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Regulatory Compliance and Supervision of Artificial Intelligence, Machine Learning and Also Possible Effects on Financial Institutions

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ABSTRACT

Financial time series forecasting is a challenging issue in the time-series field and has at- tracted many researcher's attention. Nowadays, it is one of the financial markets managers' concerns that individuals with different tastes selection and amounts of every kind of asset to be able to enter those markets, to recognize suitable opportunities and to gain good profit based on correct assessment. Today's world is that of change, and it is an essential factor in organizational success and survival to know what we expect in the future. This paper provides the detailed information about the regulatory compliance and supervision of artificial iintelligence, machine learning and also possible effects on financial institutions.

KEYWORDS: Artificial Intelligence, Machine Learning, financial institutions.

I. INTRODUCTION

[1] showed that predictive automatic trading decisions using comprehensive features are significantly better than traditional methods using using numeric features alone. The primary challenges with stock trading is the identification of profitable stocks and trading the stocks without human error and interferencr of personal sentiments in order to reap better returns. [2] combined the usage of both fundamental and technical variables for the prediction of profitable stocks using the support vectors machine learning algorithm. They systematically identified high returning healthcare stocks, and traded them with the help of an auto trading application without human error and sentiment interference and yielded 16.64% revenue at the end of three months trading. Further, Carol Anne Hargreaves, PrateekDixti and AnkitSolanki investigated whether a healthcare sector stock portfolio selected using the logistic regression will outperform the ASX All-Ordinaries Index and Healthcare Sector Index (XHJ) over the twenty days trading period. The healcthare stock portfolio returned 18.24%.

The Financial Stability Board (FSB) is established to coordinate at the international level the work of national financial authorities and international standard-setting bodies in order to develop and promote the implementation of effective regulatory, supervisory and other financial sector policies. Its mandate is set out in the FSB Charter, which governs the policymaking and related activities of the FSB. These activities, including any decisions reached in their context, shall not be binding or give rise to any legal rights or obligations under the FSB's Articles of Association.

Artificial intelligence (AI) and machine learning are being rapidly adopted for a range of applications in the financial services industry. As such, it is important to begin considering the financial stability implications of such uses. Because uses of this technology in finance are in a nascent and rapidly evolving phase, and data on usage are largely unavailable, any analysis must be necessarily preliminary, and developments in this area should be monitored closely.

Many applications, or "use cases", of AI and machine learning already exist. The adoption of these use cases has been driven by both supply factors, such as technological advances and the availability of financial sector data and infrastructure, and by demand factors, such as profitability needs, competition with other firms, and the demands of financial regulation. Some of the current and potential use cases of AI and machine learning include:

- Financial institutions and vendors are using AI and machine learning methods to assess credit quality, to price and market insurance contracts, and to automate client interaction.

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- Institutions are optimising scarce capital with AI and machine learning techniques, as well as back-testing models and analysing the market impact of trading large positions.
- Hedge funds, broker-dealers, and other firms are using AI and machine learning to find signals for higher (and uncorrelated) returns and optimise trading execution.
- Both public and private sector institutions may use these technologies for regulatory compliance, surveillance, data quality assessment, and fraud detection.

With the FSB FinTech framework, our analysis reveals a number of potential benefits and risks for financial stability that should be monitored as the technology is adopted in the coming years and as more data becomes available. In some cases, these observations are also contained in the FSB report on regulatory and supervisory issues around FinTech. They are:

- The more efficient processing of information, for example in credit decisions, financial markets, insurance contracts, and customer interaction, may contribute to a more efficient financial system. The RegTech and SupTech applications of AI and machine learning can help improve regulatory compliance and increase supervisory effectiveness.
- At the same time, network effects and scalability of new technologies may in the future give rise to third-party dependencies. This could in turn lead to the emergence of new systemically important players that could fall outside the regulatory perimeter.
- Applications of AI and machine learning could result in new and unexpected forms of interconnectedness between financial markets and institutions, for instance based on the use by various institutions of previously unrelated data sources.
- The lack of interpretability or "auditability" of AI and machine learning methods could become a macro-level risk. Similarly, a widespread use of opaque models may result in unintended consequences.
- As with any new product or service, there are important issues around appropriate risk management and oversight. It will be important to assess uses of AI and machine learning in view of their risks, including adherence to relevant protocols on data privacy, conduct risks, and cybersecurity. Adequate testing and 'training' of tools with unbiased data and feedback mechanisms is important to ensure applications do what they are intended to do.

