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Research Paper

Explore the role of artificial intelligence and machine learning in improving risk assessment

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Abstract
Although there is currently no structured framework for analysing risk, uncertainty, and the potentially disastrous outcomes of such factors, the application of artificial intelligence (AI) and machine learning (ML) in risk-sensitive situations is still in its early stages. In high-impact applications, the adoption of AI/ML systems will be heavily influenced by deductions made about risk and uncertainty. In light of this, it is imperative to have a comprehensive understanding of the range of hazards associated with AI/ML systems as well as how these risks manifest and worsen in real-world scenarios. First, the primary AI and machine learning methods that are helpful for risk management are briefly discussed in a non-technical manner. Next, an overview of how these strategies have been applied to the risk management domains of credit risk, market risk, operational risk, and compliance is given, supported by empirical data and current practise. We wrap up with some observations about the field's present constraints and predictions for its short- to medium-term future development. Overall, we paint a positive image of the use of AI and machine learning to risk management, but we also point out certain real-world drawbacks, such as the need for organisations to have the requisite skill sets, transparent practises, and appropriate data management rules.
Keywords: *Machine learning; Credit risk; AI; Risk management; Operational risk; Market risk*

I. Introduction

The way we approach financial risk management is changing and about to undergo a revolution thanks to artificial intelligence (AI) and the machine learning techniques that underpin it. As AI-driven solutions proliferate, they are grabbing hold of every aspect of risk management, including determining the appropriate loan amount for a customer, alerting traders on position risk, identifying insider and customer fraud, enhancing compliance, and lowering model risk. This overview describes the state-of-the-art machine learning and artificial intelligence techniques and their present applications. We also see a role for completely AI solutions in the future, which comes naturally once machine learning is widely used to assist organisations in managing risk.

AI and Machine learning Methods for Risk Management

Determining what AI and machine learning actually mean is a first step, and it's not always easy to make this distinction. Though even in research there is a very fluid distinction, in a glib sense the public relations and fundraising departments of startups like to adopt the more attractive AI moniker when they most typically mean machine learning. Artificial intelligence (AI) is most frequently understood as machine intelligence, with intelligence being defined in relation to human intelligence (Shieber, 2004). According to Bostrom (2014), an AI solution would involve automation for data identification, testing, and decision-making based on the testing. In real-world applications, artificial intelligence may combine machine learning with other methods like logic rules and hard coding. On the other hand, machine learning typically entails human judgements regarding the application of the generated information as well as manual data identification and testing by the data scientist. In light of the fact that most AI claims are actually just machine learning, and that pure AI is not yet technologically or organizationally ready, this section outlines the fundamental machine learning approaches used in risk management.

Supervised and unsupervised machine learning are the two main kinds of machine learning. Users analyse input data in supervised learning in order to establish an output. This is comparable to how a variety of independent variables are tested to ascertain their association with the dependent variable in classical statistics. When learning unsupervised, all you have is the input data and the desire to understand the data's structure better. The key techniques within each category and the differences between these two categories are displayed in Table 1.1. Deep learning, which we address at the end of this section, is a noteworthy category that spans both supervised and unsupervised learning and is thought to be the most closely related to artificial intelligence.

Table 1.1: Categories of machine learning techniques (*Source* van Liebergen 2017)

		Linear methods	*Non-linear methods*
Problem type	Supervised		
	Regression	• Principal components • Ridge • Partial least squares • LASSO	Penalised regression: • LASSO • LARS • Elastic nets Neural networks and deep leaning
	Classification	Support vector machines (SVM)	Decision trees: • Classification trees • Regression trees • Random forest SVM Deep learning
	Unsupervised		
	Clustering[a]	Clustering methods: K- and X-means, hierarchical principal components analysis Deep learning	

[a]Since unsupervised methods do not describe a relation between a dependent and interdependent variable, they cannot be labelled linear or non-linear

Machine learning and AI applications for risk management

This section presents an overview and analysis of real-world applications of artificial intelligence (AI) and machine learning to several risk management domains. Credit risk, market risk, and operational risk are the standard differences used in financial risk management that we use to classify risk management.

