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Machine Learning in the actuarial cycle: making the most out of your data

Historically, insurers have a lot of data available. However, monetising the value of this data is still found to be hard in practice. Moreover, smooth data processing is required to digitise and automate the value chain. While there are numerous use cases of successful isolated implementations of Machine Learning applications (e.g. digital sales and policy issuing or automated claim handling), a holistic approach often lacks and more often than not insurers encounter issues at the back-office. In this article we give our view on capturing the value of the data by transforming the actuarial modelling landscape and by making use of new concepts and techniques to connect the dots bottom-up. We introduce the concept of Not Incurred, Not Reported (NINR) reserve to link the models in the cycle and present three use cases to illustrate the added value of machine learning in our framework.

INTRODUCTION

We define the actuarial cycle as the link of the central actuarial activities of insurance: pricing, reserving and risk & capital management. These activities surround the core of the insurer's business (see figure 1). In practice little communication exists between the models that are used in each of the individual elements. Models too often make use of different data sources, granularity, modelling techniques and frequency of updating. Therefore their output is difficult to align and to compare. This results in sub-optimal pricing, inaccurate reserving, and imperfect risk quantification. All these lead to ineffective steering of the business.

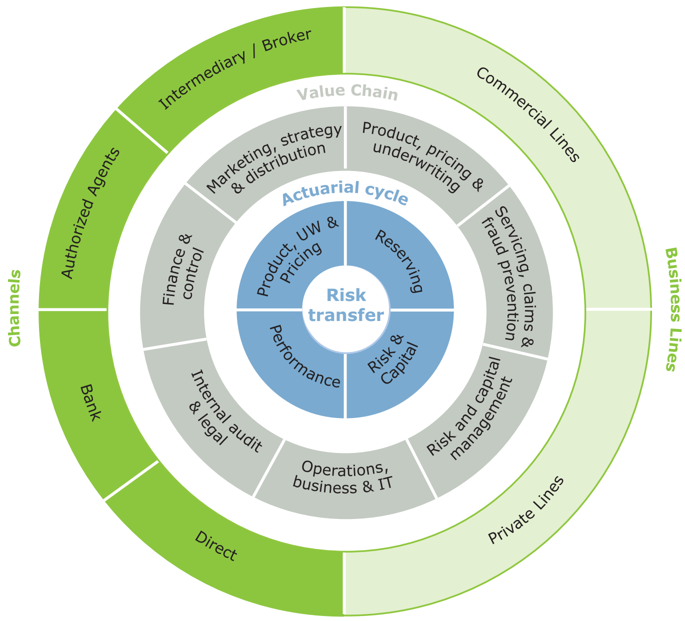

Figure 1: The insurer's context, with the actuarial cycle at the core of the insurance business

Artificial Intelligence (AI) offers great potential for the actuarial field in this respect. It can be used to add, align and boost modelling techniques to get the most out of your data.

This article emphasises the use of AI, more specifically Machine Learning, within the actuarial cycle. We will explain why the time is now to extend the use of Machine Learning models. To do so, we provide a number of success stories where we have applied these models throughout the cycle and explain what benefits this can bring to the insurer and policyholder.

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WHY NOW?

Machine Learning models are often praised for their predictive power compared to traditional models. The idea is that they are trained on a dataset and learn to recognise complex non-linear relationships that are difficult to recognise with traditional models. In addition, there are nowadays numerous of user-friendly machine learning apps (e.g. TensorFlow, Keras) and programme libraries (Sklearn) that significantly ease the training and deployment of Machine Learning models, which gives room to educate talent and increase the company's capabilities.

In practice, Machine Learning models are generally still perceived as black boxes: it is hard to gain insight into the decision-making process and see why the model makes a certain prediction. Consequently, these models often pose a trade-off between accuracy and transparency, which have made the insurance industry hesitant to implement such techniques.

In recent years the academic world has put great attention to making these models transparent. A range of new techniques and tools have been created that provide valuable insights into the decision-making process of Machine Learning models. It is possible to unbox the black-box and see which variables are listed by the model as having the greatest predictive power, how these variables impact the prediction, and what interactions between variables are spotted by the model.

