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Efficient and Reliable Solvency II Loss Estimates With Deep Neural Networks

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About the speaker

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Zoran NIKOLIĆ

Partner

Deloitte Germany

Zoran is partner in the Actuarial Insurance department of Deloitte German office.

During his 13 years' experience, Zoran has got a solid background : on modelling insurance (Life and P&C), economics generator scenario, solvency 2, accountings projects and machine-learning.

Zoran is head of the marketing development on machine learning application and industrialization for the insurance company.

Ning LIN

Senior manager

Deloitte France

Ning is senior manager in the Actuarial Insurance department of Deloitte Paris office.

During his 9 years' experience, Ning has built up a solid modelling background on insurance (Life and P&C) and finance. Ning has also worked a lot around financial performances : reporting, business plan, optimization of French Gap result and Solvency 2 ratio.

Context – Solvency II and Internal Model

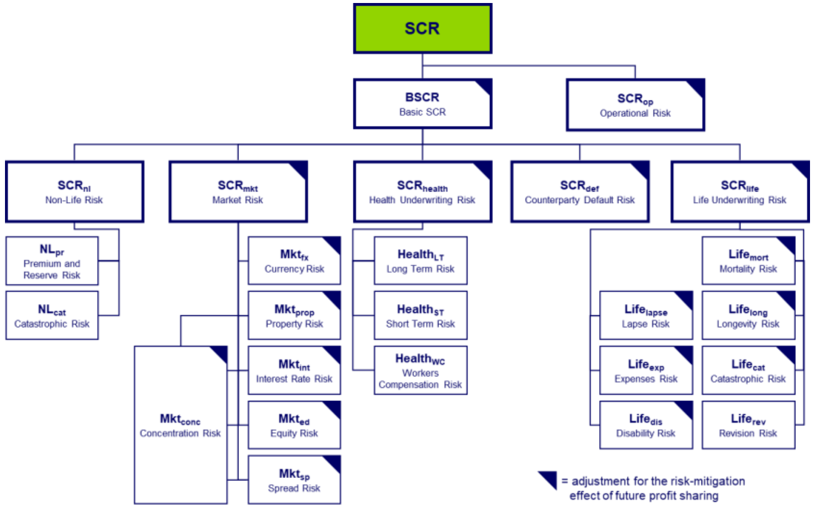
Solvency II and SCR (Solvency Capital Requirement)

- Solvency II is an EU Directive that codifies and harmonizes the EU insurance regulation.
- Solvency Capital Requirement (SCR) is the minimum capital required to ensure that the (re)insurance company will be able to meet its obligations over the next 12 months with a probability of at least 99.5%

$$SCR = VAR_{99,5\%} \text{ (loss in one year)}$$

- SCR can be calculated using:
  - either a standard formula given by the regulators (risks considered, level of stress, correlation matrix etc.)
  - or an internal model developed by the (re)insurance company

Structure of Standard formula

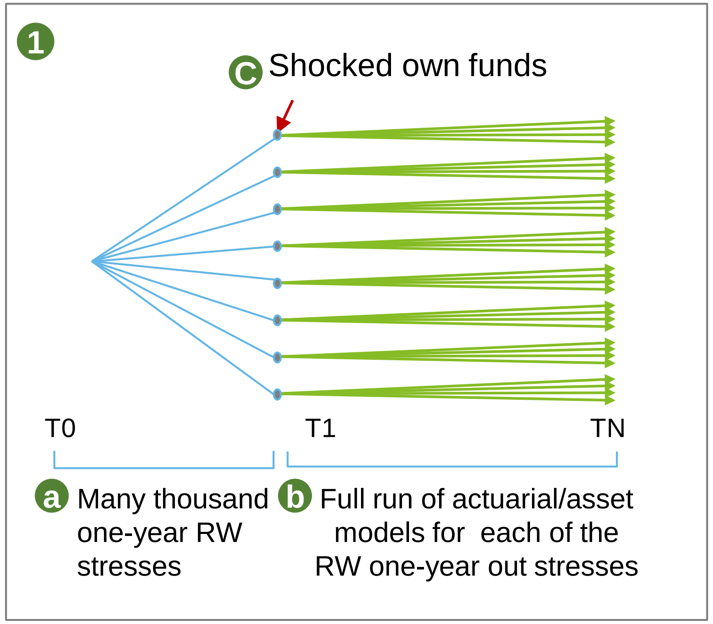


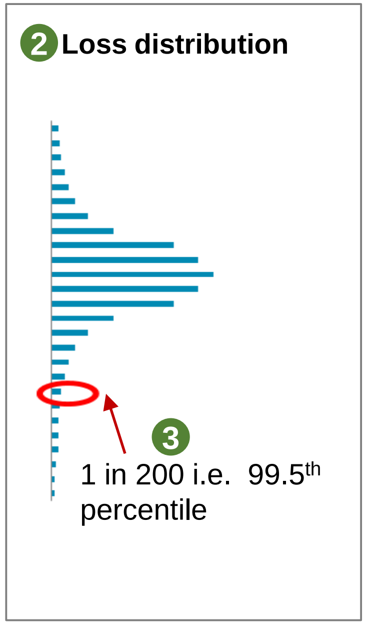
Nested simulation – the theorical approach

How should the SCR be calculated with an internal model?

