Using Explainable AI for Ratings of German Life Insurers

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Data Science & Data Ethics

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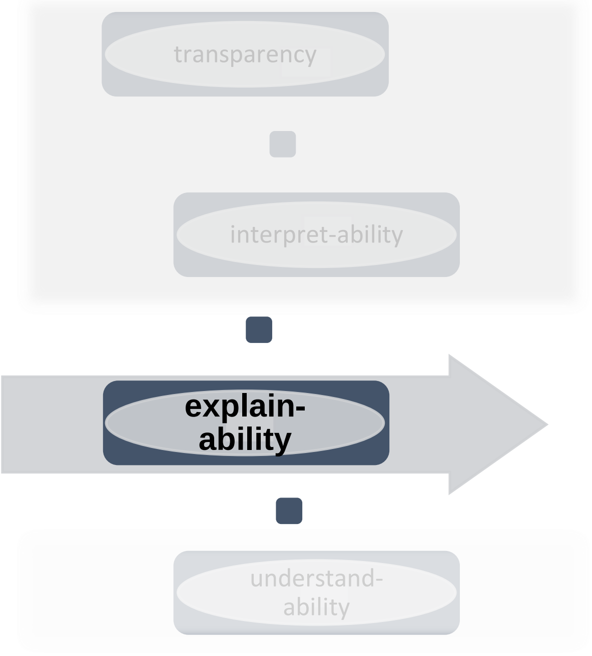
INTRODUCTION & MOTIVATION

01

APPROACHES TO EXPLAINABILITY

4 key principles of XAI[1,2,3,4]



AI as a viable practical tool to facilitate decision-making (Lossos, Geschwill, Morelli, 2021).

The requirements in evaluation of companies (incl. insurance industry) are based on *4 key principles of XAI*.

→ Ethical problems in this context include questions of the morality of automation in general, of fairness/justice and of transparency (Leidner, in prep.).

"Black Box" analysis model

→ currently provide the best predictions

Drawback → *explaining* a black-box decision-making is *extremely sophisticated*

Sources:
[1] Arrieta, et al., 2020.
[2] Doshi-Velez, Kim, 2017.
[3] Miller, 2019.
[4] Vilone, Longo, 2020.

The goal → to identify new approaches in creating machine learning models that provide high level of both accuracy and explainability.

