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Artificial Intelligence and Machine Learning Based Financial Risk Network

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Abstract*: Financial risk Network avoids losses and maximizes profits, and hence is vital to most businesses. As the task relies heavily on information-driven decision making, machine learning is a promising source for new methods and technologies. In recent years, we have seen increasing adoption of machine learning methods for various risk management tasks. Machine-learning researchers, however, often struggle to navigate the vast and complex domain knowledge and the fast-evolving literature. This paper fills this gap, by providing a systematic survey of the rapidly growing literature of machine learning research for financial risk management. The contributions of the paper are four-folds: First, we present a taxonomy of financial-risk-management tasks and connect them with relevant machine learning methods. Secondly, we highlight significant publications in the past decade. Thirdly, we identify major challenges being faced by researchers in this area. And finally, we point out emerging trends and promising research directions.*

Keywords: Artificial Intelligence, Industry, intents, examples

I. INTRODUCTION

Machine learning has been at the forefront of innovation in various fields such as Natural Language Processing, Computer Vision, and Robotics. These advancements have sparked widespread interest in applying machine learning techniques to diverse domains abundant with data. Financial Risk Management (FRM) is no exception to this trend.FRM tasks pose significant challenges due to the continuously evolving, sparse, and complex nature of financial data. Effectively quantifying and managing risk is crucial for any organization, particularly as businesses, especially financial institutions, grow larger and more intricate. The demand for sophisticated statistical models to accurately quantify and mitigate risk has never been greater. For large companies with extensive portfolios and complex financial products, accurately assessing portfolio exposure to dynamic financial markets has become increasingly challenging using traditional statistical or simulation methods. To address this challenge, there is a growing body of research focusing on the application of advanced machine learning methods to FRM datasets.

Driven by both industrial demand for intelligent risk management systems and academic goals of developing highly applicable machine learning algorithms, an increasing number of researchers are exploring sophisticated ML approaches, including Transfer Learning and Deep Reinforcement Learning, for tasks related to managing and mitigating financial risk. While the depth of literature in solving specific FRM tasks is expanding rapidly, there appears to be limited work providing an organized taxonomy to connect explored machine learning methods within the broader FRM framework. Although several surveys have covered the application of machine learning to specific FRM tasks, our survey aims to provide a comprehensive view of the literature, encompassing all major FRM tasks. For instance, while some surveys focus on financial market movement prediction or hedging market risks, they may overlook other significant exposures for companies, such as risks related to credit obligations or excessive claims.In contrast, our work seeks to unify the machine learning literature across different FRM tasks, identifying common challenges and research directions prevalent across the entire risk spectrum. Our survey presents a holistic view of the ML literature through a single FRM taxonomy that encapsulates all major financial exposure points for a company, including traditional risks such as Market, Credit, and Operational risks, as well as additional risk types.

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II. LITERATURE SURVEY

In his work, Horcher defines risk as the probability of loss and exposure as the possibility of loss. Exposure to risk is often essential for a business to thrive, and identifying risk and exposure forms the foundation of FRM.

In Risk Network AI/ML has become synonymous with improving efficiency and productivity while reducing costs. This has been possible due to the technologies' ability to handle and analyze large volumes of unstructured data at faster speeds with considerably lower degrees of human intervention. In risk management, AI/ML has become synonymous with improving efficiency and productivity while reducing costs. This has been possible due to the technologies' ability to handle and analyze large volumes of unstructured data at faster speeds with considerably lower degrees of human intervention. A major multi-class classification task in FRM is the task of credit scoring or bankruptcy prediction.

An example regression task is claim-frequency prediction where insurers try to predict the number of claims that will be made from a portfolio. Another highly cited regression task in FRM domain is volatility forecasting. This can also be seen as a supervised sequence learning problem UNSUPERVISED LEARNING Unsupervised learning refers to the task of detecting patterns from unlabelled data. In this setting, no labelled data is available. The unsupervised learning algorithms are built to solve specific problems (e.g. clustering, outlier detection, dimensionality reduction, anomaly detection) from unlabelled dataeveral models environment. The objective of the learner is to maximise the reward over its set of interactions with the environment Due to its ability to consistently explore the environment to select the optimal strategy, researchers and practitioners have used reinforcement learning algorithms for risk-optimised dynamic portfolio allocation D. SEMI-SUPERVISED LEARNING Semi-supervised learning problems are common in settings where accessing labels is possible but expensive.

