Quantifying Uncertainty for AI-based Solvency Capital Estimation

EAA e-Conference on
Data Science & Data Ethics

14 May 2024

Mark-Oliver Wolf

Fraunhofer Institute for Industrial Mathematics

REGULATORY REQUIREMENTS

1

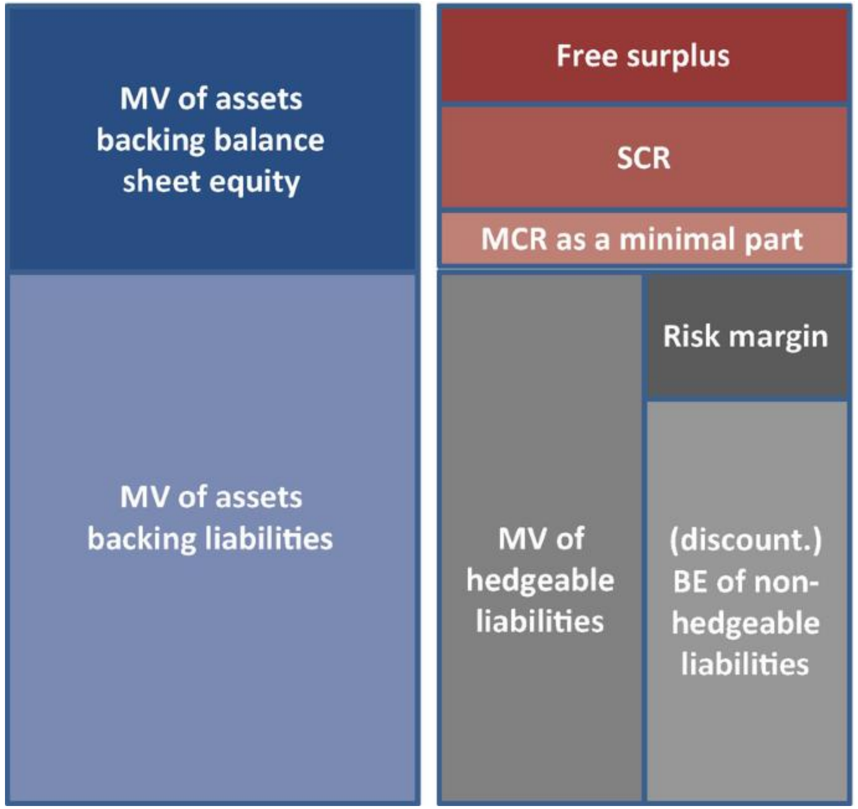
WHAT ARE WE CONCERNED WITH IN SOLVENCY II?

A VERY SHORT INTRODUCTION

Solvency Capital Requirement (SCR)

In summary:

Every insurance company must hold enough capital to cover its obligations ("liabilities") at the time of calculation to ensure that it still solvent after one year **with a probability** of 99.5%.

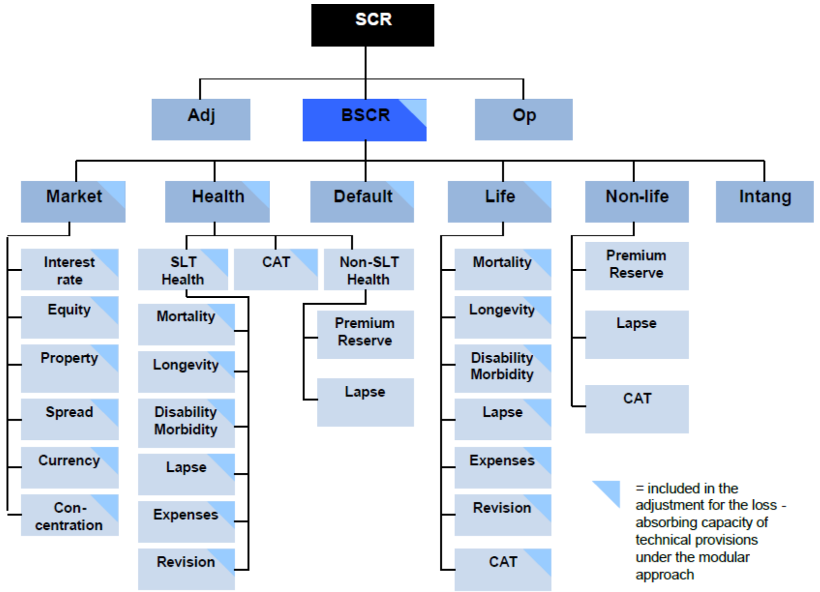


Solvency II in the Insurance Industry, Heep-Altiner et al., Part of the Contributions to Management Science book series (MANAGEMENT SC.)

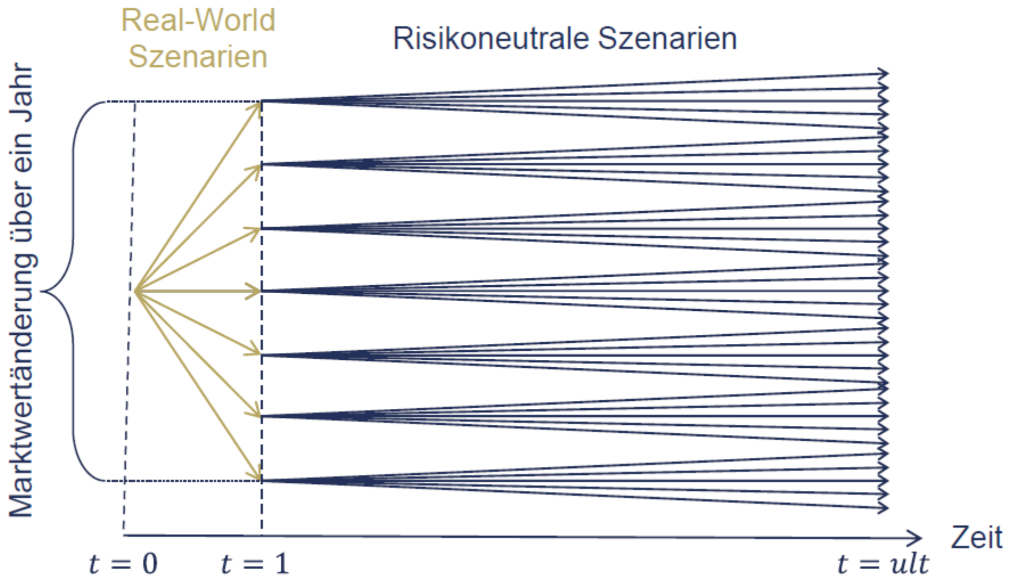
INSURERS HAVE TWO OPTIONS TO CALCULATE THEIR SCR