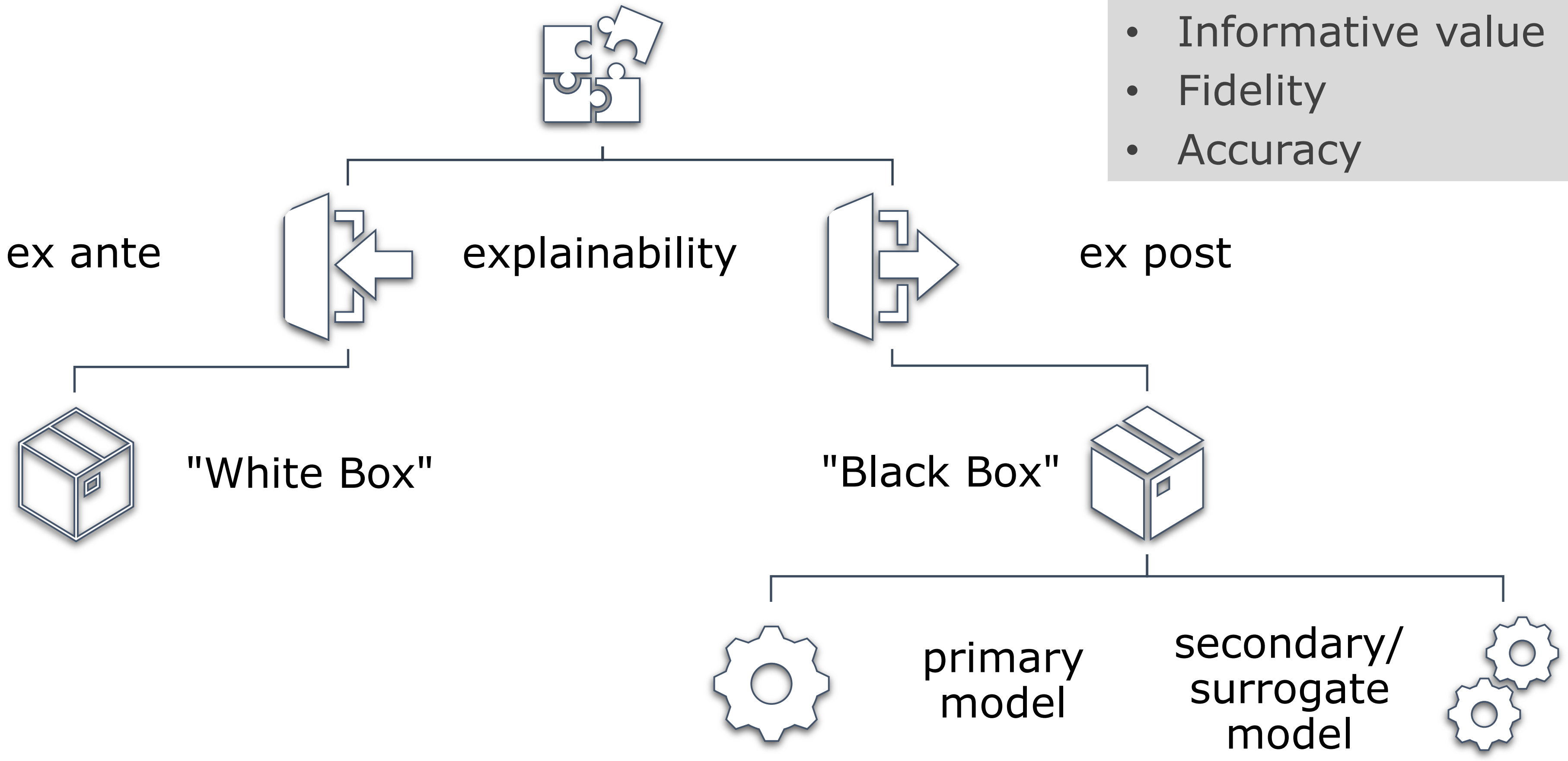
EXPLAINABLE AI IN INSURANCE

02

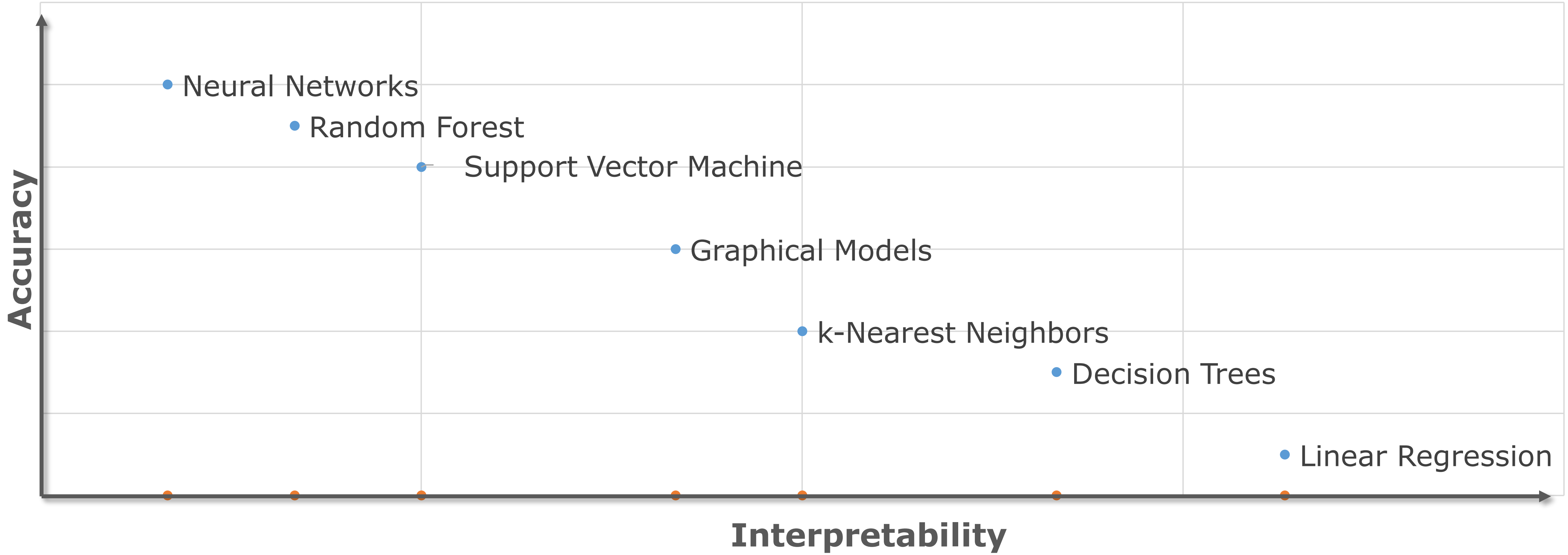
APPROACHES TO EXPLICABILITY

"Why should I trust You?"

- Informative value
- Fidelity
- Accuracy



TRADE-OFF BETWEEN INTERPRETABILITY & ACCURACY OF MACHINE LEARNING



Source: Dziugaite et al., 2020

CRITERIA FOR EXPLAINABLE AI (XAI)

