

Future of Artificial Intelligence and Machine Learning systems in financial risk management and regulatory compliance

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ABSTRACT

The paper discusses the integration of Artificial Intelligence and Machine Learning in the financial sector for improved risk management and regulatory compliance. The paper explores how AI and ML enhance risk identification, assessment, quantification, and mitigation processes, providing accurate credit and market risk evaluations using real life case studies. Furthermore, the paper also investigates how such systems can streamline compliance procedures, automate reporting, monitoring, as well as auditing tasks pragmatically and address ethical and privacy challenges regarding these systems.

Keywords: Artificial Intelligence, Machine Learning, Financial Innovation, Risk Assessment, Risk Mitigation, Regulatory Frameworks, Natural Language Processing (NLP)

1. INTRODUCTION

The combination of Artificial Intelligence (AI) and Machine Learning (ML) technology has radically transformed risk management in the financial industry, ushering in a new era of better assessment, modelling, and mitigation measures. Traditional risk assessment methodologies, which were based on historical data and deterministic models, have been overtaken by the dynamic and data-driven capabilities of AI and ML. These technologies excel in processing massive datasets in real time, detecting

detailed patterns, and identifying anomalies that human analysts may miss. They allow predictive analytics, projecting market trends, loan defaults, and liquidity problems, delivering priceless early warnings and actionable insights. Stress testing, a critical component of risk assessment, has also evolved through ML-powered simulations of severe market scenarios, allowing financial institutions to measure their resistance to unfavourable conditions. AI and ML systems have the unique ability to adapt and learn from large datasets, making them particularly adept at negotiating the complexities of financial rules. This flexibility is critical in a regulatory environment where regulations are often revised and updated. These tools enable financial institutions to analyze the impact of new legislation on their operations quickly, identify areas of noncompliance, and implement necessary modifications quickly. Automated data processing and analysis is one of the keyways that AI and ML improve regulatory compliance. These systems are capable of ingesting and analyzing massive amounts of data from many sources, such as regulatory papers, financial transactions, and market data. They can interpret regulation documents and retrieve pertinent information using natural language processing (NLP) approaches.

2. Background

The main aim of risk management is to ensure that business processes remain resilient to unforeseen events occurs. Risk management must have plans to ensure that impact of risks does not exceed the risk bearing capability of the enterprise. Risk assessment contains three phases. Phase 1 is Risk identification.

In this step, risk against various assets is calculated. It is critical that a comprehensive list of assets (tangible & non-tangible) is developed by the organization. Against each asset, its value to the organization is calculated based on its importance to the business. There are multiple factors that should be considered while calculating the value of an asset such as - Financial value of asset - Value of data stored in the asset - Business impact in case asset is not available. Phase 2 is Risk Analysis. Identified risks must be calculated and assigned a risk value. This is based on the likelihood or probability of risk occurring and the impact on the risk will cause to business in terms of money. Hence risk is calculated as $\text{Risk} = \text{likelihood} * \text{impact}$ Phase three is Evaluation: Once risks are calculated, a priority must be established to ensure highest risks are handled first. It is also important to compare the risks against the risk acceptance criteria of the organization.

AI/ML advances in recent years are changing the scope and role of technology in regulatory compliance. Regulatory technology (regtech) has assumed greater importance in response to the regulatory tightening and rising compliance costs following the 2008 global financial crisis. For the most part, technology has been used to digitize compliance and reporting processes. However, advances in AI/ML over the past few years are reshaping risk and compliance management by leveraging broad sets of data, often in real time, and automating compliance decisions. This has improved compliance quality and reduced costs.

Maturing AI/ML technology has the potential to propel further adoption of regtech in the financial sector. Increased adoption of AI/ML in regtech has significantly expanded its use cases, cutting across banking, securities, insurance, and other financial services, and covering a wide variety of activities. These include identity verification, anti-money laundering/combatting the financing of terrorism, fraud detection, risk management, stress testing, micro prudential and macroprudential reporting.