THE COMPANY HAS TO CHOOSE ONE OF THEM

Standard formula



Internal Model

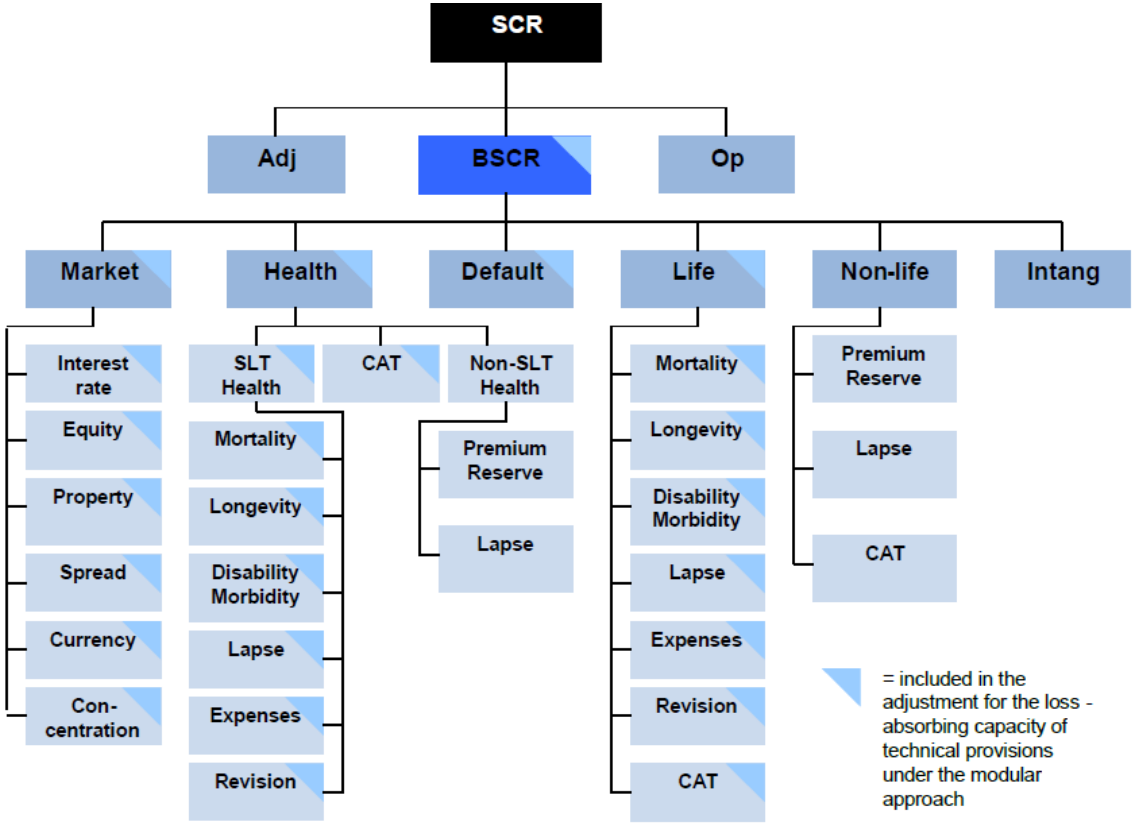


A SIMPLIFIED APPROACH THAT MIGHT HAVE HIDDEN COSTS?

A first solution:
Use standard formula procedures in accordance with Solvency II requirements.

- Highly simplified aggregation of the risks of the individual factors
- Provides little value for value-oriented corporate management
- Implicit distribution assumptions

Might be **expensive due to a high amount of tied-up capital!**



Schema to calculate the SCR in the standard formula

DAV (2015) Ergebnisbericht des Ausschusses Investment „Proxy-Modelle für die Risiko-kapitalberechnung

NESTED MONTE-CARLO SIMULATION AS A PSEUDO SOLUTION

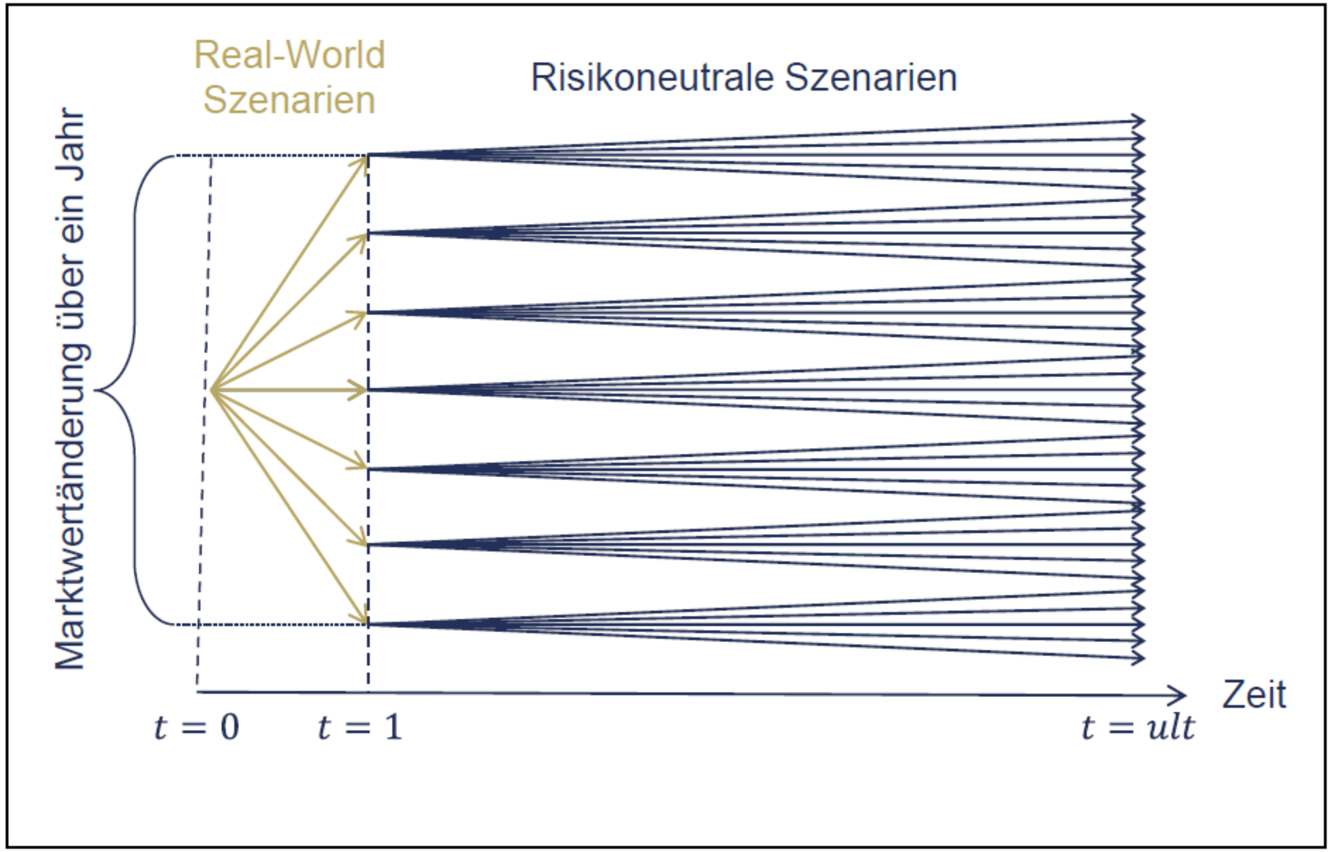
Alternative:
"Complete simulation in the internal model"

Advantages:

(Almost) exact. Perfect implementation of the internal model. Easy to understand.

Serious disadvantage:

Not efficient and cannot be used for real time projections.



Schema of nested Monte-Carlo simulation in Solvency II

WHAT ARE WE CONCERNED WITH IN SOLVENCY II?

A VERY SHORT INTRODUCTION

Solvency Capital Requirement (SCR)

In summary:

Every insurance company must hold enough capital to cover its obligations ("liabilities") at the time of calculation to ensure that it still solvent after one year **with a probability** of 99.5%.

