

MACHINE LEARNING AND PORTFOLIO MANAGEMENT: A REVIEW

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ABSTRACT. Linkages across different asset classes and relationships of innovative financial products such as cryptocurrencies and global macroeconomic events have made price and return predictions more challenging. This paper investigates how Machine Learning (ML) technologies can be implemented in two critical areas of active portfolio management. Specifically, we focus on ML techniques which can be used in (i) fundamental and technical analysis, to make better asset allocation decisions; and (ii) portfolio construction, to make more efficient and optimized portfolios. We surveyed the existent literature, including trends of ML in finance, and the main benefits and challenges such technologies can bring to the portfolio management industry. Existing ML applications' benefits outweigh some costs in terms of human resources and efficiency in financial decision making, with however some key challenges in data quality, including understanding and interpretation of ML models which need to be addressed.

1. INTRODUCTION

Various industries like healthcare, retailing, energy, and manufacturing have been adopting centralized technologies such as artificial intelligence (AI) and decentralized technologies (blockchain), with the finance and banking sector leading with investments made in such technology implementations (Cryptoverse, 2021a). Blockchain technologies enabled the existence of decentralized financial (DeFi) products, similar to those provided by traditional financial institutions. The advantage of DeFi over the traditional financial system lies in terms of a trustless ecosystem which provides investors' access to financing and investment products, without the need to open a bank account. Adoption of latest technologies in the finance arena has so far allowed for faster and cheaper transactions (Cryptoverse, 2021b). In the same vein, innovative financial products such as Bitcoin (BTC) futures, Ethereum (ETC) futures, Bitcoin Exchange Traded Fund Futures (BTC ETF) have emerged fast since the first cryptocurrency came out in 2009 (CME, 2022). Portfolio management also rapidly evolved with cryptocurrency portfolio management applications such as Delta and Blockfolio which enable investors to manage their portfolios of cryptocurrencies and altcoins using different tools

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like advanced charting, order books, and portfolio tracking. AI and other technologies' invasion in the finance industry is however no without any cost. With aggressive technology implementations in portfolio management, significant job losses are expected in the medium term (Buchanan, 2019). This study provides an overview of the different applications of ML in portfolio management, including challenges and opportunities, to be able to better gauge the impact of ML (being a subset of artificial intelligence) on the investment management industry and the broader economy. While the hot topic of ML and portfolio management can cover various critical areas such as client profiling, security analysis, asset allocation and portfolio construction, portfolio rebalancing, and monitoring of portfolio performance, we focus exclusively on asset allocation and portfolio construction. The primary goal of portfolio construction lies in the ability to mix financial assets which have individual risk and return attributes to achieve a desired portfolio risk and expected return. Decisions to make such allocations efficient and eventually optimal are traditionally based on security analysis driven mostly by fundamental and technical analysis. While fundamental analysis includes the use of financial statements, financial ratios audited reports, board of management speeches and interviews, consensus estimates and news headlines, technical analysis rely mostly on using charts to capture historical characteristics on price, volume, open interest, among others, to predict future price movements. Although the finance literature is replete of evidence of fundamental analysis in valuation of financial products, more recent work includes Gurrib and Kamalov (2021) who used machine learning to predict BTC price movements. In the same vein, Gurdgiev and O'Loughlin (2020) report that investor sentiment is a good predictor of the direction of cryptos. Chen et al. (2020) also found that a rise in fear leads to high trading volume and negative returns. Similarly, recent work using technical analysis include Gurrib et al. (2022) who found that, despite oil price drops, speculators can generate positive returns on energy cryptos using Fibonacci retracements, a widely used technical analysis indicator. Gurrib et al. (2021) found Ichimoku clouds to be useful in stock price predictions in the energy sector. Gurrib and Kamalov (2019) improved the Relative Strength Index (RSI), another popular technical analysis tool, yielding higher annualized returns and risk for foreign currency and energy markets for developed and emerging economies. The field of technical analysis is growing with more innovative tools including fractal adaptive moving average (Gurrib & Elsharief, 2016), double crossover moving average strategies (Gurrib, 2016), and Average Directional Index (Gurrib, 2018b).

1.1. Relationship between blockchain based markets and other financial markets. Although cryptocurrencies are recent additions to asset classes, the relationship between cryptocurrencies and other financial markets is not straightforward. For instance, Liu and Tsyvinski (2018) looked at whether cryptocurrencies and equity markets behave in the same fashion, by analyzing whether returns of Bitcoin (BTC), Ripple's (XRP) and Ethereum (ETH) are compensated by risk factors sourced from equity markets. Their findings support significant betas and alphas from the capital asset pricing model. The shared relationship

