Technical reserving in non-life insurance : A literature review of aggregated and individual methods.

[*]Ayyoub SAOUDI[1], Fatima EL KASSIMI[2], Jamal ZAHI[3]

[*1,2,3] University Hassan 1st, Faculty of Economics and Management, LM2CE, Settat, Morocco

[*] E-mail : ayyoubsaoudi3@gmail.com

Abstract:
Estimating reserves in non-life insurance involves assessing the risks the insured faces and determining the amount of actuarial reserves needed to cover those risks. To estimate reserves, actuaries often use various methods, the most popular of which are deterministic methods, such as the Chain Ladder, and stochastic methods, such as the Mack model. These latter use simple statistical models considering the insured's historical data to estimate future losses. They basically rely on Run-off triangles of aggregated data by year of occurrence and development year. However, this aggregation often leads to a loss of relevant information. A powerful alternative could be Individual reserving, which incorporates information about the claims experience and policyholders' individual characteristics through machine learning algorithms. This article reviews the various actuarial literature on reserve estimation in non-life insurance.

Keywords: *Reserves, Chain Ladder, Mack model, Run-off triangles, individual reserving, machine learning.*

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1. Introduction

Risk permeates every aspect of our daily existence, with its intensity fluctuating across a spectrum ranging from simple risks to those bearing potential detrimental financial, human, or physical repercussions. Safeguarding against these risks becomes imperative, as an individual or legal entity may be unable to endure their consequences independently, hence resorting to an insurance agreement in this context; reserving aims to ascertain the total amount necessary to cover the expenditures arising from such contracts.

Establishing and monitoring these reserves is crucial to ensure the insurance company's financial stability. [1] pioneered the calculation of reserves, notably by employing the Chain Ladder (CL) method, which remains one of the actuary's most commonly utilised techniques. This method estimates future settlements by aggregating insureds' past data claims through loss development triangles. Despite its computational efficiency, the CL method has faced various criticisms. Stochastic methods were then introduced to gauge the fluctuations in these triangles addressing the uncertainty associated with deterministic techniques and their outcomes.

As advancements in information technology have emerged, actuaries have embraced the integration of machine learning algorithms such as artificial neural networks (ANN), Gradient Boosting, Support Vector Machine (SVM), and other similar techniques to enhance the accuracy of their estimations. These algorithms have proven advantageous in estimating individual reserves by incorporating specific claims information and characteristics unique to each policyholder. In light of this perspective, this article surveys the array of actuarial research conducted in technical reserve estimation.

The remainder of our study will be structured into four primary sections. The second section delves into classical reserving methods while appraising the various actuarial research endeavours that have employed these approaches, encompassing deterministic and stochastic methods. The third section focuses on utilising statistical learning algorithms in reserve estimation, catering to aggregated and individual data. The fourth section conducts a comparative analysis of diverse reserving methods, while the fifth section summarises the preceding sections.

2. Traditional reserving methods

The aggregation of claims by year of occurrence and year of development has long been a customary practice employed in representing insureds' claims experience through loss development triangles. This methodology, commonly referred to as the Chain-Ladder technique, was initially formulated by [1] in 1938 and has since gained wide acceptance among actuaries due to its comprehensibility and ease of implementation. Its fundamental premise involves projecting future claim payments by drawing upon historical payment data. Supplementary approaches, such as the Bornhuetter-Ferguson, Cape Cod, and Benktander-Hovinen methods, predominantly build upon the foundational principles of the Chain-Ladder technique. By leveraging Run-off triangles, one can effectively monitor

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the progression of claims costs and attain valuable insights into their distribution, thereby aiding in determining appropriate modeling techniques. In instances where claims exhibit a Gaussian distribution, deterministic methods may be considered, whereas stochastic methods are typically employed for modeling other types of distributions.

2.1. Conceptual Framework

An inverted production cycle sets the insurance business apart from any other industry. Unlike most industries, insurers establish premium rates prior to determining their expenses. Consequently, insurance companies are compelled to accurately allocate reserves for their claims, ensuring their ability to meet future obligations and maintain financial stability. Furthermore, reserves are critical in an insurance company's balance sheet.

The process of estimating these reserves, commonly known as reserving, has long been a subject of deliberation within the actuarial community. Extensive actuarial literature addresses the intricacies of technical reserves, with notable contributions from researchers such as [2] and the seminal works of [3], among others.