Problem(s):

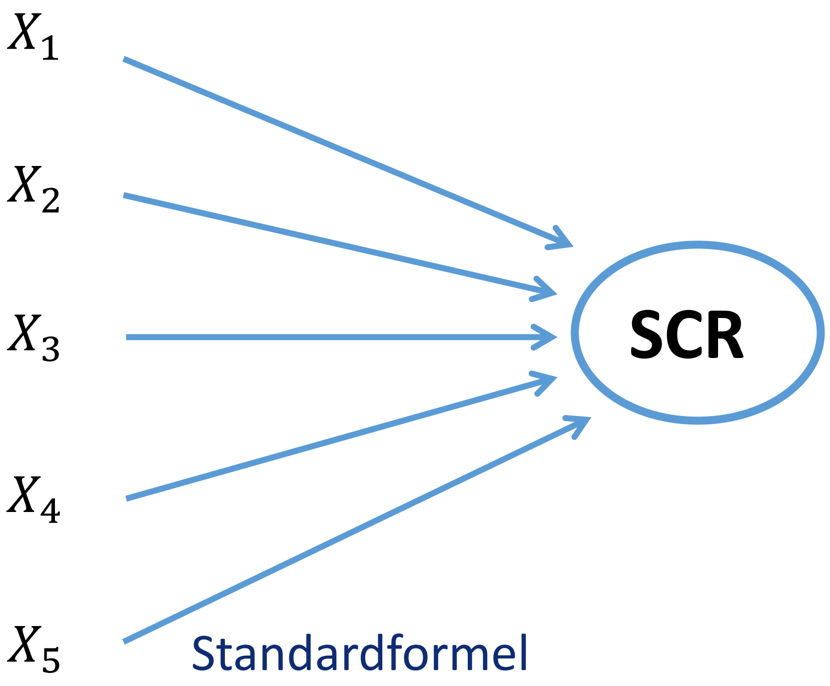
- How can the SCR (or the SCR quotient) be calculated **reliably and efficiently**? Are we able to reuse previous results?
- Do solutions exist that are sufficiently **customizable**, but do **not** have to be **completely new developments**?

THE LEAST-SQUARES MONTE-CARLO TECHNIQUE

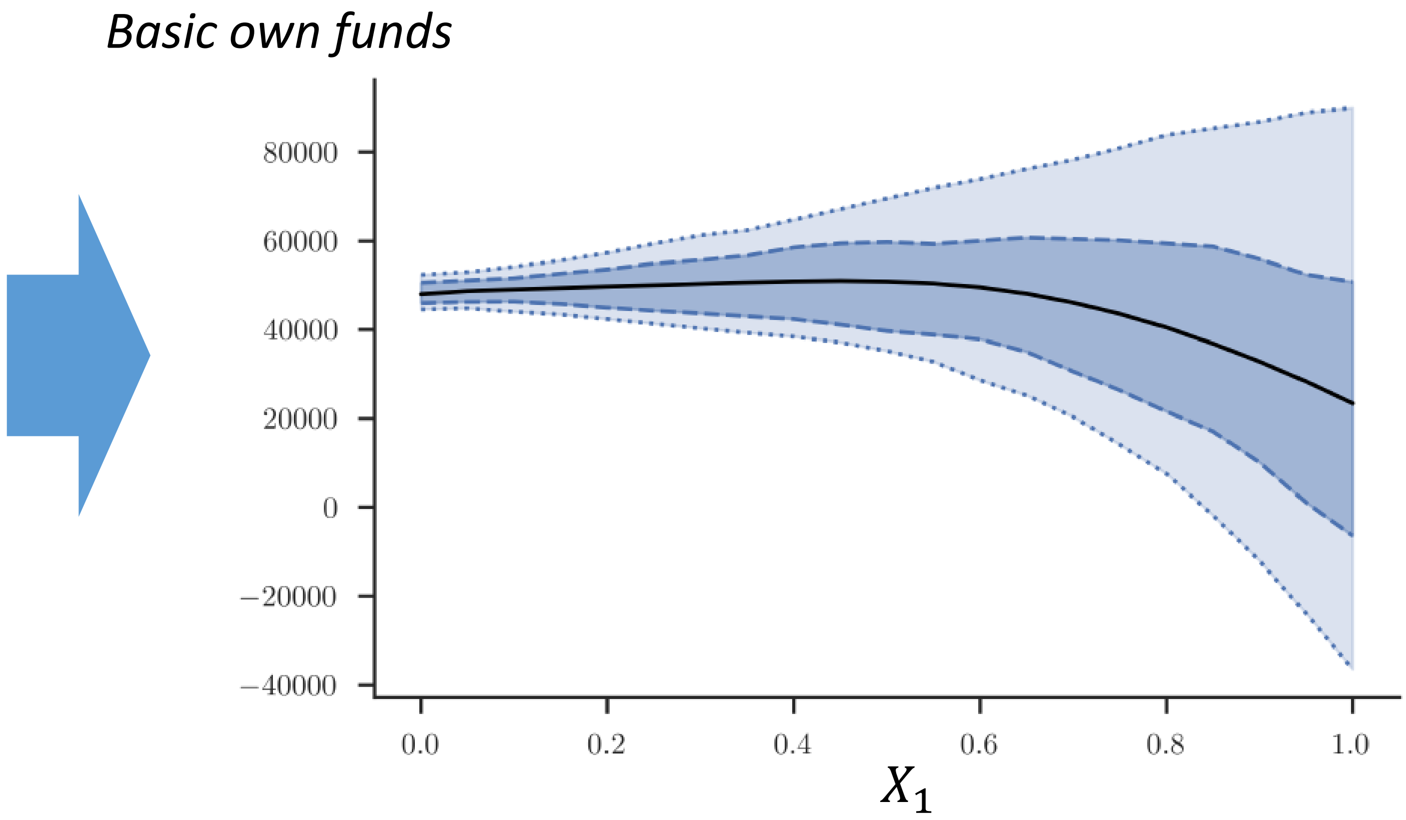
2

WHY IS THE CALCULATION OF THE SCR ESSENTIALLY JUST A FUNCTION?

USING REGRESSION, WE CAN LEARN A MODEL BASED ON EVALUATED DATA POINTS



Standardformel oder internes Modell

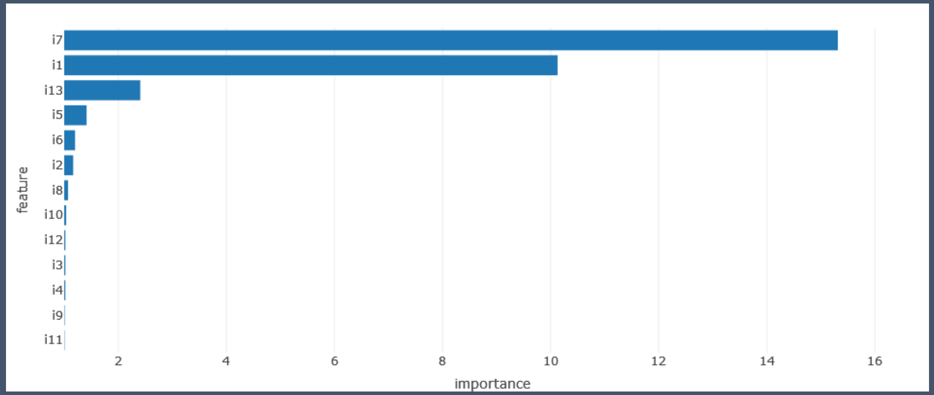


RANKING AND CLUSTERING ALLOW US TO FIND REPRESENTATIVE RISK FACTORS

THIS REDUCES THE TIME AND EFFORT REQUIRED TO COLLECT AND PREPARE THE DATA ENORMOUSLY!

