Smart migration

rethinking insurance

msg life

Smart migration

Modernisation often involves a semi-manual migration of large policy portfolios and complex actuarial functions. This is expensive and laborious. Artificial intelligence promises a way out. Its use increases efficiency in the migration process and helps life insurers tackle long-overdue projects at lower costs and in a shorter time frames. Actuarial functions are transferred automatically and linked to a modern policy management system.

By Axel Helmert and Volker Dietz*

The biggest things that drive expenses when migrating life insurance portfolios are products and data migration, accounting for around 65 per cent of the costs. The traditional method of transferring tariffs to a new target system means an immense effort for actuaries and developers. It includes the analysis of (old) tariffs, some of which are documented in paper-bound documents and have to be researched in one or more legacy systems. If no suitable functionalities are available in the target system, this has to be expanded manually. This step is also complex and unwanted – it increases the complexity of the target system or leads to discrepancies between the source and the target system. In this situation, the use of AI offers an automated solution for a large number of calculations.

AI-BASED MIGRATIONS

Until now, AI applications in the insurance industry have been focused on areas of work such as customer communication outside of the core actuarial fields – to see them used in the live actuarial computation module is something completely new. Policy migrations are often an excellent time to use AI-based methods. Contracts (data) and knowledge (functions) which define the behaviour of the contracts in the future are transferred from an (old) source system to a (modern) target system. The source system can normally generate enough training material – an ideal field of application for supervised learning. A laborious analysis of the knowledge incorporated in the old system becomes unnecessary and can be replaced by machine learning.

As part of the migration projects that have been carried out in recent years, we have developed numerous approaches to automation and optimisation. These are also being used and have brought gradual progress. However, the essential and expensive step of learning the source system's algorithms and mapping them in the target system has so far only been able to be accomplished by (human) intelligence.

It takes profound industry-specific know-how and extensive AI expertise to put AI-based methods into practice. Deep neural networks (DNNs) play a key role in this regard. Since the 1990s, there has been theoretical evidence that neural networks with only one inner layer are universal function approximators capable of approximating many mathematical functions with a given accuracy. In 2017, it was demonstrated that this is theoretically possible thanks to deep neural networks with many inner layers and significantly less computational effort. This enables practicable approaches to approximate mathematical functions – including those from actuarial mathematics – with very high accuracy using DNNs. At msg life, DNN architectures and training methods which are able to map actuarial functions with a high level of precision have been developed as part of preliminary studies over the past two years. The theoretical feasibility of the method and of its automatability have been proven.

* English translation of the article "Intelligent migrieren" published in Versicherungswirtschaft edition 02-2021.

MACHINE LEARNING WITH SPECIFIED MEASURABLE QUALITY, RELIABILITY AND EFFICIENCY

The highly accurate mapping of mathematical functions for operational use in computing cores places high demands on the architecture and training of neural networks in terms of quality, reliability and efficiency. In order to comply with actuarial and regulatory requirements for the quality of the DNN, the DNN has to generate an output with the same input that deviates only by a predefined (small) value from the results of the learned function of the source system. The quality should be at least as good as that of comparable conventional projects. The advantage of our field of application lies in the good training possibilities, as sufficient training material (including output) can be generated with the source system.

Another important requirement is reliability. Life insurance policies have a long term and are subject to change. The DNNs should be able to reliably calculate the learned functions for all possible future inputs with the desired quality, that is, also for inputs that have not been explicitly trained. And last but not least, the efficiency of the solution approaches is of great importance in order to save time and effort compared to the conventional approach. The approaches have to be reusable or be able to optimise themselves automatically using AI (metalearning). Network training will be carried out with reasonable resources in terms of time and computing capacity. In addition, the resulting network architecture must not have an overly complex structure. Runtime behaviour and storage requirements in the operative application are also relevant. In addition to these requirements, the question of how explainable and comprehensible the results are also plays a major role. If the results are called into question, for example, in the context of a complaint by a policyholder, it has to be possible to present the method of calculation in an understandable manner.

