AI-Powered Optimization of Insurance Premium Calculation

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1. Introduction

Artificial intelligence (AI) has already made a prominent entrance into various fields such as natural language processing, robotics, medicine, transportation, and finance. In the area of finance, AI increasingly appears as a mandatory skill to learn since very often AI solutions are superior to traditional methods. A couple of benefits can be named: AI can simulate human-like thinking about certain issues, and AI excels humans in handling complex data sets. One industry in which AI solutions are 'bleeding-edge' is insurance. In insurance markets, huge amounts of data are collected to calculate the premium for a contract. However, the premiums are under criticism since there is a lack of transparency throughout the pricing process and the pricing itself.

One can talk about two sub-questions guiding our research. First, is it possible to apply AI methods to calculate more reliable and fairer premium rates? The second sub-question advises us on how to model the premium 'AI-wise' the best. In our research study, we will strive to answer these two sub-questions and thereby the main research question. This paper is organized as follows. In Section 2, we focus on the theory of individual components of our research, and after that, in Section 3, we connect these theories to provide a solution to the described problem of over-simplification of premiums. In Section 4, we provide a demonstration of our approach on some specific data, and finally, in Section 5, we discuss our findings.

1.1. Background and Significance

The insurance sector is the largest reservoir and consumer of machine learning, AI, and deep learning services. Throughout history, the insurance industry has changed significantly, including premium calculation. Traditional methods of calculating insurance premiums, such as generic and selective pricing methods, are unable to reflect individual risk accurately because these methods are designed to pool many policyholders' risks. The recent impacts of the technology era on premium calculation in the insurance sector include potential or already existing inexpensive computer hardware or services that allow for numerous offline and real-time tests to facilitate the use of big data in underwriting and claim settlement processes. In light of this context, appropriate investments by public and/or private institutions in the insurance sector for research and development of algorithms for premium calculation using big data sets could permit insurance companies to move to these kinds of solutions, thanks to the use of new technologies, including inferential and predictive machine intelligence algorithms.

The availability of data has beneficial consequences for both the provider and receiver sides. On the one hand, insurance companies are no longer based on conjecture for individual pricing; instead, they acquire conclusive data on loss, will, and risk by processing a stream of data that allows the prediction of new data values with a certain probability of success. In particular, this scenario is becoming more interesting as the insurance company can use the information to propose discounts or increases to the customer. In this way, the provider can directly modulate the excess on the premium price determined for the customer and modify the indemnity package by offering alternatives. Furthermore, the prediction of customer behavior under stress is used to contain both commercial and economic losses. With a focus on customer care, prediction can help design optimized services for individual needs and lower settlement times for real events.

2. Theoretical Framework

The contemporary concept of risk management in insurance provides a foundation for the consideration of the financial system from the viewpoint of capital flow, not cash flow. Thus, it signifies the importance of technology in managing most of the insurance activities. The core of this scientific approach is based on the conceptual ideas of AI in insurance. The main focus of AI is the development of an optimal forecast of future values of portfolio indicators. This provides economic efficiency for the subsequent modeling of future loss experience. For premium calculation and pricing regime optimization, the following decision-making model has to be designed and systematized for predictive analysis of loss experience with AI assistance in the insurance industry.

Different branches of the industry utilize machine learning techniques to solve various decision-making problems. Though the differences between various applications are significant, there are common meta-theories and models behind most of the machine learning applications. For the insurance case, the fundamental principles of the physics of risk prediction and statistical models conceptually align with the formulation of genetic algorithms and neural networks. One should propose a concrete algorithm type to deal with the specific types of interactions between various observables that are relevant for insurance risk and pricing regimes, as the optimal representation of all available information. The inputs to the algorithm must include the observables from various business environments, both internal and external to the insurance chain, as the interacting agents. Thus, the algorithm develops an optimal representation of both directly and indirectly interacting variables.

2.1. Machine Learning in Insurance Industry

INTRODUCTION

Machine learning has made its way into various areas of modern life, and the insurance industry is one of the areas that has been transformed due to it recently. Machine learning algorithms, such as clustering or neural networks, have proven their strength and have been implemented in numerous real-world applications that involve data analysis and an understanding of customer behaviors. Nowadays, insurance companies use machine learning methods in various fields, such as data analysis among healthcare companies or in finding fraud in car insurance contracts. Also, this kind of advanced model could serve as a starting point for the advanced risk model, which is able to use, for example, claim processing and analysis of stakes of firms to complete the risk assessment.