Overall, AI and machine learning applications show substantial promise if their specific risks are properly managed. The concluding section gives preliminary thoughts on governance and development of models, as well as auditability by institutions and supervisors.

II. AI AND MACHINE LEARNING IN REGULATORY COMPLIANCE AND SUPERVISION

AI and machine learning techniques are being used by regulated institutions for regulatory compliance, and by authorities for supervision. RegTech is often regarded as the subset of FinTech that focus on facilitating regulatory compliance more efficiently and effectively than existing capabilities. The total RegTech market is expected to reach $6.45 billion by 2020, growing at a compound annual growth rate (CAGR) of 76%. SupTech is the use of these technologies by public sector regulators and supervisors. Within SupTech, the objective of AI and machine learning applications is to enhance efficiency and effectiveness of supervision and surveillance. While there can be overlap in the terms, the two applications are discussed here separately. Some of the examples below are from the academic community. While not yet being applied by regulatory or supervisory bodies, they represent potential applications in this sector. The use cases are grouped by the function for which they are used, namely regulatory compliance; regulatory reporting and data quality; monetary policy and systemic risk analysis; and surveillance and fraud detection.

RegTech: applications by financial institutions for regulatory compliance

For analysing unstructured data, RegTech can use machine learning combined with NLP. Besides being applied to the monitoring of behaviour and communication of traders for transparency and market conduct, machine learning together with NLP can interpret data inputs such as e-mails, spoken word, instant messaging, documents, and metadata. This in turn begs the issue of the boundaries for the employee surveillance policy. Some regulated institutions are experimenting with cases seeking to enhance their ability to comply with product suitability requirements.

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NLP could be used by asset management firms to cope with new regulations. In the EU, investment managers have to comply with specific requirements in the Markets in Financial Instruments Directive (MiFID II), the Undertakings for Collective Investments in Transferrable Securities (UCITS) Directive, and the Alternative Investment Fund Managers Directive (AIFMD). Firms could potentially leverage NLP and other machine learning tools to interpret these regulations into a common language. They could then analyse and codify the rules for automation into the integrated risk and reporting systems to help firms comply with the regulations. This could bring down the cost, effort and time needed to interpret and implement new and updated regulations for fund managers.

Knowing the identity of customers ('know your customer' or KYC) is another area where AI and machine learning are applied to address one of the biggest pain points in the financial industry, both with regards to user experience and regulator expectations. The KYC process is often costly, laborious, and highly duplicative across many services and institutions. Machine learning is increasingly used in remote KYC of financial services firms to perform identity and background pre-checks. It is predominantly used in two ways: (1) evaluating whether images in identifying documents match one another, and (2) calculating risk scores on which firms determine which individuals or applications need to receive additional scrutiny. Machine learning-based risk scores are also used in ongoing periodic checks based on public and other data sources, such as police registers of offenders and social media services. Use of these sources may enable risk and trust to be assessed quickly and often cheaply. Firms can use risk scores on the probability of customers raising "red flags" on KYC checks to help make decisions on whether to proceed with the time and expense of a full background check. Nonetheless, concerns about their accuracy have kept some financial services from incorporating these tools.