These algorithms learn from both labelled and unlabelled data and make predictions on the unlabelled date. Due to the complexity of acquiring labels in many real-life problems (e.g. finance, healthcare), the topic is highly relevant for applied machine used in financial risk engineering) but are computationally expensive for large portfolios. Therefore, several ML-based methods are used to approximate the result of full portfolio simulation based on simulation results of a much smaller subset DEEP LEARNING Deep learning is a form of machine learning that extracts multi-layered representations of the features, approximating a non-linear composite function that forms a hierarchical transformation of features into labels. This learning method is highly suitable for understanding patterns from complexwhere agents need to dynamically redistribute portfolios within volatile financial markets to minimise risk and/or maximise return. Interested readers can find a comprehensive overview of deep reinforcement learning and its recent.

III. PURPOSE

The purpose of the provided text is to highlight the increasing importance of applying machine learning techniques in Financial Risk Management (FRM). It emphasizes the challenges posed by the evolving, sparse, and complex nature of financial data and the need for sophisticated statistical models to accurately quantify and mitigate risks. The text also underscores the growing interest among researchers and practitioners in leveraging advanced machine learning approaches, such as Transfer Learning and Deep Reinforcement Learning, to address FRM tasks. Furthermore, it discusses the lack of a unified taxonomy connecting machine learning methods to various FRM tasks and proposes to fill this gap by providing a comprehensive survey that encompasses all major FRM tasks. Ultimately, the goal is to offer a holistic view of the machine learning literature within the FRM domain and identify common challenges and research directions across different types of financial risks.

IV. OBJECTIVE OF SYSTEM

The objective of the text is to discuss the application of machine learning in Financial Risk Management (FRM). It aims to highlight the challenges faced in managing financial risks and the increasing demand for sophisticated statistical models to effectively quantify and mitigate these risks. Additionally, the text addresses the growing interest among researchers and practitioners in utilizing advanced machine learning techniques for FRM tasks, such as predicting financial market movements and hedging risks. It also points out the need for a unified taxonomy to organize the literature on machine learning methods applied to various FRM tasks. Ultimately, the objective is to provide a comprehensive survey that encompasses all major FRM tasks, offering insights into common challenges and research directions in the field.

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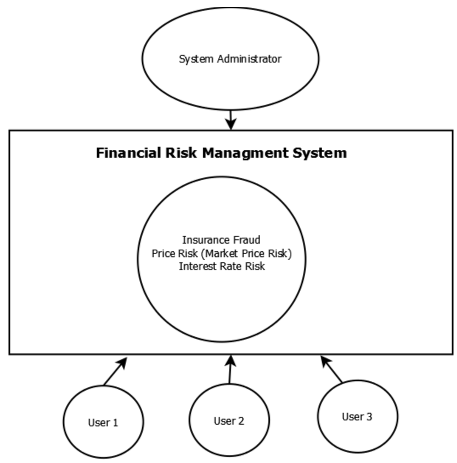
V. PROPOSED SYSTEM

Because of the recent exponential rise in attack frequency and sophistication, the proliferation of smart things has created significant cybersecurity challenges. Even though the tremendous changes cloud computing has brought to the business world, its centralization makes it challenging to use distributed services like security systems. Valuable data breaches might occur due to the high volume of data that moves between businesses and cloud service suppliers, both accidental and malicious.

SYSTEM ARCHITECTURE



Fraudulent insurance claims represent a significant source of preventable losses for insurers globally. Among different segments, Property & Casualty (P&C) insurance experiences the highest volume of fraudulent claims, particularly in areas such as auto insurance and workers' compensation.

