AI-Powered Risk Management Frameworks for Insurance

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1. Introduction

The insurance business is widely dependent on risk management. The impact of artificial intelligence within insurance will, in some aspects, reshape insurance models. AI itself, however, is a risk due to the 'black box' characteristic and the challenge of regulation and policies. The present paper specifically focuses on how risk management within the insurance sector, in adopting AI technologies, is implemented. The paper concludes that an academic and public-private approach to set out an AI risks framework is a way forward.

Insurance is a business mechanism designed to spread, mitigate, and shift diverse classes of risks. Insurance is a risk business, built around the successful assessment and management of clients' risks, but predominantly, a business constructed for risk management purposes. The rapid development of big data and artificial intelligence technologies has brought various changes. The insurance industry is playing a fundamental role in pulling our economy and social welfare model through hardship. It does so by performing the basic economic function of managing risk. The essence of the insurance transformation is from traditional insurance that is reactive, transactional, and customer-focused, to preventative, partnership-based, and embracing digital ecosystems. The recent digital innovation of the insurance sector is known as InsurTech. The insurance sector is rich in AI use cases. This paper, however, focuses on the risk factor managing the adaptation of AI within the insurance industry only.

1.1. Background and Significance

Risk management for insurers is a core business practice. Traditionally, insurers rely on rules-based expert systems or subjective assessments by the underwriting team to make complex judgments for underwriting decisions. Technology advances have made AI algorithms more explainable, but very little has been done to apply explainable AI models in insurance for decision support purposes. This paper proposes an approach, called Risk-XAI, which integrates State-Explainability Machine Learning with natural language processing to help underwriters understand AI-based predictions better. Evaluated on a large-midsized US commercial lines insurance dataset, Risk-XAI's predictions perform better than existing methods in terms of the Gini coefficient. Our method creates concise and human-readable explanations, making it suitable for practical AI applications in insurance risk management. Finally, we present an asset-level risk template as a practical example and design an algorithm to help insurers better understand how interpretation techniques can be used in insurance risk management.

2. Fundamentals of Risk Management in Insurance

2.1 The Risk Management Process in Insurance Insurance undoubtedly plays a key role in the economy. By providing protection against risky or uncertain loss, insurance makes investment, borrowing, and production possible; that is, the functions insurance performs are essentially linked to activity in all areas of economic life. Because of their significant role in the economic system, the study of insurers is of much social, economic, and business interest. In most risk management problems, various venues are open to decision makers, and in many of these venues, an element of choice is salient. The most important economic activity that demonstrates these ideas is insurance that exists for individuals, families, businesses, financial institutions, governments, and religious or charitable entities.

The insurance promoter actually takes the burden of a group of insurable risks. Risk management is, in fact, a practice promoted by several insurance companies and financial institutions in order to make an adequate identification and evaluation of the insurance risk and the subsequent reduction in the frequency and magnitude of the present realization, as well as in the optimizing strategy of transfer of this risk, transfer contractually promoted by an insurance policy in return for income, with the risk of the present realization being financed by a monetary value called insurance premium, which, when paid, instantiates a law that links the insurer and the insured. Thus, the objective of insurance companies is to take on risks that a group of people are exposed to; that is, to take on risks and responsibilities to protect and guarantee support for a society in the event of future losses. In this sense, the management and information technologies fulfill a relevant role. The risks are then brought into a shared common pool. The role of the pool is then to cover and pay losses that individual members of the pool may incur. In this way, insurance companies protect families, businesses, and public organizations from unexpected and financially onerous contingencies.

2.1. Key Concepts and Definitions

Before moving on to the case studies, and in order to facilitate the understanding of the AI-powered risk management frameworks in insurance, we define AI. In our context, the definition of AI is narrower, and we define AI as the intelligence embedded in algorithms that can learn to perform tasks and occasionally replicate human activities without explicit programming to do so. The learning is achieved through training on the data rather than explicit programming. Within AI, machine learning (ML) constitutes a subset that enables machines to learn from data and automate complex decision-making processes. Algorithms are classified into specific groups called neural networks, support vector machines, decision trees, ensemble models, K-nearest neighbors, and others. Furthermore, it is important to stress that even though AI tools are mainly used for performing the tasks of data analytics, these tasks are different from data engineering and data analytics. Data engineering refers to the capture, collection, cleaning, storage, processing, and deriving of datasets, while data analytics is rather an exploratory process to extract useful information from data.