- LIME technique (Local Interpretable Model-agnostic Explanations)

$$\xi(x) = \arg\min \mathcal{L}(f, g, \pi_x) + \omega(g)$$

- Shapley values (Shapley 1951)
  - game theory

- other methods

TAXONOMY FOR MODEL-AGNOSTIC METHODS

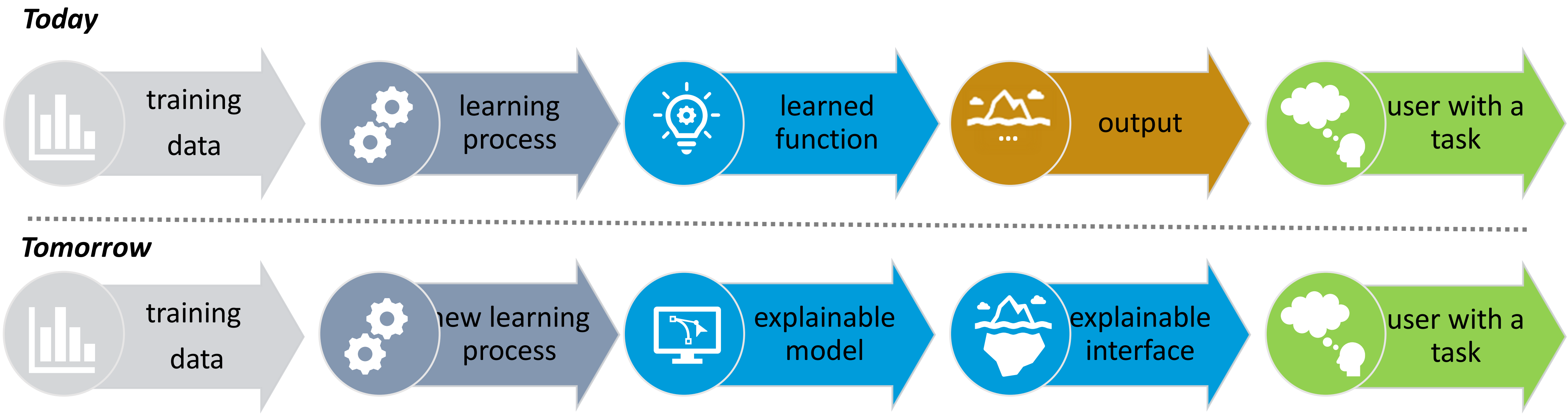
What to explain?

How to explain?

	Global	Local	Data
Profile	Partial Dependence Plot (PDP) Individual Conditional Expectation (ICE)	Ceteris Paribus Plot	
Parts	Global Feature Importance Leave-One-Covariate-Out (LOCO)	SHARP Attribution Break-Down Attribution	Graphical Networks
Distribution			Histogram Boxplot Barplot

Source: Biniecki and Biecek, 2021

EXPLAINABILITY BY DESIGN



Source: Woody, 2018

XAI ON ETHICAL LEVEL

“PRINCIPLE OF TRANSPARENCY AND EXPLAINABILITY”

- “Insurance firms should adapt the types of explanations to specific AI use cases and to the recipient stakeholders.
- Insurance firms should strive to use explainable AI models, in particular in high-impact AI use cases, although, in certain cases, they may combine model explainability with other governance measures insofar as they ensure the accountability of firms, including enabling access to adequate redress mechanisms.
- Explanations should be meaningful and easy to understand in order to help stakeholders make informed decisions.
- Insurance firms should transparently communicate the data used in AI models to consumers and ensure that they are aware that they are interacting with an AI system, and its limitations.”

Source: EIOPA, 2021, p. 40.

USE CASE OF RATINGS FOR GERMAN LIFE INSURERS

03

A HYBRID RATING MODEL WITH EXPERT KNOWLEDGE

Holistic Solvency business model

- ***externally*** available data
  - reassessment of book value balance sheet to market value balance sheet
  - e.g. interest rate sensitivity of the liabilities side
- ***internal*** company data
  - e.g. estimate of economic equity capital
  - relevant scale and reference values

