Dynamic Exposure Aggregation and Automated Risk Scoring: AI-Based Systems for End-to-End Insurance Risk Management Automation

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1. Introduction

Insurance underwriting, the process of identifying a risk, determining the size and likelihood of loss, and deciding what the policy terms and prices should be, has been a tool to meet the goal of insurance, i.e., mitigating predictable risk. However, insurability and insurable risk have grown more complex due to changes brought about by technological innovation like the Internet of Things, blockchain, telematics, fintech, and peer-to-peer insurance. In the era of data-driven insurance, the use of artificial intelligence is growing rapidly in the insurance industry, especially due to the need for risk prediction and risk pricing.

AI systems are expected to enable better accuracy — through estimation, forecasting, computations, and likelihood of claims — and improve dynamic risk parameter scanning, e.g., volume of sales, geographic distribution, new business attraction costs, and turnover rates. In addition, the approach would also resolve the trade-off between the use of automation and the availability of relevant data, reducing the risk of mismanagement. Despite the advantages accrued, there are few studies contributing to the introduction of risk-specific AI systems for insurance, and therefore, understanding AI applications would be an interesting area of future research. The aim of this paper is to shed some light on the potential of AI when it comes to running an insurance business and the implications, in particular, for risk management and coverage. The main steps of the analysis are the following: First, pick some important aspects of insurance risk theory and the related management. Second, present a snapshot of some evidence of AI applied to insurance and financial contexts. Third, pose a new challenge: to address the potential use of AI as a stand-alone tool for managing some risks from an economic and financial perspective. Furthermore, I propose to discuss two main problems.

1.1. Background and Significance

Risk management in the insurance sector has evolved significantly, customarily in line with advancing technologies. The rationale was to develop data-driven tools that would revolutionize the economic management of risks. In real-life modern financial markets, the challenges of managing risk have been magnified owing largely to the volume and volatility of financial transactions in an increasingly interlocked global market. Such is the pace of financial and economic dealings today that they are inconceivable without defending against perils of pure risk and hazards of financial risk. In a world consumed by data and algorithms, effective decisions are blind to effect and grounded on independent computation and assessment.

Perhaps one of the eagerly awaited breakthroughs could be the use of intelligent systems to improve the process of risk transfer, especially when such risk mitigation and financing have to take place in the market. Various intelligent system approaches are already available, each one reaping benefits for the insurer. Predictive models that alert insurers to risks using standard underwriting data are already in play. Such systems demonstrate that the contemporary insurance industry is turning data into insights. The industry already consumes vast volumes of data from traditional and non-traditional sources, and insurers use predictive modeling and advanced analytics to identify patterns and forecast possible risks.

However, traditional machine learning methods also face challenges posed by big data as data complexity and variability increase. Conventional actuarial analyses do not take into account these levels of complexity. The insurance industry’s capability to control its risks can be severely hampered as a result, exacerbating losses. Admittedly, the progress in AI has yet to trickle down to insurance in any significant way. Yet there has never been a greater need for AI to revolutionize actuarial methodologies – non-traditional data sources are already being factored into insurer data, yet we lack an informed actuarial assessment of what effect these factors can have in pricing insurance or managing risk.

Anyone who has ever lived in a flood-prone area and opted not to purchase flood insurance, on the grounds of the 'supposedly rare' impact of natural disasters, only to be rendered homeless by an unexpected flood will testify that the idea of flat rejection of an adverse outcome as 'inconceivable' is itself highly questionable. Fundamental actuarial attributes and behavior of the economic entities can no longer be analyzed. Thus, in an innovation-prone environment like the financial market, improvements and evolution of AI that assist the insurer in a holistic manner are urgently required. Crucially, AI should not be seen as a tool in the risk management toolkit for the insurance practitioner but rather as a reliable solution to counter traditional actuarial hurdles.

1.2. Research Objectives

The development of AI-based systems in insurance is gaining the attention of both academics and practitioners; however, the present literature does not adequately address the AI-based data usage in insurance. Therefore, the central and principal objectives of this study encompass investigating the practical application of AI-based systems in the management of risks in the insurance sector. Obviously, the paramount goal of the insurance business as a risk management institution is to check and mitigate the dimensions of the risk it takes. In these days of digitalization, speech and decision-making processes are databased and are run by machines to build customer profiles and for risk assessment. With this in mind, in this study we target two central questions aimed at mainly:

Evaluating the effectiveness of AI-based systems in respect to information and data to estimate risk, i.e., to get an impression of their power to estimate possible outcomes of risk. How can insurers employ information and data to predict the generation of risks and their control, or about both the contingency level issue and their side effects over time and their cross-functional nature?;