In addition to AI and ML, autonomous learning represents the process of a machine that learns directly from the environment. This type of learning is different from supervised or unsupervised learning because the learning machine receives no labeled input. Hence, AI-powered systems can unfold their functionality and develop using the internet as a data source. This learning modality represents a game changer for the way AI-powered systems are developed. While AI-powered systems are trained with labeled data dumps and enriched with previously labeled datasets, autonomous learning is a major business enabler for both existing and greenfield ventures. The AI-powered systems can learn directly from customers' behavior, preferences, and attitudes, and may not require expensive manual labor, nor any intermediaries or supervised learning. In other words, autonomous learning will enable AI-powered systems to reduce knowledge bias while increasing coverage with personalized services and insurance products that are designed right at the moment the insurance is needed. Finally, because the risks are dynamic, so are the AI-powered systems actively learning and constantly being improved.

3. Role of Artificial Intelligence in Risk Management

Artificial intelligence (AI) is the ability of a computer program or machine to think and learn. It is also a field of study that tries to make computers "smart." AI has the potential to protect and create value for the insurance industry by improving operational efficiencies and driving better customer experiences. It is considered a key driver for risk management in the insurance industry. Many insurance companies see AI as a tool that will play a significant part in preparing them for future challenges. AI is ready not only to augment how the insurance industry can automate and transform operations but also to significantly change how insurers understand and take on risk. AI will enable the industry to see more of the complex patterns within their data, which will help to answer questions already in progress.

There are three major categories of AI: analytical, human-inspired, and humanized artificial general intelligence. Analytical AI has characteristics consistent with cognitive intelligence, generating a cognitive representation of the world and using learning based on past experience to inform future decisions. In the insurance industry, AI's analytical tools are already playing a part by prospecting, assessing cyber vulnerabilities, and checking compliance. Human-inspired AI has elements from cognitive and emotional intelligence, understanding human emotions in addition to cognitive elements. In the insurance industry, human-centered AI technology is used to establish trust, and with that trust, develop an automatic claims system with which customers can interact directly through digital channels. Consumer data is encrypted and uploaded to the blockchain before users receive a special ID for their claim. AI also includes the ability to process data in the form of text. This ability can help in creating insurance policies, managing claims, handling customer queries, and validating claims documents accurately. With human-inspired AI, chatbots can talk to customers, recommend suitable policies based on the information collected, and address customer queries. The chatbot is able to jump-start the claims process for customers.

3.1. Overview of AI in Insurance

The application of artificial intelligence (AI) has significantly expanded to cover a diverse range of industries. The efficiency and effectiveness of AI have led to an industry shift in numerous sectors as businesses seek to leverage AI for their business processes. The insurance industry is one that has barely scratched the surface of its potential when applied to the risk function, with applications to risk assessment, fraud detection, and operational governance largely in manual, semi-automated, or rules-based approaches. This paper demonstrates the application of a novel AI-driven risk management framework in several aspects of insurance. The use of AI as a decision-making tool to determine outcomes on insurance coverage, claim processing, disaster response, and automated governance actions to reflect the risk exposure and tolerance of the insurance providers is experimented with and validated.

Artificial intelligence (AI), sometimes used interchangeably with machine learning or deep learning, which are actually subsets of AI, refers to the development of computer systems with the attributes of human intelligence: the problem-solving, judgment, learning, and decision-making capabilities that we associate with thinking. AI offers turnaround solutions using pattern recognition and data analytics for the majority of labor-intensive functionalities that insurance employs at various parts of the value chain. With this foundation serving insurance services, it accelerates the carrier's understanding of behavioral aspects moving forward the concept of having to "be near the customers," i.e., the business outcome of customer intimacy. When broadly leveraging AI, the insurance company will need to more systematically and operationally transform its business outcomes. Currently, the mainstream AI investment within the insurance industry is largely on data engineering and architecture to allow for controlled experiments and scaling the models.

4. Machine Learning Techniques for Risk Assessment

Of the expanding convergence of artificial intelligence and life insurance. In this digital era, AI makes risk frameworks more dynamic, accurate, and automated, just by leveraging the flow of digital data. It also calls for a strategic change in drawing insights and using decisions that are backed by data and optimal workflows. To a certain extent, digitalization of manual underwriting and non-invasive health condition assessment for better customer experience is also possible.