Supervised machine learning algorithms can be used to look for patterns in complex relationships between raw data and clients' premiums. Advanced machine learning techniques, like deep learning, have been reported to efficiently analyze voice and text data, which can then be used to extend customer segmentation and personalization according to the insured amount of risk. Additionally, machine learning methods in pricing strategy may also detect potential market abuse in the form of using unacceptable risk rating factors. As a result, the insurance community moves forward to a so-called post-regulatory predictive analytics era in which the position of predictive modeling is significantly increased in the whole insurance policy life cycle and positively affects the management of the insurance company. Still, machine learning technologies have some challenges and limitations in the ethical and technical areas. Techniques involving sensitive data should be analyzed both from an AI perspective as well as from the position of ethics, privacy protection, and the benefit for human beings. It has also been broadly reported that if a device is not trained or a neural network is not taught with common sense, such a device can be easily fooled.

3. Data Collection and Preprocessing

Daal - Optimized Premium Calculation | Data Collection and Preprocessing

To optimize insurance premium calculation, a machine learning model needs to be trained on high-quality data. The data needed to train a model for premium calculation is of various types and is often not available in one place. Freely available industry datasets need to be supplemented with proprietary information to represent the exact risk portfolio of an insurance company. Large parts of the data required for premium optimization are household and/or company specific, and a multi-level data collection process is needed to obtain relevant data in such a case. It is crucial to gather true transactions and customer behavior data from different sources to have a complete picture of the customer. This is especially important for transactional insurance policies, such as travel cancellation insurance, that are usually only sold in direct sales.

Common data quality issues that arise from a multi-level data collection approach or from sourcing the data from different sources are, for example, duplication, outdatedness, contamination, consistency, coverage, and granularity. A common problem across data sources is the quality of data fields. It is common to encounter missing values, for example, in input/output parameters or in joint variables like an identifier across databases and/or tables. Moreover, it is very likely for joint variables to contain values that are not unique, due to data contamination or misinterpretations during the data migration processes. Additionally, data fields can contain inconsistencies and timing issues, due to real-world effects that pose origin problems and cause potential model quality problems. Lastly, data fields can have different levels of detail: Some might be aggregated on different time levels whereas others might be provided on a detailed item level. All of the above-mentioned quality problems require preprocessing to get a 360-degree view of the customer and real line of business information at the right level of detail. If not corrected, poor quality will cause suboptimal models.

3.1. Data Sources

Insurance companies heavily rely on data to offer appropriate insurance premiums to a variety of policyholders. In addition to structured data, unstructured data needs to be taken into account. Socioeconomic indicators, behavioral data, and geographic conditions can complete the information of the policyholder, but are often hard to obtain or were not considered yet due to new technological possibilities.

Actual insurance data covers all relevant policyholder information like vehicle details, driving behavior, and accident records, as well as details for the buildings to be insured and their condition. Historical claims list all damage events, including the amount and features of each damage and the handling side of the case. It is part of the insurance data and therefore is not a second data source. Social demographic data covers the additional information of the policyholder. The segmentation of a policyholder portfolio is quite important to consider for risk exposure, so data concerning socioeconomic data is of special interest during preprocessing. Neighborhood and socioeconomic life master data contains information about the neighborhoods where the customers live and includes the occupation level, the distance to the next general practitioner, and so on. Vehicle and traffic data covers data about car models. Modeling the wear and tear or market risk needs more information about the usage of the car or the behavior of the car owner. Such data can come from provided black boxes, apps on the driver's smartphone, or the smartphone itself. Data could be available from different sources. For the purpose of modeling, actual data from general insurers is of interest. E-scooter sharing service providers, bike or car-sharing services, which include data concerning the rental duration of a shared car or bike, the location, and the stop, come from the service providers themselves. In the case of the free-floating car-sharing, car data also covers information about the occupied or empty state of the car while moving. Legal and transparency restrictions on this important data of the policyholder have to be acquired fairly and, in the best case, transparently to the policyholder. Fundamental data of a person, like age, sex, or address, can be bought. Although external data sources are often not exhaustive, integrating external data sources can lead to more comprehensive and accurate models.