Showing ways how AI methods can boost the potential level of similar operations by providing efficient working solutions for the management of practical situations. In addition, we find the review of real-world insurance challenges with a focus on key operational improvement actions for insurance companies, whose main objective is the control of risks, for the repair of current policies and practices as far as operational development, such as infrastructural knowledge, are validated by trends, AI, and data analytics issues, among the biggest ones. In the same context, we aimed at considering and analyzing the repercussions of AI-based activities as environmental issues. In the context of a more direct approach, we also aimed at providing officers and lawmakers useful directions on insurance methods and processes by examining the conclusions of tools, trends, and experimentation. Furthermore, we wish to make the insurance market implementers aware of the progress of technology, namely AI, reasoning how this technology can be beneficial to more effective and efficient solutions. This research aimed to measure the RAR of AI-based tools and would help practitioners exploit the available data for risk estimation.

2. Fundamentals of Insurance Risk Management

Risk is inherent in all business, and it is more prominent in the insurance sector. Insurance risk is defined as an event that could create a loss for an insurer. The key issue of insurance risk management is to quantitatively measure the amount of risk to which the insurer is exposed. It does not involve methods only but requires a judgment of the amount of risk, too. A potential event can commonly lead to various types of risks: operational risks, underwriting risks, financial risks, and cyber risks. The types of risk are main issues in the insurance sector and have been taken into great consideration. The methods commonly used for insurance risk evaluation can be classified in various different ways. For instance, it divides the management or failure risk into the following classes: financial risk and loss-influencing decision risk. The latter class comprises credit risk, market risk, business risk, underwriting risk, systematic risk, and actuarial risk. For discussing the technology change, the discussion utilizes these categories and proceeds to define each of them.

Modern insurers mainly depend on human experts to assess the risk before making a decision on whether to undergo the loss. The traditional risk factors, for example, age, sex, habit, and working environment, can effectively predict the rate of claims to a certain extent. There are, however, limits to assessing risk value based on individual circumstances, which do not allow a precise assessment of the loss exposure. In insurance practices, evaluating the premium of motor vehicle insurance and also life insurance, for example, are the main issues. Thus, the service provider needs to maintain competitive products. Traditional methods to assess the risk have declined. The insurer requires an effective tool to evaluate the risk and the potential losses in order to develop the service that the company can provide. Hence, the integration of technological change, that is, AI technologies as well as machine learning, in the risk management processes is in great demand by many insurance companies. This underscores the urgency for innovative solutions to reduce risks in the insurance businesses.

2.1. Definition and Types of Insurance Risks

In the global insurance community, the issues and challenges of risk management are currently the focus of research by many practical experts and academics. The risks that an insurance company accepts are traditionally classified into internal and external categories. Insurance risks are viewed as risks that are inherent in the ordinary operations of an insurance company. Among these risks, specialists highlight several major types, including insurance underwriting risk, insurance operational risk, insurance market risk, insurance liquidity risk, insurance credit risk, and some additional risks. Insurance underwriting risk is the possibility of claims within a portfolio of insurance contracts being different in size or number from the assumptions of the underwriter who wrote the portfolio. Insurance operational risk is the risk of loss resulting from people, processes, and systems, as well as external events over which an insurer has little or no control that could reduce an insurer's ability to meet its obligations and/or affect the insurance funds.

Insurance market risk is the risk of loss to an insurer arising from changes in market factors, such as movements in equity prices, interest rates, and real property prices. An illustration of interest rate risk can be provided by insurance contracts with policy loans embedded. Such contracts are exposed to interest rate movements due to the policyholder's option to change the premium used to purchase units of the cash-investment component of the contract. If the policyholder reduces the premium, then the asset leverage, or investment gearing, of the contract increases, and consequently, some multiple of the loss is incurred by the insurer. This may be due to an exogenous fluctuation in interest rates, such as a rise in economic interest rates.

2.2. Traditional Methods of Risk Assessment

Accurate and efficient risk assessment is at the heart of any insurance. In the insurance industry, multiple methods of risk assessment can be used, both qualitative and quantitative. Among quantitative methods, statistical evaluations of various data types are most common. In different cases, statistical data mining techniques are used, as well as various simulation methods. Among qualitative methods of insurance risk assessment, expert valuation and system analysis approaches are used. Classical methods for risk assessment are generally based on historical statistical data, aggregated and standardized to comply with the rigid rules of model analysis, which is designed to protect insurance companies from moral hazard and adverse selection risks. These approaches allow insurers to assess risks, establish appropriate insurance premiums, and legal terms of an insurance contract with policyholders.

Standard risk assessment methods based on historical insurable events, economic development approaches, and actuarial models of policyholder-insurance company interaction are recommended in regulatory documents. The key weakness of any risk model and any insurance contract is the probability that the risks in the future may differ from the risks in the past on which the model is based. The insurance market is changing because of the global, economic, political, technological, and social spectrum. With the growth of the emerging risks, as well as the dynamics of current market risks, the sophistication of risk management in insurance has increased. Consequently, the traditional methods have some limitations such as dependency on historical data, random statistical trends, and strict criteria for defining the insurable interest. This observation has become more important with the recent development of AI tools and applications.