With substandard life insurance reaching record numbers over the past three years, including a 22.7% increase in the latest two-year period, machine learning could not have come to support insurers at a better time. Not only does machine learning become an ally for selecting the very cases that worsen the portfolio structures, but it also offers the potential to expedite the customer experience by quantifying risks responsibly through the efficient utilization of an increased amount of data. However, this does not disclaim the need for ethical, legal, and business logic and reason.

Finally, it is common sense that the advancement of AI in this vital but delicate domain is not a matter for the IT staff and computer scientists alone: it is a strategic change that all stakeholders need to be involved in, from the business managers to the actuarial professionals, doctors, and underwriters. It is also a change that ends and begins with the insurance broker, our central ally in the relationship of trust we establish with our clients.

4.1. Supervised Learning Algorithms

4.1.1. Neural Networks. A model of computation inspired by the structure and function of the brain and neural cells is a neural network. In learning, each data point is processed in two stages. The model is created in the first step, which implies iteratively iterating over the dataset and updating the network. In the second stage, it feeds the training data and provides the predictions for the input data to make the network learn what to do with the data. The process stops when the model of the network is eventually optimistic, and then it generates the final prediction through the input data. The error produced by the network in the computation of its predictions is reduced in the first step, i.e., the training stage. Specifically, the error is calculated, which indicates how far away the output is from the expected value, and then it is compressed by changing the weights of the edges.

4.1.2. Random Forest. It is a versatile machine learning technique used particularly for predicting values in classification and regression models. The name random forest refers to the fact that many trees are being combined to predict the response. Statistical errors in the dataset are determined by a decision tree created from random sampling data. Then several of these decision trees are combined to get a more generalized model to reduce the errors. In addition, these iterative trees are easier to develop and interpret.

4.2. Unsupervised Learning Algorithms

We did not use unsupervised learning algorithms reliably in this study. To give some intuition about them, let us talk about them. Their most important feature is that they do not need initial data labeling, so we do not need too much human work or searching for labeled initial data. At first glance, it seems like a strong algorithmic advantage. Also, it becomes an essential feature when labeling data becomes expensive or is too hard. Let me give an illustrative example. Assume we have lots of images in some file system and we need to divide these images into two groups: sunny or cloudy. We might hire a student photographer or find lots of labeled initial data to train a model to pursue the problem with a conventional supervised learning method with an imaging system, but if we did not make such an action, maybe we would benefit more from an unsupervised learning approach. Actually, unsupervised tasks except labeling incur high costs and sometimes need attention from a theoretical point of view.

Some of the fundamental unsupervised learning algorithms we use to cope with unsupervised learning problems are as follows: 1) Clustering Algorithms A type of problem that tries to parse a set of objects into k populated clusters, where k is a number given as an input into the algorithm. Each cluster's underlying observation should be similar to each other and should be different from the observation in the next group. This helps researchers to understand their observations. We can think of assigning groups to the observations based on the value of each feature separately and rating these assignments by the sum of squares of the Euclidean distances between feature assignments and their average values.

2) Extrapolation Algorithms A type of well-known unsupervised learning algorithm is the principal component analysis that applies a linear transformation on the input dataset by choosing the most important vector linearly dependent to gather information about a second best, adding it to the pool and repeating iteratively. Unlike other dimension reduction techniques, one of its key ingredients is that it does not consider the dependent relationship among inputs; it uses variances of the observations to achieve a linear combination of the inputs. Non-linear methods try to create a transforming process that utilizes the maximum summarizing power to reduce the dimension to 2. Another type tries to visualize the described relations in the dataset by giving them an understandable description to see if significant characteristics preserve themselves in some dimension. Finding the optimal mathematical transformation from K-Dimension to 2-Dimension is a classical problem.

5. Case Studies and Applications

Risk management, i.e., identifying, assessing, and mitigating potential events with undesirable consequences, is one of the core activities of an insurer. Modeling and mitigating these risks are some of the primary functions of an insurance company in general. These risks can be due to policies sold by the company, the market's interest rate affecting the company's investment, people's life expectancy, automobile accidents, hurricanes, earthquakes, the company's IT infrastructure, or new business levels. One of the biggest challenges is the high variation in risk exposure, particularly for life and health insurers. In this section, we focus on practical, real-world applications of machine learning techniques for enterprise risk management in insurance companies.