1. Project distribution of own funds in 1 year
   - For Life liabilities with guarantees, this would require many thousand real world scenarios with thousands of market consistent scenarios for every real world (RW) scenario
2. Calculate the difference between simulated own funds and current own funds to obtain losses in each scenario
3. Order losses to construct a distribution and pick 99.5th percentile to obtain the 1 in 200 loss

Illustrative: nested stochastics





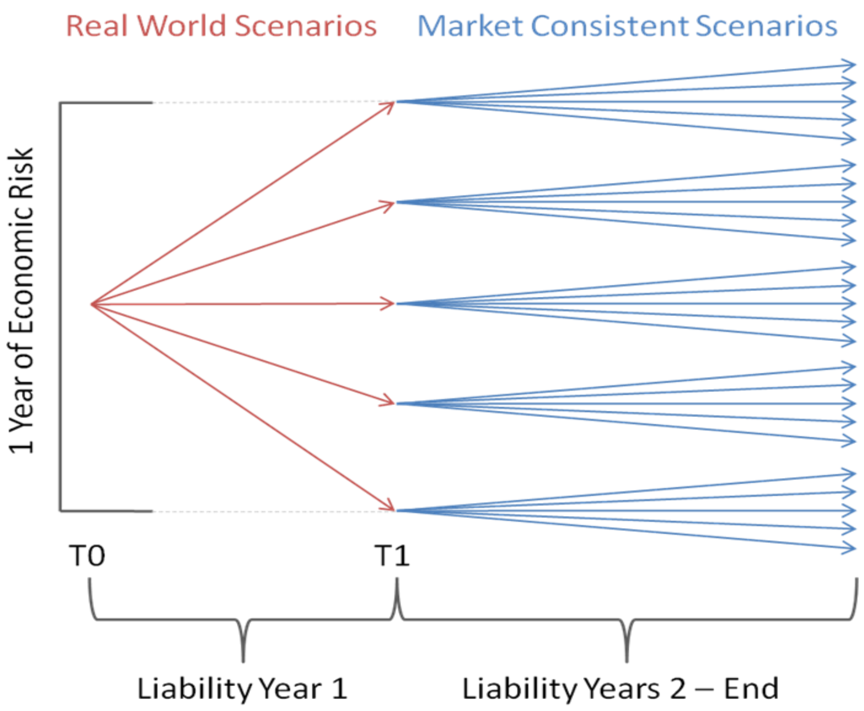
What is the challenge?

- For insurers with complex organizational structures and portfolios where liabilities have options and guarantees, **computational challenges** make this approach impossible to achieve