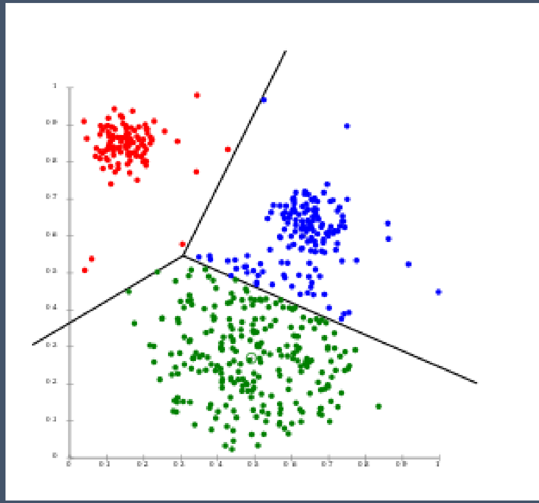
Ranking

Model independent: Pearson's R
Model dependent:
F-regression, mutual info regression, SHAP Values, Permutation Feature Importance



Clustering

Different risk factors **that are similar** are grouped together and represented by a risk factor.



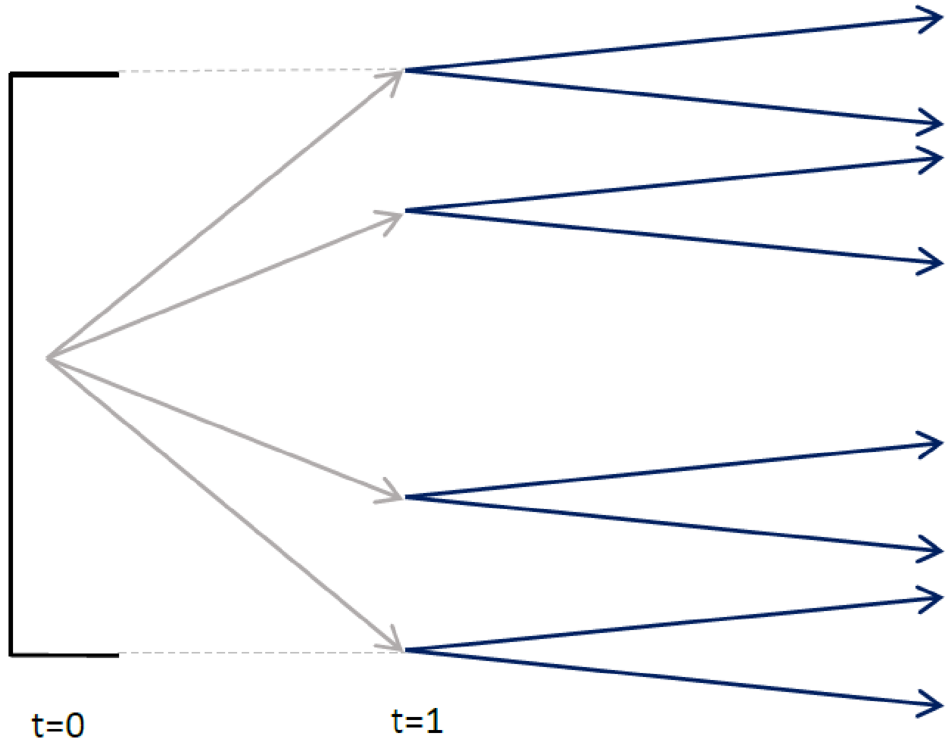
https://en.wikipedia.org/wiki/Cluster_analysis

THE LEAST-SQUARES MONTE-CARLO TECHNIQUE TO SPEED UP THE PROCESS

Least-Squares Monte Carlo

Reduce the **number of expensive paths** dramatically

- **Train a regression function** as a substitute for the expensive simulation of the inner loop
- **Validate** the regression function
- **Simulate** new external scenarios needed for SCR calculation and obtain value via the obtained regression function



Scheme of the choice of calibration paths in the LSMC approach (from DAV (2015))

CHOICE OF REGRESSION MATTERS, BUT METHOD INTRODUCES NEW INTRICALITIES

Choice of regression method

Linear regression

- Good fit to data for regression function with many terms
- For a given number of terms, the optimal solution ("best fit") is obtained exactly by solving a system of linear equation.

Neural networks

- Better fit to data possible
- Best solution can only be approximated numerically

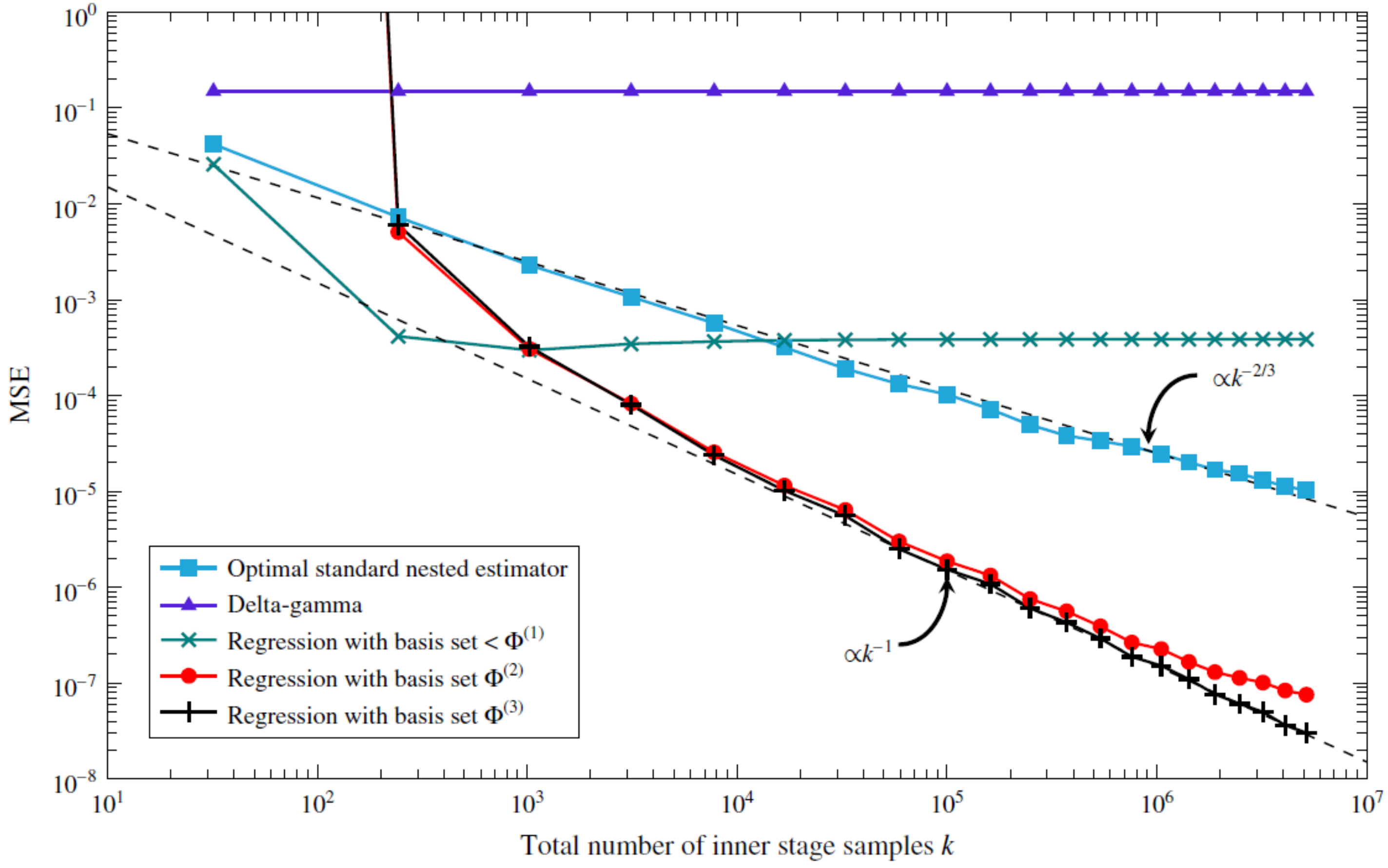
Possible problems:

