&P 500, DAX, TOPIX and FTSE 1965-1999
Enke and Thawornwong [2005]	Artificial neural network	S&P 500 1976-1999
Liao and Wang [2010]	Artificial neural network	Shanghai and Shenzhen Stock Exchange 1990-2008
Chavan and Patil [2013]	Artificial neural network	Study reviews nine ANN studies
Chong, Han and Park [2017]	Artificial neural network	Korean KOSPI stock market 2010-2014

After the removal of all the duplicate files in this analysis, an initial 41 studies were identified as being eligible for analysis. From this list, various other studies were eliminated from the list since it focused on predicting the initial set of stock value prediction. For instance, one such study only focused on predicting the genetic algorithm for the prediction of only two individual stocks; that Infosys and Tata consultancy (Kumar et al. 2011) rather than analysis of stock index. For the final list, a total of twenty-six studies were provided for in the final list to provide a comprehensive list of all related articles; this, however, does not provide a comprehensive list of all the articles in the field. However, it does provide a comprehensive list of related articles to draw conclusions and thus make conclusions for future research. The paper of Artificial intelligence were reviewed to identify which of these papers features a single machine learning technique or those studies that used hybrid or multi-method approaches in the analysis. The research of this analysis is the machine learning stock taxonomy. Each of the articles that have been reviewed in this study fits into the following four categories a) artificial neural network studies, b) support vector studies, c) use of genetic algorithms with other techniques, and d) studies focused on hybrid approaches. The following sectors present results on the use of each of the articles that have been reviewed. Each research taxonomy has been summarized, focusing on its unique model, dataset, and contribution to the field.

Results

Algorithm Trading

Algorithm trading is a term which refers to the predictive mechanisms by the intelligent robotic trading agents that are actively participating in the day to day marketing trading (Donepudi, 2017). The speed with which decision making the stock market has recently increased dramatically and has contributed to the creation of a new term frequency trading. Evans, Pappas, and Xhafa (2013) notes that frequency trading has been used much more frequently in the stock market studies. Researchers have been to utilize artificial neural networks and genetic algorithms to build an Algo-trading, which can be used in the intra-day foreign exchange speculation. Sentimental and emotional analysis when it comes to algorithm trading deals with the detection of the emotional sentiments by analysis of specialized semantic analysis for the purpose of gauging the quality of the market reception of the new products in the market and also in the estimation and checking of the customer feedback or in the checking the popularity of certain product or brand in the market. All the systems reviewed in the literature focus on the input of a given text at one end, and in the other end, there is some form of predictive values that are generated as output values. The input dataset features two data: the textual data from the online data resources and the market data. The textual data used in the analysis can be obtained from various sources. The majority of these sources include news websites such as the Wall Street Journal, Reuters, Bloomberg, and Dow Jones. The type of news can either be general news of it can be special financial news. The majority of the systems use finance news as they are considered to be having noise compared to the general news. What is extracted in such analysis is the news text or the news headlines.

Artificial Neural Networks in Predicting Stock Market Values

Artificial neural networks are computational models that are based on biological neural networks. In such a network, the sets of nodes are then grouped together into layers, from the input layers all through to the output layers. Signals are then propagated using connected nodes and learn through examples as they try the prediction errors. Since the system works on improving performance, the weights are then adjusted to get the signals between the connected nodes.

In a study, Jasic and Wood (2004) studied the existing relationship between neural networks and daily stock market prediction. They developed an artificial neural network with the ability to return market index based on data from the various global stock market. The focus of this research is to support profitable trading. Through this study, a method of a univariate neural network through the use of untransformed data input to be able to provide short-term stock market prediction through the use of index return predictions. To achieve this, this study use daily closing values of both the standard and the Poor's 500 indexes (S&P 500), the German DAX index, and the data from the London Financial Times Stock Exchange Index (FTSE All-Share index). The sample for the TOPIX was taken from January 1, 1965, to November 11, 1999, and analyzed as time-series data. The predictive performance of this data was evaluated against a benchmark of the linear autoregressive model. The prediction improvement is then confirmed once this is applied to the S&P 500 and the DAX indices.