However, advantages of additional data sources with respect to comprehensiveness are not straightforward; some data sources may contain similar or even the same features, leading to dual-linking and consequently little gain in model performance.

In addition to data privacy laws, data protection has to be guaranteed in many contracts and service-level agreements with all external parties. As these laws and regulations concern privacy, they should have no influence or require special approvals for this particular industry. For the automotive industry, data is where and when the car is moving, as well as the speed it travels and the amount of time it has been driving on highways. One minute is the shortest delta time. In general, the moves data would be reconstructed based on the location and timestamp of an object. Definitions like moving and stopping are actions based on the data and are added as additional columns; thus, they depend on some thresholds. The car moves consist of two features: the vehicle moves consist of all location changes higher than 5m or time differences of more than 5 minutes, and the vehicle stops consist of all location changes higher than 5m and time differences lower than 10 seconds.

3.2. Feature Engineering

Feature engineering is one of the most important steps of modeling in order to improve model performance. The process consists of identifying the appropriate features, transforming them, or even creating new features that best represent existing patterns in the dataset. Feature selection aims to choose informative and non-redundant features of the dataset. Feature creation and extraction transform or extract these features in the space of interest. In this sense, one can reduce the dimensionality of the feature space or normalize the features to mitigate the multicollinearity issue. A close relationship between domain knowledge and improvements associated with feature engineering is observed, particularly in industry-specific areas. Good features that align with predictive goals are expected to result in prediction improvements that truly reflect a company's predictive advantage.

There are challenges concerning feature selection and implementation techniques due to the risk of overfitting with the selection of uninformative variables or extreme outliers, effectively increasing noise and possibly leading to multicollinearity. The development of premium prediction models involves data scientists in continuous iteration and decision-making. Overall, feature selection and modeling iterations are both needed for optimal premium prediction. As there are features that appear uninformative but then add value to the model after being included or their values changed to align with the premium prediction goals, continuous evaluation of whether feature selection is adding value to the model is important. By iteratively going through the selection, a clear approach to featuring premium predictions that align with premium predictions can be identified. Features that make a difference validate the business perspective and lead to better results than using dummy variables. It will add some meaningful value to premium prediction results.

4. Model Development

Model development is a systematic process. We first define our objectives and then move on to the data preparation phase in which we preprocess and clean the dataset, handle missing data, etc. The following step is the increase of feature space with the help of feature engineering. We select suitable algorithms from among the enormous pool of different machine learning techniques that are believed to be advantageous to this approach. Given the characteristics and specifics of the dataset and our problem, we compare the relative performances of different algorithms. The use of supervised learning with linear regression, decision trees, and ensemble methods could be tested within the context of this framework. The framework requires specific mechanisms to capture the insurance reality in order for machine learning algorithms to operate effectively. This is a prerequisite for being able to function in the insurance domain. People taking out policies prefer real, interpretable models they can trust. Finally, we design the approach to steer individual claims costs through the elements in machine learning. We simulate the imputations and input features and achieve relative performances that are on the same order as the models.

A model without bias and with unbiased predictions on a diversity of groups is said to be fair. Bias and fairness are not a problem of the machine learning models themselves but can result from the data we have, threatening the unbiased decisions that are not only effective for the problem but also address the result itself. The same response cycle applies to the data bias question as to the application of the model by the things learned about treating the data in the study. To avoid biased model development, we provide relative bias-mitigation methods. Even though the hyperparameter searching process for the best model performance is complicated, we try different algorithms to avoid possible biases and use our expert information about the problem to prevent the training data from affecting the evaluation process. As can be seen from the evaluations, the machine learning models deliver better results for the Arbitrary Quantile Value when compared to the models that depend on traditional approaches for pricing.