LSMC Methodology Design Framework

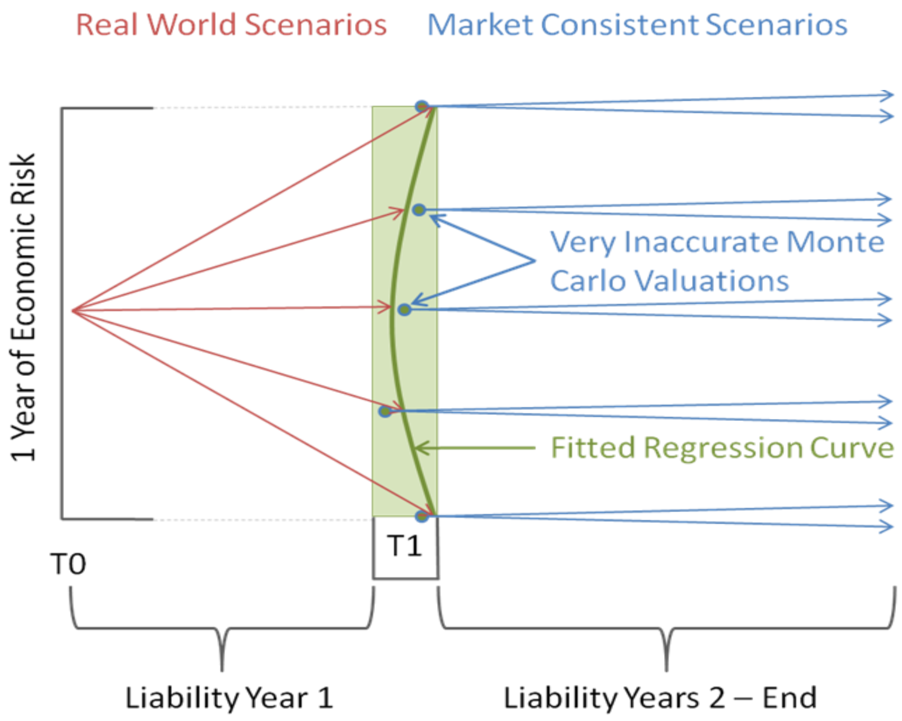
Least Squares Monte Carlo

Nested simulation



Fast and business-effective SCR computation

LSMC



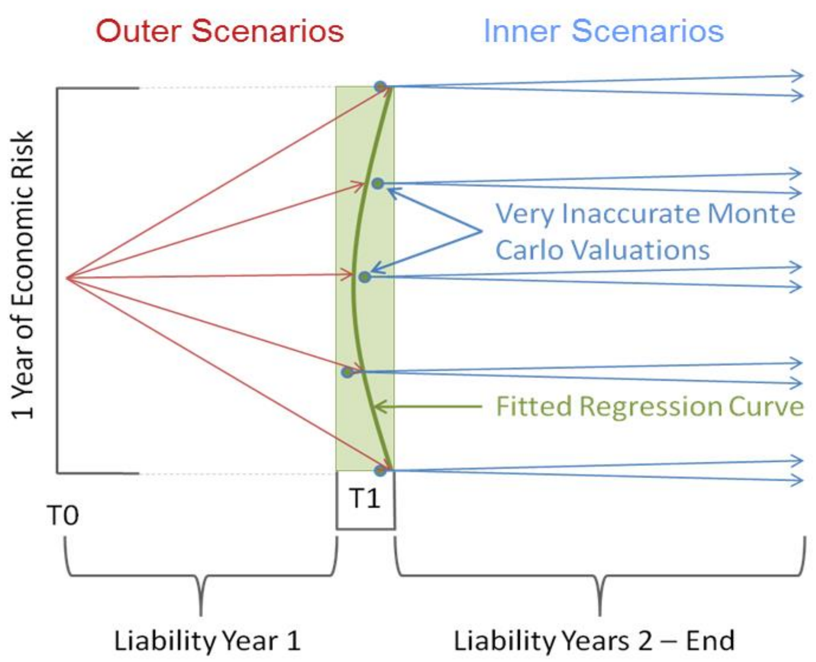
- Complex interaction within companies and liabilities have options and guarantees pose computational challenges which make this approach infeasible

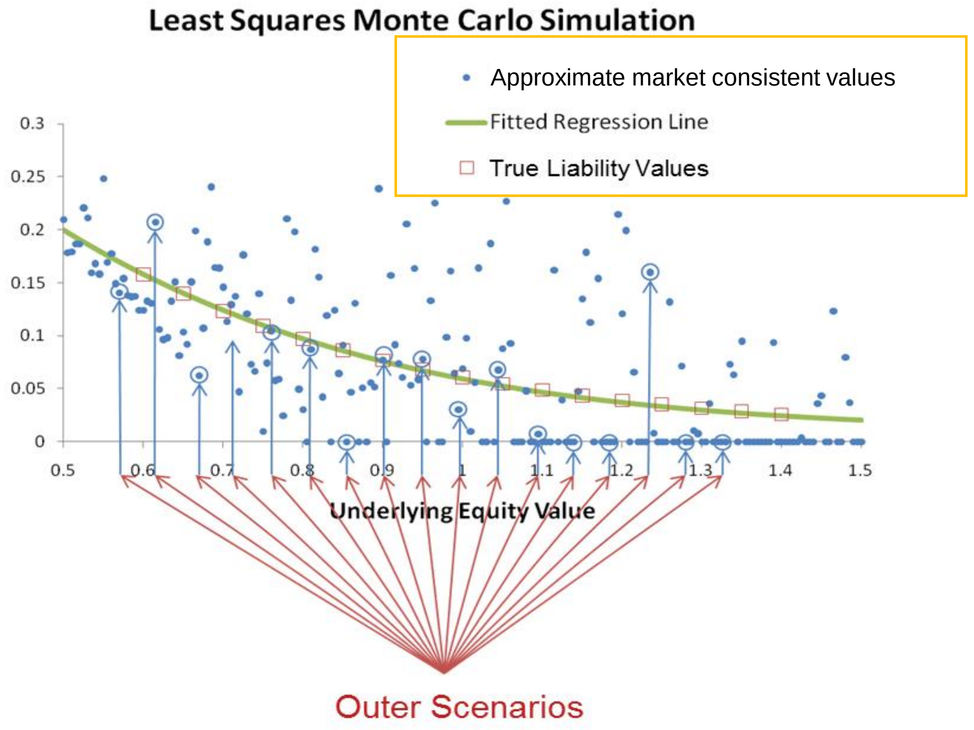
- Each real world scenario is valuated for a very limited number of risk neutral scenarios (e.g. 2)
- A function is calibrated based on the these fitting points

LSMC Methodology Design Framework

Least Squares Monte Carlo

- Monte Carlo proxy modelling approach combined with least squares regression
- Fits a (multi-dimensional) regression surface through approximate Monte Carlo valuations