among cryptocurrencies is backed by Phillip et al. (2018) who reported that over 200 cryptocurrencies display many diverse stylized facts including long memory. Katsiampa, Corbet, and Lucey (2019) who studied volatility spillover effects, provided evidence that time-varying conditional correlations exist and are mostly positive. Comparatively, Corbet et al. (2018) found cryptocurrencies markets to have only limited connectivity with other asset classes such as commodity, equity and bond markets. Gurrib (2019) reported that price indices of cryptocurrencies were not strong predictors of energy cryptocurrency and energy commodities. Gurrib (2018a) similarly reported that using an index constructed from most used fossil fuels could not forecast key equity market indices movements during the 2000 technology crisis. Likewise, Gupta et al. (2017) argued that volatilities in futures markets rose gradually and are unrelated to other financial markets' volatilities. Gurrib, Elsharief & Kamalov (2020) investigated the effectiveness of using blockchain based energy cryptos onto the top energy stocks of the US S&P Composite 1500 Energy Index using various techniques including machine learning (ML) and found that energy cryptos did not have a significant impact on equity portfolios.

1.2. Relationship between financial products and macroeconomic events.

While the relationship among financial markets is mixed, it gets further complex when it comes to potential significant linkages between financial products and macroeconomic news. For instance, Gurrib (2020) found that a unified financial condition index provides poor predictions of the the most actively traded US based currency pairs. Kristoufek (2013) looked at the formation of BTC price and proposed that it cannot be explained by macroeconomic factors mainly because cryptocurrencies are not issued by a specific institution, suggesting that global news may play more important roles than local news. This argument was supported by Bouoiyour and Selmi (2015), who also reported that BTC is more of a speculative bubble rather than being related to market forces. Wang and Vergne (2017) used newspaper mention of BTC as a proxy for “buzz” and found that high “buzz” was followed by low BTC returns. Gurrib et al. (2019) looked at the effect of macroeconomic news on the top market capitalized based cryptocurrencies and recommended the use of high frequency data to look at intraday news and crypto price movement relationships. Compared to the above authors, Van Wijk (2013) focused on macroeconomic factors, such as stock market indices, oil prices and exchange rates, and found that certain foreign currency pairs, such as Euro/USD and oil prices, share sizable relationships with BTC in the long run. Lee (2014) studied the relationship between the attractiveness of BTC and its demand and found this relationship was dependent on the type of news released at a specific time. Liu & Tsyvinski (2018) analyzed the exposure of BTC, XRP and ERP returns to macroeconomic factors and reported non-significant relationships. With some background on the complexity between financial markets, between different asset classes and macroeconomic events, this paper looks at how ML (a subset of artificial intelligence) can be used in portfolio management, in the areas of asset allocation and portfolio construction, with a view to obtain better portfolio optimized results using latest machine learning techniques. Due to

existing complexity across financial markets, and lack of consensus on the effect of macroeconomic events on innovative financial products such as cryptocurrencies, it is important to consider technologies such as ML which can help improve portfolio performance eventually. This study contributes to the literature by focusing on asset allocation and portfolio optimization using ML, thereby allowing portfolio managers to encompass how such technologies can be beneficial and/or pose serious challenges if implemented across functional areas of investment finance. The rest of the paper provides some literature review with some guidance where ML and finance research is heading, followed by how different ML techniques can help achieve better results in the key areas of (i) asset allocation and (ii) portfolio optimization. We rest out case with some conclusive remarks.

2. LITERATURE REVIEW

Before we dig into the advantages and challenges of ML in portfolio management practices, it is important to appreciate how research in ML has exploded in recent years. ML has been applied in various industries including healthcare (Kamalov et. al, 2021), education (Kamalov, Sulieman & Calonge, 2021), security (Kamalov et. al, 2020), forecasting (Rajab et al., 2022), finance (Kamalov, 2020) and others

Bartram, Branke & Motahari (2020) provides evidence of an exponential increase in the number of Scopus research-based publications mentioning ML or artificial intelligence as keywords over the period 1996-2018. We similarly searched “machine learning and finance” on Google Scholar in early 2022 with results showing 39600 research work containing those keywords. At this juncture, it is important to point out that AI and ML are terms which have been used interchangeably in finance, where ML is effectively a subset of the broader AI concept. While ML encapsulates the use of machines to make decisions by relying on historical data and learning, AI relates to the use of computers to imitative cognitive functions of humans (Gu, Kelly & Xiu, 2020). Recent ML applications in finance include (Kamalov, Gurrib & Rajab, 2021; Kamalov, Gurrib & Thabtah, 2021; Kamalov, Thabtah & Gurrib, 2021; Kamalov, Smail & Gurrib, 2020a; and Kamalov, Smail & Gurrib, 2020b). The explosive amount of research work in the field of ML in finance, can be explained due to the area of technology, as a contributing factor, which has been evolving rapidly recently. Recent developments in technology can be summarized as (i) an increase in storage capacity with a more rapid computer processing, (ii) more variety and volume of data, and (iii) easier accessibility and understanding of ML algorithms, bypassing a lot of previously needed expertise in computer engineering. Although ML is primarily adapting the different parameters of computer models (such as statistical, econometric, probabilistic) by using data progressively, ML applications in the finance industry, have mostly been using some rather specific classes of ML techniques. Generally, these models consist of decision trees and random forests (RF), support vector machines (SVM), genetic algorithms (GA), natural language processing (NLP), least absolute shrinkage and selection operator (LASSO), artificial neural networks (ANN) and cluster analysis (CA). Among of these different