Attention is also put into spotting and creating fairness in your model. You do not want your model to discriminate on illegal or sensitive attributes such as gender. Fairness of the model can be spotted with metrics that, for example, are originally used to calculate the degree of inequality in an economy; or that are based on anti-discrimination laws that prohibit unfair treatment of people.

Transparency and fairness help data scientists to unbox the black box and affect the trade-off between accuracy and transparency in favour of Machine Learning.

Use Case 1: Machine Learning in Pricing

In the first selected case study we applied machine learning in pricing to predict the frequency of claims in a motor portfolio. Two techniques have been applied, Random Forest and the Neural Network. We compared the Machine Learning models with the "traditional" GLM in terms of predictive power, interpretability and easiness to build. Building a GLM that is able to adequately predict frequency, requires strong insurance expertise. For instance, variables and interaction terms (e.g. age*gender) to include in the model chosen manually. Therefore, senior pricing specialists are often assigned to build the GLM.

Alternatively we approached the development of the Machine Learning models primarily from a data science perspective. We let the Machine Learning models find complex relationships in the data to show us which (combination of) variables were most predictive. In just a matter of weeks, we were able to create a Machine Learning model that not only matched the success of the traditional GLM, but also provides novel and useful insights into the data that can also be incorporated back into the traditional models. Variables and interaction terms that have high predictive power in the Machine Learning models were incorporated in the GLM. Machine Learning was furthermore used to optimize the binning of variables (e.g. the binning of car brands into top, middle and low segments) which is normally done manually.

Use Case 2: Machine Learning in Reserving

In a reserving use case we used a Gradient Boosting Machine Learning technique (XGBoost) for our prediction of expected claims for unexpired risk per individual policy in each month. We define this reserve as the NINR – Not Incurred, Not Reported claims, which is comparable to the claims estimate within the best estimate premium provision. Our study showed that our methodology is better at capturing seasonal patterns in claims and gave a better fit for different subsets of the portfolio than the usual premium provision claims estimation at the aggregated portfolio level.

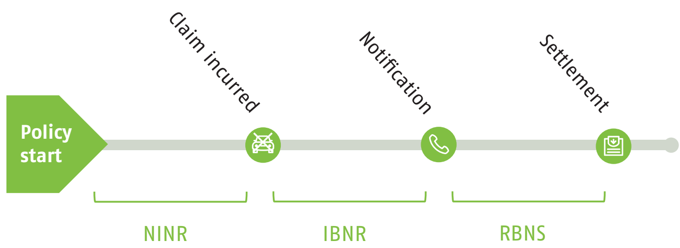

Figure 2: Claim stages and the relation between NINR, IBNR and RBNS.

We found that the introduction of the NINR at policy level gives more accurate and less volatile premium reserves and Machine Learning models are fit for use. Furthermore, the NINR is based on the real risk premium as defined in the pricing and thus also aligned with the latest portfolio developments. Considering the transition rate from forecasted claims (NINR) for each month to reported and incurred claim reserves (RBNS and IBNR) allows us to conceptualise an integrated pricing and reserving framework that integrates the information in the actuarial cycle.

The complex interactions that we can model using Machine Learning algorithms can be visualised in interactive dashboards. In turn these can steer an insurance company's focus on different markets and offer insight into the main sources of underlying risk. Changing risks due to portfolio developments are captured in the earliest stage, making the insurer agile and able to react swiftly.