In their quest for solvency assurance, insurance companies have dedicated significant efforts to developing methods that accurately estimate technical reserves based on historical loss experience. This research has led to categorizing reserving methods into two primary categories: deterministic and stochastic approaches.

Deterministic methods, considered the classical approach, are relatively straightforward to implement as they provide reserve estimates by determining the fluctuations in the distribution of potential outcomes. Furthermore, they offer the advantage of depicting the evolution of an insurance portfolio's expenses by using aggregated data represented in a loss development triangle format. These qualities have solidified the status of deterministic methods as a standard practice among actuaries in matters related to reserving. However, over time, the limitations of these methods have become evident. They tend to overlook the risks inherent in the insurance business and do not provide accurate measures. While the reserve estimate for a well-controlled insurance line may be more precise than that of a poorly managed line, the estimate for a short-tailed line is likely to be more accurate than that of a long-tailed line [4]. Nevertheless, quantifying this accuracy proves challenging, a drawback that stochastic methods successfully address.

Stochastic models aim to furnish measures of variability and accuracy by treating the reserving process as a data analysis exercise, constructing a reserving model within a statistical framework. This approach allows for diagnostic tests of fitted models, such as goodness-of-fit assessments and residual analyses [4]. Stochastic methods are utilized to quantify uncertainty in the triangles derived from deterministic methods and rely on stochastic parametric modeling as their foundation.

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2.2. Deterministic and stochastic reserving

Actuaries often use the Chain Ladder method for estimating technical reserves due to its simplicity of application. This method was developed when computers were not readily available, which explains using a simple formulation such as Run-off triangles that cross the years of occurrence with those of development.

The classical actuarial literature has long considered the Chain Ladder method a simple algorithm for estimating technical reserves. However, the beginning of the 1990s marked its integration into a statistical framework *via* stochastic models capable of generating similar algorithms. As a result, several extensions of the classical model have emerged. Authors such as [2] showed that the age-to-age factors techniques could be considered weighted regressions. In his seminal paper "Which Stochastic Model is Underlying the Chain Ladder Method," Mack proposed a stochastic model to quantify the variability of technical reserves using the CL method. The development of stochastic methods continued with [5], who invented the Munich Chain Ladder (MCL) model; this method states that paid losses and incurred losses are often correlated and that the insurer can take advantage of this correlation by transferring any past conjunction of the two into a future projection. Subsequently, [6] proposed a bivariate model that uses two variables to construct estimators that account for the correlation between these variables and are used to estimate the error in predicting a variable with a single predictor as part of the CL method. [7], then extended this Braun model using a natural optimality criterion to develop a multivariate version of the CL method, which solves the additivity problem. Similarly, [8] proposed a new extension of MCL called JAB Chain by taking into account some measures; time-varying slopes, integration into a single model, and joint estimation of all factors. Furthermore, [9] propose another additive multivariate reserving model, allowing the simultaneous study of individual settlement sub-portfolios while deriving a mean square error of prediction (MSEP) estimator for the ultimate loss predictor of the total portfolio.

On the other hand, [10] proposed a Bootstrap approach to estimate the reserve prediction distributions produced by the MCL model; they applied this algorithm to the dependent data to make Bootstrap distributions, allowing for correlations. [11] propose to calculate age-to-age factors and determine the Outstanding loss reserve (OLR) for Run-off triangles using a multivariate reserving method.

A robust alternative using the Generalized Linear Model (GLM) to overcome the sensitivity of the CL method to outliers is presented by [12], in which they offer a diagnostic tool that can immediately detect claims that have an abnormally positive or negative influence on the reserve estimates. Furthermore, [13] introduces a compound stochastic Poisson model, which considers the delay between the occurrence and reporting of a claim and between the time of reporting and settlement. These two sources of uncertainty are estimated separately in the so-called double LC. [14] have developed a complete stochastic cash flow model of outstanding liabilities for the model developed by [13]. Their model leads to lower solvency requirements for insurance companies that choose to collect count data and replace the conventional CL method.

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A common practice of non-life actuaries is often estimating tail factors, i.e., the portion of the claim that still needs to be reported or settled. Among the most popular models used to estimate the development of tail factors are those proposed by [15].