3. Risk Management

3.1 Application to credit risk

Credit risk is economic loss that emanates from the failure of a counterparty to fulfill its contractual obligations (e.g., timely payment of interest or principal), or from the increased risk of default during the term of the transaction. Traditionally,

financial firms have employed classical linear, logit, and probit regressions to model credit risk (Altman, 1968 as cited in Aziz, Saqib & Dowling, Michael, 2018). However, there is now an increased interest by institutions in using AI and machine learning techniques to enhance credit risk management practices, partially due to evidence of incompleteness in traditional techniques. The evidence is that credit risk management capabilities can be significantly improved through leveraging AI and machine learning techniques due to its ability of semantic understanding of unstructured data. The use of AI and machine learning techniques to model credit risk is not a new phenomenon though it is a growing one.

3.2 Application to market risk.

Market risk is the risk that emanates from investing, trading, and from having exposure to financial markets. A 2017 Financial Stability Board report 'Artificial Intelligence and Machine Learning in Financial Services' provides a comprehensive overview of current applications of machine learning to market risk management and is recommended reading. Trading in financial markets inherently involves the risk that the model being used for trading is false, incomplete, or is no longer valid. This area is known as model risk management. Machine learning is particularly suited to stress testing market models to determine inadvertent or emerging risk in trading behaviour. (Woodall (2017) as cited in Aziz, Saqib & Dowling, Michael., 2018) describes a variety of current use cases of machine learning for model validation, including the French investment firm Nataxis which at the time of writing was running over 3 million simulations a night using unsupervised learning to establish new patterns of connection between assets and investigating further any simulations that emerged from the testing that showed 'errant' patterns compared to average estimates. Woodall also notes how Nomura uses machine learning to monitor trading within the firm to verify that unsuitable assets are not being used in trading models. An interesting current application of model risk management is the firm yields.io which provides real time model monitoring, model testing for deviations, and model validation, all driven by AI and machine learning techniques. Another area of focus within the category of market risk of importance to large trading firms is understanding the impact of their trading on market pricing. (Day

(2017) as cited in Aziz, Saqib & Dowling, Michael. 2018) explores how large trading firms are using AI, and particularly clustering techniques, to avoid the costs of trying to trade into and out of large positions in illiquid markets. He provides a quote from Capital Fund Management, one of the largest hedge funds in France with \$11 billion under management, claiming that up to two thirds of their profit from trades can be lost due to market impact costs. Machine learning techniques significantly help with this issue by identifying connections between assets that are not easily observable and thus allow entering desired positions through a series of related assets rather than taking a large position in a single asset.

3.3 Data management for Risk

Mitigation

After the fiscal crisis of 2008-09, many new regulations and supervisory measures were introduced that required FIs to report more detailed and more frequent data on more aspects of their business models and balance sheets. Under the new capital regime, banks report large exposures, liquidity measures, collateral, and capital levels. Stress tests are based on all kinds of firm data including loan-level balance sheet data and qualitative aspects of the business model. The Federal Reserve's CCAR exercise requires FIs to consider the impact of more than 2000 economic variables on their business. For insurers, Solvency II has dramatically increased reporting requirements. These processes create substantial amounts of reporting data that need to be well-defined and structured, aggregated across the group, and delivered in-time with supervisors. Regulators have, therefore, introduced numerous initiatives to improve the quality of supervisory data and the ability of financial institutions to deliver these data. The Basel Committee's Principles for Risk Data Aggregation (Basel 239) sets standards for G-SIBS to improve their IT systems and reporting structures. IFRS 9 aims to improve the quality of supervisory data. Apart from reporting data, FIs are increasingly able to gather copious amounts of low-quality, unstructured, high-frequency data. These include outputs from consumer apps and other digital interactions with clients, metadata from payment systems, and external data sources, such as social media feeds, which can be mined to gauge insights on market sentiment. This type of data is typically called "big data." With practically all aspects of FI's

business model regulated and supervised with detailed risk metrics, running a bank, insurer, or asset manager is increasingly becoming a matter of optimization within hundreds of constraints. To compete effectively, they need to find this optimum while also mining consumer data for detailed insights on client preferences and behavior. The extensive set of machine learning approaches is well situated to deliver this analytical power in different contexts due to its ability to cope with (or better said, its need for) extremely large datasets and the granularity of analysis. For the mining of high-quality, structured supervisory data, more conventional machine learning techniques are typically applied. To mine high frequency, low quality "big data" sources, Google-like deep learning and neural network techniques are applied, which cope with these data due to their representation learning abilities.