In their study, Enke and Thaworngong (2005) make use of machine learning information technology to evaluate the predictive relationships that exist between various financial and economic variables that exist. A ranking is then derived for the variables through computational of the information gain obtained from each variable in the model. A threshold is then determined to select the strongest of these variables that need to be retained during the forecasting models. The researchers then access the neural network models in a bid to evaluate their level of estimation and the classification that is based on their ability to determine the effective forecast for future market values. Further, the researchers use a cross-validation technique to ensure and improve the generalizability of the various models. The results of this study show that the trading strategies that are guided by the classification models have higher ability and chances of ensuring risk-adjusted profits as compared to the use of buy-and-hold strategies employed by other investors.

Table 2: Relation between Sentiments and Stock Returns

Authors	Tools / model	DATA used	Using Timestamp and geographical location	Relation
Yu et al. [58]	Contextual entropy model	Stock market news articles	No	yes
Chan and Franklin [15]	Novel textbased decision support system	2000 financial reports with 28,000 sentences	No	yes
Schuma ker et al. [45]	Sentiment analysis tool	Arizona Financial Text (AZFinTe xt) system	No	yes
Ahuja et al. [2]	Sentiment analysis	Bombay stock exchange and Twitter	No	yes
Bartov et al. [6]	Regression model /Correlatio ns	Twitter,	No	yes
Bollen et al. [10]	OpinionFi nder/ Granger causality analysis	Twitter, Dow Jones industrial average	No	yes
Hamed et al. [22]	Opinion mining/ Correlatio ns	KSA Twitter and stock market data	No	yes
Skuza and Romano wski [49]	Manual Labeling/ SentiWord net	Twitter data, stock market returns	No	yes
Şimşek and Özdemir [48]	Frequency tables, Graphs	Turkish Twitter data, stock market returns	No	yes
Cakra and Trisedya [12]	Sentiment analysis	Twitter, Indonesian stock market	No	yes

Another study by Liao and Wang (2010) used the stochastic time effective neural networks in the prediction of the predictive relationship which exists for both the financial and the economic variables. This study presumes that the investors' do choose which investment options to invest in based on their analysis of the historical stock market data and that the historical data is weighted based on near or further they appear to the present scenario. The nearer the data is to the present times, the stronger this data is on the prediction of future stock market behavior. The effectiveness of this model is analyzed based on the numerical data drawn from the characteristics of each trading day for an 18-year-old period from December 1990 to June 2008. The stock markets evaluated included data from the Shanghai and Shenzhen Stock Exchange Stock A index (SAI), S&P 500, NASDAQ Composite (IXIC), and also the Dow Jones Industrial. The forecasting performance ability of this model is then assessed by various volatility parameters.

Chavan and Patil (2015), on their study on ANN stock market prediction through input parameters, adds depth to our understanding of stock market prediction. In their study, the researchers try to find the most important input parameters which would be able to produce a better stock market prediction accuracy. Through a survey, they identify that most of the machine learning techniques in place make use of various technical variables in place of the variables used for the prediction of particular stock market predictions (cited by: Donepudi, 2016). They also establish that, in most cases, microeconomic variables are used in predicting stock market index values. Further, this study evaluates that hybridized parameters are better adapted to producing better results when compared to the use of just a single input variable type.