A HYBRID RATING MODEL WITH EXPERT KNOWLEDGE

Methodological peculiarities

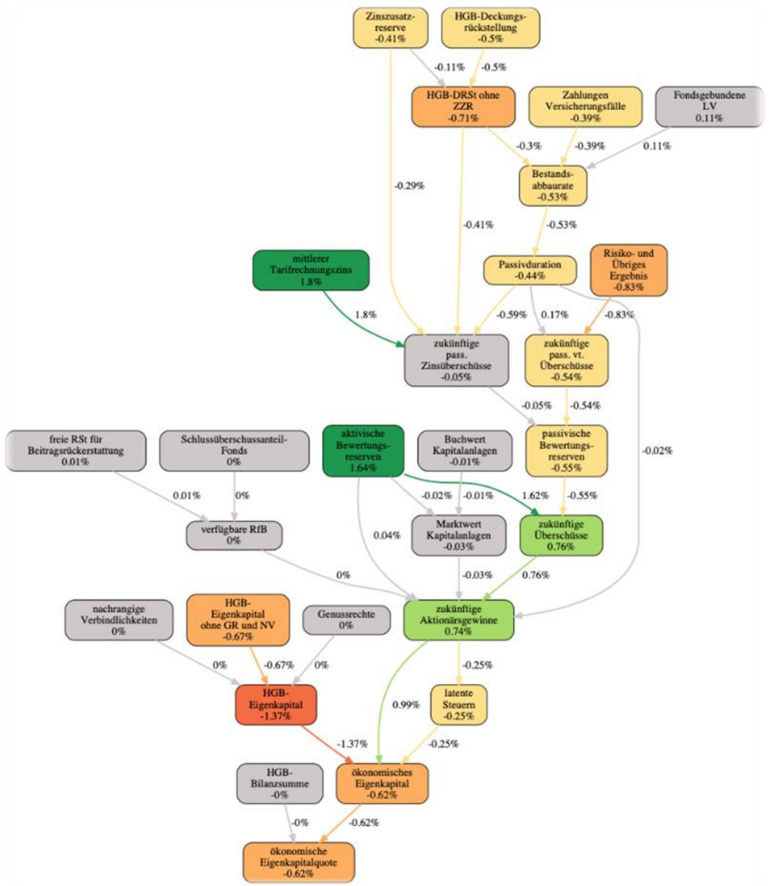
→in given *causal model*

structured Neural Network	Shallow Learning/ Small Data

In contrast to typical Deep Learning approaches

→ *each node/ each neuron* is *interpretable*

→ *as* it *corresponds to a model variable*.



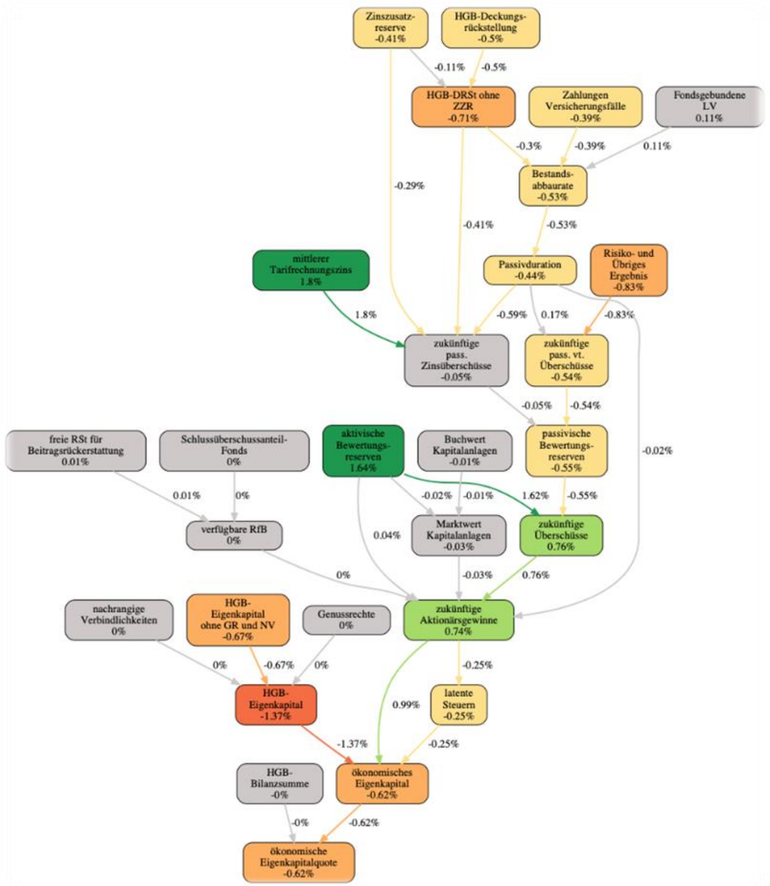
Source: RealRate, Analysis of financial strengths of Allianz Life Insurer, Financial year 2020

THE EXPLAINABLE CAUSAL GRAPH 1/6

OPTIMISATION AS A CLASSICAL, NON-LINEAR PROBLEM

Additional constraint makes a case peculiar, as certain nodes / neurons / variables are just not causally linked to each other.