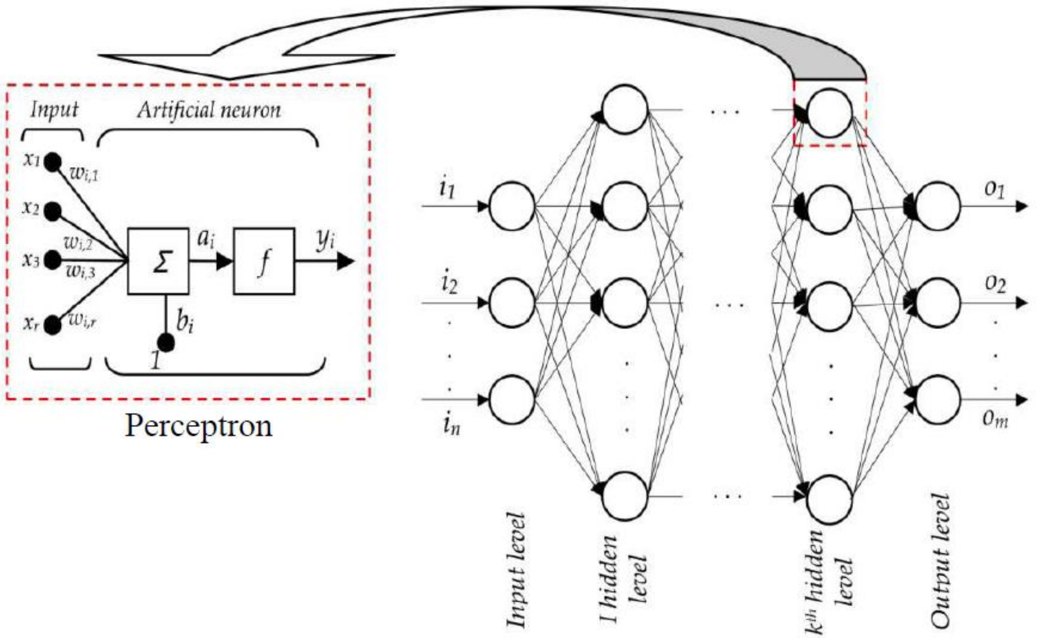


In classical LSMC polynomials are used as proxy functions

Neural Networks application for approximation of Risk Capital

Introduction to Our Use Case

- Core idea: Use the same LSMC approach which is already successfully implemented in the industry, but substitute polynomials with neural networks.
- Neural networks can be used to very sophisticated real-life problems, but they can also perform a “normal“ regression through LSMC fitting points.
- A neural network consists of:
  - A set of nodes (neurons) connected by links
  - A set of weights associated with links
  - A set of thresholds or levels of activation
- A design of a neural network requires:
  - The choice of the number and type of units
  - The determination of the morphological structure (layers)
  - Setting up of other parameters of the training process
  - Initialization and training of the weights on the interconnections through the training set



Settings and Data

Inputs

15 – 16 inputs describing 1y stresses:

- changes in the risk-free yield curves
- performance of equity
- performance of property
- credit risk
- Mortality level/trend
- Longevity level/trend
- expenses

Outputs

Predict: Best Estimate Liabilities conditional on 1y real world stresses (1 output)

Training

Training Set

- 6,000 or 25,000 1y real world scenarios
- 2 risk neutral simulations

Validation Set

- 256 1y real world scenarios
- With each 1,000 risk neutral simulations

Target

99.5% Value-at-Risk Set (VaR Set)

- 49 real world scenarios
- With each 4,000 risk neutral simulations

Base Scenario

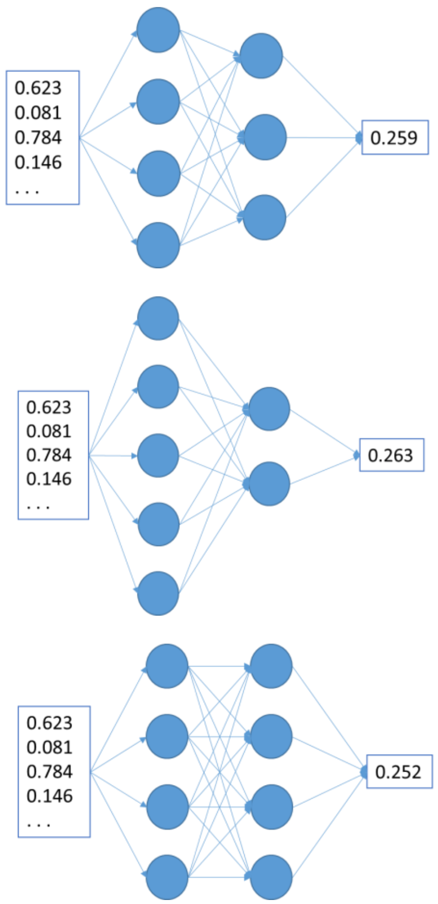
- 16,000 risk neutral simulations

(The real target is SCR = Base – 99.5% VaR)