Traditionally, insurers have relied on manual methods to detect fraud. However, these approaches have inherent limitations, leading to undetected fraudulent activities that impose considerable strain on insurers. Moreover, relying solely on historical fraud data means that new fraudulent schemes may go unnoticed. Sampling methods used to analyze claims for fraud may also inadvertently allow some fraudulent claims to slip through the cracks.

Furthermore, the traditional approach is ill-equipped to handle the vast influx of data and information from diverse sources in an integrated manner. This limitation arises because the traditional system operates in isolated silos, making it challenging to effectively process and analyze data from multiple sources.

VI. CONCLUSION

We have reviewed recent machine-learning applications in financial risk management. We identified areas that have been well-studied and also areas that require further research efforts. The well-studied areas include volatility forecasting, credit rating, bankruptcy prediction, fraud detection. In these tasks, advanced machine-learning models, including deep-learning models, have been extensively used. On the other hand, areas such as mortality forecasting, loss reserving, or claims modelling have not attracted an equal level of attention. In terms of models, although important research challenges still exist in the more traditional statistical models, more high-value open problems involve the more advanced machine-learning models. The FRM domain has much to gain from leveraging recent breakthroughs in machine learning, particularly deep learning, applied to other domains. These include the new uncertainty estimation methods in computer vision, robust algorithms for small, noisy, or nonstationary data. Finally, some generic machine-learning questions are particularly central to FRM and will likely drive further machine-learning development. In particular, federated learning systems have the potential to ensure private and more secure learning using sensitive financial data.

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REFERENCES

[1] R. C. Cavalcante, R. C. Brasileiro, V. L. F. Souza, J. P. Nobrega, and A. L. I. Oliveira, ‘‘Computational intelligence and financial markets: A survey and future directions,’’ Expert Syst. Appl., vol. 55, pp. 194–211, Aug. 2016.

[2] J. De Spiegeleer, D. B. Madan, S. Reyners, and W. Schoutens, ‘‘Machine learning for quantitative finance: Fast derivative pricing, hedging and fitting,’’ Quant. Finance, vol. 18, no. 10, pp. 1635–1643, Oct. 2018.

[3]T.-M. Choi, H. K. Chan, and X. Yue, ‘‘Recent development in big data analytics for business operations and risk management,’’ IEEE Trans. Cybern., vol. 47, no. 1, pp. 81–92, Jan. 2017.

[4] A. Bahrammirzaee, ‘‘A comparative survey of artificial intelligence applications in finance: Artificial neural networks, expert system and hybrid intelligent systems,’’ Neural Comput. Appl., vol. 19, no. 8, pp. 1165–1195, Nov. 2010.

[5] G. Kou, X. Chao, Y. Peng, F. E. Alsaadi, and E. Herrera-Viedma, ‘‘Machine learning methods for systemic risk analysis in financial sectors,’’ Technol. Econ. Develop. Economy, vol. 25, no. 5, pp. 716–742, May 2019.

[6] D. Bisias, M. Flood, A. W. Lo, and S. Valavanis, ‘‘A survey of systemic risk analytics,’’ Annu. Rev. Financial Econ., vol. 4, no. 1, pp. 255–296, Oct. 2012.

[7] P. O. J. Kelliher, D. Wilmot, J. Vij, and P. J. M. Klumpes, ‘‘A common risk classification system for the actuarial profession,’’ Brit. Actuarial J., vol. 18, no. 1, p. 91–121, 2013.

[8] S. Emerson, R. Kennedy, L. O’Shea, and J. O’Brien, ‘‘Trends and applications of machine learning in quantitative finance,’’ in Proc. 8th Int. Conf. Econ. Finance Res. (ICEFR), 2019. [Online]. Available: https://ssrn.com/abstract=3397005

[9] K. A. Horcher, Essentials of Financial Risk Management, vol. 32. Hoboken, NJ, USA: Wiley, 2011.

[10] P. Christoffersen, Elements of Financial Risk Management. New York, NY, USA: Academic, 2011