The current role of machine learning and explainability in actuarial science

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Abstract. Actuarial science seeks to evaluate, predict and manage the impact of future events. Nowadays, the actuary faces the challenge of predicting and managing risks efficiently, with a universe of information growing exponentially in real-time and with a business dynamic that demands constant competitiveness and innovation. The techniques associated with data engineering and data science open a window of tools that seek, through technology, to improve the processes of product design, pricing, reserves and establishment of market niches practically and realistically, considering the pros and cons that brings the availability and constant updating of information, as well as the computational times that this implies. Therefore, this article aims to review the application of Explainable Machine Learning techniques as an alternative to the development of more efficient and practical actuarial models.

Keywords: Machine Learning, Actuarial Models, Explainability

1 Introduction

Actuarial science, seeking risk modelling through mathematical and statistical techniques, faces new challenges every day, both in the volume of existing information to improve its modelling capacity and the nature of the different problems. The techniques associated with Artificial Intelligence and Machine Learning provide a series of tools whose purpose is to improve the processes of product design, pricing, reservations, and establishment of market niches practically and realistically [1]. However, there is an essential limitation in the practical application of complex models that are difficult to interpret and audit, which is related to the strict regulations that regulate the financial sector, as it is a systemic risk business and of vital importance for the world economy, so that for specific processes this type of model is usually ruled out. In this sense, the use of explainable AI technique - Local Interpretable Model-Agnostic Explanations (LIME) [2], The Partial Dependence Plots (PDPs) [3] - would make it possible to understand and evaluate the capacity of the results of the proposed models and investigate the relationships between variables, thus facilitating the understanding and monitoring of the adequacy of these models.

The analysis of the main issues related to the article could be divided two main lines are identified and presented below.

2.1 Artificial Intelligence in actuarial science

In the actuarial field, standard models and different combinations of techniques that are already well established in the field continue to be applied; however, in recent years, different works have appeared related to the application of techniques more closely linked to Artificial Intelligence, such as the following: Genetic Algorithms [4] [5], Artificial Neural Networks, Regression Trees [6], Random Forests and Fuzzy Logic [1]. Regarding the specific application of machine learning techniques to the area of insurance, it is usual to find applications from ANOVA applications to classification models by trees and random forests [6]; Markov Decision Process (MDP) [7], fuzzy generalized probabilistic OWA (FGPOWA) [8] and SMuRF [9] in order to improve precision and computational performance.

2.2 Explainable in actuarial science

Data science has evolved rapidly as computational capacity has advanced, and so has the complexity of the models and the difficulty of understanding the relationship of variables. This is the reason why in the last two decades, there has been an increase in the analysis and application of explainability techniques as a final step in the development of Machine Learning models. This set of techniques includes the application of graphical analysis such as LIME [2], X-Shap [10] or Partial Dependence Plots (PDPs) [3]. These techniques provide a graphical explanation of the influence of the variables on the predictions made by the model. Other approaches are those based on game theory, in which the interaction effects between characteristics and the understanding of the structure of the global model based on the combination of many local explanations of each prediction are explored. [11]. It is also worth mentioning the copulas analysis, where it is possible to intuitively construct the relationships between them using the statistical properties of the variables [12]. Any machine learning technique that intends to be applied to real problems in the finance and insurance area must offer transparent and replicable modelling that allows for review and audibility by control agencies and stakeholders. Since this has been a permanent limitation in applying sophisticated or black box models, a further challenge lies in the definition of a framework for the development of explainability analysis within this context [13]. The alternatives based on model agnostic methods that allow, in an aggregated manner, the evaluation of relationships between variables, facilitating the global understanding of the models, should be highlighted. [14]. [15] [16].

The case study involves using different models to estimate the probability of credit default (PD), in line with the requirements of IFRS 9 for an Expected Loss model, for the U.S. Trade and Industry debt portfolio. For this purpose, use was made of public and freely available information published by the World Bank, where there are quarterly default rates for different types of portfolios and information on macroeconomic variables with the same updating periodicity. In the model adjustment process, the classic models based on Autoregressive Vectors are those that offer the best results, in addition to presenting by definition a reasonable degree of interpretability, while in terms of predictive power, the neural network models (NARX and ANN) are those that offer the best results. However, their results cannot be directly explained. An approach based on locally over-trained decision trees was used, making it possible to establish the relationships between the variable to be explained and the independent variables. Specifically, it is possible to identify that both models preponderate the influence of *Expenses at real prices for personal consumption in Durable goods*, this may reflect the direct relationship between the production of goods and services, and the investment and consumption in the medium term. In the final segmentation, *net savings* are included as a decisive factor. However, despite the favorable results, associated with the predictive capacity of the evaluated models, it is not common to see their application, as it is not possible to clearly identify the type of relationships established. Applying explanatory models, it is possible to reinforce the relationship of relevant variables to compare the logic established by the models, facilitating their understanding and revision.

4 Conclusions and Future Work

Currently, a window of possibilities is open for the application of explainability models to actuarial science problems. This is mainly due to the possibility to develop a standardization of the review using explainability techniques in the review and audit processes of artificial intelligence models, which to date have demonstrated better predictive capacity, and their limitation is associated with their understanding and replicability. These kinds of techniques help the companies to create more risk models in the machine learning way.

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