3. Reserving using machine learning algorithms

Statistical learning methods have become increasingly popular among actuaries for pricing [16] [17] and reserve estimation. This section reviews the various actuarial works using Machine Learning (ML) for reserving. But before we dive into these works, it is worthwhile to focus on adapting ML methods to the actuarial reserving context and the modifications required to fit them to the reserving data or *vice versa*. An overview of contributions using machine learning for individual reserving will be presented toward the end.

3.1 Adapting the reserving problem to Machine Learning

The reserving data is often unstructured: since the number of settlements and the time required to settle a claim is ignored at the time of reporting, individual claims cannot be stored in spreadsheets. For this reason, actuaries typically group claims information into Run-off triangles. However, these latter can be expressed as regression problems, even though their estimation does not appear to be related to regression. Indeed, the CL method can be considered as a cross-log-linear regression if we consider the GLM formulation that appeared in the work of [18]. Moreover, the software implementation of the distribution-free CL model of [19] in the open-source R, namely the Chain Ladder *package*, uses a variety of linear regression models to estimate the age-to-age factors of CL. Moreover, more sophisticated reserve estimation models have been fitted using hierarchical Bayesian and generalized linear mixed models (GLMM).

If a reserve estimation model can be expressed as a regression problem, applying machine learning methods for reserving purposes would be possible. In the recent actuarial literature, there is a plethora of work on reserving using ML algorithms, and the following section will be dedicated to presenting the essence of this work.

3.2 Statistical Learning Applied to Aggregate Data

Regression modeling through generalized linear models (GLMs) has grown in popularity over the past decades after the publication of landmark papers in the actuarial literature, such as [20], now considered standard actuarial tools, representing one of the most widely used tools for assessing IBNR variability. Since then, many non-parametric models for aggregate reserving have been proposed, such as the Generalized Additive Models (GAM) of [4], which provide a specific methodology for smoothing CL development factors and automatically estimating tail factors as part of the model fitting process. The framework also provides estimates of reserve variability, something that could be useful in formulating and calibrating dynamic financial analysis models. In addition, [21] propose an extension of GLMs to model not only the variation parameters but also the shape and scale parameters of a relevant number of

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distributions as a function of dependent variables such as accident and development years. These are the generalized additive models for variation, scale, and shape (GAMLSS). Furthermore, [22] introduce new non-parametric neural network-based models for reserve estimation, namely support vector regression (SVM) and Gaussian process regression. These algorithms learn certain types of nonlinear structures in the claims data using the residuals produced by a reference model, Mack's CL.

3.3 Statistical learning applied to individual methods

The increase in the information collected by insurance companies has prompted actuaries to explore new approaches to take advantage of these new techniques and improve the reserving process by including individual characteristics of claims, features that may have an impact on their evolution, for instance, the branch of activity (health insurance, automobile insurance, etc.), the severity of the claim and the age of the claimant.

The first use of statistical learning for individual reserving dates back to [23], extending neural networks' scope to actuarial reserving. With the application of ML, actuaries are again faced with challenges related to the nature of the data (static or dynamic). Indeed, the evolution of certain variables over time (such as the insured's age and the number of paid claims) requires incorporating these dynamic variables to model claims payments. In this sense, [24] presents an ML-based approach to estimating reserves using covariates associated with the policy and its holder and any information about the claim since its reporting date.

There are several contributions in the actuarial literature that mobilize tree-based ML algorithms, such as [25], who propose an approach using gradient boosting *via* decision trees. Their results are compared to traditional aggregated techniques such as GLM and Mack's model. This algorithm has the advantage of being efficient on structured data and gives fast calculations. Their contributions show that generalized linear models could be unstable in estimating loss reserves. On the other hand, [26] proposes an ML algorithm for individual reserving *via* regression trees. This approach considers the number of payments instead of the amount of paid claims. Regression trees are very flexible in incorporating information about personal characteristics. However, they could be more robust. Other techniques, such as random forests or ANNs, can overcome these problems. Furthermore, [27] developed a machine learning-based method called Extra Trees and explained how to construct specific subsets of data for training and evaluating machine learning algorithms. They also provide a comparison between the individual approach and the CL method.

An early use of ANNs goes back to [26], who developed a stochastic scenario generator, which trains a neural network to predict individual claims based on a portfolio of risks. [28] continues with a neural network to estimate future cash flows for each claim reported. Using exclusion layers, he adapted the neural network to incomplete time series of past individual claim payments. On the other hand, [29] presents a framework for forecasting individual claims using Bayesian mixture density networks. The proposed approach incorporates claims information from structured and unstructured data sources, produces multi-period cash flow forecasts, and generates different scenarios of future payment patterns.