THREE-STAGE PROCESS FOR IMPLEMENTATION

We have been working on a prototype since the beginning of 2019 to demonstrate feasibility while complying with quality standards and achieving essential savings. A highly automated three-stage procedure was developed that learns selected actuarial functions – with sufficient quality – from a source system that is being replaced (Level 1: learning). The process then transfers the things it has learned to a target system (stage 2: transferring). Finally, it establishes communication with the target system (stage 3: linking). Relevant are functions that are complex, poorly documented or are not present in the target system and are time-consuming to analyse, implement and test. This is where we expect the greatest economic benefit. The result must be comprehensible

STEP 1: Selection of functions to be learned

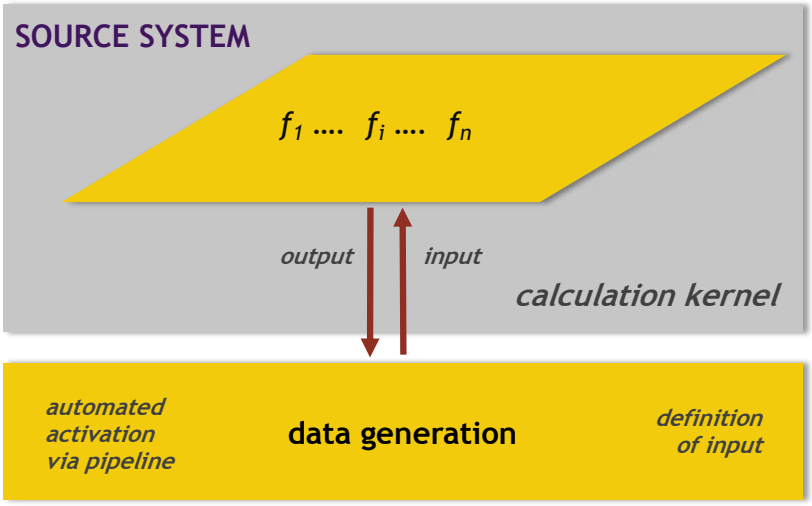

Image 1:
Selected functions to be learned (step 1).

STEP 2: Active learning - design and quality of DNNs

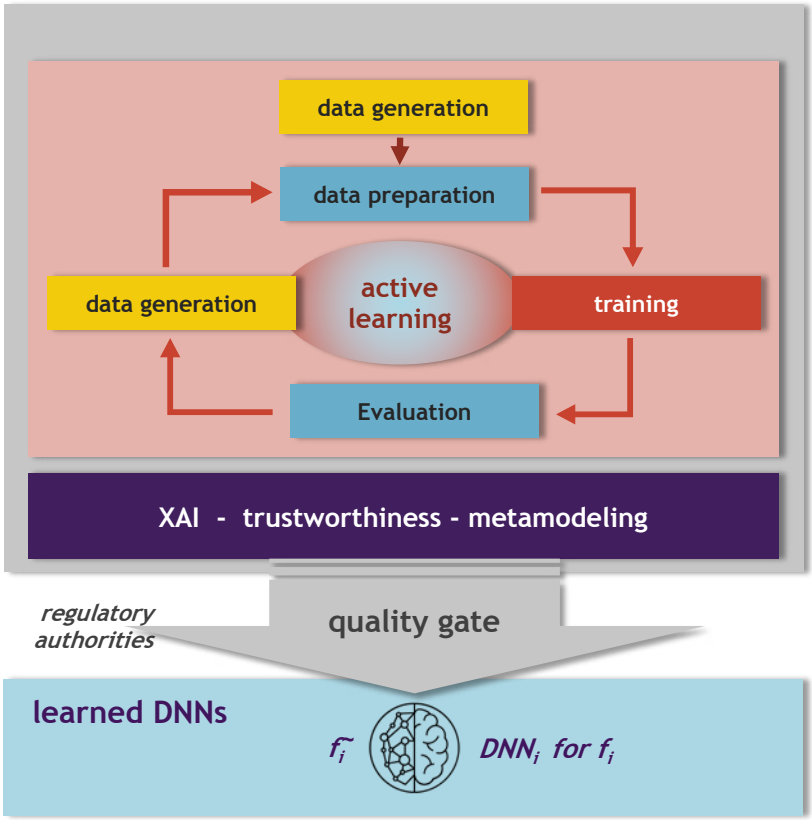

Image 2:
Active learning – design and quality of DNNs (step 2).

and explainable to the user. The process is implemented via an automated pipeline. It includes tests of stability, security and performance at all the points required for this specialisation, ensuring seamless operations.

Level 1 involves machine learning methods, such as training deep neural networks (DNNs). The pipeline supplies data, launches the training and monitors the results. If the quality is insufficient, it generates more training data and restarts the training. This is called active learning. The architecture of the DNNs and the parameters for the training process are determined fully automatically using advanced automated machine learning (AutoML) techniques. If the DNNs have successfully passed the quality gate, the pipeline supplies a ready-to-run piece of software that approximates the learned function with sufficient quality. During stage 2, a matching technical representation of the DNN is automatically transferred to the target system's model memory. In stage 3, the DNNs are linked with business operations in the correct manner for this technical situation by supplying product-based contextual information. The technical representation in the target system is mainly provided in the form of a Java API.