categories, Bartram, Branke & Motahari (2020) support that NLP, ANN and RF gained more attention relative to others in the last five years. NLP includes techniques to process natural language data such as audio and texts. This is beneficial when extracting information from financial news providers such as CNBC, Thomson Reuters and Bloomberg, or sections of financial statements and other reports which are of interest to different stakeholders such as the portfolio analysts, shareholders, prospective investors, and creditors. On the other hand, ANN are non-linear regression models which learn the relationship between a training set of input and desired output data, and then use the relationship model to predict the output of previously unused inputs. Last, but not least, random forests average the outputs of several decision tree models to yield better forecasts, where a decision tree classifies units based on features.

3. ML IN ASSET ALLOCATION

Asset allocation and return prediction decisions are heavily based on technical and/or fundamental analysis. While fundamental analysis is based on estimating the fair or intrinsic value of financial products such as stocks and bonds (Lev & Ohlson, 1982; Lev, 1989; and Bernard, 1994), technical analysis attempts to find historical patterns and use these to determine future price movements. Various fundamental analysis models are the dividend discount model (Subramanyam and Venkatachalam, 2007; Bodie et al., 2009), multiples-based models (Reilly and Brown, 2002; Faerber, 2008), and discounted cash flows models (Bodie et al., 2009, Penman, 1992). In line with the previous findings where NLP has been used more extensively in recent literature, fundamental analysis has benefited from NLP model significantly. In fact, ML models based on NLP can extract valuable information from different sources of financial information such as news announcements (Ke, Kelly, & Xiu, 2019; Schumaker & Chen, 2006; Gurrib & Kamalov, 2021), institutional reports (Azimi & Agrawal, 2021), and Twitter headlines (Singh et al., 2022). Compared to conventional textual analysis techniques such as dictionary-based models which extract only individual words, ML can also embed both sentence structure and contextualization. Technical analysis benefited more specifically from the use of algorithmic trading, where trading models or systems can collect and analyze high frequency data and act upon those within a fraction of seconds, without the need of human intrusion, in a more efficient manner. Due to the complex relationships involved across financial markets and increasing number of financial products on the marketplace, ML models can provide close to real time decisions. Most ML models use price or volume to predict future return movements of a variety of different asset classes such as ANN in equity markets (Fischer & Krauss, 2018); decision trees in equity markets (Coqueret & Guida, 2018); genetic algorithm in foreign currency market (Manahov, Hudson & Gebka, 2014); LASSO in the U.S. equity market (Chinco, Clark-Joseph & Ye, 2019); ANN in foreign currency and commodity futures (Dixon, Klabjan & Bang, 2017); NLP in equity markets (Renault, 2017) and NLP in the cryptocurrency market (Gurrib & Kamalov, 2021). LASSO based models, which are ordinary regression which diminish spurious coefficient estimates to zero thereby improving

out of sample performance dramatically, have also gained traction around asset allocation decisions (Gu et al., 2020). For instance, these models would provide key information which industry or sector is the most important predictor of returns in other specific industry or sectors (Rapach et al., 2019). This lead and lag relationship among industry or sector returns can shed light which industries are first movers relative to news announcements, suggesting portfolio managers the need to focus on these key industries or sectors when important structural changes occur. These structural changes can be caused by economic, regulatory, or even environmental forces. For example, the returns from an energy-based exchange traded fund (ETF) can be critically affected by the performance of non-oil related sectors, sectors which would not generally be considered in traditional based modelling. At the security analysis level, LASSO models can track, out of large number of predictive return variables, factors bearing the highest explanatory values for future returns estimates (Feng, Giglio & Xiu, 2020). In the same vein, Bew et al. (2019) trained a Bayesian ML model based on actual brokers/analysts' recommendations and found that best results are achieved when there is agreement between analyst recommendations and the forecasts of the ML model. Relying on such recommendation provide valuation information as to which stock(s) should be considered for buying, holding or selling. ANN are also successful in predicting asset returns. For instance, Gu et al. (2020) found that ANN with three layers significantly outperformed other models including gradient boosted regression trees, ordinary least squares regressions, random forests and LASSOs. ANN's success can be attributed to neural networks' abilities to capture non-linear characteristics, due to its relatively larger number of available structures making ANN a relatively more effective learner. Dixon & Polson (2019) extended fundamental factor model using neural networks to allow for statistical interpretations, ranked fundamental factors such as price to earnings ratio (P/E), price to book value (P/BV) and enterprise value (EV), and found ANN to yield lower out of sample mean forecast errors than other models. Similarly, Alberg and Lipton (2017) used features from fundamental factors on U.S. stocks using recurrent neural networks and reported an improved equity portfolio performance. Similar results were found in Bianchi, Büchner & Tamoni (2021) who found deep neural networks to yield better excess returns in bond markets relative to dense and sparse linear regressions. It is important to note however, that in some cases (for example Arrieta-ibarra & Lobato 2015), other models like support vector machines can outperform neural networks models, depending on parameter specifications. Consequently, to reduce bias in model selection, an ensemble approach has been recently adopted, where an average of different ML model results is used, as opposed to results from a single model (Borghi & De Rossi, 2020). Furthermore, a critical area in asset allocation relates to the co-variability which exists among each pair of financial products to be included in a subsequent portfolio. Alternatively stated, the estimated covariances under the Markowitz portfolio model plays an important role since these would affect the portfolio risk value. Lopez de Prado (2016) used hierarchical cluster analysis to substitute the covariance structure of financial product returns with a tree structure. This led to more stable and robust weights in the portfolio allocation.