Performance of the methods depends on the **quality/quantit**y of existing data

Neural networks tend to over-fit, **application requires experience and understanding**

Position of the regulators is not yet finally clear with neural networks => explainability!

COMPARISON OF DIFFERENT LINEAR REGRESSIONS BASIS SETS AND THE NAIVE APPROACH TO ESTIMATE THE VALUE-AT-RISK BY BROADIE ET AL (2015)



M. Broadie, Y. Du, and C. C. Moallemi, "Risk Estimation via Regression," *Operations Research*, vol. 63, no. 5, pp. 1077–1097, Oct. 2015, doi: 10.1287/opre.2015.1419.

ESTIMATIONS AND FORECASTS WITH NEURAL NETWORKS

3

ARTIFICIAL NEURAL NETWORKS AS A STARTING POINT

Artificial Neural Networks:

Every node outputs $z_{j,k}$ with:

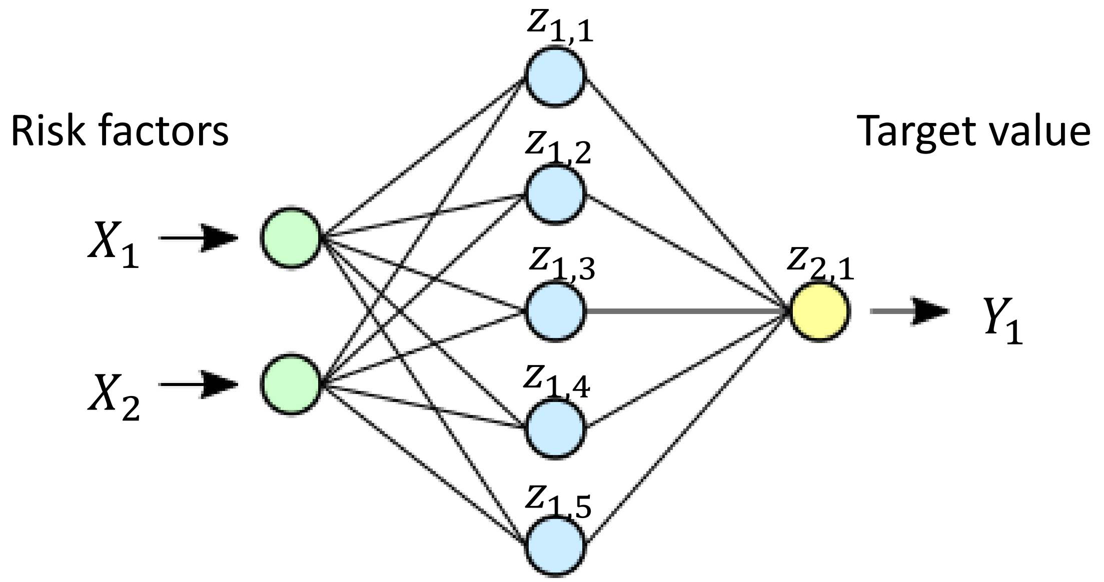
$$\mathrm{z_{j,k}} = \varphi\left(\sum_{i=1}^{n_j} w_{j,i} z_{j-1,i} + w_{j,0}\right),$$

where

$w_{j,i}$ … trainable weight

$w_{j,0}$ … trainable bias

φ … activation function



A COMPARISON OF TEN TRAINED NETWORKS, THEIR ENSEMBLE AND A POLYNOMIAL REGRESSION

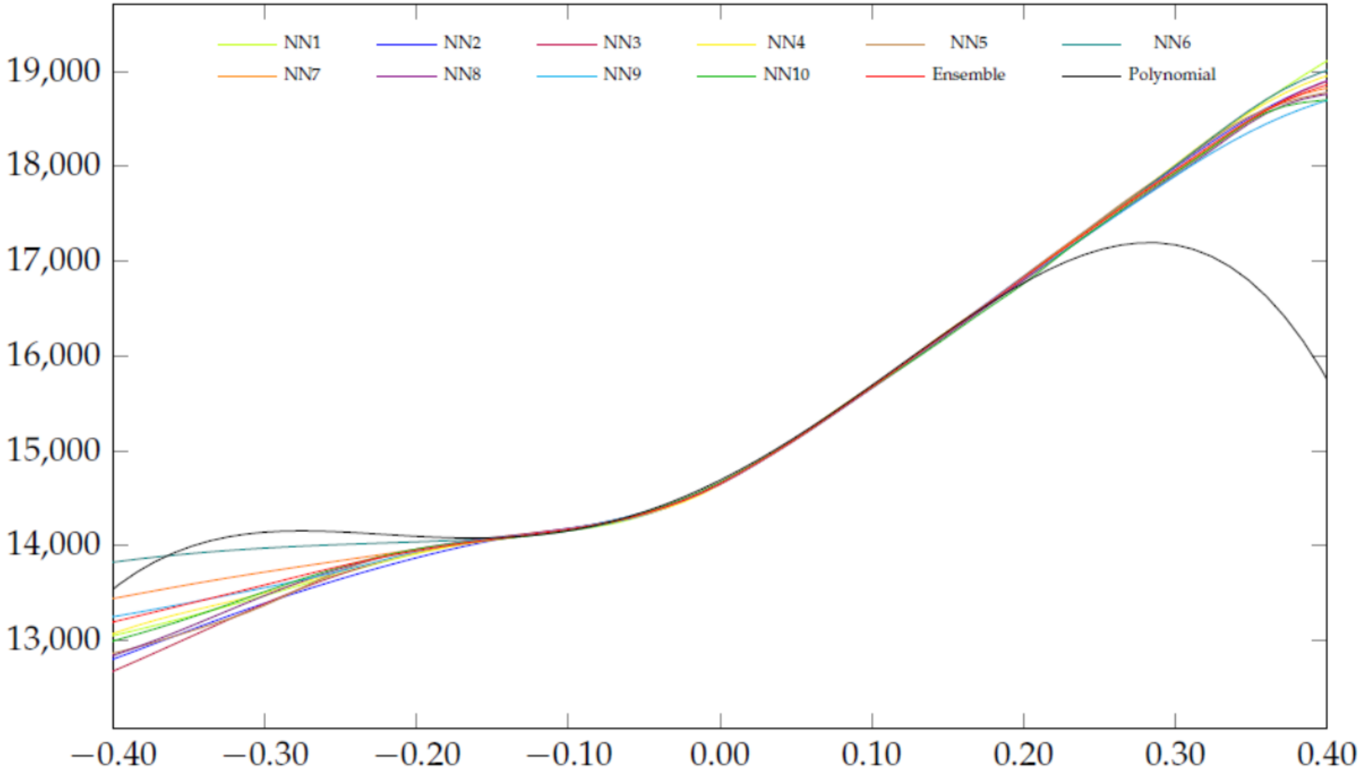


Figure A4. One-dimensional curves of the 10 best performing neural networks, their ensemble and the polynomial with respect to X_8.