The model – Calibration

Procedure

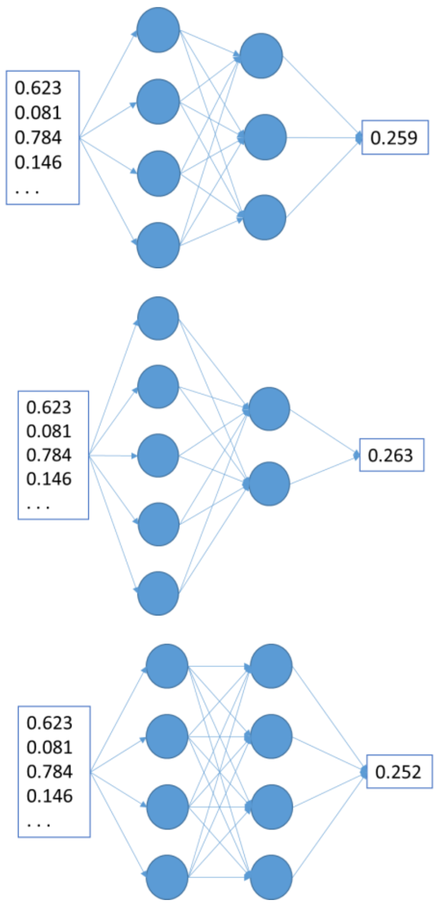
- Train 150 neural nets with different configurations (hyperparameters)
- Configurations of hyperparameters selected by a quasi random procedure



The model – Calibration

Procedure

- Train 150 neural nets with different configurations (hyperparameters)
- Configurations of hyperparameters selected by a quasi random procedure
- **Select best 10 models**
- **Based on mean absolute error (MAE) in validation set**

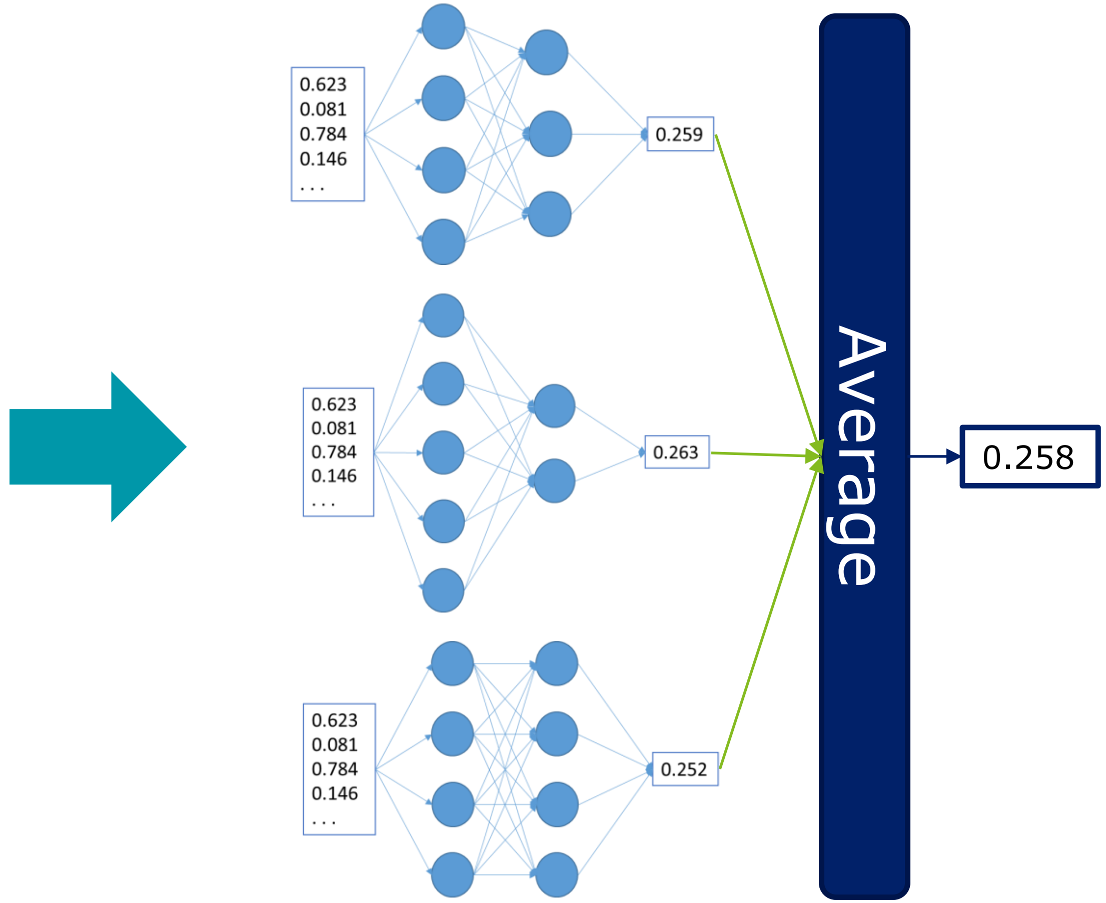


The model – Calibration

Procedure

- Train 150 neural nets with different configurations (hyperparameters)
- Configurations of hyperparameters selected by a quasi random procedure
- Select best 10 models
- Based on mean absolute error (MAE) in validation set
- **Build ensemble (by averaging over 10 best models)**