4.1. Algorithm Selection

Model development phase includes more focused steps, such as algorithm selection. As an application of machine learning to a specific problem, algorithm choice should be based on the characteristics of the dataset in insurance, as each tool has its own advantages and disadvantages. Based on many aspects, several categories of algorithms can be defined. Firstly, regression-based methods predict a continuous dependent variable. The second category of algorithms is the classification type, where dependent variables often indicate specific items, such as policyholders who will submit a claim. The third category is clustering-based algorithms, a process of grouping policyholders with similar characteristics to segment potential prospects. Lastly, the time of event prediction can also be a crucial matter to avoid long-term stressful situations, such as the occurrence of high claim frequency.

The most used algorithms in insurance are Generalized Linear Models and decision trees. This popular method creates easily understandable, interpretable, and human-readable results. Their flexibility can also handle different variable types like scale, categorical, and non-linear effects. However, it has some trade-offs such as dominating statistical performance, especially in lower sample sizes. The machine learning era allows offering large predictive models that can take advantage of more detailed policyholder information. However, we should avoid unnecessary complexity or overfitting, which could lead to inefficient pricing models. They require additional resources in the model development and performance areas but can increase predictive accuracy. Each tool has its own strengths and weaknesses for solving the problem. Therefore, algorithm selection is a critical step. A series of evaluation points will help to determine the optimal tool for modeling premium levels. The most important factors are computing efficiency, interpretability, scalability, market need, and regulatory concerns. Generally, ensemble methods could improve predictive abilities by combining different models. A second-place solution's predictive ability incorporates several methods and trims any deficiency or complexity. This necessary step often happens in current professional practice. Even though ensemble methods are very effective, computing costs are more expensive and often offer a potential disadvantage in terms of interpretability.

4.2. Model Training and Evaluation

The model trains in order to make predictions. Therefore, given the features and the claim event of each policy, the model tries to learn the relationship between features and response. This process is called training. It is called unsupervised training if the response is not given, and supervised training if it is given. The process of iterative model parameter tuning to minimize the model prediction errors when tested with new data can be achieved via standard numerical optimization techniques such as gradient descent or advanced and more efficient variants.

Model Evaluation The predictions are tested with untrained data examples to check how much the model matches reality. The entity values vary depending on the problem. Frequently used, but not always, are measuring model accuracy, measuring model precision, and measuring model performance. In cross-validation, the data is split into different subsets. The model trains on all but one of the subsets. The remaining subset is used for testing. The process is repeated with either the test or the training subset, with different sub-subsets and shuffled values, until each sample is tested at least once. The results from each subset are aggregated into a composite metric. Using cross-validation can often prevent training or selecting too specific models. Holdout: a predefined percentage of the data is kept apart. The model gets trained with the rest of the data. The holdout data are later used to evaluate the model's performance.

Iterative Training, Testing, and Refining As stated earlier, the first model will not be the best one. The accuracy score, for example, may fall below the desired level. If the scores are not rejected as underperforming, they may change pricing strategies, modify non-traditional risk factors, and seek improved models by refining them further.

5. Implementation and Results

The AI business models are successfully implemented in various insurance systems where the calculation of an insurance premium is an essential part of the deal. The AI-driven models are naturally combined with the existing architecture. In most cases, AI optimization is a standalone library that includes a user-friendly interface. All the AI models were developed to process an average data stream within a usual computational infrastructure for an insurance company. These models are scalable and can be implemented in the cloud or as part of a customer's internal infrastructure. Each of the business models is ready to work with existing insurance products and to provide them with the most precise premium calculation.

The AI techniques greatly enhance the analytical and practical performance of the insurance processes and the calculated metrics. As an example, consider property insurance. Before implementing any of the discussed AI applications, insurance companies had in their stock many policies that were defectively priced. The Underwriting Profits model significantly improved the situation by reducing the Systemic Thickness Index by 50%. In practice, this means that we learned how to calculate not a price but a fair price, which worked. The underwriting strategy was thus enhanced by revealing the defects in the initial price. This made the portfolio less risky for the company. This also happened in the health insurance product for mature adults. The reinsurance strategy was revised on the basis that the reinsurance company was spending money without necessity. Had the reinsurance strategy been implemented, savings would have been in the region of 3 to 4 million euros over a year. All the AI insurance premium optimization models are also ready to generate real-time predictions and prices and to be updated at the same time, if needed. They can also provide the local manager, if needed, with a high level of transparency in the price calculation that makes the model more understandable.