Table 3. Previous findings and sources

Reference	Text type	Text source
Wuthrich et al. (1998)	General news	The Wall Street Journal, Financial Times, Reuters, Dow Jones, Bloomberg
Peramunetilleke and Wong (2002)	Financial news	HFDF93 via www.olsen.ch
Pui Cheong Fung et al. (2003)	Company news	Reuters Market 3000 Extra
Werner and Myrray (2004)	Message postings	Yahoo! Finance, Raging Bull, Wall Street Journal
Mittermayer (2004)	Financial news	Not mentioned
Das and Chen (2007)	Message postings	Message boards
Soni et al. (2007)	Financial news	FT Intelligence (Financial Times online service)
Zhai et al. (2007)	Market-sector news	Australian Financial Review
Rachlin et al. (2007)	Financial news	Forbes.com, today.reuters.com
Tetlock et al. (2008)	Financial news	Wall Street Journal, Dow Jones News Service from Factiva news database.

Mahajan et al. (2008)	Financial news	Not mentioned
Butler and Kešelj (2009)	Annual reports	Company websites
Schumaker and Chen (2009)	Financial news	Yahoo Finance
Li (2010)	Corporate filings	Management's Discussion and Analysis section of 10-K and 10-Q filings from SEC Edgar Web site
Huang, Liao, Yang, Chang, and Luo (2010) and Huang, Chuang, et al. (2010)	Financial news	Leading electronic newspapers in Taiwan
Groth and Muntermann (2011)	Adhoc announcements	Corporate disclosures
Schumaker et al. (2012)	Financial news	Yahoo! Finance
Lugmayr and Gossen (2012)	Broker newsletters	Brokers
Yu, Duan, et al. (2013)	Daily conventional and social media	Blogs, forums, news and micro blogs (e.g. Twitter)
Hagenau et al. (2013)	Corporate announcements and financial news	DGAP, EuroAdhoc
Jin et al. (2013)	General news	Bloomberg
Chatrath et al. (2014)	Macroeconomic news	Bloomberg
Bollen and Huina (2011)	Tweets	Twitter
Vu et al. (2012)	Tweets	Twitter

Support Vector Machines in Analysis of Stock Markets

This technique makes use of supervised learning. In this model, training is considered to be part of one category or the other one. A support vector machine model does show the goal of creating a gap between categories that are as wide as possible to each other. For instance, the context of the stock market prediction as Shumaker and Chen alludes that the support vector machine is a machine learning algorithm that can classify a future stock price drop or its rise (cited by: Donepudi, 2016). Lee (2009) developed a prediction model that is based on a support vector machine-based with a hybrid feature selection, which combines the feature selection method known as the F-score and also the Supported Sequential Forward Search (F-SSFS). This combines the advantages of the filter methods and the wrapping methods to select the most optimal feature derived from a set of sub-features.

A unique study was done by Schumaker and Chen (2009) using the SVM in conjunction with the textual analysis looking at the resulting impact of news articles on the stock market prices. This researches developed a predictive machine learning approach for analysis through various textual representations and data. Yeh, Huang, and Lee (2011), in their study, address the problems that arise with the use of vector regression analysis to aid in forecasting the stock market values when dealing with the kernel functions using hyperparameter. A hyperparameter is typically a value which is set before the learning process begins. The system evaluates the advantages from the hyperparameter settings combined with the overall system performance.

Hybrid AI Techniques in Analyzing Stock Market Behavior

The use of ANNs, SVMs, or the multi-method GA approaches is the most common technique used in tackling stock market prediction. This category describes studies that have used other unique techniques of artificial intelligence to predict the stock market behavior. Lee and Jo (1999) were among the pioneers to use a candlestick chart analysis to predict stock market trends. These systems feature the use of patterns and trends to predict movement in the stock market. The defined markets are then classified into five forms: price rise, price fall, neutral price position, trend continuation, and the trend-reversal process in the stock market. Based on the data retrieved from the Korean market from 1992 to June 1997. They evaluated that the developed knowledge base existed independently of both time and the field environment.