For example, the excess return per unit of risk was more than 30% higher than found under a traditional Markowitz (1952) model.

4. ML IN PORTFOLIO CONSTRUCTION

ML can also play a vital role in the execution step of the portfolio management process, and more specifically in the portfolio construction stage. After having selected specific financial products (like stocks, bonds, commodities, cryptocurrencies) from a mix of different asset classes (like equity, fixed income, and alternative investments), a portfolio is usually constructed, while keeping in mind some targeted portfolio risk and return. Some specific assumptions are typically imposed on the portfolio construction, such as ensuring the highest Sharpe ratio (excess return per unit of risk) or setting the smallest portfolio risk possible given a set of financial products (a minimum variance portfolio). Traditionally, the Markowitz Portfolio Theory (MPT) framework has been adopted to estimate the expected return and risk of the portfolio. The model is however subject to a few critics. Firstly, the correlation matrix becomes unreliable when return correlations across financial instruments in the portfolio changes. Positive (negative) correlations increase (reduce) the portfolio risk, where positive correlations would defeat the purpose of adding those financial instruments in the portfolio in the first place. Alternatively stated, positive correlations reduce diversification benefits. Violating the assumption of stable returns correlations weaken the reliability of the Markowitz model (Lopez de Prado, 2016). Secondly, optimal portfolios which have the highest Sharpe values, are subject to uncertainty. Specifically, expected returns are susceptible to future events which had not been witnessed in past return performance. As expected returns affect the optimized weights, this introduces the possibility of unstable weights which can perform poorly on out of sample periods. ML tackles those two issues by (i) estimating more reliable return and risk values, and (ii) using alternative non-linear approaches to yield optimal portfolios with more robust performance for out of sample periods. For example, Yu, Wang & Lai (2008) used a ANN which extended the Markowitz mean-variance framework to allow for skewness features when constructing the optimal portfolio. Similarly, Zimmermann, Neuneier & Grothmann (2002) used more robust future expected return estimates in their ANN portfolio model by including a Black & Litterman (1992) framework and reported higher out of sample excess per unit of risk. Inspired by biological evolution such as reproduction, mutation and selection, evolutionary algorithm (EA) also started to play an important role in portfolio construction. While a conventional mean-variance portfolio selection aims at simultaneously maximizing the expected return of the portfolio and minimizing portfolio risk, various constraints exist in the real-world such as minimum buy-in thresholds or a limit to the number of different assets in the portfolio. This leads to a non-convex search space. Branke et al. (2009) found that envelope-based multi-objective EA outperformed existing other models. In the same vein, Skolpadungket, Dahal & Harnpornchai (2016) included further objectives during optimizing a portfolio, by include a variable for model misspecification, and reported a superior Sharpe ratio than when relying on only

risk and return. Last, but not least, with massive explosion of financial products such as ETF, ML can provide some benefits in terms of mirroring benchmarking portfolio's performance, without necessitating all the individual assets required to create the benchmark portfolio. For instance, Lowe (1994) support that ANN can provide a good proxy of the UK market index, the FTSE 100, by using on 7 stocks, as opposed to 100 stocks. The author essentially introduced feedforward network in portfolio management, where ANN can approximate non-linear relationships in the data and optimize the portfolio by minimizing tracking error, while capturing some of the FTSE 100 risk factors. This provides several benefits including reduced transaction costs during periods of portfolio rebalancing, and reduction in the costs of portfolio management in monitoring and reporting. In the same line of thought, Heaton, Polson & Witte (2017) support the use of deep learning (DL) hierarchical models which can improve portfolio performance, given the extent of big data and complexity among different data. The authors suggest that such DL allows to capture complex non-linear relationships, which are for now, not visible in traditional financial/economic theory.