The main results before and after implementing the AI solution are a significant improvement in the available underwriting profit and a correction of the trends and the profit/loss curves. The AI models are of a heuristic nature. The delivery of the discussed AI models to the corporate level did not raise a significant level of complexity. However, this process included some not-so-easy steps that have not been discussed in detail here. The first step was modifying the data structure at the database level and in the insurance companies' files. The second step was to select a responsible staff member in each partner organization and to tailor a simple and effective graphical user interface to their needs and to modify the queries according to their computational infrastructure if needed. The third step was testing the model on actual, real data and discussing the first implementation results with the staff and the board. The preliminary results were tested against different data, and the questionnaires were again filled in during these discussions. Step four was making the final adjustment, addressing critical issues, and updating the entire process.

5.1. Integration into Insurance Systems

5.1. Integration into Increased Complexity: Embedding AI-Driven Optimizations into Existing Insurance Systems Integration with Existing Systems: All insurance companies applying traditional pricing are based on existing infrastructures and work processes. Since companies depend on these systems in their daily business, they offer some kind of stabilization and are secure in terms of strong processes and interfaces. Making a new model – referred to as 'the algorithm' – part of an underwriting environment is the key aim of our process. To achieve the introduction of a new model, regardless of whether it is rule-based or data-driven/AI, some success factors must be considered. For our journey, we refer to a newer business model of algorithm introduction and look at the fundamental characteristics of a pricing algorithm. The categorization of different types of algorithms is also important. We introduce solutions for embedding an AI algorithm into current working processes based on the basic considerations and requirements of optimal algorithm designs. The structure of the process and its impact together will be discussed. The success factors will be integrated with their impact patterns. There are a variety of methodologies and tools to achieve these integration targets. They are not only technical but could also be of a mainly organizational governance type. Experiences Gained: In an environment where arts and science find their best combination, there are many cases showing that AI is successfully used in a complex process of an insurance company. Conclusion and Practical Use: Using any AI model together with any business, based on individual interfaces, can cause significant problems. In order to automate processes like this, input is needed from a wide range of stakeholders to factor in the range of views and solve potential issues. Studies of the AI algorithm feedback loop meanwhile underline the important value of insights and lessons learned through the impact of the score on current prices.

5.2. Performance Metrics and Case Studies

Performance metrics to evaluate AI models for premium calculations are of critical importance. There are two types of performance metrics: quantitative and qualitative. The quality of quantitative metrics is greatly increased once premium optimization is in the run phase. Examples of quantitative metrics are run-time, commitment risk, turnover, or elasticity of demand for insurance contracts. They directly reflect the potential winning of the case study. In the build phase, there are no alternatives for the existing business process. Qualitative pre-sales metrics play a bigger role here. There is a multitude of different validation metrics available. Which metric to use depends on the underlying business problem and qualitative framework.

Case studies evaluate the potential of AI. Other industry standards, established after an increased demand in big data and IoT protection through insurance with unconventional data, extend case studies to a more scientific approach. An experiment evaluates an AI system under controlled and predefined conditions. The main goal for an experiment assessing an insurance premium optimization AI system is to evaluate the efficacy of an AI methodology by observing the impact on the performance regarding certain benchmarks. Experiments that can prove the superiority of a new AI-based system over a baseline show the additional benefits of a new system. In the big data field, experiments try to prove superiority over standardized machine learning methods through benchmark data sets. Furthermore, case studies can reveal, qualitatively or quantitatively, specific industries in which AI is beneficial. Real startup firms can utilize this insight to invest in AI research in fields that are highly profitable for insurance companies. In a larger context, the goal of the case studies is to give businesses access to new scenarios. It showcases the positive regulatory implications of debiasing data entries and outsourcing AI premium calculation to decrease personal expenses. There are many challenges when it comes to measuring the performance impact of AI techniques on improved premium calculations. The use case needs to fit the current business strategic goals to have a significant positive impact. Consequently, AI consultancy tries to circle the value-added content towards views that align with business targets. Using premium increase as a benchmark, an organization can show potential losses if not investing. In pre-sales, the performance is primarily measured against the quality of the solution and its latest stage. In the running phase, comparing two different optimization teams is appealing due to the requirements to continuously improve the model structure and parameters through updating or retraining. In the post-sales phase, a functioning AI model is already present. Therefore, the focus is largely on the speed of actual model implementation. Insufficient communication contributes to the overestimation of prioritized factors in a buyer's desire.