4. AI and ML in regulatory compliance

Artificial Intelligence (AI) has emerged as a transformative force in the realm of regulatory compliance, with its application extending across a spectrum of critical use cases. An exemplary instance lies in the domain of anti-money laundering and combating the financing of terrorism (AML/CFT) compliance. Here, AI and machine learning (ML) powered technologies, harnessing the analytical prowess to dissect unstructured data and discern intricate patterns in consumer behavior, have proven instrumental in the reduction of false positives—an issue that traditionally dominated AML/CFT alert systems. By effectively winnowing down false positives, financial institutions can now strategically allocate their resources, channeling efforts towards cases with a higher degree of suspicion. Another noteworthy application resides in the sphere of mapping and updating regulatory obligations. AI and ML-based applications have been pivotal in assisting financial institutions in the identification and rapid adaptation to relevant regulatory mandates. This dynamic approach not only streamlines the compliance process but also contributes significantly to cost containment. In the realm of conduct risk management, AI, and natural language processing (NLP) have been harnessed to meticulously monitor sales calls conducted by employees of financial institutions. The overarching goal is to ensure strict adherence to regulatory requirements pertaining to the accurate disclosure of features and risks associated with offered financial

products. This vigilant oversight substantially bolsters regulatory compliance within the industry. Furthermore, on a broader scale, many global banks have embraced AI and ML-enabled data analytics to elevate their analytical capabilities in scrutinizing complex balance sheets and stress testing models. This strategic adoption of AI facilitates alignment with the rigorous demands of stress testing regulatory requirements. In summation, the profound impact of AI in the intricate landscape of regulatory compliance is undeniable. Its versatile and transformative capabilities, as evidenced in these diverse applications, hold the potential to redefine and optimize compliance practices across financial institutions, fostering a more efficient, cost-effective, and secure regulatory environment.

5. Privacy and Ethical Considerations with AI and ML in finance

The increased deployment of AI in financial services can provide important benefits to financial consumers and market participants, by improving the quality of services offered and producing efficiencies to financial service providers. At the same time, AI-based applications in finance can give rise to new challenges (e.g. related to lack of explainability) or amplify risks that already exist in financial markets (e.g. related to data management and use). Policy makers and regulators have a role in ensuring that the use of AI in finance is consistent with promoting financial stability, protecting financial consumers, and promoting market integrity and competition. Emerging risks from AI technique deployment must be identified and mitigated to support and promote responsible AI. Existing regulatory and supervisory requirements may need to be clarified and sometimes adjusted to address some perceived incompatibilities of existing arrangements with AI applications. Policy makers should consider sharpening their focus on better data governance by financial sector firms, aiming to reinforce consumer protection across AI applications in finance. Some of the most important risks raised in this note relate to data management: data privacy, confidentiality, concentration of data and possible impact on the competitive dynamics of the market, but also risk of unintended bias and discrimination of parts of the population and data drifts. The importance of data is undisputed when it comes to training, testing and validation of ML models, but also when defining the capacity of such models to retain their predictive powers in tail event

situations. Policy makers could consider the introduction of specific requirements or best practices for data management in AI-based techniques. These could touch upon data quality, adequacy of the dataset used to depend on the intended use of the AI model, and safeguards that provide assurance about the robustness of the model when it comes to avoiding potential biases. Appropriate sense checking of model results against baseline datasets and other tests based on whether protected classes can be inferred from other attributes in the data are two examples of best practices to mitigate risks of discrimination. The validation of the appropriateness of variables used by the model could reduce a source of potential biases. Tools could be developed and used to monitor and correct conceptual drifts. Requirements for more transparency over the use of personal data and opt-out options for it could be considered by authorities. Policy makers could consider disclosure requirements around the use of AI techniques in the provision of financial services and that may impact the customer outcome. Financial consumers need to be informed about the use of AI techniques in the delivery of a product, as well as potential interaction with an AI system instead of a human being, to be able to make conscious choices among competing products. Clear information around the AI system's capabilities and limitations should be included in such disclosure. The introduction of suitability requirements for AI-driven financial services, like the ones applicable to the sale of investment products, could be considered by authorities. Such requirements would help financial service providers better assess whether prospective clients have a solid understanding of how the use of AI affects the delivery of the product

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