Important: VaR Set & Base Scenario unseen in Training



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The model – Calibration

Quasi Random Search

Hyperparameters

■ Batch size:	150 – 450
■ Layers:	3 – 7
■ Dropout:	0 – 0.4 (constant after each layer)
■ Nodes:	50 – 200 (constant in each layer)
■ Initializers:	[uniform, glorot, normal]
■ Learning Rate:	0.0007 – 0.0015

Fixed for all configurations

■ Optimizer:	adam
■ Activation:	sigmoid

Results

4 different datasets

- Company 1 / Company 2 / Company 3 / Company 4, three life and one health insurer
- Run procedure with both 6k and 25k training samples (real world fitting scenarios in the classical LSMC language
- Run each procedure twice in order to see whether the results are very unstable

Benchmark

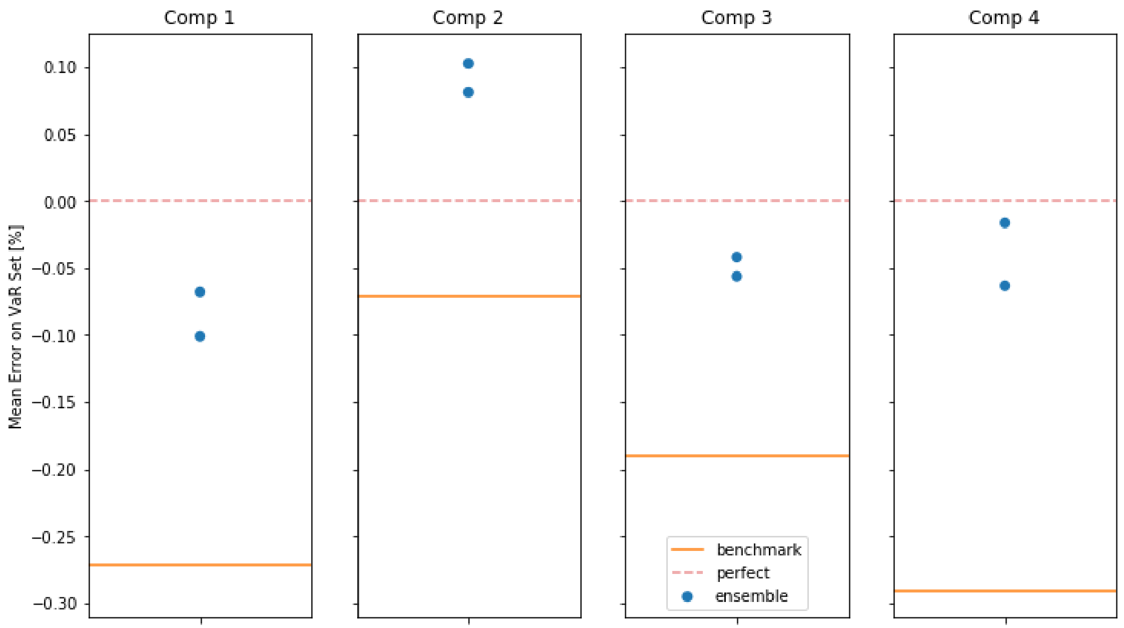
- Polynomial regression from classical LSMC as explained above – the current state-of-the-art proxy model in the insurance industry
- For the sake of simplicity we have always used 25k training samples (even when comparing with 6k training samples in neural networks)

Results

For **6k training** samples and all four companies - **99.5 % VaR**

99.5% Value at Risk Set

- 6K Training Samples
- Runtime: ~3-6h [1]
  - Can be parallelized trivially
- Significantly better than benchmark
- Appears very stable within and across companies