5. CHALLENGES FOR SUCCESSFUL ML IMPLEMENTATIONS

While the various benefits which ML bring to asset allocation and portfolio management are quite apparent as discussed, some important challenges need to be tackled. First, while sophisticated ML models such as ANNs can provide superior results to traditional human based approaches, such models can also make wrong decisions by imposing improper focus on spurious relationships among variables. For instance, Avramov et al. (2019) find that ANNs find that some models which were trained to select stocks with high returns select illiquid stocks. Second, such models also add to the complexity when it comes to interpretation. Simply put, portfolio managers would have a hard time explaining what the optimized algorithm equation is all about, since it would not necessarily be based on financial or economic theories. This can potentially lead to a weak assessment of how ML models would behave in highly unpredictable events, which could result in systemic risk, where various ML are making the same errors simultaneously. For example, if various firms or investors are adopting contrarian-based strategies, and the wrong model assumptions have been set, the complexity of ML models would not provide the ability to the user to monitor and avoid potential systemic risk. Further, due to the significant cost of creating new algorithms, this would tend to suggest companies tend to acquire above off-the-shelf ones which are adopted by many investment companies, at lower costs. Third, portfolio performance attributions become more challenging, particularly, in times of poor performance. For example, Barra trading models which decompose risk based on multi-factors to explain short term fluctuations in stock returns, do so mostly via linear relationships between returns and factors. With ML models not imposing linear constraints, it becomes more challenging to explain to portfolio clients as to why portfolios did not achieve as expected. Scarce work has been done so far to facilitate ML successful implementations in the finance industry, to a level which is easier to understand, interpret and convey to portfolio clients (Molnar, 2020).

Last, but not least, even though a bigger amount and variety of data is available compared to one decade earlier, data quality remains a critical area. To avoid a garbage-in garbage-out outcome with ML, there should not only be a sufficiently large dataset to train the ML models, but also a need to avoid replacing missing values with statistical values like average. While all portfolios' product disclosure statements (PDS) will formally write that past performance is not necessarily guaranteeing future performance, ML models can fail in predicting future asset prices or returns if these models are not sufficiently trained with past extreme events data. This can result in a higher possibility to ML models failing during a crisis (Patel & Lincoln, 2019).

6. CONCLUSIVE REMARKS

Technology involvement in all key sectors of an economy has tremendously been felt in the last decade. This has been helped with various events such as cryptocurrencies adding new financial products like Bitcoin and Bitcoin futures to the asset management industry. More importantly, machine learning and its broader term (artificial intelligence) has moved into various areas of portfolio management including asset allocation, algorithmic trading, portfolio construction, portfolio performance, and robo-advisory services. For the purpose of this study, we focused on the asset allocation and portfolio construction and how ML models have been implemented to some extent. Various ML models have been successfully implemented in diverse asset classes ranging from equity, bond and alternative investments such as cryptocurrencies, in determining future price or return movements. While these ML models also bring more efficient, timely and less human (biased) interventions, there are still some important challenges ML face in these areas. These relate to data quality, data sufficiency, and portfolio performance attributions. Most importantly, the ease to understand, interpret and explain ML model performance to portfolio clients, particularly in times of poor portfolio performance, need to be addressed. Till then, portfolio analysts and managers can continue to encompass simple ML models into their traditionally human based work, to manage actively portfolios, on a timely basis.

REFERENCES

1. Alberg, J., & Lipton, Z.C. (2017). Improving Factor-Based Quantitative Investing by Forecasting Company Fundamentals, ArXiv, <https://arXiv.org/abs/1711.04837v2>
2. Arrieta-ibarra, I., & Lobato, I.N. (2015). Testing for Predictability in Financial Returns Using Statistical Learning Procedures. *Journal of Time Series Analysis*, Volume 36, No. 5, 672–86. <https://doi.org/10.1111/jtsa.12120>
3. Azimi, M., & Agrawal, A. (2021). Is Positive Sentiment in Corporate Annual Reports Informative? Evidence from Deep Learning, *The Review of Asset Pricing Studies*, Volume 11, Issue 4, 762–805. <https://doi.org/10.1093/rapstu/raab005>
4. Bartram, S.M., Branke, J., & Motahari, M. (2020). Artificial Intelligence in Asset Management. Research Foundation Literature Review, CFA Institute Research Foundation.
5. Bernard, V.L. (1994). Accounting-based valuation methods, determinants of market-to-book ratios, and implications for financial statements analysis. Working paper. (University of Michigan. Business School. Faculty Research). No. 9401.