3. Machine Learning in Insurance Risk Management

Machine learning is a subset of artificial intelligence that is centered on the development of algorithms which enable systems to learn from data. A fundamental property of machine learning is its ability to process large, complex datasets and identify patterns in them. This is achieved via automated model training processes that result in the development of a model that can predict future outcomes or reveal further insights on data given to them. Moreover, machine learning models are built to self-adapt and improve over time as more data is received, which is a key advantage of this technology over traditional 'static' models. A machine learning model, therefore, continually learns data as it is input to the system, improving prediction accuracy over time.

Machine learning models have a myriad of applications within the insurance industry, particularly in risk assessment and evaluation, hence decision-making. For example, machine learning models can establish correlations between personal attributes and a subject's risk profile. There are many instances in which machine learning applications have improved risk assessment, and by extension the insurance services delivered. One area in which machine learning algorithms were trained on copious climate and weather data was in the subjective evaluation of crop worth, which is more efficient but also less biased when using machine learning models. The accuracy of flood mapping for risk assessment in the insurance industry has also been increased with the use of machine learning over traditional methods. The improvement in striking a delicate balance between fairness and accuracy that can be achieved with machine learning credit risk prediction models is also being considered by the banking sector. Overall, not only can machine learning models analyze large datasets, which the human mind is dramatically ill-equipped to do, but they can also sift out the crucial bits of data from the irrelevant content. Moreover, when compared to a traditional risk evaluation method, one advantage is that machine learning methods 'see' things that evaluators may not necessarily be inclined to pick up on. Finally, the personalization and tailoring of insurance policies to individual lifestyles and risk profiles is also facilitated with the implementation of machine learning-based tools.

3.1. Overview of Machine Learning

Machine learning (ML) is a subfield of artificial intelligence (AI) that aims to build models that can learn from experience or training, as contrasted with traditional computer programs that generally execute predetermined instructions. A schoolbook definition proposes that a "machine" be dubbed a learning computer program after an experience using mystery if its adaptations at experience do not become sharply better. Therefore, ML embraces software systems that have the capacity to continuously progress as they are exposed to new instances of the task that they are trying to solve. One of the keys to correctly applying ML to your insurance companies is to accurately recognize the tasks you are trying to model and then to pick the most appropriate learning algorithms for the tasks. Below we give a very high-level classification of ML algorithms followed by the most important tasks involved in the insurance sector.

ML algorithms can be broadly classified into supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, one is essentially mimicking a data-generating process whose result is a prescribed "target variable" given a set of "explanatory variables." The features can be numeric, for example, age and income. Unsupervised learning is used when only a set of features arrives, without a target. Reinforcement learning, which is closer to a branch of computer science called Control Theory, uses a reward program to generate the sole incentive for the intelligent agent to learn. At the high level, the main feature distinguishing ML from conventional computer programming stems from the data-driven nature of ML. With traditional programming algorithms, humans explicitly write down a series of complicated, often rigid instructions, inputting data, and receiving an output, with no ability to learn.

3.2. Applications in Insurance Industry

This section presents an overview of the current state of the applications of machine learning and related technologies in actual use cases within the insurance industry. It provides practical examples of problem definitions and conceptual models for new trends. In this context, the most prominent cases introduce machine learning in property and casualty insurance for use in fraud detection. Furthermore, machine learning is employed in an increasing number of cases, for example, in health insurance. There are also examples of how machine learning can be used for pricing models, including in data-poor regimes, and the operation of an insurance company for risk assessment, customer segmentation, and policy management.

One of the most innovative and increasingly explored areas where machine learning has been proven to provide added value to the insurance industry is predictive modeling across a range of actuarial fields, particularly in predictive modeling to support pricing and underwriting decisions. While the end goal for insurance is to protect people from an uncertain future, predictive models support a different kind of forecast: expected experience in probability terms. Predictive modeling can help businesses make faster and better decisions, ensuring that actuaries, underwriters, and risk managers are factoring in all relevant information and insights when choosing which risk or contract to assess or prioritize. It also enables more detailed predictive and economic forecasts. By not only estimating the average loss and revenue at a market level but also for individual segments, predictions provide root-cause and correlative details that lead decision-makers towards profitable decision support.