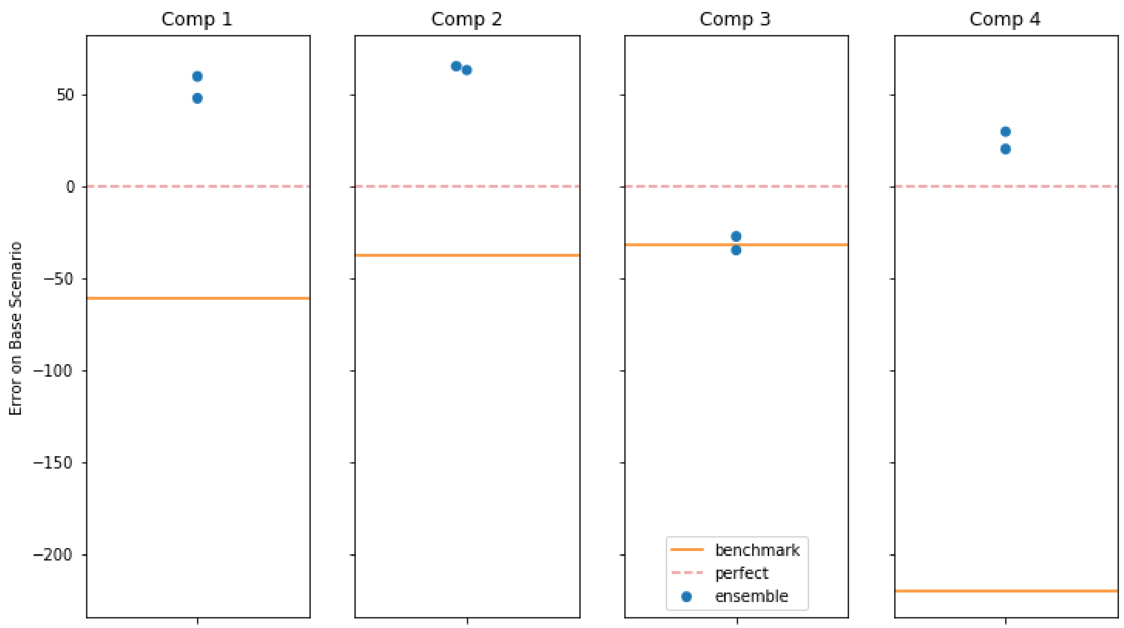
[1] On a laptop with *nvidia GeForce 940MX*. Only rough reference time - not reproducibly measured as laptop was used otherwise during training.

Results

For **6k training** samples and all four companies - **Base Scenario**

Base Scenario

- 6K Training Samples
- Similar to benchmark
  - Except for Company 4
- Seems stable within and across companies

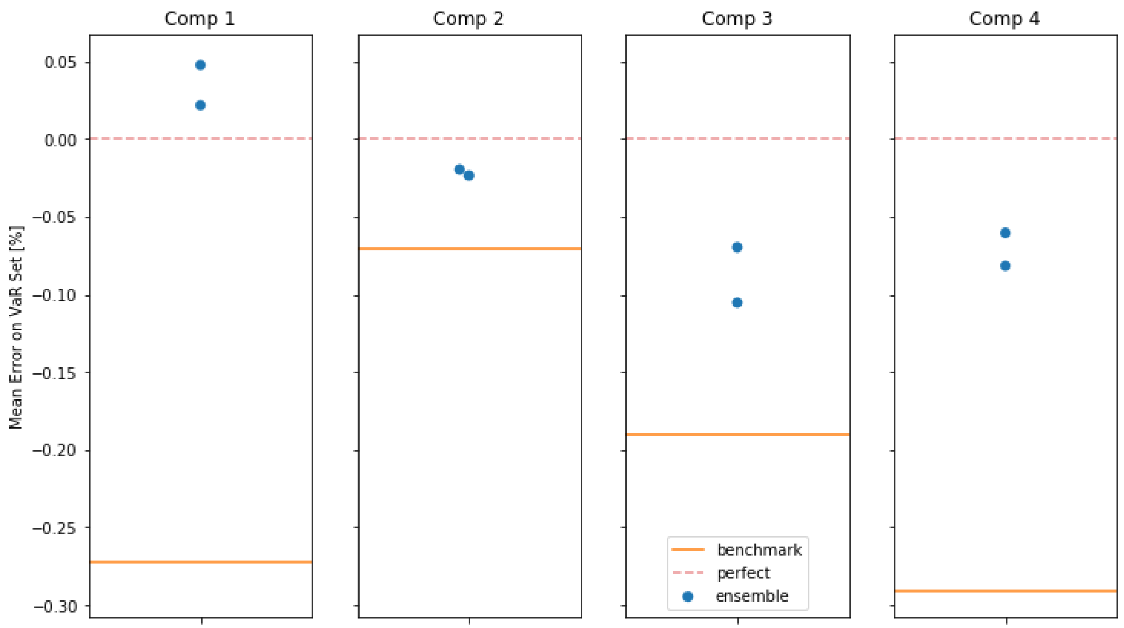


Results

For **25k training** samples and all four companies - **99.5% VaR**

Base Scenario

- 25k Training Samples
- Runtime: ~10-20h ^1
  - Can be parallelized trivially
- Significantly better than benchmark
- Seems stable within and across companies