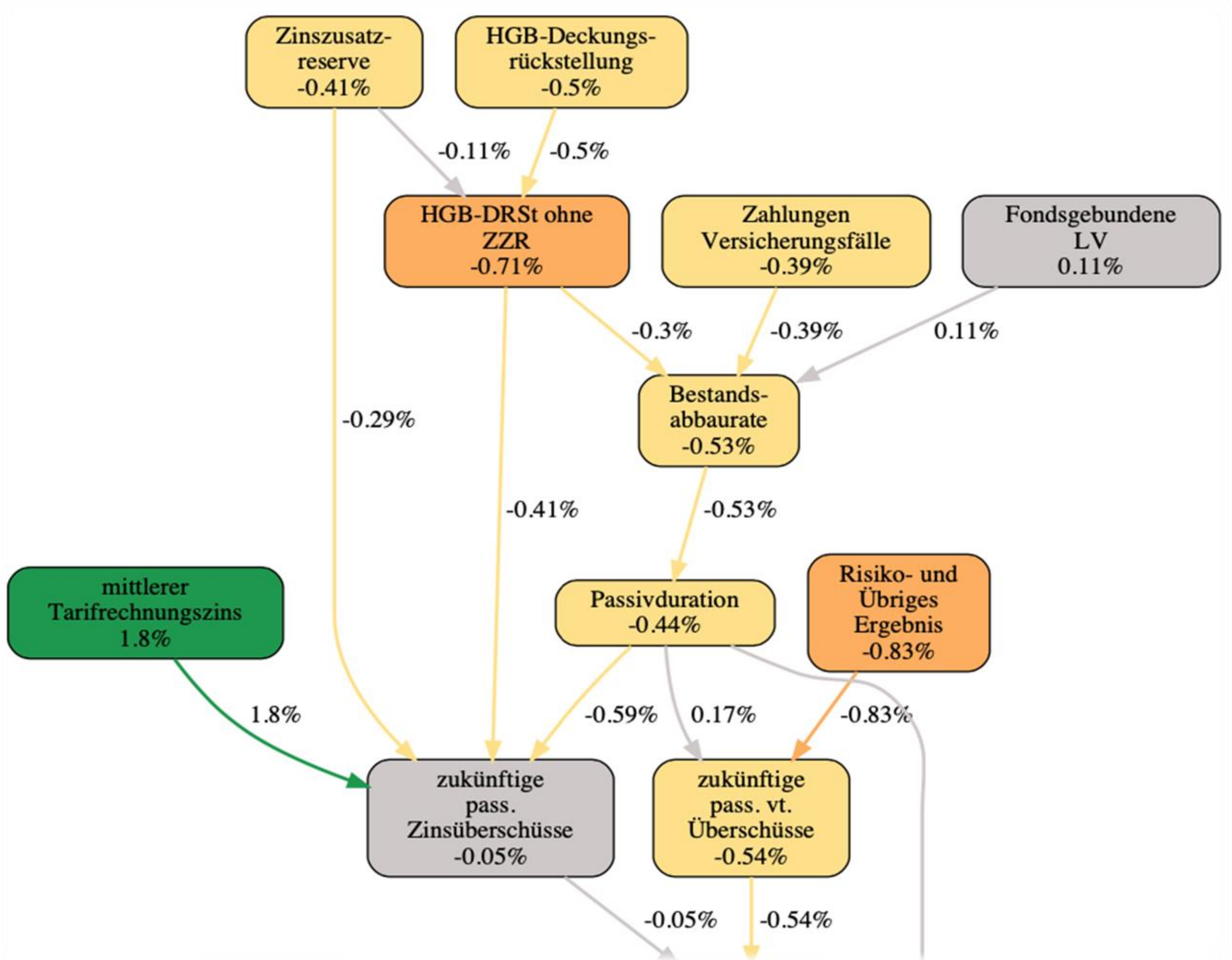
This was technically implemented as a structural neural network (SNN).



Source: RealRate, Analysis of financial strengths of Allianz Life Insurer, Financial year 2020