A.-S. Krah, Z. Nikolic, R. Korn (2020) *A least-squares Monte Carlo framework in proxy modeling of life insurance: Neural networks*, Risks 8(4)

TWO DIMENSIONAL VISUALIZATION SHOWS STRONG DEPENDENCE OF RISKFREE INTEREST RATE AND STOCK INVESTMENT

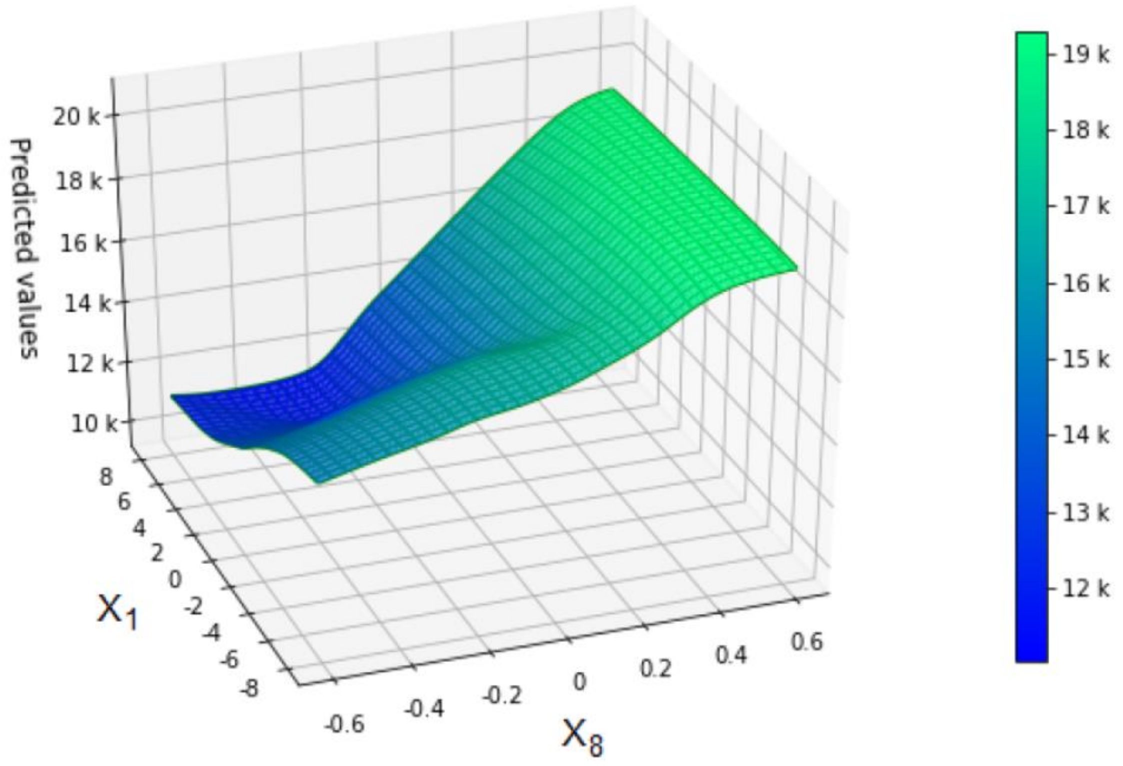


Figure A5. Two-dimensional curve of the ensemble of 10 best performing neural networks with respect to X_1 and X_8.

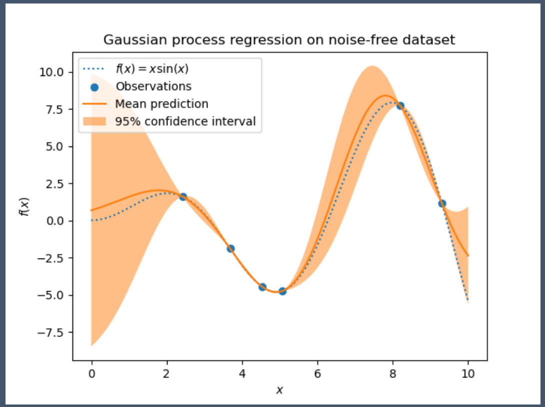
CERTAINTY WITH AI-BASED FORECASTING? – PROBABILISTIC MODELS

4

HOW CAN WE USE THE ADDITIONAL INFORMATION FOR MORE EXPLAINABILITY?

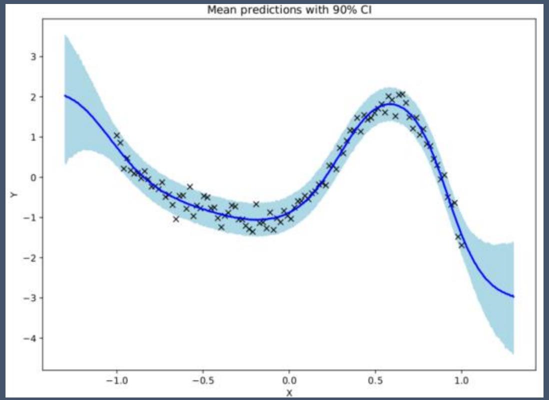
Gaussian Process Regression:

Kernel method with Bayesian approach, evaluates new data based on already known, **similar data**.
Parameters have learnable distributions.



Bayesian Neural Networks:

Artificial NNs with Bayesian approach, Weights of the network have distributions which are learned from data.

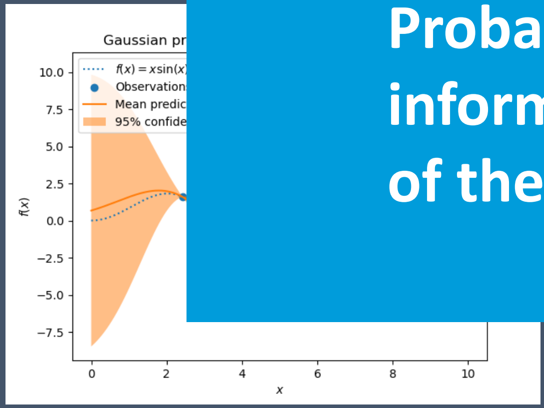


https://scikit-learn.org/stable/modules/gaussian_process.html

HOW CAN WE USE THE ADDITIONAL INFORMATION FOR MORE EXPLAINABILITY?

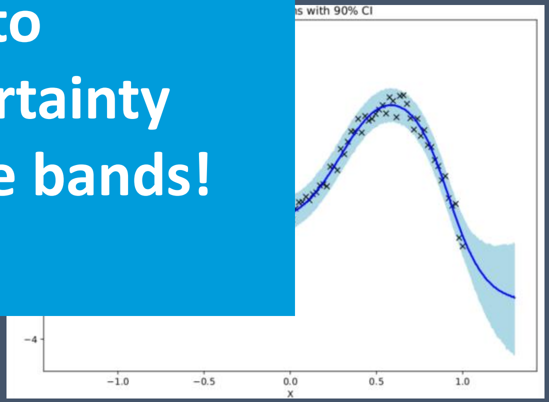
Gaussian Process Regression:

Kernel method with
evaluates new data
similar data.
Parameters have lea



Bayesian Neural Networks:

an approach,
have distributions
lata.