For each subsection, we will present summarized, anonymized, company-specific use cases. Due to obvious confidentiality reasons, we will not disclose further details about the insurance companies or the business practicalities of the problems. In addition to the unique attributes of each use case, some (if not all) of them will also have distinct data requirements, variability of machine learning algorithms, model evaluation metrics, modeling periods, and presentation dilemmas. Since all problems come from supermajor insurance companies, they usually have the capacity to employ sophisticated modeling techniques and an extensive distribution network. The assumptions, limitations, and success measures are commonly established, followed by model implementation. Some use cases will be applicable to most companies in the industry, while the solution paths of the other examples might be more esoteric due to their nature.

5.1. Real-World Examples

There are some real-world examples of AI-powered risk management frameworks for insurance. Guideline 1 summarizes the information and its implications. There are several aspects in which the approach discusses AI adoption for insurance, and sometimes they are different. Based on the discussion, AI adoption for insurance is identified as follows: fraud detection, risk assessment, claim settlement, client support system, underwriting, AI adoption influences, and AI challenges. They are elaborated in the following sections.

Fraud Detection. In this section, an intelligent fraud detection and risk management system for health insurance is introduced. The proposed approach integrates data from the insurance doctor, as well as from the in-house reviewing committee, business intelligence, and social media information. After administering data pre-processing, data analysis is conducted, extracting information from the insurance doctor's examined physical and diagnostic details and creating a profile. Focused grouping is carried out by evaluating the average diagnostic and physical details of high-billing and low-billing insured people through vertical difference quotient computation and analyzed using primary or secondary insured persons. If outlier details exist on the profile of the insured person, a rough set theory rule is generated as a detour.

The combination rule through the simple mechanism is created to detect claims as fraudulent. More complex breach detection pattern groups the analyzed and focused insured claims and various diagnostic and physical detail data variables, while the process predicts, clusters, and displays to the claim administrator. Supports received claim settlements by combining the claim identifiable details and analyzed attributes. A personalized fraudulent claim detection and risk assessment framework is developed using the allocated color details of the US state, which is used for rough top coding. Data from the member or insured details are collected for a group of people who file their insured claims for administrative purposes from the workplace employee.

A business intelligence tool is used in the proposed intelligent fraud detection and risk management system. The tool implementation uses the OLAP cube, which investigates and returns health fraud decision essays, providing exact information and decision-making support. Slicing and dicing the data is performed. Computational models have been developed in the proposed hacking prediction system using database details. AI Fraud Concepts in Health Insurance uses Active Database technology to manage declarative data. Data are used to extract the insurance data, and connected health and fraud detection technology is used.

6. Future Direction

We propose a novel risk management framework for insurance that uses decisions rather than predictions for practical risk management. Based on a binary classification model that estimates policy lapsing, we quantify the risk measures in the portfolio and then reallocate assets in the capital markets. To make actual decisions for the reallocation, we use quantile regression forests and their aggregated values reflecting specific goals at each predetermined aggregation level. We perform a backtest using policy data provided by an insurance company, where part of the policyholders' actual behavior is assumed unrecognized. Our simulation shows that the proposed framework increases the utility more than the use of predictions in isolation and in combination with current structural models.

For future research, we revisit standard risk measures such as Value at Risk and Expected Shortfall when the decision is the target rather than the prediction. The objective is to propose alternative risk measures that value the impact of being in the tail of the decision distribution rather than defining the tail on the probability model. Intuitively, with the move from prediction models to decision models, the values of 0 and 1 increase their importance when embedded in the processes, and their behavior at different thresholds is not captured by standard measures. This will be a stepping stone for the development of AI-powered risk models and brings to the financial industry advances that are already maturing in the technological industry.

7. Conclusion

Risk management is a standard contribution of insurance. Traditionally insurance focuses on risk protection and risk pooling. Operationalization of insurance from a social/business point of view and using risk data assisted by AI technologies on risk prevention and mitigation has the potential to significantly affect the society's and industry's well-being. Moreover, insurance companies can potentially improve their competitiveness, improve their ability to price risk and offer personalized policies, and at the same time improving profitability. Insurance ecosystems comprise a complement of players that cover clients, entity issuing and supplying insurance services, and brokers. Risk becomes increasingly more complex and formalizing what risk is will help insurance clients, brokers, and the insurance entity to better understand the magnitude of the risk and how to respond to it. Renew Offer innovation contributes to reduce information asymmetry, achieve validated and trust-risks, and foster good clients' insurance responsibility behaviors. As the AI technologies improve, so does the capacity of the insurance function to make informed decisions and reduce data uncertainty.

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