4. Challenges and Opportunities

AI-based systems integrate machine learning and artificial intelligence (AI) to aid in the automation of activities and decision-making functions in companies. In the context of an insurance organization, AI has great potential as an enabler and disruptor. However, innovation in the context of AI presents challenges as well: numerous ethical considerations associated with the use of AI affect the ability of companies to actually derive value from current technologies. AI is often criticized for being a 'black box,' with the processes that lead to certain decisions being unknown due to the volume and complexity of data used in various algorithms. A number of industries have seen developments in AI integrated directly into existing services. While innovations in insurance are not necessarily as intricate as those of other industries, the complexity of insurance is high and likely minimizes the space for rapid and ground-up innovation. A slow transformation is also seen in insurance underwriting and risk management operations. Innovations in insurance must be largely focused on risk management and the needs of workers in response to changes driven by supply chain transformation, impacted by COVID-19 and further offshoring, and changes to the management and use of natural resources. Many insurance companies prefer to have full control over the underwriting and risk management process. The successful automation and implementation of AI risk management techniques in insurance businesses require the understanding and compliance of insurance products with relevant terms and legal requirements. Regulations can also be increasingly difficult to navigate as they constantly change and evolve with technological improvement.

4.1. Ethical and Regulatory Considerations

Introduction

In this chapter, we will comprehensively look at how AI-based systems for automating risk management in insurance, in particular the actuarial function, comply with global industry practices and regulations for insurance. However, before going into the detail of developing and deploying AI-based systems, we will discuss previous research about the opportunities and challenges these systems have for actuaries, consumers, and financial regulators.

Ethical and Regulatory Considerations

In the context of this proposed AI system, we believe the following ethical and regulatory considerations may be pertinent: Will these systems be explained to customers and stakeholders who will be on the receiving end of the AI's decisions? Do the AI systems protect the personal data and data privacy of insurance buyers? Is there a practical and meaningful way for the customer to give informed consent to a decision provided by an AI? As these systems become more powerful and trusted, what might be the systemic risk issues that might be faced by deploying these systems? Is there more of a case for customers to have access to the systems' algorithms and projections if they wish? Are the recommendations and operation of the system in use consistent with human ethical and other behavior? As the system is based on past information and experience, is the underlying data representative, and has the system been trained with up-to-date data and with diverse datasets? Has regulatory advice been sought? In the context of the proposed AI, the answers to the above may inspire increased confidence if answered positively. We suggest, however, that a robust ethical framework with an expert panel to guide and monitor is implemented, and potential future uses are communicated to build trust with stakeholders.

4.2. Integration with Existing Systems

In the insurance industry, the majority of companies are equipped with well-established and difficult-to-abandon systems, known as core insurance systems, for creating policies, issuing contracts, handling claims, and paying out benefits. Although these systems are outdated, insurance companies are usually wary of any abrupt transitions; in most cases, those systems provide a sufficient service for company operations. Second, insurance companies often donate a lot of money and time to link brokers, agents, insurance partners, banks, clearing houses, debt collectors, industry standard setters, SMS providers, etc. Understandably, these companies and the people who represent them are interested in using our services without needing considerable changes. Therefore, the main requirement such a system must meet is interoperability with legacy solutions.

Given the above, not everyone is willing to face the challenges of being a guinea pig, even if it means a great competitive advantage. As a result, rapid development and deployment using a new AI system for integration would provide a natural advantage through the boosting of the next IT revolution, namely an offer to those without a big formal system, an opportunity to get in on the AI act themselves now that there is a legacy system to exploit our product. Insurance companies will lose out on a lucrative and disruptive market with a significant lead if they do not make this step first to the system, opening the market up for general proposal acceptance. This emerging nascent market will primarily reflect the current legacy system of the parent company, which we intend to maintain for a decade or two yet.

5. Future Directions and Conclusion

We believe that AI and advanced machine learning represent the future in insurance risk management. The previous sections have shown the challenges and perils that have gradually come into focus during the last years. It is high time for industries acting in the insurance market to embrace the opportunities that AI-driven processes may bring. AI-based systems are most likely to reshape important parts of insurance companies. At the same time, AI systems should be properly understood, and continuous research should support proactive parties involved in the insurance market.

This paper has highlighted that new technology processes and highly automated systems can support us in working on the above challenges; promising developments of automatic processes in claims, underwriting, pricing, risk assessment, improving claim procedures, customer satisfaction, and risk aversion are already underway. We have also shown the relevance of the topic since several ethical implications arise from automated processes. There are several areas that deserve deeper research starting from the previous results. First of all, there is a need for clarifying the extent of the deployment of AI in the underwriting process and how the present challenges will be addressed. Secondly, how the role of insurance players will be modified by automation and how incumbent and potential startups will be able to exploit such opportunities. Insurance regulators should also follow the novel processes, and the AI supervising financial bodies should possibly push insurers to a greater reliance on AI. Finally, insurers and IT providers should collaborate by following the ethical principles suggested. In the challenging environment of AI and automated practices in the insurance industry, there is a clear need for dynamic and continuous learning to face the emerging risks by proactively seeking early warnings and possible solutions.