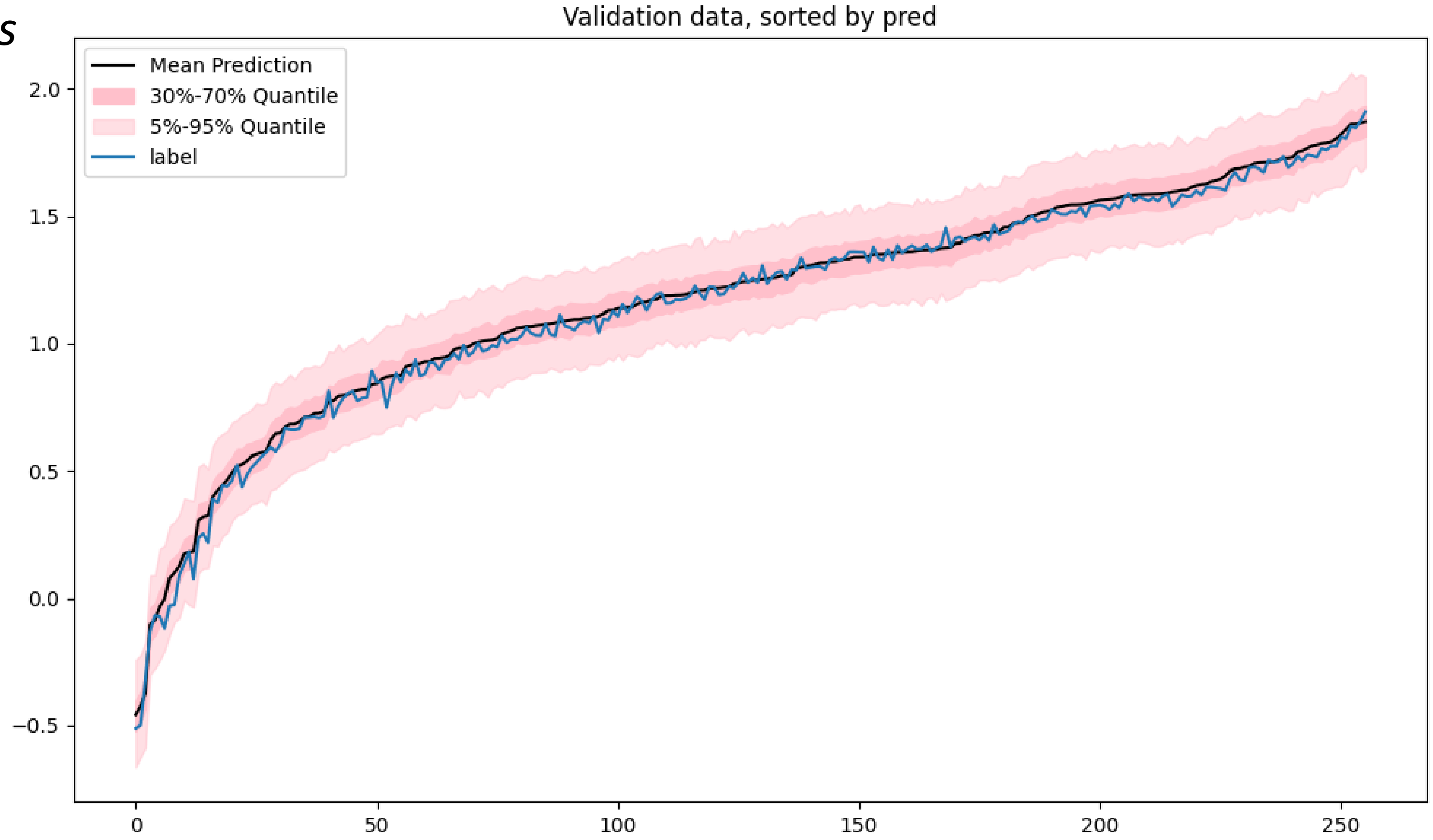


Probabilistic AI models are able to inform us about safety and uncertainty of their prediction via confidence bands!

https://scikit-learn.org/stable/modules/gaussian_process.html

USING THE EXAMPLE OF THE PUBLIC DAV DATA SET FOR SCR CALCULATION WITH AN INTERNAL MODEL

Basic own funds



Various risk factors, ranked by their prediction of the basic own funds

THE AI MODEL TELLS US WHEN IT IS CERTAIN ABOUT THE PREDICTION

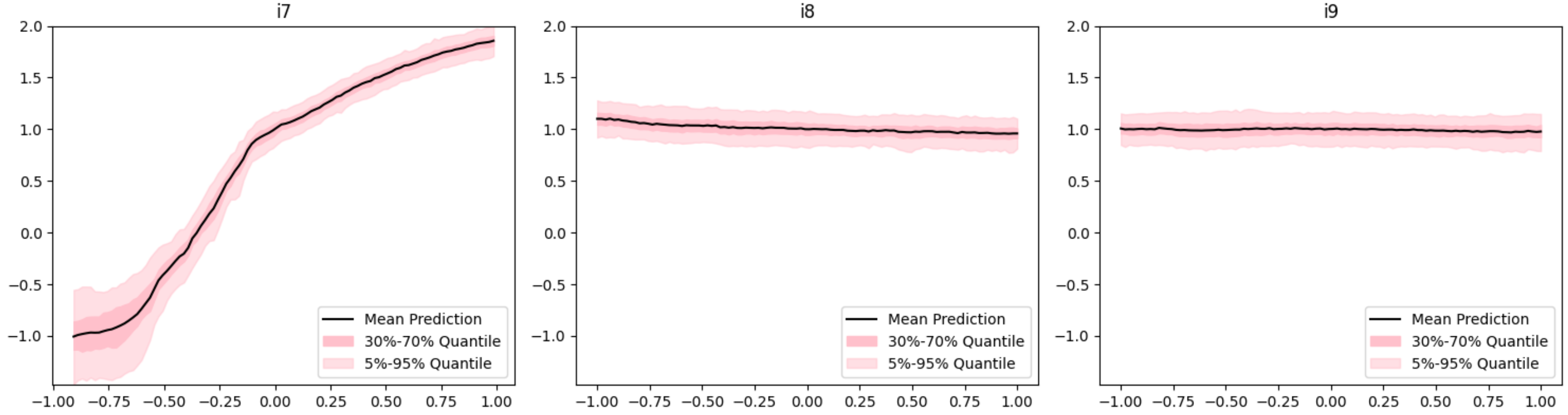
We look at the model in the middle of the training data

We vary one risk factor and set all other risk factors to a fixed value within the data

We observe:

→ **Small** confidence bands

→ The AI model is **certain** of the **prediction** (mean prediction)