Application to Credit Risk

Credit risk is the possibility of suffering financial loss if counterparty defaults on a contract and fails to pay interest or principal on time, or if there is a higher chance of default during the transaction's duration. Credit risk has historically been modelled by financial institutions using classical linear, logit, and probit regressions (Altman, 1968). But because there is evidence that traditional approaches are insufficient, institutions are becoming more interested in utilising AI and machine learning tools to improve credit risk management practises. There is proof that by utilising AI and machine learning approaches, credit risk management capabilities can be greatly enhanced because of their capacity to comprehend unstructured data semantically. When Altman and colleagues first compared an alternative neural network algorithm to traditional statistical methods of distress and bankruptcy prediction back in 1994, they found that combining the two greatly increased accuracy (Altman et al., 1994).

Machine learning has become more accessible due in part to the complexity of evaluating credit risk. This is shown in the expanding credit default swap (CDS) market, where a number of unknown factors need to be considered in order to estimate the cost of default in the event that a default occurs as well as the probability of a default event (credit event). Son et al., (2016) demonstrate that nonparametric machine learning models involving deep learning outperform conventional benchmark models in terms of prediction accuracy and in terms of offering workable hedging strategies using daily CDS of various maturities and rating groups from January 2001 to February 2014.

Large volumes of possible data are involved in the consumer and SME lending sectors, which are depending more and more on machine learning to make better loan decisions. Khandani et al. (2010) offer a machine-learning technique based on SVM and decision trees for consumer lending that can save up to 25% in costs when evaluated on real lending data. More recently, using data from UniCredit Bank, Figini et al. (2017) demonstrate how a multivariate outlier identification machine learning technique enhances credit risk estimation for SME lending.

Application to Market Risk

The risk associated with trading, investing, and generally being exposed to financial markets is known as market risk. An organised summary of the ways in which machine learning can support market risk management is given by Kumar (2018). The benefits are highlighted at every turn, starting with data preparation and continuing through modelling, stress testing, and giving a validation trail for model explanation.

Trading on financial markets always carries the risk that the model being utilised is out-of-date, inaccurate, or both. Model risk management is the term used to describe this field. When it comes to identifying unintentional or developing risk in trading conduct, machine learning is especially well-suited for stress testing market models. 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, is one of the many current use cases of machine learning for model validation that Woodall (2017) describes. Other use cases include the investigation of any simulations that emerged from the testing that showed "errant" patterns compared to average estimates. Additionally, Woodall mentions how Nomura monitors trading within the company using machine learning to ensure that trading models are not using inappropriate assets. The company yields.io, which offers real-time model monitoring, model testing for deviations, and model validation—all powered by AI and machine learning techniques—is an intriguing example of a modern model risk management tool. Day (2017) investigates the use of AI, namely clustering techniques, by big trading organisations to cut expenses associated with entering and exiting large positions in illiquid markets. He quotes Capital Fund Management, one of the biggest hedge funds in France, which has $11 billion under management, saying that market impact charges can cost investors up to two-thirds of their trading profits. This is where cluster analysis and deep learning models come in very handy (Calvalcante et al., 2016; Heaton et al., 2017).

Reinforcement learning, in which market trading algorithms are integrated with the capacity to learn from market reactions to trades and adjust future trading to take into account how their trading will effect market prices, is one direction the industry is headed (Hendricks and Wilcox 2014). Based on experiments with trading data from the foreign exchange market, Chandrinos et al., (2018) suggest another intriguing path: using a combination of neural networks and decision tree techniques, the system alerts traders in real-time when underlying trading patterns change while they are trading.

Application to Operational Risk

In order to manage operational risk, a company must determine the likelihood of a direct or indirect financial loss resulting from a variety of possible operational failures (Moosa, 2007). These risks might originate from external occurrences (such as frauds, weak computer systems, control failures, operational errors, neglected procedures, or natural disasters) or from internal sources within the institutions (such as insufficient or failing internal processes, people, and systems). The rise in operational risk exposures, particularly for financial businesses, has led to a need for AI and machine learning-based solutions due to their increased number, diversity, and complexity (Choi et al. 2017).