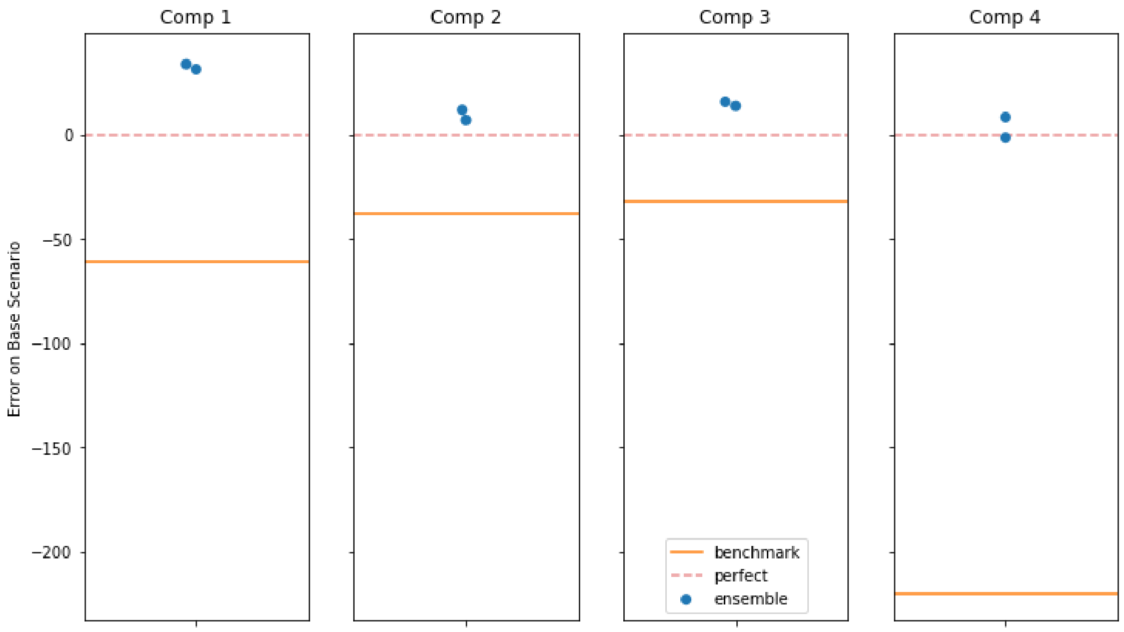
[1] On a laptop with *nvidia GeForce 940MX*. Only rough reference time - not reproducibly measured as laptop was used otherwise during training.

Results

For **25k training** samples and all four companies - **Base Scenario**

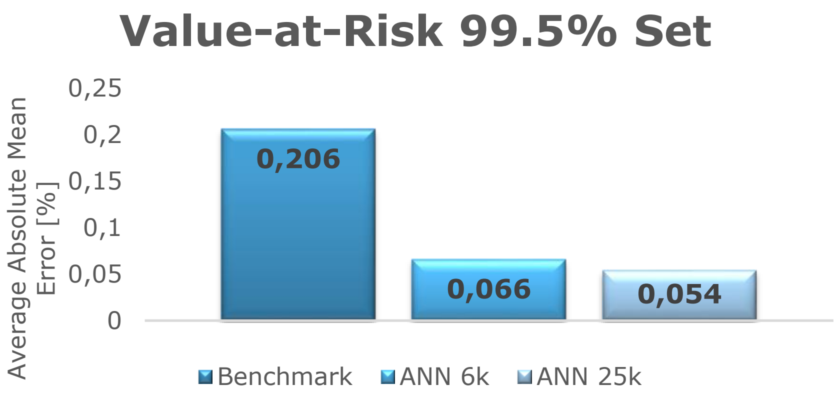
Base Scenario

- 25K Training Samples
- Significantly better than benchmark
- Seems very stable within and across companies

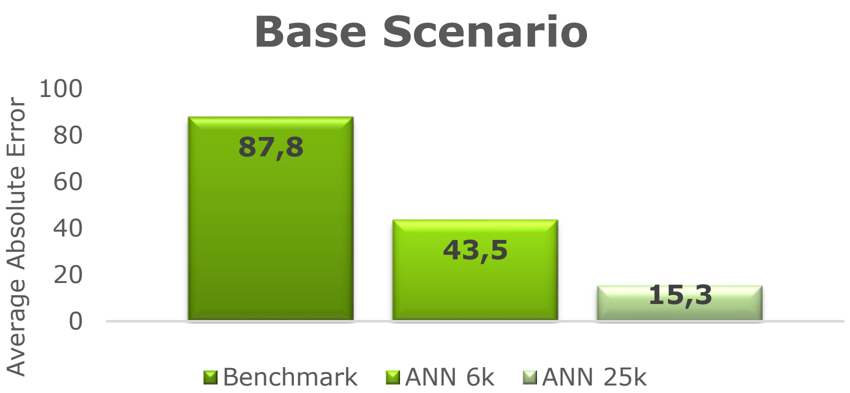


Summary

- **Good stability** of the procedure
- **Further tests** with other configurations planned (e.g. not only sigmoid)
- **Significantly better** than classical LSMC on both Base Scenario and Value-at-Risk 99.5% set, even when a smaller number of training samples than in the LSMC benchmark used



Average over all tested companies and ensembles



Average over all tested companies and ensembles

Thank you for your attention

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