6. Bew, D., Campbell R.H., Ledford, A., Radnor, S., & Sinclair, A. (2019). Modeling Analysts' Recommendations via Bayesian Machine Learning. *Journal of Financial Data Science* 1(1): 75–98. <https://doi.org/10.3905/jfds.2019.1.1.075>
7. Bianchi, D., Büchner, M., & Tamoni, A. (2021). Bond Risk Premia with Machine Learning. *The Review of Financial Studies*, Volume 34, Issue 2, 1046–1089. <https://doi.org/10.1093/rfs/hhaa062>
8. Black, F., & Litterman, R. (1992). Global Portfolio Optimization. *Financial Analysts Journal*. 48(5): 28–43. <https://doi.org/10.2469/faj.v48.n5.28>
9. Bodie, Z., Kan, A., & Marcus, J. (2009). *Investments*. 8th Ed. McGraw-Hill Irwin.
10. Borghi, R., & De Rossi, G. (2020). *The Artificial Intelligence Approach to Picking Stocks: Machine Learning for Asset Management*, Chapter 4, Ed (Emmanuel Jurczenko), Wiley. <https://doi.org/10.1002/9781119751182.ch4>
11. Bouoiyour, J., & Selmi, R. (2015). What does Bitcoin look like? (MPRA Paper No. 58091). Germany: University Library of Munich.
12. Branke, J., Scheckenbach, B., Stein, M., Deb, K., & Schmeck, H. (2009). Portfolio Optimization with an Envelope-Based Multi-Objective Evolutionary Algorithm. *European Journal of Operational Research* 199 (3): 684–93. <https://doi.org/10.1016/j.ejor.2008.01.054>
13. Buchanan, B.G. (2019). *Artificial Intelligence in Finance*. Alan Turing Institute. doi: <https://doi.org/10.5281/zenodo.2612537>
14. Chen, C., Liu, L., & Zhao, N. (2020). Fear sentiment, uncertainty, and bitcoin price dynamics: the case of COVID-19, *Emerging Markets Finance and Trade*, Vol. 56 No. 10, 2298–2309, doi: <https://doi.org/10.1080/1540496X.2020.1787150>
15. Chinco, A.M., Clark-Joseph, A.D., & Ye, M. (2019). Sparse Signals in the Cross-Section of Returns. *Journal of Finance* 74(1): 449–92. <https://doi.org/10.1111/jofi.12733>
16. Coqueret, G., & Guida, T. (2018). Stock Returns and the Cross-Section of Characteristics: A Tree-Based Approach. SSRN. <https://doi.org/10.2139/ssrn.3169773>
17. Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28–34. <https://doi.org/10.1016/j.econlet.2018.01.004>
18. Cryptoverze (2021a). The Impact Of Blockchain Technology On Economic Environment. Available on: <https://cryptoverze.com/the-impact-of-blockchain-technology-on-economic-environment/> [Accessed on 1st Jan 2022]
19. Cryptoverze (2021b). Bitcoin's next step to adoption – infiltrating traditional finance. Available on: Bitcoin's next step to adoption - infiltrating traditional finance — Cryptoverze [Accessed on 21st Jan 2022]
20. Dixon, M., & Polson, N.G. (2019). Deep Fundamental Factor Models. arXiv, 1903.07677. <https://arxiv.org/abs/1903.07677>
21. Dixon, M., Klabjan, D., & Bang, J.H. (2017). Classification-based Financial Markets Prediction Using Deep Neural Networks. *Algorithmic Finance* 6(3–4): 67–77. <https://doi.org/10.3233/AF-170176>
22. Faerber, E. (2008). *All about stocks*. 3rd Ed. McGraw Hill.
23. Feng, G., Giglio, S., & Xiu, D. (2020). Taming the Factor Zoo: A Test of New Factors. *The Journal of Finance*, 75(3): 1327–1370. <https://doi.org/10.1111/jofi.12883>
24. Fischer, T., & Krauss, C. (2018). Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions. *European Journal of Operational Research* 270(2):654–69. <https://doi.org/10.1016/j.ejor.2017.11.054>
25. Gu, S., Kelly, B.T., & Xiu, D. (2020). Empirical Asset Pricing via Machine Learning. *Review of Financial Studies*, 33(5): 2223–73. <https://doi.org/10.1093/rfs/hhaa009>
26. Gupta, S., Choudhary, H., & Agarwal, D. (2017). Hedging efficiency of Indian commodity futures: an empirical analysis. *Paradigm* 21(1):1–20.
27. Gurdgiev, C., & O'Loughlin, D. (2020). Herding and anchoring in cryptocurrency markets: investor reaction to fear and uncertainty, *Journal of Behavioral and Experimental Finance*, Vol. 25, 100271, doi: <https://doi.org/10.1016/j.jbef.2020.100271>