According to Sanford and Moosa (2015), artificial intelligence (AI) may help organisations at several phases of the risk management process, including identifying risk exposure, measuring, estimating, and analysing its consequences. Selecting the right risk-reduction plan and locating tools that enable transferring or trading risk can also be aided by it. Thus, the application of AI techniques to operational risk management is growing into new areas, such as the analysis of large document collections, the execution of repetitive processes, and the detection of money laundering, which necessitates the analysis of large datasets. The initial application of AI techniques to operational risk management was to try to prevent external losses, such as credit card frauds. Another frequently mentioned risk management use case for AI and machine learning is the identification of financial fraud. Here, banks look at the best ways to safeguard their data, systems, and ultimately their customers in an effort to prevent financial crime. Improved process automation with artificial intelligence (AI) can speed up repetitive activities, reduce human error, process unstructured data to filter out pertinent content or bad news, and assess problematic clients and networks by determining an individual's connection. It is possible to monitor traders and employees using the same network analysis. Using a combination of trade data, electronic, and phone communications records, banks can notice emerging patterns of behaviour to predict latent risks and identify relationships between employees by using clustering and classification techniques to create behavior-based trader profiles. Additionally, it gives banks the ability to create and rank warnings according to the kinds of suspicious activity and degree of risk involved. Ngai et al. (2011) offer a comprehensive summary of the fundamental AI methods utilised in financial fraud detection, highlighting decision trees and neural networks as the two primary methods.

The Challenges and Future of Machine Learning and AI for Risk Management

Before AI and machine learning techniques for risk management can reach their full potential, a few important practical challenges must be resolved. The availability of appropriate data is the most crucial of these. While machine learning packages for Python and R can easily process images, perform natural language processing, and read any kind of data from Excel to SQL, the pace at which machine learning solutions are being proposed has not kept up with the ability of businesses to appropriately organise the internal data they have access to. Data is frequently stored in distinct silos across departments, maybe on different systems, and possibly with internal political and legal constraints limiting data exchange.

The availability of qualified personnel to use these novel approaches is another problem (Wilson et al. 2017). The true accuracy of machine learning systems raises practical concerns as well. The final important concern regarding ethics and transparency that AI-driven solutions must further address is introduced by this last point. Since the models in the increasingly popular deep learning method of machine learning operate on hidden layers between the input data and the output decision, transparency is particularly problematic. Such a black box system can lead to problems with regulatory compliance, particularly when it comes to proving model validity, and is not conducive to efficient risk oversight. A more theoretical concern associated with this is that models utilised by several organisations may converge on comparable trading optimums, resulting in both systematic risk and firm loss. More general ethical concerns exist as well.

Additionally, AI will provide more precise real-time data on all kinds of risks the company is taking. Real-time guidance will become more and more prevalent as data organisations focus more on using AI. Pre-emptive awareness of risks is the next step after having real-time knowledge of the risks being incurred. To some extent, being able to reliably predict business hazards ahead of time—whether they be credit, operational, or market risks—is the holy grail of an AI-driven risk management system.

This capability is provided by machine learning approaches, which traditional statistical techniques could never hope to match. A truly AI risk management system, which would automatically step in to prevent unnecessary risks, quickly unwind dangerous exposures, and dynamically modify the firm's risk appetite based on the system's estimation of the broader risk environment, would not be technologically impeded, to think even further ahead. Even still, those risks will still need to be handled because of that, which will keep risk management specialists happily engaged for the foreseeable future (despite a rapidly changing environment).

II. Conclusion

In a variety of businesses, artificial intelligence (AI) is vital to risk management. AI may assist organisations in more effectively and efficiently identifying, analysing, and mitigating risks by utilising sophisticated algorithms and machine learning approaches. The following are some particular applications of AI in risk management (1): Risk identification: By evaluating data from a variety of sources, including financial records, social media, news stories, and customer reviews, AI algorithms can assist in the detection of possible dangers. This can assist companies in keeping an eye out for new dangers and proactively mitigating them. (2) Risk assessment: By examining past data and finding trends and correlations, AI can assist in determining the likelihood and severity of dangers. This can assist companies in ranking risks and allocating resources appropriately. (3) Fraud detection: By examining vast amounts of data and spotting questionable trends and behaviours, AI can assist in the detection of fraudulent activity. By doing this, businesses can save money and preserve their good name. (4) Credit risk management: By analysing borrower data and forecasting default likelihood, artificial intelligence (AI) can assist financial organisations in assessing credit risk. Lenders can lower their risk exposure and make better-informed judgements as a result. (5): Cyber security: By examining network traffic, spotting irregularities, and highlighting possible security breaches, AI can assist in the detection and prevention of cyber threats. This can assist businesses in safeguarding their private information and averting losses. Through data analysis, pattern and trend identification, and prediction based on past data, artificial intelligence (AI) can enhance risk management and offer insightful information. It's crucial to remember that AI cannot solve all problems; rather, to make wise risk management judgements, it must be combined with human knowledge and discretion.

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