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Calculating Capital Requirements and Optimizing Asset Allocation with Deep Neural Networks

DEEP LEARNING FOR INTERNAL MODELS

The developments in AI tools and the increasing awareness of their effectiveness over the last decade, invite the challenge to improve current mathematical tools to calculate capital requirements of insurance companies.

Machine Learning (ML) and Deep Learning (DL) methods have the potential to improve the accuracy and efficiency of Internal Models for calculating, among other metrics, the Solvency Capital Requirement (SCR) for insurance companies. These methods can be used to better reflect the complex and often non-linear relationships between different risk factors and to identify patterns and trends in the data that may not be apparent through traditional modeling approaches.

In this research, a DL proxy model is developed that challenges the industry standard proxy model: Least-Squares Monte Carlo (LSMC). The aim is to either outperform the benchmark LSMC proxy in terms of accuracy and/or computational performance of the calculation of Own Funds (OF) and other Solvency II (SII) metrics (SCR, SII Ratio, Operating Capital (OC)). In terms of accuracy of calculating these metrics, together with the computational performance, this DL proxy model shows promising results.

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DL INTERNAL MODEL

SII requires insurers to hold capital necessary to stay solvent in 99.5% of considered scenarios over a one year horizon. The projection of scenarios is often done with a stochastic cashflow model and Monte-Carlo simulations. To derive the probability distribution of the OF accurately, the use of fully nested Monte-Carlo simulations becomes computationally infeasible (e.g. 300M simulations).

To address this, techniques to derive this distribution with a smaller and carefully chosen subset of scenarios have been developed. These techniques include curve-fitting, replicating portfolios and proxy function fitting. Proxy functions obtained through least squares regression have shown to get accurate results and take a fraction of the time. One study showed that for 320k scenarios, the full nested approach took 16 minutes while a LSMC approach took only 25 seconds (Bauer, Bergmann, & Reuss, 2010).

In this research, a DL model (see Figure 1) is used as a new type of proxy for an Internal Model. A fully connected feedforward neural network is used with six hidden layers and exponential linear unit (ELU) activation functions. To test this DL proxy function, a synthetic balance sheet is created representing an average life insurer. A cashflow model (CFM) calculates the projected OF as a function of the risk drivers. Fitting scenarios are generated and the corresponding OF is calculated with the CFM. Different versions of the model are created with a varying amount of noise on the fitting data, to simulate the effect of inaccurate inner scenarios. The fitting scenarios are used to train a DL proxy or the benchmark LSMC proxy (similar to (Krah, Nikolic, & Korn, 2018)). The proxy model is then used to obtain the OF-distribution over a 1-year time horizon under 300k real-world scenarios to calculate the SII metrics.

Additionally, Strategic Asset Allocation (SAA) parameters are added to the model to find optimal asset strategies. Adding these parameters will make an optimization procedure possible after fitting of the proxy function.

RESULTS – SII METRICS ACCURACY

The accuracy of the proxy models on real-world data is tested on a range of SAA parameter configurations. For the OF mean absolute error (MAE), the DL proxy model outperforms the LSMC proxy model only for the version without noise, performs equal with low noise, and underperforms for the models with medium to high noise (see Table 1). Overall, the accuracy of the OF and SCR of both the LSMC and DL proxy models is within 2% of the total initial asset value (100M). The results show that the DL proxy has a harder time to fit out-of-distribution (Gaussian) data than the LSMC proxy, likely caused by overfitting on the noisy data. Fitting the DL proxy models took fifteen minutes while the LSMC proxies took about one hour.