Uses for macroprudential surveillance and data quality assurance

AI and machine learning methods may help to improve macroprudential surveillance by automating macroprudential analysis and data quality assurance. A series of new reporting requirements across jurisdictions has led to a greater volume and frequency of reported data, as well as greater resources required from financial institutions to complete reporting on time. In some cases (for example, transactions data in MiFID, AIFMD templates, etc.), the volume of data received can be challenging for the authorities receiving the data, such that it cannot be used to its full potential using traditional methods. Moreover, substantial errors, blank fields, and other data quality issues are often more prevalent in new datasets, and additional checks and data quality assurance are needed. Machine learning can help improve data quality, for example, by automatically identifying anomalies (potential errors) to flag them to the statistician and/or the data-providing source. This may allow for both lower-cost and higher- quality reporting and more efficient and effective data processing and macroprudential surveillance of data by authorities.

Similarly, AI and machine learning could help trade repositories (TRs) tackle data quality issues, increasing the value of TR data to authorities and the public. Authorities report that overcoming data quality issues continues to be a key challenge to making full use of TR data. Application of machine learning techniques may help TRs – for over-the-counter (OTC) derivatives or (where applicable) other types of transactions, such as exchange-traded derivatives or securities financing transactions – improve data quality. Specifically, appropriately trained machine learning algorithms could help identify data gaps, data inconsistencies, and fat-finger errors, as well as match likely pairs of transactions and/or interpolate missing data. The same techniques can be used by authorities, themselves. In this context, the Autorité des marchés financiers du Québec reports that it has successfully tested in its FinTech Laboratory a supervised machine learning algorithm able to recognise distinct categories from unstructured free text fields in OTC derivatives data, such as the floating leg of swaps. Implementation of alerts based on this algorithm is underway to automatically detect transactions that are not compliant with mandatory clearing requirements.

III. POSSIBLE EFFECTS OF AI AND MACHINE LEARNING ON FINANCIAL INSTITUTIONS

AI and machine learning have the potential to enhance the efficiency and profitability of financial institutions, while reducing their costs and risks, through various channels. Greater profitability could aid the build-up of buffers and ultimately benefit system-wide stability:

a. AI and machine learning may enhance machine-based processing of various operations in financial institutions, thus increasing revenues and reducing costs. For example, if AI and machine learning help to identify customers' needs and better target or tailor products to profitable customers, financial institutions could more efficiently allocate resources toward serving those customers that account for substantial fees or have the potential for future growth. Automating routine business processes may allow for lower operating costs.

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b. AI and machine learning can be used for risk management through earlier and more accurate estimation of risks. For example, to the extent that AI and machine learning enable decision- making based on past correlations among prices of various assets, financial institutions could better manage these risks. Tools that mitigate tail risks could be especially beneficial for the overall system. Also, AI and machine learning could be used for anticipating and detecting fraud, suspicious transactions, default, and the risk of cyber-attacks, which could result in better risk management. But AI and machine learning based tools might also miss new types of risks and events because they could potentially 'overtrain' on past events. While AI and machine learning tools hold potential to improve risk management, the recent deployment of these strategies means that they remain untested at addressing risk under shifting financial conditions.

c. The data intensity and open-source character of research in AI and machine learning may encourage collaboration between financial institutions and other industries, such as e- commerce and sharing economy businesses.

Nonetheless, use of AI and machine learning risks creating 'black boxes' in decision-making that could create complicated issues, especially during tail events. In particular, it may be difficult for human users at financial institutions – and for regulators – to grasp how decisions, such as those for trading and investment, have been formulated. Moreover, the communication mechanism used by such tools may be incomprehensible to humans, thus posing monitoring challenges for the human operators of such solutions. If in doubt, users of such AI and machine learning tools may simultaneously pull their 'kill switches,' that is manually turn off systems. After such incidents, users may only turn systems on again if other users do so in a coordinated fashion across the market. This could thus add to existing risks of system-wide stress and the need for appropriate circuit-breakers.