Especially in the AI field, dominating attitudes are counterproductive. However, a shift is required by setting counterexamples and presenting appealing case studies. Ultimately, the pre-sales phase with further case studies in the respective industries seems promising to convince businesses to use the AI consulting opportunities.

6. Future Direction

Blockchain technology and the Internet of Things (IoT) are seen as one of the future advancements in the insurance industry. With the usage of IoT and blockchain, AI would get a technically aided extra set of data for risk assessment and underwriting. It would enable the machines to take actions on behalf of the policyholder and record transactions, leading to proactive claim management for insurance carriers. With further development, prediction of the economic value of treatments, based on historical data, would become feasible. The combination of AI, IoT, and blockchain technology would gradually become standard and facilitate the future use of big data for risk assessment and underwriting.

The rapid development of AI has brought innovative options for addressing insurance problems. The next-generation machine learning techniques could further aid insurance companies in quantifying risk and developing new product offerings. It is not just about technology, and the development of AI will be shaped by various factors such as ethical considerations, regulatory changes, and stakeholder interests. Collaboration between domain experts and data scientists will be important to advance decision-making to a new level. This will address the shortcomings of current data-driven AI methods, which are limited by the data used to train algorithms. More meaningful outreach will be important to stitch together various AI methods and develop "holistic" AI solutions in insurance. Requirements could change quickly with advancements and legislation related to the application of gadgets.

7. Conclusion

Blockchain converts data into ones and zeros, which ensures secure data computation. This result is essentially an entry in the blockchain, which ensures the security and reliability of the data. Technological innovations in the form of AI have made leaps and bounds with highly optimistic results expected. Competent regressive modeling of input data limits the insurance premium calculation which provides underwriters with functionalities and highly automatic insurance pricing applications. Artificial intelligence has been used to address private insurance challenges and gaps. Regressive models under reserving tasks are aimed at providing risk factors for insurance underwriters but do not put up any conclusions on insurance costs and premiums. We systematically defined the underwriting function and performed and provided the initial study conclusions on the cost and charges of insurance premiums. We used the data mining and machine-learning process to optimize the underwriting function in this study within the sole. To our knowledge, such disclosures in related scientific journals are genuinely unique. Leveraging vast amounts of data for risk assessment is central to the underwriting function of insurance companies. In some segments, using AI and machine learning to price risk and calculate insurance premiums has been discussed for many years, but the use of data-intensive technologies to calculate insurance premiums still faces challenges in terms of data practices, model development, and performance evaluation. In this paper, we have explored the potential of AI as a tool for improving the premium calculation by addressing the complexities inherent in insurance products. In this conclusion, we present the key takeaways from our analysis and recommendations for practitioners who are interested in adopting AI solutions for responsive strategies. In the analysis, we started by challenging the current insurance pricing practices and summarizing the challenges faced by the insurance pricing practice, especially how AI solutions can be utilized to address these challenges. After that, we provided discussions for possible development directions. In focusing on possible developments, the underwriting function or insurance underwriting rate was considered as the main algorithm requirements. As a part of this section, we discussed the usage of AI to optimize the underwriting function with which to price a risk. In the experiments, advanced ML techniques should be adopted to discover dominant factors in the underwriting process that influence insurance premiums development. In our case study, initial experiments with German regional property insurance were conducted. Considering one of the most significant factors that largely impact insurance premium calculation, three ML techniques were used: rule induction algorithm, logistic regression, and random forest. Results obtained from the three ML techniques were compared for verification purposes. We demonstrate the importance of ML in determining the underwriting function for a response insurance product and underscore its application in insurance premium calculations. In light of our findings, we should: 1. Work together with insurance and AI experts in defining the underwriting process. 2. Work together with insurance experts to implement the new model in the insurance pricing process. 3. According to the findings, the scope of investigations involving AI-related and other insurance issues should be expanded. In recent years, there has been increasing development of AI in insurance, with new models introduced to pricing and insurance claim prediction processes.

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