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Tree-based algorithms for reserving purposes continue their proliferation. In 2019 [30] introduced an approach using the classification and regression trees (CART) algorithm, showing that individual claims reserving can be promising, especially in the context of long-term risks. On the other hand, [31] extend this algorithm to consider the data's truncation and introduce plug-in estimators. Their results show that complete knowledge of the claims cycle is crucial to predict individual reserves efficiently.

[32] propose a composite model, modeling frequency and severity models separately (to isolate factors that may affect claim frequencies but not severities) using the CART algorithm. The multi-period predictions required to estimate reserves are obtained by combining the one-period predictions through a simulation procedure. They then compared the result with the classical CL method.

It is possible to further improve the performance of ML algorithms through ensemble methods that combine multiple algorithms at once, boosting prediction performance over a single model, decreasing variance *via* Bagging, and reducing bias *via* Boosting. These ensemble methods allow the global system to rectify the error if one of the algorithms does not perform correctly. However, they are less interpretable than a single algorithm and can result in a black box model.

The Gradient Boosting algorithm [33] XGBoost, also known as the Extreme Gradient Boosting algorithm, has been widely used by several researchers in different fields. Its first use for individual claims reserving estimation can be traced back to [34].

Random Forest, as the XGBoost algorithm explained above, is a well-known decision tree ensemble algorithm in machine learning. This algorithm is widely used in the literature on individual claims reserving. Furthermore, [27] confirm that a Random Forest can replace the implemented Extra Trees and can thus be considered for the prediction of individual claims reserves, in the sense that it overcomes the problems inherent to the lack of robustness encountered with single regression trees.

4. Comparative analysis of reserving methods

Finally, it is necessary to conduct a comparative analysis of the different reserving methods. This approach consists of breaking down the functioning of each technique and highlighting the associated advantages and limitations. The results are presented in the table below.

Table 1 Comparative analysis of reserving methods

	Aggregated reserves	Individual reserves
Operating principal	▪ Aggregation of claims by year of occurrence and year of development, ▪ Use of loss development triangles, ▪ Calculation of age-to-age factors, ▪ Estimating the lower triangle, ▪ Calculation of ultimate burden and IBNR.	▪ Use real-time data *via* telematics, ▪ Incorporate personal characteristics of policyholders as well as claims information, ▪ Model individual events for each claim (opening, closing, reopening), the average cost, and frequency of occurrence of a claim, ▪ Estimate individual reserves in continuous time.

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Main methods	▪ Deterministic methods (CL, London Chain, Bornhuetter Ferguson), ▪ Stochastic methods (Mack, GLM, GAM, Bayesian models, Bootstrap), ▪ Machine Learning (Neural Networks, CART, Bagging, Random Forests, SVM).	▪ Machine Learning (Neural Networks, CART, Bagging, Random Forests, SVM).
Advantages	▪ Provides a simplified visualization of the evolution of the amount of claims. ▪ Deterministic methods are simple to implement and easy to understand, ▪ Stochastic methods provide an estimate of the level of reserve accuracy, ▪ ML algorithms provide accurate results with fast calculations.	▪ Provide real-time monitoring of the amount of individual claims, ▪ Provide a clearer view of the claims experience of each insured and detect the riskiest profiles, ▪ Do not require adjusting the data to a suitable distribution family, ▪ Make it possible to detect the importance of variables that may influence the frequency or claims severity, ▪ Model average claim frequencies and severities separately.
Limits	▪ Aggregation of data leads to a significant loss of information. ▪ Assumptions are not always valid in the real world, ▪ Stochastic methods are complex and challenging to apply.	▪ Requires a massive database (Big data), ▪ Implementation costs are too high (Telematics and connected objects), ▪ Some algorithms qualified as black boxes are difficult to interpret, such as (Random Forest, Bagging, Gradient boosting, and XGBoost).

Even though aggregated reserving offers advantages such as efficiency, as it analyzes data at a portfolio level, stability by smoothing out fluctuations, and statistical reliability through actuarial models. Nevertheless, this technique lacks granularity, may not be suitable for specialized policies, and may have late detection of emerging trends. On the other hand, Individual reserving offers advantages such as granularity, providing a precise estimation of reserves, a tailored approach to address claim complexities and early detection of high-cost claims or emerging trends. However, this technique can be time-consuming, subjective, and may overlook the overall portfolio risk.