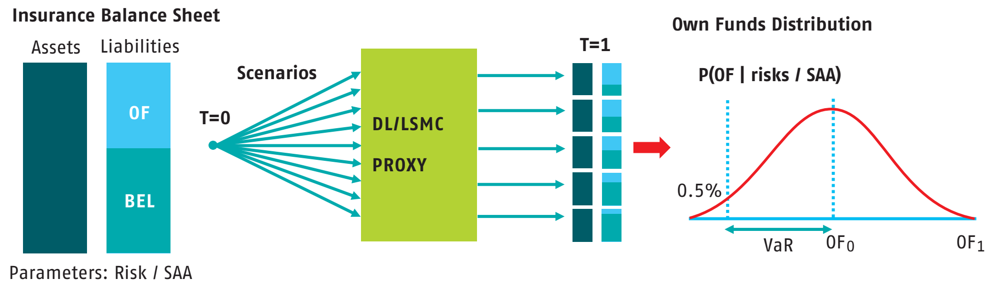

Figure 1. Process overview of deep learning Internal Model. The initial simplified balance sheet at T=0 is projected to T=1 with the scenarios and the proxy model. Then the OF distribution is derived from these projections.

Version	Proxy	OF MAE	SCR MAE	OC MAE	SII Ratio MAE (%)
V1 (no noise)	DL	0.35	0.41	0.61	5
	LSMC	0.72	0.71	1.03	9
V2 (low noise: 2%)	DL	0.58	0.69	0.80	9
	LSMC	0.72	0.67	1.00	9
V3 (medium noise: 5%)	DL	0.85	1.37	1.70	17
	LSMC	0.76	0.72	1.11	10
V4 (high noise: 10%)	DL	1.53	1.33	1.58	17
	LSMC	1.31	1.17	1.61	15

Table 1. OF and SII metric accuracy results on real-world scenarios of all proxy models. Green indicates the most accurate proxy type (MAE in millions).

SAA OPTIMIZATION

Additionally, an SAA optimization of the OC is performed with the DL proxy. A particle swarm optimization (PSO) is performed for the optimization of all five SAA parameters to maximize the OC. In Figure 2, an example is given of how two asset parameters can be optimized to improve certain SII metrics.

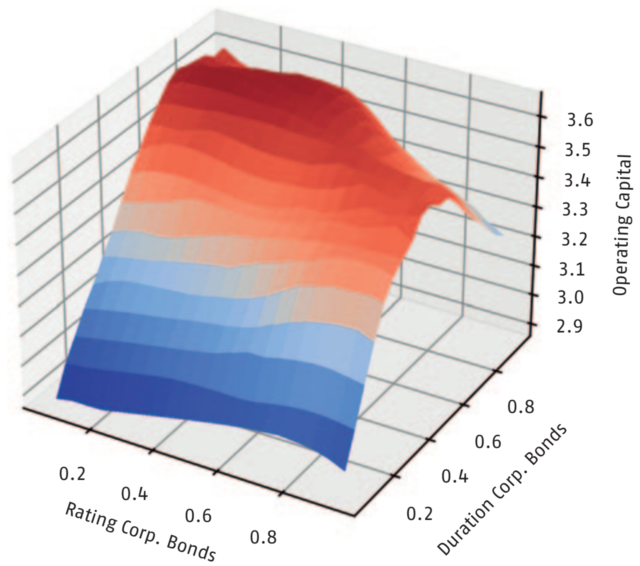

Figure 2. Example of how OC varies as a function of SAA parameters.

CONCLUSION AND OUTLOOK

The DL proxy shows improved or at least comparable results for a large range of settings, conceptually proves that a DL proxy could be used in the industry to obtain accurate results. There are still many improvements to be made to the set-up of the DL proxy. A hyperparameter grid search could potentially lead to further improved results. Next to that, other regularization techniques can be added in case of noisy data, and different architectures tested.

Further research is needed to fully understand the potential and limitations of ML/DL methods in the insurance industry. The focus for the foreseeable future of these methods will likely be application for internal uses only. It can be used to give insights into the financial risks of the company given different scenarios, to forecast the results of different asset strategies and for estimating the SCR. ML/DL methods can be seen as too 'black box', especially for reporting purposes, due to the lack of a clear formula describing the fitted function which limits the interpretability. ■

Bibliography

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