28. Gurrib, I. (2016). Optimization of the Double Crossover Strategy for the S&P500 Market Index. *Global Review of Accounting and Finance*, 7(1), 92-107. <https://doi.org/10.21102/graf.2016.03.71.07>
29. Gurrib, I. (2018a). Can an energy futures index predict US stock market index movements? *International Journal of Energy Economics and Policy* 8(5):230-240. <https://www.econjournals.com/index.php/ijeeep/article/view/6622>
30. Gurrib, I. (2018b). Are key market players in currency derivatives markets affected by financial conditions? *Investment Management and Financial Innovations*, 15(2), p183-193. [http://dx.doi.org/10.21511/imfi.15\(2\).2018.16](http://dx.doi.org/10.21511/imfi.15(2).2018.16)
31. Gurrib, I. (2019). Can energy commodities affect energy blockchain-based cryptos? *Studies in Economics and Finance* 36(4):682-699. <https://doi.org/10.1108/SEF-10-2018-0313>
32. Gurrib, I. (2020). Unified Financial Condition Index and the most actively traded USD based Foreign Currency pairs, *Institutions & Economics*, 12(4), 93-127. <https://ijie.um.edu.my/article/view/26892>
33. Gurrib, I., & Elshareif, E. (2016). Optimizing The Performance Of The Fractal Adaptive Moving Average Strategy: The Case Of EUR/USD. *International Journal of Economics and Finance*, 8(2), p171-178.
34. Gurrib, I., & Kamalov, F. (2019). The implementation of an adjusted relative strength index model in foreign currency and energy markets of emerging and developed economies. *Macroeconomics Finance Emerging Market Economies*, 12(2):105-123. <https://doi.org/10.1080/17520843.2019.1574852>
35. Gurrib, I., & Kamalov, F. (2021). Predicting bitcoin price movements using sentiment analysis: A machine learning approach, *Studies in Economics and Finance*, Vol ahead of print. <https://doi.org/10.1108/SEF-07-2021-0293>
36. Gurrib, I., E. Elsharieif, & Kamalov, F. (2020). The Effect of Energy Cryptos on Efficient Portfolios of Key Energy Listed Companies in the S&P Composite 1500 Energy Index, *International Journal of Energy Economics and Policy*, 10(2), 1-15. <https://doi.org/10.32479/ijeeep.8676>
37. Gurrib, I., Kamalov, F., & Elshareif, E. (2021). Can the leading us energy stock prices be predicted using the Ichimoku cloud? *International Journal of Energy Economics and Policy*, 11(1), 41-51. <https://doi.org/10.32479/ijeeep.10260>
38. Gurrib, I., Kweh, Q.L., Nourani, M., & Ting, I.W.K. (2019). Are cryptocurrencies affected by their asset class movements or news announcements? *Malaysian Journal of Economic Studies*, 56(2):201-225. <https://doi.org/10.22452/MJES.vol56no2.2>
39. Gurrib, I., Nourani, M., & Bhaskaran, R.K. (2022). Energy crypto currencies and leading U.S. energy stock prices: Are Fibonacci retracements profitable? *Financial Innovation*, Vol 8, Issue 8, <https://doi.org/10.1186/s40854-021-00311-8>
40. Heaton, J.B., Polson, N.G., & Witte, J.H. (2017). Deep Learning for Finance: Deep Portfolios. *Applied Stochastic Models in Business and Industry* 33 (1): 3-12. <https://doi.org/10.1002/asmb.2209>
41. Kamalov, F. (2020). Forecasting significant stock price changes using neural networks. *Neural Computing and Applications*, 32(23), 17655-17667.
42. Kamalov, F., Sulieman, H., & Santandreu Calonge, D. (2021). Machine learning based approach to exam cheating detection. *Plos one*, 16(8), e0254340.
43. Kamalov, F., Cherukuri, A., Sulieman, H., Thabtah, F., & Hossain, A. (2021). Machine learning applications for COVID-19: A state-of-the-art review. *arXiv preprint arXiv:2101.07824*. Chicago
44. Kamalov, F., Moussa, S., Zgheib, R., & Mashaal, O. (2020, December). Feature selection for intrusion detection systems. In *2020 13th International Symposium on Computational Intelligence and Design (ISCID)* (pp. 265-269). IEEE.
45. Kamalov, F., Gurrib, I., & Rajab, K. (2021). Financial Forecasting with Machine Learning: Price Vs Return, *Journal of Computer Science*, 17(3), pp. 251-264. <https://doi.org/10.3844/jcssp.2021.251.264>