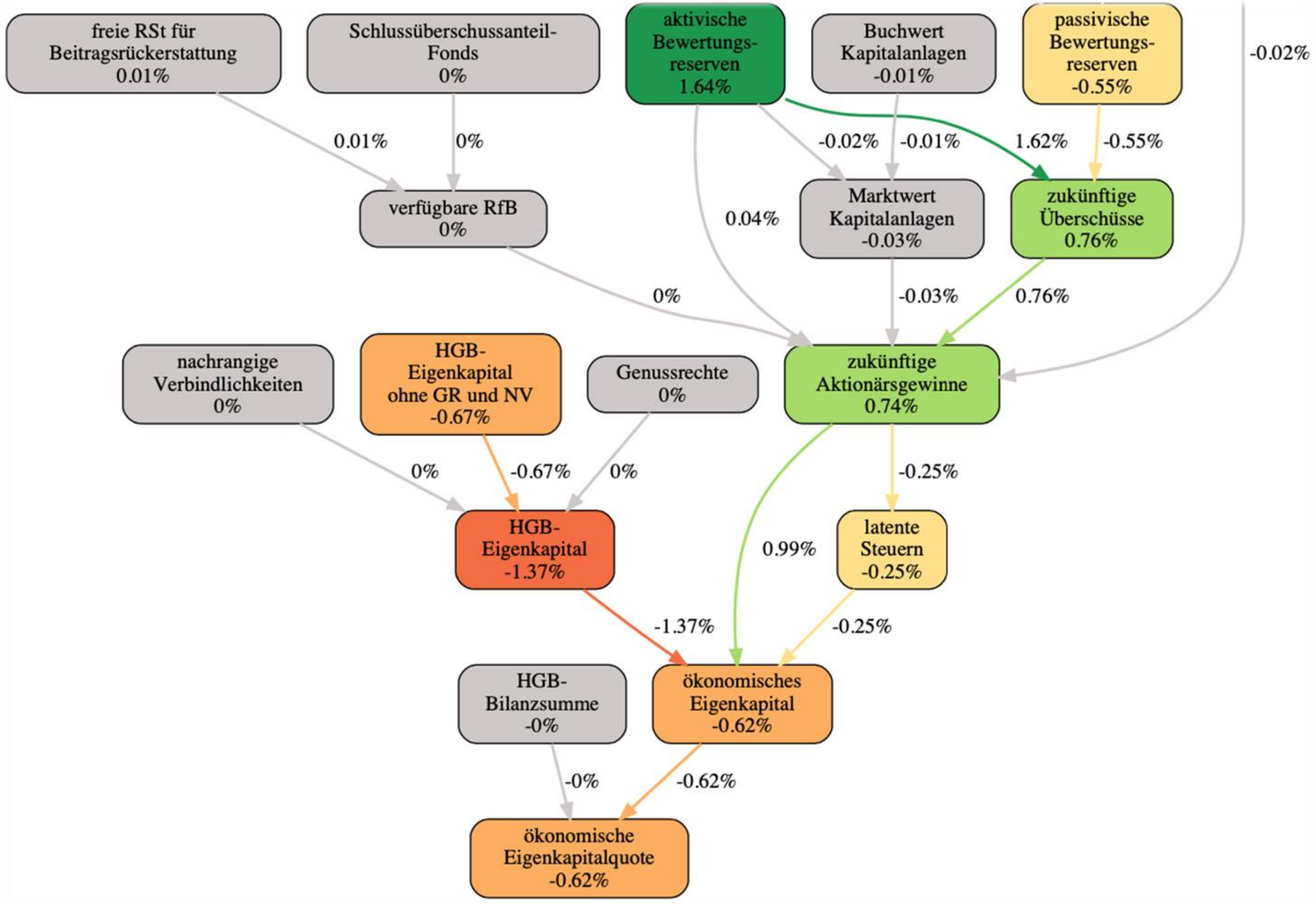
THE EXPLAINABLE CAUSAL GRAPH 2/6

USE-CASE EXAMPLE



Source: RealRate, Analysis of financial strengths of Allianz Life Insurer, Financial year 2020

USE-CASE EXAMPLE



Source: RealRate, Analysis of financial strengths of Allianz Life Insurer, Financial year 2020