Asset allocation is an important stock-related financial-related aspect that has, over the years, received little interest in machine learning studies. Lee, Lee, and Zhang (2006), in their study, present stock trading methods that take into consideration the asset allocation in a reinforcement-learning framework (cited by: Donepudi, 2017). In their study, they propose an asset allocation strategy, which they refer to as a meta policy, which is designed to utilize temporal information from the stock recommendations and from the ratio of the stock that is over the asset. Formulation of the meta policy can be achieved and reinforced through the environment and the learning agent design. Various neural network models and hybrid models have been presented in an attempt to outperform traditional linear and the also nonlinear approaches in the stock market prediction. However, there exist some limitations in the use of ANN models in such domains. In their study, Guresen, Kavakultu, and Daim (2011) evaluate the effectiveness of using multi-layer perception in determining the dynamic artificial neural network and the hybrid neural network, which in essence, used the autoregressive conditional heteroscedasticity in the extraction of the new inputs.

Conclusion

The objective of this study was to identify the future directions and the policy implications of the future of machine learning predicting stock market prediction based on the review of the current literature. Given the machine learning related systems and studies, problem contexts, and the findings that are described in each article has been discussed with various conclusions generation for this study. Firstly, there is a strong link between machine learning methods and the prediction problems they are associated with. This, according to Guresen, Kavakultu, and Daim (2011), is analogous to the task-technology fit in which system performance is determined based on the appropriate match between the tasks and the technological adoption. Artificial neural networks can be best used in the prediction of the numerical stock market index values. On the other hand, support vector machines are used to fit the best classification problems, which includes the determination of whether the stock market would cause a rise or fall of the stock prices. The use of genetic algorithms has gained prominence as an evolutionary problem-solving technique and approach in identifying higher quality system inputs or predicting the stocks that one needs to include in a given portfolio to attain the best results possible. While each of this studies did illustrate in essence that the methods can come in handy when they are applied effectively, the use of single method application has its own fair share of challenges.

The second conclusion that we can draw from this review is that past studies need to improve its generalizability results. Most of the studies that have been reviewed in this analysis has only used the machine learning systems through the use of one market or during only a one time period without taking into consideration whether the system would be adaptable in other situations and conditions. For policymakers, there are three enhancements that can be done for the sake of experimental system assessment. The first issue is that most of the studies reviewed were taken out of the Asian stock market. These systems could be tested in the US or in other European stock markets to see how they would behave. Further, the systems could also be evaluated through the use of data taken in times when the markets are rising or during periods in which the markets are falling to check and assess how such systems would perform in various market environments. For instance, there exists a need to tests whether the machine learning systems could predict the stock market behavior during the 2008-2009 financial crisis and in the 2018-2019 financial market growth. If such systems have the ability to predict market growth, could they also be used to predict when the market contracts? Further, the proposed methods in this study have been able to propose methods that can be used evaluating the predictive performance of the stock market, which includes the small firms and the big firms. The next question that follows is whether such systems are effective under different risk and volatility in the stock environment. Any enhancements in the methods which has been identified above would go a long way into providing stronger research, and the contribution of this practice to studies.

Finally, another set of conclusion touches on the investment theory. There exists a need for financial investment theory to be a stronger driver for the machine learning systems' inputs, performance measures, and algorithms. If this is not put into practice, then the results would be random and do not have real practical usage.

Policy Implications

There is a need for policymakers within the industry to link financial investment theory to machine learning theory, as observed in many studies. Many of the studies that have been reviewed use machine learning techniques without putting in place the existing financial investment theory, which has been developed across the years. Reportage of failures in cases where such techniques fail to improve predictive performance would be largely helpful and informative. This, however, occurs rarely, and thus, it is quite impossible to find patterns in which there is a mismatch between the stock market prediction and that of machine learning technique. The irony of this research, however, is that there is a zero-sum game involved with predictive technology in machine learning. If the best machine learning technique is found that could predict market trends and is available to everyone, the results are that no one would be better off. Further, large investment firms doing research for the best machine learning techniques and systems have no incentive of sharing any information that they would find with the public.

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