In addition, if AI and machine learning based decisions cause losses to financial intermediaries across the financial system, there may be a lack of clarity around responsibility. For example, if a specific AI and machine learning application developed by a third party resulted in large losses, is the institution that conducted the trading solely responsible for the losses? Or would regulators or other parties be able to pursue potential claims against the application developer? Could more widespread use of AI and machine learning, including by non-traditional market players, impact the nature of supervision? Furthermore, there are open questions about (identifying) potential collusion among trading applications that rely on deep learning. Specifically, if algorithms interact in ways that would be considered collusion if done by human agents, then as with human agents, proof of intent may be an issue. In this light, there may be a number of legal uncertainties (see annex A). Finally, the lack of transparency around applications may be problematic for both institutions and regulators when it may not be possible to understand how undesired events occurred and when steps may need to be taken to prevent a recurrence.
Any uncertainty in the governance structure in the use of AI and machine learning might increase the risks to financial institutions.[85] If each investor makes their investment without fully understanding the applications and his or her possible losses in tail events, the aggregate risks could be underestimated. In addition, any uncertainty in the governance structure could substantially increase the costs for allocating losses, including the possible costs of litigation. In this regard, financial institutions applying AI and machine learning to their businesses need to establish well-designed governance and maintain auditability.

IV. NEURAL NETWORKS

The application of neural networks in machine learning in stock trading has predominantly gained importance in recent times.The theory of a neural network computation providesinteresting techniques that replicate the human brain andnervous system.

Neural networks are typically organized in layers and layers are made up of a number of interconnected nodes which contain an activation function. Generally speaking, a neural network is a set of connected input and output units where each connection has a weight associated with it. During the learning phase, the network learns byadjusting the weights so as to be able to correctly predict orclassify the output target of a given set of input samples. Given numerous neural network architecture, multi-layer feed-forward neural networks were implemented in this study to comparetheir predictive ability against the logistic regression, decision trees model and an artificial intelligence system.

Neural networks have beenwidely used for financial forecasting due to its ability tocorrectly classify and predict the dependent variable. [5] used neural networks for stock selection and showed that there is positive relationship between predictions of the trained networks with the equities appreciation, which may result in better earnings for investment. During the training phase,the predictor variables are fed making it an input layer.The weighted inputs are fed to the hidden layer and the weighted inputs of the hidden layer are fed into the other hidden layers.This

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process continues till the last hidden layer in the network.The weights of the last hidden layer are fed to the output layer which gives predictions for a given set of input samples.

Paper Trading

Each stock portfolio had an investment of $3 000, with each stock having almost $10 000 invested in. At the end of each month the stocks are sold and the return on investment for the portfolio is computed and compared with the stock market performance.

V. RESULTS

Modelling and Paper Trading Results

The ‘area under the curve’ and ‘recall’ are key metrics for evaluating machine learning model results. As a rule of thumb ‘recall’ and ‘area under the curve should be at least 0.7.The ‘recall’ and ‘area under the curve’ measures were very good, so paper trading went ahead.

Algorithms	Recall	Area Under Curve	Return On Investment (%)
LOGISTIC REGRESSION	0.97	0.926	0.39
DECISION TREES	0.85	0.935	0.94
NEURAL NETWORKS	0.93	0.969	0.39

Table 1: Paper Trading Results for April 2017

Table 1 above, presents the results for the paper trading of the 3 stock portfolios, Neural Networks, Decision Trees and Logistic Regression.

The market return on investment was 0.64%. The decision tree portfolio outperformed the stock market performance. But the Logistic Regression and Neural Network Model Portfolios were less than the market performance but not significantly different from the market performance.

Again, the ‘recall’ and ‘area under the curve’ metrics were generally very good. The market return on investment for May 2017 was -3.56%. All 3 models predicted the same top 3 stocks which performed extremely well.