The black-box nature means that humans cannot comprehend the representation of the actuarial functions through DNNs in a machine-learned form. An additional step at the end of the pipeline provides the required explainability. Metamodelling approaches can transform black-box models into understandable function descriptions. They are saved in the model memory along with the DNNs. Alternatively, another approach for a solution is to document the learned function by using resources from the source system.

STEP 3: Deploy of DNNs in target system

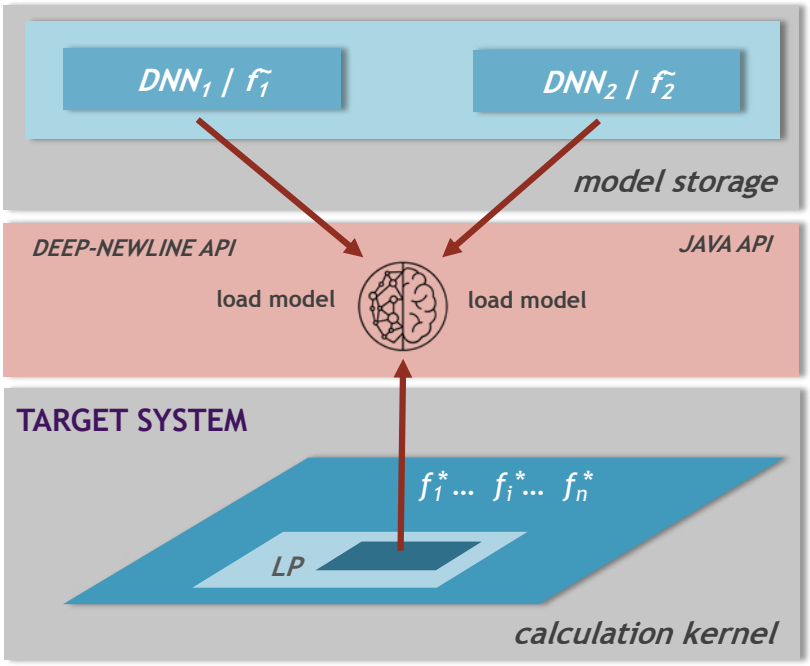

Image 3:
Allocation of DNNs in the target system (step 3).

The new technology is already being integrated into the policy administration system msg.Life.Factory as a separate component. This makes it possible for our customers to use it as soon as the necessary quality has been achieved. The impact of use can also be examined and evaluated from the outset in a complete portfolio administration system. It is important that the DNNs should not replace the entire computing core. The idea is a cooperation between conventional computing cores and DNNs. It makes sense and is possible to proceed successively. We only use the new technology where we are successful from a professional, regulatory and technical point of view and where the business case pays off.

REDUCING COSTS PER POLICY

Important and so far expensive stages of migrations can be automated with our solution. This saves time and money with regard to analysis and implementation. Automation makes it easier to work in parallel, which shortens the timeline and reduces overhead costs. Combined with other optimisation measures that are currently being analysed, this results in a reduction of costs of up to 25 per cent and shortens the duration of the project by up to a third, depending on the scope and type of the migration project. This makes necessary IT modernisation projects in the life insurance industry economically viable. A modern IT platform also leads to a lasting reduction in costs per policy and increased operational efficiency. At the same time, it enables new digital business models such as self-services or participation in ecosystems, thus ensuring the competitiveness of life insurers overall. The system has already provided proof of its performance internally. In addition, a major European insurer providing real data for research and development work is already examining how the prototype can be used productively in selected situations.

However, it is also clear that this is a revolutionary technology for life insurance and that a lot of work still needs to be done before it can be widely used in the insurance world. In particular, a great deal of persuasiveness will be necessary for many different stakeholders. During this time, work on the technology will continue to be intensified and the acceptance of the results increased. Finally, we would like to point out that the approach also has great potential for application in other insurance sectors and even in other industries. Securing acquired knowledge and combining it efficiently with new knowledge is an age-old problem – and not just in IT.

Axel Helmert,
Managing Director of msg life Central Europe GmbH,

and Volker Dietz, head of the msg life AI Team
Central Europe GmbH

rethinking insurance

msg life ag | Humboldtstraße 35
70771 Leinfelden-Echterdingen, Germany
Phone: +49 711 94958-0
Email: contact@msg-life.com
www.msg-life.com