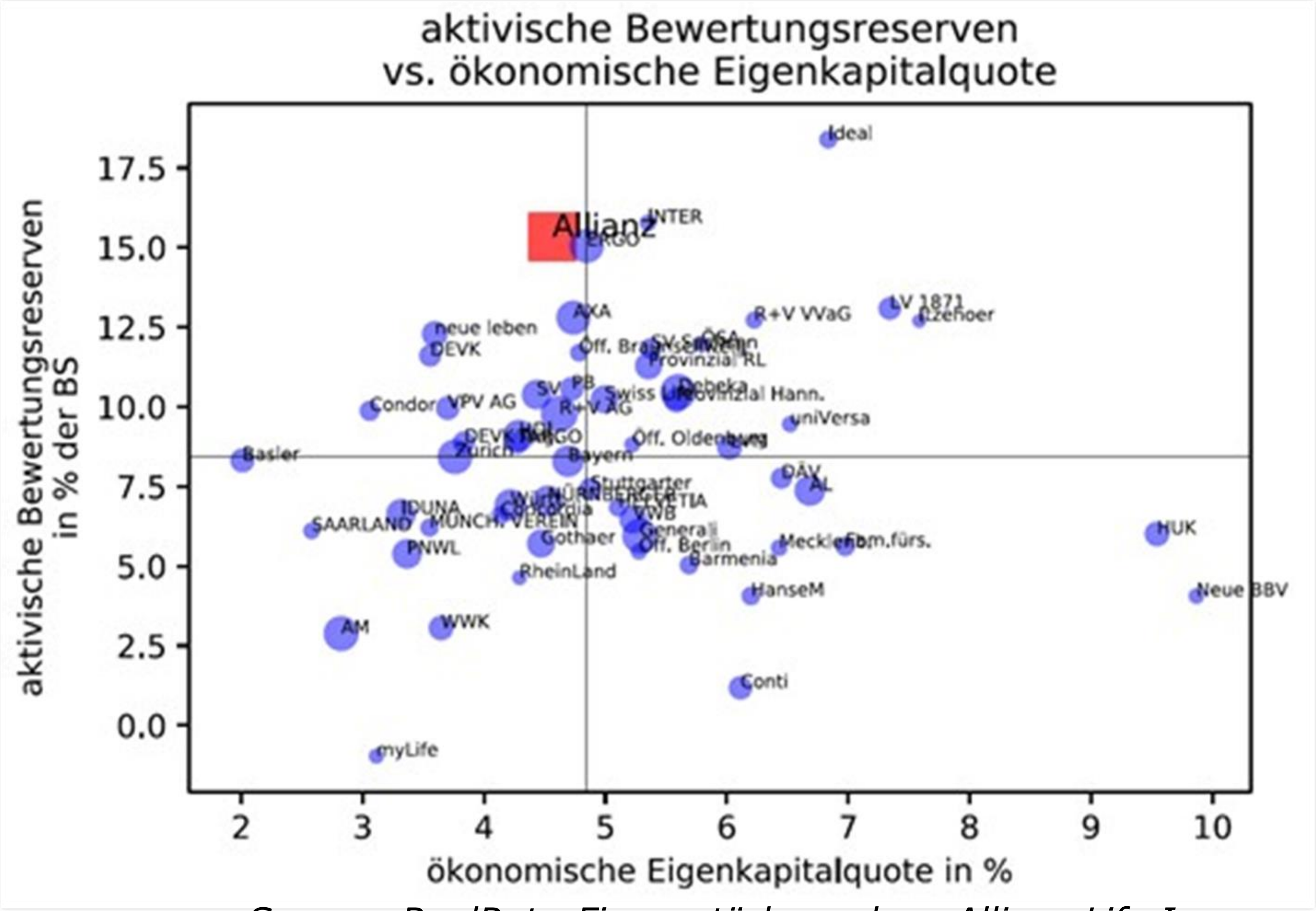
THE EXPLAINABLE CAUSAL GRAPH 4/6

USE-CASE EXAMPLE

Causal structure is *the same* for all companies

still

Quantification of individual effects *is specific* for each case



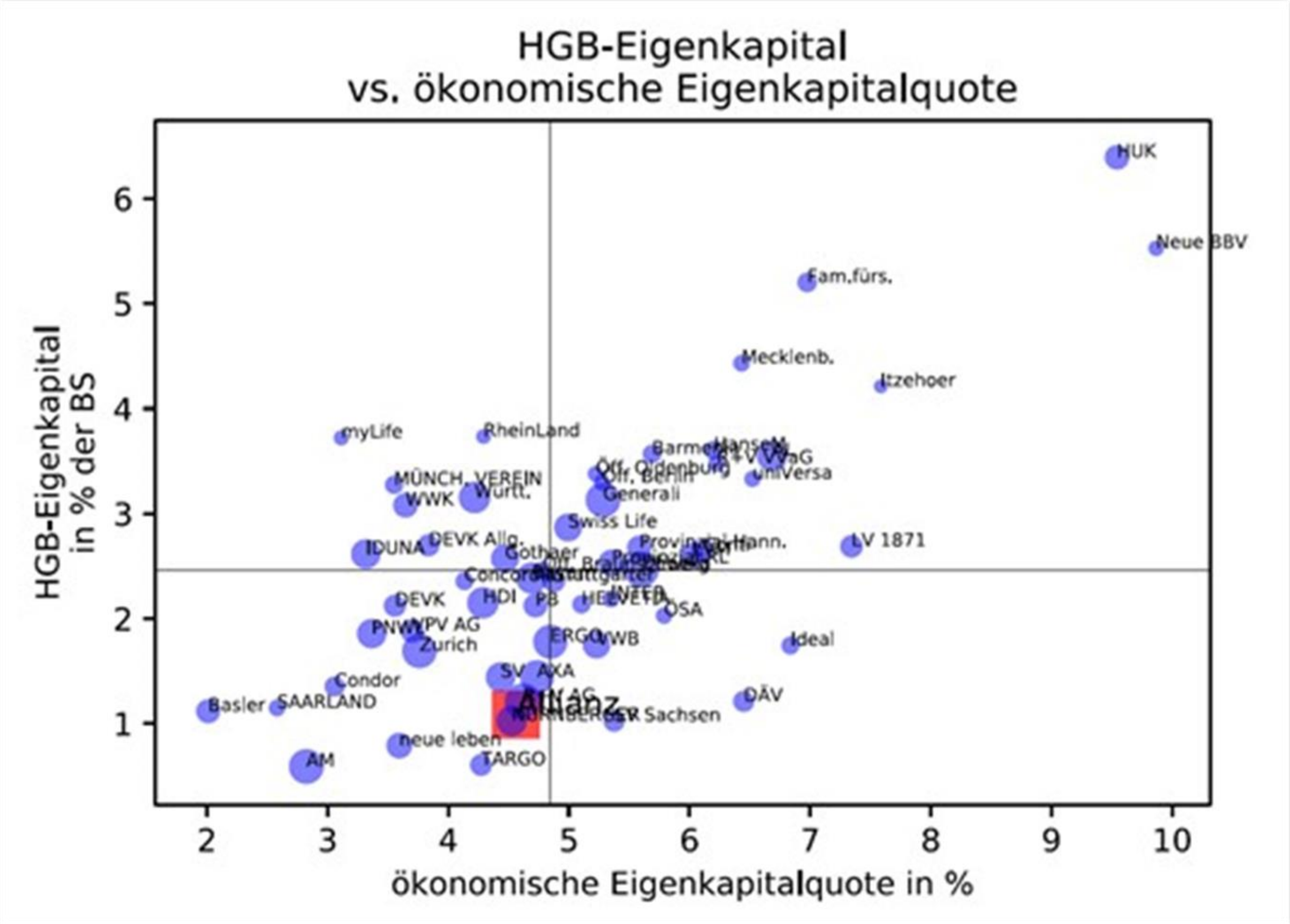
Source: RealRate-Finanzstärkeanalyse Allianz Life Insurer: Scatterplot of asset-side valuation reserves and economic equity ratio

USE-CASE EXAMPLE

In an overall market overview:

it is especially *suitable for a benchmark*

or peer group analysis.



