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Efficient SCR Estimation Using Machine Learning Algorithms

Machine Learning algorithms are rapidly taking over the predictive modelling field. The flexibility of these state-of-the-art algorithms might turn out to solve one of the toughest problems in Solvency Capital Requirement ('SCR') estimation: accurately approximating the non-linear effects of complex options and guarantees on the market value of liabilities. This article investigates the application of Artificial Neural Networks ('ANN') as an alternative for polynomial based curve-fitting. The accuracy of the SCR calculation is significantly improved upon with Neural Networks, even when using a dataset as small as 10 data points.

INTRODUCTION

Solvency II requires insurers to calculate the SCR. In an internal model setting, calculating the SCR requires many simulations, i.e. stochastic revaluations of the entire balance sheet, which are very time consuming. Reducing the amount of simulations can be achieved through the application of a proxy model. Part of the complexity in calculating the SCR in a proxy model arises from the complex non-linear relations between movements in risk factors (e.g. credit spread risk) and corresponding movements in the market value of liabilities. Traditional approximation methods lack the flexibility to capture the non-linear effects of changes in risk factors on the market value of certain liability portfolios. This might lead to the capital requirements being under- or overestimated.

In practice, a number of different approaches to estimate the SCR are used. A polynomial based curve-fitting approach is the most commonly applied technique. This research focuses on the application of ANNs as an alternative for this polynomial based approach. An advantage of ANNs over polynomials is that they are theoretically able to capture any relationship that is in the data. The challenge is to make the ANN provide accurate and stable predictions on a small dataset, as these models typically have a large number of parameters.

To determine whether Neural Networks are an improvement over polynomials, the market risk SCR of a synthetic balance sheet is estimated. In particular, the non-linear relationship between changes in the volatility adjustment and the market value of liabilities is examined. The asset side of this balance sheet consists of bonds with various ratings and durations. The liabilities of this balance sheet are represented by (simple) deterministic future pension payments. This balance sheet is sensitive to credit spread risk (corporate financial, non-financial and sovereign) and interest rate risk.

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TRADITIONAL APPROACH FOR ESTIMATING THE SCR IN AN INTERNAL MODEL

Ideally, insurers perform a full stochastic simulation to determine the change in market values of assets and liabilities under e.g. 100,000 real-world economic scenarios. Due to the existence of complicated payoff structures of insurance liabilities, for each real-world scenario a full stochastic risk-neutral balance sheet revaluation would have to be performed. Executing such a full stochastic nested Monte Carlo scheme is computationally infeasible in practice.

To overcome the computational burden of a nested simulation, insurers usually apply an approximation approach. This requires selecting a small number of real-world scenarios (e.g. 5 – 15) for each risk factor. For the selected scenarios, the market value of liabilities is estimated by means of a full stochastic simulation. The change in the risk factor value versus the change in the market value of the corresponding liability portfolio represents a 'fitting point'. To be able to estimate the change in the market value of the liability portfolio for each possible real-world scenario, a polynomial regression is estimated on these fitting points to represent the relationship between the changes in risk factors and the market value of liabilities. This is illustratively shown in Figure 1.

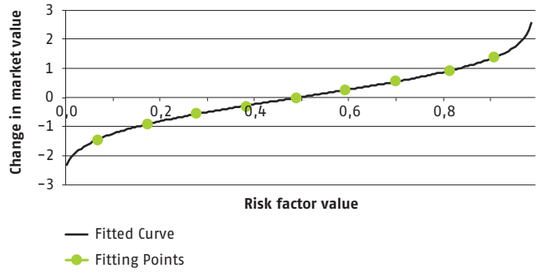

Figure 1: Illustration of a proxy modelling technique

APPLICATION OF MACHINE LEARNING TECHNIQUES

An alternative to polynomial regression techniques is the use of ANNs. An ANN is a mathematical structure inspired by the biological neural network of the brain. ANNs consist of a number of layers. Each of these layers consists of nodes, which output a linear combination of the previous layers. ANNs may have an arbitrary number of layers, each with an arbitrary number of nodes. Their potential large size give ANNs the universal approximation property, which means that they are theoretically able to capture any relation between changes in risk factors and the market value of liabilities. However, this flexibility also makes Neural Networks prone to overfitting.

Due to their possibly large number of layers and nodes, Neural Networks can consist of many parameters. This possibly large number of parameters causes the majority of applications to be in the big data domain. In the setting of calculating the SCR in an internal model, the main challenge is fitting the Neural Network on a small number of fitting points. With this data restriction in mind, networks up until three layers of three nodes each were tested. This approach results in relatively simple Neural Networks with a limited number of parameters, which reduces the risk of overfitting. The estimate for the market value of liabilities is calculated based on an average of the best 800 Networks out of a grand total of 1,000. This 'best 800' number is chosen based on 20 times the generation of 1,000 networks. In those 20 runs, the top 800 networks showed stable and accurate predictions.

RESULTS

To compare the performance of the polynomial proxy model with the Neural Network proxy model, the market risk SCR is calculated based on a full nested stochastic simulation using the synthetic balance sheet described in the introduction. Table 1 shows that ANNs significantly improve the accuracy of the SCR compared to a polynomial based approach. Whereas the polynomial approach underestimates the SCR by EUR 274 million (46%), the SCR based on the ANN differs by only EUR 4 million (< 1%).

SCR estimation Method	SCR	Error
Full stochastic	595 M	–
Polynomial	321 M	274 M
ANN	599 M	4 M

Table 1: Results of SCR estimation based on a Neural Network and polynomial based curve-fitting approach.

The improvement in SCR estimation can be ascribed to the more accurate representation of changes in the volatility adjustment (through changes in credit spreads) and the corresponding changes in the market value of liabilities. This improvement is depicted in Figure 2.

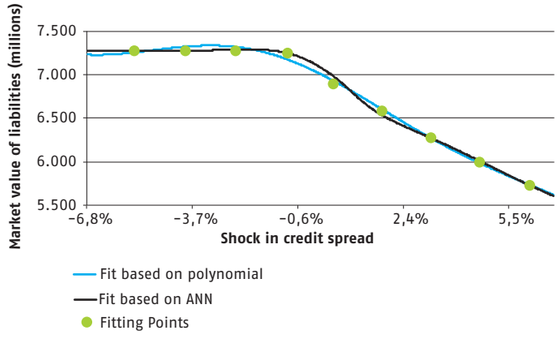

Figure 2: Comparison of a regression based on a polynomial approach versus an ANN for changes in credit spreads versus changes in the corresponding liability market value.

APPLICABILITY IN PRACTICE

The results of this article show that the use of Machine Learning techniques and in particular Neural Networks offer the potential to further improve the accuracy of SCR calculations. The complex relationship between the volatility adjustment and the market value of liabilities is better explained with a Neural Network than with a polynomial curve fitting approach. Similarly, the Neural Network approach described in this article could also be applied to complex liabilities such as separated accounts, variable annuities and products with path-dependent payoffs.

Although performance based on Neural Networks outperform traditional techniques, they are not (yet) applied in practice. In its vision document on supervision for 2018-2022[1] the DNB indicates that they want to give room to the opportunities provided by technological improvements. To apply techniques such as Neural Networks in practice, the inherent risks of such models need to be well understood by both the insurance industry as well as the regulator. To do so, the traditional skill set of employees needs to be enriched with knowledge of data science and corresponding models. ■

1 – "Visie op Toezicht 2018 – 2022", DNB