X_7 X_8 X_9

THE AI MODEL TELLS US WHEN IT IS UNCERTAIN ABOUT THE PREDICTION

We look at the model at the edge of the training data

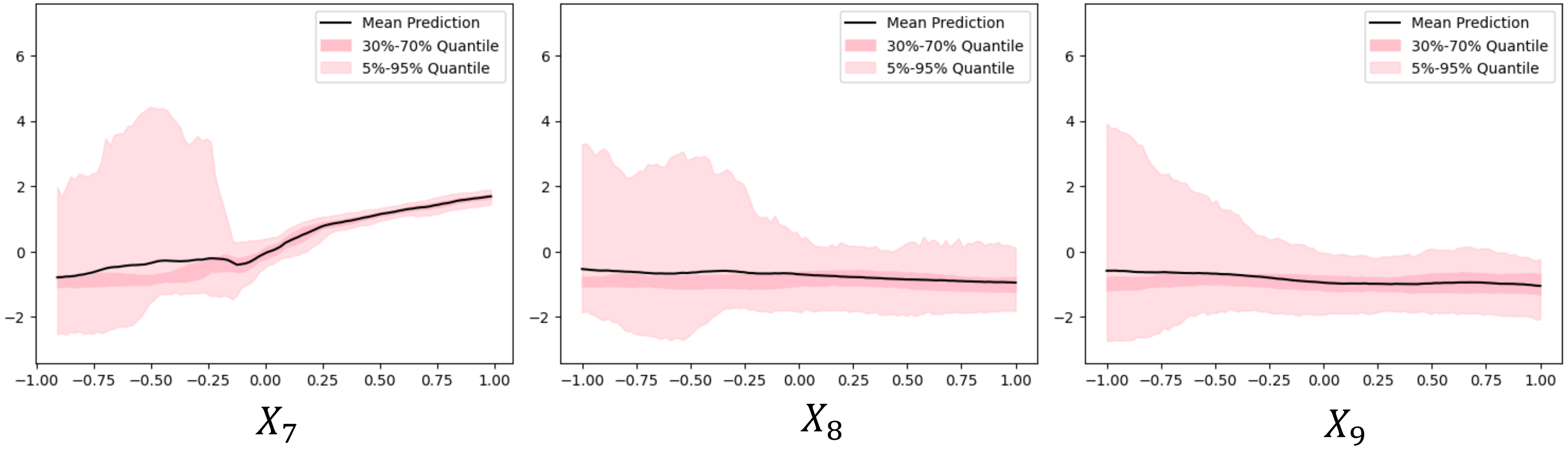
We vary one risk factor and set all other risk factors to a fixed value at the edge of the data

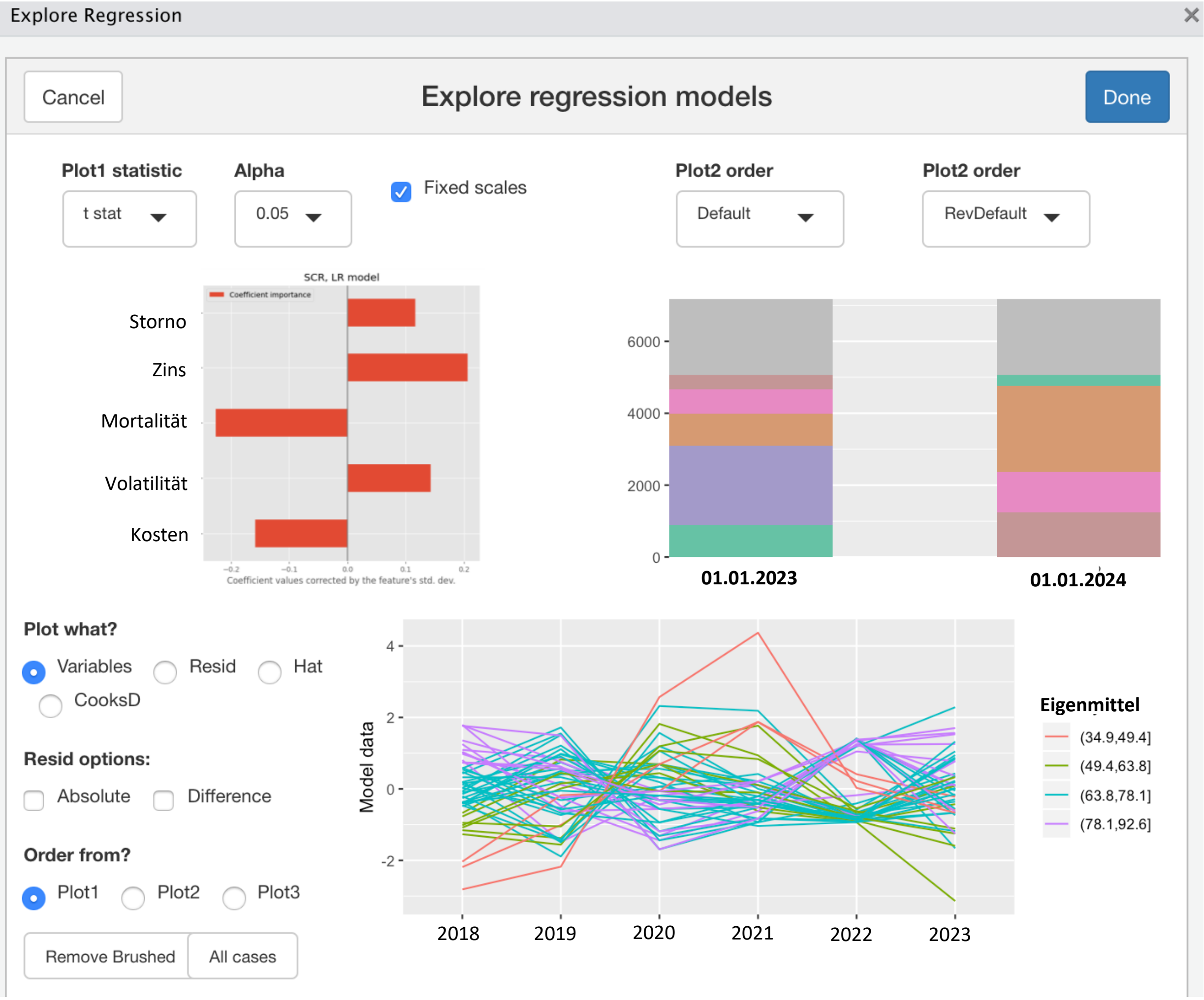
We observe:

→ Partially **large** confidence bands

→ Prediction (mean prediction) not always at the median

→ The **AI model informs us** about its **uncertainty** at the edge of the training data





Example of a web app

- An **app accessible** via the **browser on the intranet** for **monthly updated estimates** of the basic own funds, SCR and solvency ratio.
- Possible **effects** of changes in **selected risk factors** are shown.
- **Explainability** of past basic own funds, SCR and solvency ratio values.
- Data remains **internal** and is **not uploaded** to a **cloud**.

- **Nov. 2023 - Present:**
  PhD Student of Prof. Ralf Korn, topic: "Mathematical and Machine Learning Aspects of the Solvency Capital Requirement Calculation.“
- **Oct. 2023 – Present:**
  Research Coordinator for Actuarial and Financial Mathematics at Fraunhofer ITWM
- **Mar. 2022 – Sep. 2023:**
  Applied Researcher in Actuarial and Financial Mathematics at Fraunhofer ITWM
- **2017 - 2022:**
  B.Sc. and M.Sc. in (Actuarial and Financial) Mathematics at Technische Universität Kaiserslautern

ABOUT ME

Mark-Oliver Wolf

Fraunhofer ITWM
Institute for Industrial Mathematics

Thank you very much for your attention

EAA e-Conference on
Data Science & Data Ethics

14 May 2024

Contact

Mark-Oliver Wolf

Fraunhofer ITWM

+4963131600-4161

mark-oliver.wolf@itwm.fraunhofer.de