Source: RealRate-Finanzstärkeanalyse Allianz Life Insurer: Scatterplot of HGB equity and economic equity ratio

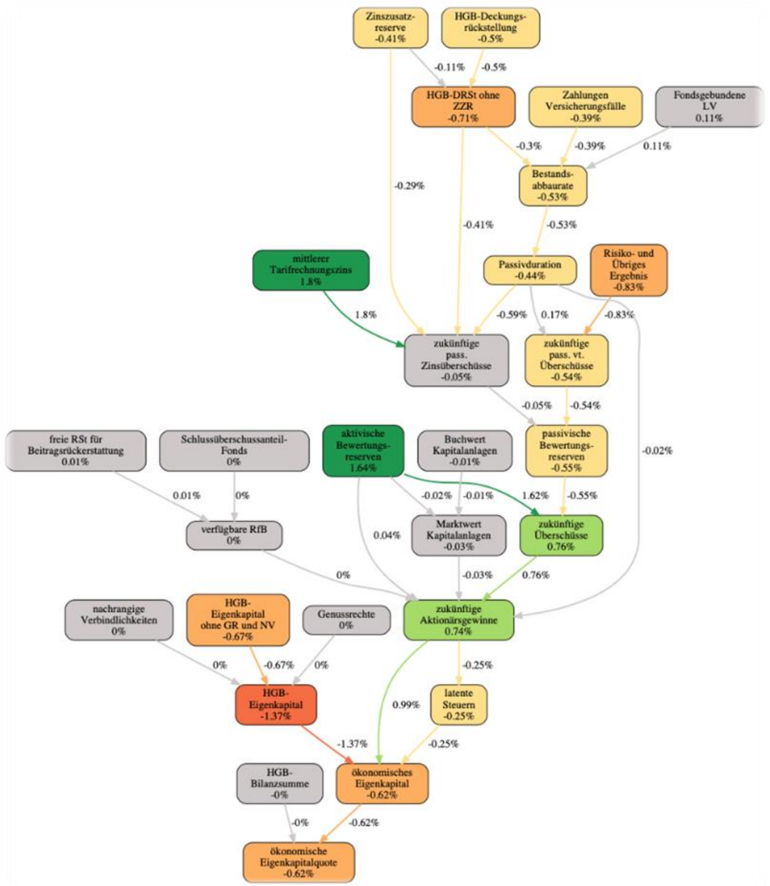
USE-CASE EXAMPLE

Typical modelling cycle of a hybrid model approach:

- Define input
- Define causal structure
- Machine learning/ estimation
- Evaluation
- Model modification

The methodology facilitates model validation and brings the following advantages:

- Explainability
- Transparency
- Small Data vs Big Data
- Speed & Scalability



Source: RealRate, Analysis of financial strengths of Allianz Life Insurer, Financial year 2020

SUMMARY, CONCLUSION & FUTURE WORK

04

SUMMARY, CONCLUSION & FUTURE WORK

Explainable AI & ethic implications in economic sense:

4 key principles of XAI → insuring adherence to ethical principles → Ratings & German Insurers.

Novel hybrid model & Interrelations derived form structure:

more viable/ comprehensive/ traceable/ replicable approach

Future Work: much broader spectrum of practical application (incl. other industries/ countries/ entities, as well as micro- and macro scale goals & objectives)

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Dr. rer. pol., DAV actuary, management consultant and expert advisor

- **Academic studies:** graduate economist, graduate business instructor
- **PhD** in the Research Training Group of the Humboldt University and the Free University of Berlin in the field of multivariate time series analysis
- **Founder** and **CEO** of Fintech Startups
- As a founder of the **rating company RealRate** (Santa Clara and Berlin) has been elected as one of the top InsurTech CEOs.

Goal/objectives:

- bringing modern statistical methods to the market in an application-oriented and transparent way

Key topics:

- Risk management
- Rating
- Artificial Intelligence

ABOUT ME

Holger
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- **Academic studies:** Graduate in mathematics at the Heinrich Heine University Düsseldorf
- **Research assistant** and **PhD** in Controlling at the Westphalian Wilhelms University of Münster
- **Professorship** for Insurance Management at the Coburg University of Applied Sciences and Arts (since 2012)
- 2006-2021 Active at GDV in the area of Solvency II/risk management

Goal/objectives:

- Teaching and research in controlling and risk management
- Studying the ethical issues in the application of AI methods in the insurance sector

Key topics:

- Controlling and risk management
- Insurance superviison (Solvency II)
- Digitalisation and telematics
- Health promotion and insurance

ABOUT ME

Mirko
Kraft

Coburg University of
Applied Sciences and Arts
Department of Business and
Economics

- **Academic studies:** Computational Linguistics, English and Computer Science at FAU Erlangen-Nuremberg and Lancaster University, Computer Speech, Text and Internet Technology at Cambridge University
- **PhD** in Computer Science, University of Edinburgh
- **Professorship** for explainable and responsible artificial intelligence in insurance at Coburg University of Applied Sciences and Arts
- ***Visiting Professor** of Data Analytics*at the Computer Science Department of the University of Sheffield

Goal/objectives:

- Academic work and research on controlling and risk management
- Researching the ethical issues in the application of AI methods in the insurance sector

Key topics:

- natural language processing (NLP) / computational linguistics
- Information Retrieval (IR)
- applied machine learning (ML)
- Language and Text Technologies Applications

ABOUT ME

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Thank you very much for your attention