46. Kamalov, F., Gurrib, I., & Thabtah, F. (2021, September). Autoregressive and neural network models: a comparative study with linearly lagged series. In 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT) (pp. 175-180). IEEE.. <https://doi.org/10.1109/3ICT53449.2021.9581812>
47. Kamalov, F., Smail, L., & Gurrib, I. (2020, November). Stock price forecast with deep learning. In 2020 International Conference on Decision Aid Sciences and Application (DASA) (pp. 1098-1102). IEEE.. <https://doi.org/10.1109/DASA51403.2020.9317260>
48. Kamalov, F., Smail, L., & Gurrib, I. (2020, December). Forecasting with Deep Learning: S&P 500 index. In 2020 13th International Symposium on Computational Intelligence and Design (ISCID) (pp. 422-425). IEEE.. <https://doi.org/10.1109/ISCID51228.2020.00102>
49. Kamalov, F., Thabtah, F., & Gurrib, I. (2021, September). Autocorrelation for time series with linear trend. In 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT) (pp. 181-185). IEEE. <https://doi.org/10.1109/3ICT53449.2021.9581809>
50. Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters*, 29, 68-74. <https://doi.org/10.1016/j.frl.2019.03.009>
51. Ke, Z.T., Kelly, B.T., & Xiu, D. (2019). Predicting Returns With Text Data. National Bureau of Economic Research, NBER Working Paper 26186. <https://doi.org/10.3386/w26186>
52. Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports*, 3(3415), 1-7. <https://doi.org/10.1038/srep03415>
53. Lee, T.B. (2014, February 3). These four charts suggest that Bitcoin will stabilize in the future. *Washington Post*. Retrieved from <https://www.washingtonpost.com/news/the-switch/wp/2014/02/03/these-four-charts-suggest-that-bitcoin-will-stabilize-in-the-future/>
54. Lev, B. (1989). On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research. *Journal of Accounting Research*. Volume 27, 153 – 193.
55. Lev, B., & Ohlson, J.A. (1982). Market-based empirical research in accounting: A review, interpretation, and extension. *Journal of Accounting Research*. Volume 20, 249 – 322.
56. Liu, Y., & Tsyvinski, A. (2018). Risks and returns of cryptocurrency (NBER Working Paper No. 24877). Cambridge, MA: National Bureau of Economic Research. <https://doi.org/10.3386/w24877>
57. Lopez de Prado, M. (2016). Building Diversified Portfolios that Outperform Out of Sample. *Journal of Portfolio Management* 42 (4): 59–69. <https://doi.org/10.3905/jpm.2016.42.4.059>
58. Lowe, D. (1994). Novel Exploitation of Neural Network Methods in Financial Markets. In *Proceedings of 1994 IEEE International Conference on Neural Networks*, vol. 6, 3623–28. Orlando, FL: IEEE.
59. Manahov, V., Hudson, R., & Gebka, B. (2014). Does High Frequency Trading Affect Technical Analysis and Market Efficiency? And If So, How? *Journal of International Financial Markets, Institutions and Money* 28: 131–57. <https://doi.org/10.1016/j.intfin.2013.11.002>
60. Molnar, C. (2020). Interpretable Machine Learning: A Guide for Making Black Box Models Explainable. <https://christophm.github.io/interpretable-ml-book/>
61. Patel, K., & Lincoln, M. (2019). It's Not Magic: Weighing the Risks of AI in Financial Services. London: Centre for the Study of Financial Innovation. http://www.csfi.org/s/Magic_10-19_v12.Proof.pdf
62. Penman, S.H. (1992). Return to Fundamentals. *Journal of Accounting, Auditing & Finance*. 7(4): 465– 482.
63. Phillip, A., Chan, J.S.K., & Peiris, S. (2018). A new look at Cryptocurrencies. *Economics Letters*, 163, 6-9. <https://doi.org/10.1016/j.econlet.2017.11.020>
64. Rajab, K., Kamalov, F., & Cherukuri, A. K. (2022). Forecasting COVID-19: Vector Autoregression-Based Model. *Arabian journal for science and engineering*, 1-10.

65. Reilly, F., & Brown, K. (2002). Investment Analysis and Portfolio management. 7th Ed. South-Western.
66. Renault, T. (2017). Intraday Online Investor Sentiment and Return Patterns in the U.S. Stock Market. *Journal of Banking & Finance* 84: 25–40. <https://doi.org/10.1016/j.jbankfin.2017.07.002>
67. Schumaker, R.P., & Chen, H. (2006). Textual Analysis of Stock Market Prediction Using Financial News Articles.” *AMCIS 2006 Proceedings*, 185: 1431–40. <https://pdfs.semanticscholar.org/db74/80f28a68b95ed35701b84a282d6ebd8eb366.pdf>
68. Singh, S., Nandy, A., Das, P., Bhowmik, S., Biswas, S., Sen-Gupta, R., & Mandal, S. (2022). A Novel Approach for Data Scraping and Sentiment Analysis from Twitter using Machine Learning Techniques, *American Journal of Electronics & Communication*, Volume 2, Number 3, 1-6(6). <https://doi.org/10.15864/ajec.2301>
69. Skolpadungket, P., Dahal, K., & Harnpornchai, N. (2016). Handling Model Risk in Portfolio Selection Using Multi-Objective Genetic Algorithm. In *Artificial Intelligence in Financial Markets: New Developments in Quantitative Trading and Investment*, edited by Christian Dunice, Peter Middleton, Andreas Karathanasopolous, and Konstantinos Theofilatos, 285–310. London: Palgrave Macmillan. https://doi.org/10.1057/978-1-137-48880-0_10
70. Subramanyam, K.R., & Venkatachalam, M. (2007). Earnings, cash flows, and Ex post intrinsic value of equity. *The Accounting Review*. 82(2): 457-481.
71. Van Wijk, D. (2013). What can be expected from the Bitcoin? (Working Paper No. 345986). Rotterdam: Erasmus Universiteit Rotterdam.
72. Wang, S., & Vergne, J.-P. (2017). Buzz factor or innovation potential: What explains cryptocurrencies’ returns? *PloS ONE*, 12(1), 1-17. <https://doi.org/10.1371/journal.pone.0169556>
73. Yu, L., Wang, S., & Lai, K.K. (2008). Neural Network Based Mean–Variance–Skewness Model for Portfolio Selection. *Computers & Operations Research*, 35(1): 34–46. <https://doi.org/10.1016/j.cor.2006.02.012>

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