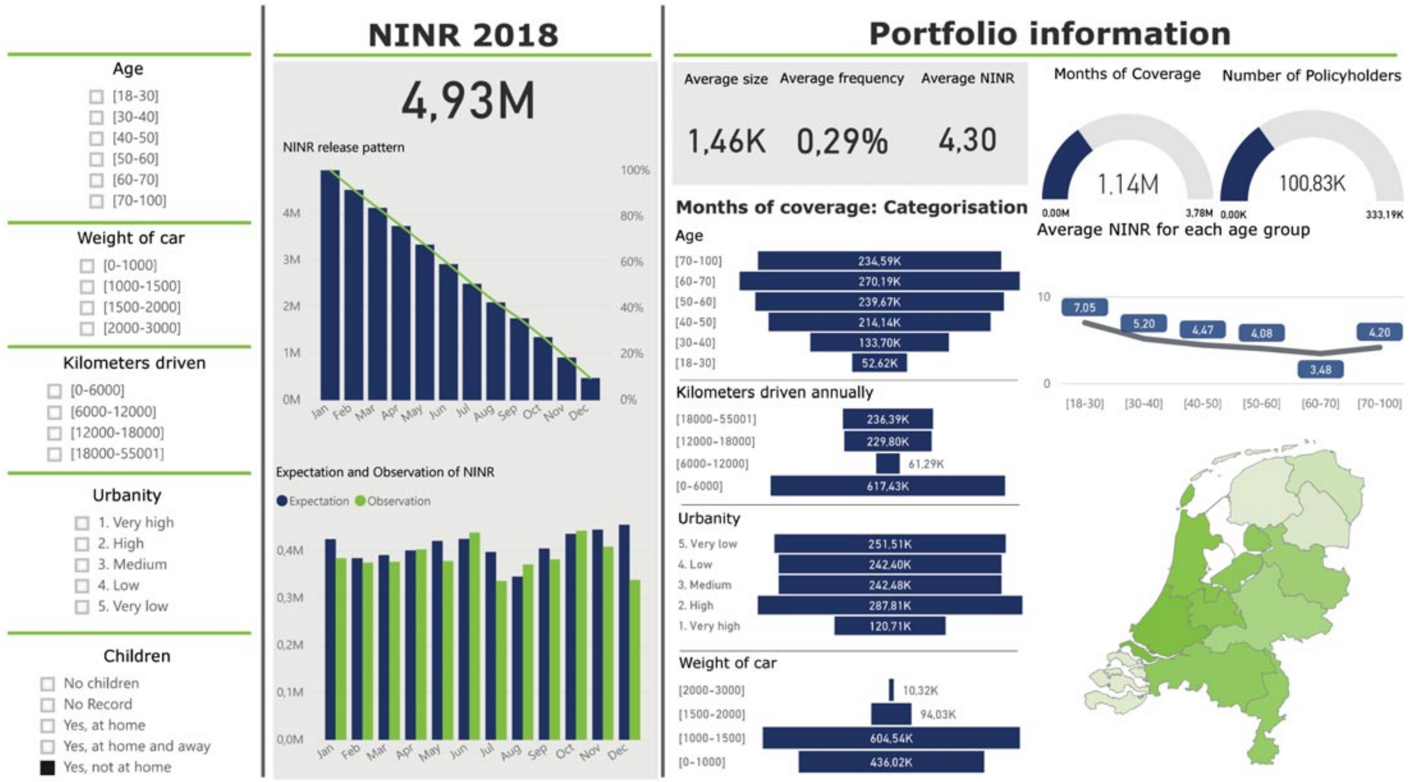

Figure 3: Example of a claims development Dashboard

Use Case 3: Machine Learning in Risk Management

A great application in Risk modelling is found in the article on the use of Neural Networks in SCR calculation (Frerix et al.) in this edition of "De Actuaris". Additionally, in a use case we created a "hybrid" large claim model that uses both Machine Learning and extreme value theory. Our model has so far proven to identify large claims in early stages with an accuracy of over 80%.

We used Machine Learning to cluster claims according to their specifications and policyholder and claim information to identify the probability of a policy having a large claim or the probability of a claim becoming large. In addition, we used Extreme Value theory to estimate the claim severity distribution under the condition that it becomes a large claim. The model helps our clients to account upfront for the effect of smaller claims becoming large over time. Thereby reducing "unexpected" developments and with that also reducing the volatility in P&L. The model can help insurers throughout the value chain, in underwriting (e.g. improved pricing, enhanced acceptance) and claim and risk management (e.g. lowering capital needs, triage of claims and reserving).

A BRIGHT FUTURE

In this article we presented a framework that connects the actuarial cycle by modelling all claim stages on policy level and where data is used more effectively. Machine Learning broadens the palette of techniques and is not always the black-box it used to be anymore, as new techniques have blurred the trade-off between accuracy and transparency. Our use cases show that Machine Learning can be used to give better input in more traditional methods (e.g. GLM models in pricing), as stand-alone model (e.g. to estimate the NINR reserves) or in combination with other techniques (e.g. for large claim modelling). With this small set of use cases we already show the wealth of opportunities for actuaries to use Machine Learning techniques to add value across the whole actuarial cycle to create a bright future for this work field. ■