ALGORITHMS	RECALL	AREA UNDER THE CURVE	RETURN ON INVESTMENT (%)
LOGISTIC REGRESSION	0.95	0.936	8.13
DECISION TREES	0.71	0.969	8.13
NEURAL NETWORKS	1	0.985	8.13

Table 2: Paper Trading Results for May 2017

ALGORITHMS	RECALL	AREA UNDER THE CURVE	RETURN ON INVESTMENT (%)
LOGISTIC REGRESSION	0.95	0.936	3.56
DECISION TREES	0.71	0.969	2.62
NEURAL NETWORKS	0.92	0.985	5.74

Table 3: Paper Trading Results for June 2017

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Again, the 'recall' and 'area under the curve' metrics were generally very good. The market return on investment for June 2017 was -0.15%. All 3 stock portfolios outperformed the market by at least 2.5 times.

V. CONCLUSION

Network effects and scalability of new technologies may in the future give rise to additional third-party dependencies. This could in turn lead to the emergence of new systemically important players. AI and machine learning services are increasingly being offered by a few large technology firms. Like in other platform-based markets, there may be value in financial institutions using similar third-party providers given these providers' reputation, scale, and interoperability. Machine Learning models such as the Logistic Regression, Decision Tree and Neural Network was used and the experimental results confirmed that the machine learning models were very good at identifying top performing stock portfolios that outperform the stock market. In all three consecutive time periods, stock portfolio performance was positive. This paper provided the detailed information about the regulatory compliance and supervision of artificial iintelligence, machine learning and also possible effects on financial institutions.

REFERENCES

[1] Jiang Peng. Research based on Support Vector Machine (SVM) of Stock Timing in Quantitative Trading [D]. Nanchang. Jiangxi University of Finance and Economics, 2019.

[2] Wu Weixing. Application of Random Forest in Quantitative Stocks selection of Technical Indicators [D]. Chengdu. University of Electronic Science and Technology of China, 2018.

[3] Tan Zheng, Yan Ziqin and Zhu Guangwei. Stock selection with random forest: An exploitation of excess return in the Chinese stock market [J]. Heliyon, 2019, 5(8): e02310.

[4] Kola Vasista, "Foreign Capital Issuance and Participants in the Securities Market", International Journal of Research and Analytical Reviews, VOLUME 2, ISSUE 4, OCT. – DEC. 2015

[5] Kola Vasista, "A Research Study On Major International Stock Market", International Journal of Research and Analytical Reviews, VOLUME 4, ISSUE 3, JULY – SEPT. 2017

[6] Kola Vasista, "A Review On The Various Options Available For Investment", International Journal Of Creative Research Thoughts - IJCRT (IJCRT.ORG), Volume 7, Issue 2, April 2019, ISSN: 2320-2882

[7] Kola Vasista, "A Detailed Study On The Factors Influencing The Price Of a Stock", International Journal of Novel Research and Development, Volume 2, Issue 8, August 2017, ISSN: 2456-4184

[8] Kola Vasista, "Objectives And Importance Of Capital Markets And The Role Of Financial Institutions", International Journal of Emerging Technologies and Innovative Research (www.jetir.org), ISSN:2349-5162, Vol.2, Issue 9, page no.475-478, September-2015,
Available :http://www.jetir.org/papers/JETIR1701762.pdf

[9] Kola Vasista, "An Overview On Provident Fund, Pension Funds, Pfrda, Insurance Companies And Irda", International Journal of Emerging Technologies and Innovative Research (www.jetir.org), ISSN:2349-5162, Vol.5, Issue 10, page no.284-287, October-2018,
Available :http://www.jetir.org/papers/JETIR1810A93.pdf

[10] Chen Lili. The research for quantitative analysis of stock price predict based on BP neural network theory [D]. Zhejiang University of Technology, Hangzhou, 2017.

[11] Zhang Xinyu. Multi-factor Quantitative Stock Selection Scheme Planning Based on Random Forest Algorithm [D]. Shanghai Normal University, Shanghai, 2019.

[12] Chen Yang. Research on forecasting and investment strategy of Shanghai-Shenzhen 300 Index based on Support Vector Machine [D]. Northwest University, Xi'an, 2019.