Combining individual and aggregated reserving techniques can balance accuracy, efficiency, and portfolio management. Leveraging the strengths of each method through data analysis, actuarial judgment, and ongoing monitoring of claim experience. This approach will help insurers make informed decisions regarding reserve allocations while mitigating the limitations associated with each method.

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5. Conclusion

In conclusion, the issue of reserving non-life insurance has long been a subject of considerable interest among actuaries due to its critical significance. The actuarial literature has explored numerous approaches to estimate reserves in order to attain improved accuracy. Initially, deterministic methods, known for their simplicity of implementation and interpretation, were widely employed. However, these methods may exhibit shortcomings in accuracy as they need to adequately account for factors that could influence future losses, resulting in potential underestimation or overestimation of required reserves. Conversely, stochastic methods have addressed this limitation by offering a high degree of accuracy while considering the uncertainty and variability of future losses. Nonetheless, these techniques often necessitate complex mathematical models and entail substantial implementation and utilization costs.

Another class of reserve calculation methods encompasses machine learning algorithms. These methods present a compelling alternative due to their ability to handle vast amounts of data, computational efficiency, and estimation accuracy. Nonetheless, their implementation can pose challenges and may incur significant costs. It is noteworthy that all aforementioned methods rely on aggregated data, thereby confining the scope of actuaries to runoff triangles. The advent of telematics has revolutionized the potential of machine learning techniques by exploring novel approaches such as individual reserving and incorporating information pertaining to claims experience and individual policyholder characteristics. These individual methods hold promise in offering real-time, meticulous monitoring of potential losses.

It is essential to recognize that no single method of non-life reserving surpasses all others. The choice of method should consider various factors, including the desired level of accuracy, associated costs of implementation and utilization, and data availability. Selecting the most suitable method that aligns with the insurer's specific needs requires a careful evaluation of each method's advantages and disadvantages. Insurers can strike a harmonious balance between accuracy, efficiency, and portfolio management by integrating individual and aggregated reserving techniques. Actuaries can capitalize on the strengths of each method through diligent data analysis, informed actuarial judgment, and continuous monitoring of claim experience. This comprehensive strategy empowers insurers to make well-informed decisions concerning reserve allocations while mitigating the limitations associated with each method.

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References:

[1] E. Astesan, Les réserves techniques des sociétés d'assurances contre les accidents d'automobiles, Librairie générale de droit et de jurisprudence, 1938.

[2] M. Thomas, «Measuring the variability of chain ladder reserve estimates, Spring, Vol 1,» Casualty Actuarial Society E-Forum, pp. 101-182, 1993.

[3] M. Denuit et A. Charpentier, Mathématiques de l'assurance non-vie , Tome 1, Economica, 2004.

[4] P. England et R. Verrall, «A FLEXIBLE FRAMEWORK FOR STOCHASTIC CLAIMS,» casualty actuarial society, pp. 1-38, 2001.

[5] G. Quarg et T. Mack, «Munich Chain Ladder: A Reserving Method that Reduces the Gap between IBNR Projections Based on Paid Losses and IBNR Projections Based on Incurred Losses,» Blätter der Deutschen Gesellschaft für Versicherungs- und Finanzmathematik, vol. 26, n° %14, p. 597—630, 2004.

[6] M. Braun, «The Impact of Regret on the Demand for Insurance,» Journal of Risk and Insurance, pp. 737-767, 2004.

[7] C. Prohl, Schmidt et Klaus, «Multivariate Chain–Ladder,» pp. 1-14, 2005.

[8] B.Verdier et A. Klinger, «JAB Chain Long-tail claims development,» ASTIN, 2005.

[9] K. T. Hess, K. D. Schmidt et M. Zocher, «Multivariate loss prediction in the multivariate additive model,» Insurance: Mathematics and Economics, pp. 185-191, 2006.

[10] H. Liu et R. Verrall, «Bootstrap Estimation of the Predictive Distributions of Reserves Using Paid and Incurred Claims,» CASUALTY ACTUARIAL SOCIETY, VOLUME 4/ISSUE 2, pp. 121-135, 2008.

[11] M. Merz et M. Wüthrich, «Modelling The Claims Development Result,» Casualty Actuarial Society E-Forum, Fall 2008, pp. 542-568, 2008.

[12] Verdonck et Debruyne, «The influence of individual claims on the chain-ladder estimates: Analysis and diagnostic tool,» Insurance: Mathematics and Economics, pp. 85-98, 2011.

[13] R. Verrall et J. P. Nielsen, «Prediction of RBNS and IBNR claims using claim amounts and claim counts,» 10.2143/AST.40.2.2061139, 2010.

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[14] M. D. Martínez Miranda, B. Nielsen, J. P. Nielsen et R. Verrall, «Cash flow simulation for a model of outstanding liabilities based on claim amounts and claim numbers,» ASTIN Bulletin, pp. 107-129, 2011.

[15] T. Mack, «The standard error of Chain Ladder reserve estimates: recursive calculation and inclusion of a tail factor,» Astin Bulletin, p. 361–366, 1999.

[16] F. El kassimi et J. Zahi, «Health insurance pricing using CART decision trees algorithm,» International Journal of Computer Engineering and Data Science, Volume 2–Issue 3, pp. 5-9, 2022.

[17] F. El kassimi et J. Zahi, «Proposition d'un modèle de tarification en assurance maladie obligatoire à travers le Modèle Linéaire Généralisé,» Alternatives Managériales Economiques, Vol. 4, No 4, pp. 462-481, 2022.

[18] A. Renshaw et R. Verrall, «A Stochastic Model Underlying the Chain-Ladder Technique,» British Actuarial Journal, vol. 4, issue 4, , pp. 903-923, 1998.

[19] T. Mack, «Distribution-free Calculation of the Standard Error of Chain Ladder Reserve Estimates,» ASTIN Bulletin, 23, pp. 213 - 225, 1993.

[20] J. Zhou et J. Garrido, «A loss reserving method based on generalized linear models,» Society of Actuaries, 2009.

[21] G. A. Spedicato, G. P. C. ACAS et S. Florian, «The Use of GAMLSS in Assessing the Distribution of Unpaid Claims Reserves.,» Arlington: Casualty Actuarial Society E-Forum, vol. 2., pp. 1-15, 2014.

[22] H. Lopes, j. Barcellos, J. Kubrusly et C. Fernandes, «A non-parametric method for incurred but not reported claim reserve estimation,» International Journal for Uncertainty Quantification Volume 2, Issue 1, pp. 39-51, 2012.

[23] P. Mulquiney, «Artificial Neural Networks in Insurance Loss Reserving,» JCIS, 2006.

[24] M. Wuthrich, «Machine Learning in Individual Claims Reserving,» Swiss Finance Institute Research Paper, pp. 16-67, 2016.

[25] M. Pigeon et F. Duval, «Individual Loss Reserving Using a Gradient Boosting-Based Approach,» Risks, 2019.

[26] M. Wuthrich, «Machine learning in individual claims reserving,» SCANDINAVIAN ACTUARIAL JOURNAL, p. 465–480, 2018.

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[27] M. Baudry et C. Robert, «A machine learning approach for individual claims reserving in insurance,» WILEY, pp. 1-29, 2019.

[28] A. Gabrielli, «A NEURAL NETWORK BOOSTED DOUBLE OVERDISPERSED POISSON CLAIMS RESERVING MODEL,» Cambridge University Press, pp. 25-60, 2019.

[29] K. Kevin, «Individual claims forecasting with Bayesian mixture density networks,» Kasa AI, 2020.

[30] O. Lopez, X. Milhaud et P. Thérond, « A TREE-BASED ALGORITHM ADAPTED TO MICROLEVEL RESERVING AND LONG DEVELOPMENT CLAIMS,» ASTIN Bulletin, pp. 741-762, 2019.

[31] O. Lopez et X. Milhaud, «Individual reserving and nonparametric estimation of claim amounts subject to large reporting delays,» Scandinavian Actuarial Journal, pp. 34-53, 2020.

[32] M. De Felice et F. Moriconi, «Claim Watching and Individual Claims Reserving Using Classification and Regression Trees,» Risks , pp. 1-36, 2019.

[33] Friedman, Jerome, H. Trevor et R. Tibshirani., «The Elements of Statistical Learning,» Springer Series in Statistics, vol. 1., 2001.

[34] F. Duval et M. Pigeon, «Individual loss reserving using a gradient boosting-based approach.,» Risks, 7(3),, 2019.

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