MACHINE LEARNING APPLICATIONS IN FINANCE & INSURANCE

QX-CLUB KÖLN/BONN/DÜSSELDORF

DR. CHRISTIAN JONEN – GENERALI DEUTSCHLAND AG

7th of March, 2023

GENERALI

TODAY AGENDA

01. MOTIVATION

02. SOLVENCY II INTERNAL MODEL BASED ON NEURAL NETWORKS

03. PRICING AMERICAN OPTIONS WITH NEURAL NETWORKS

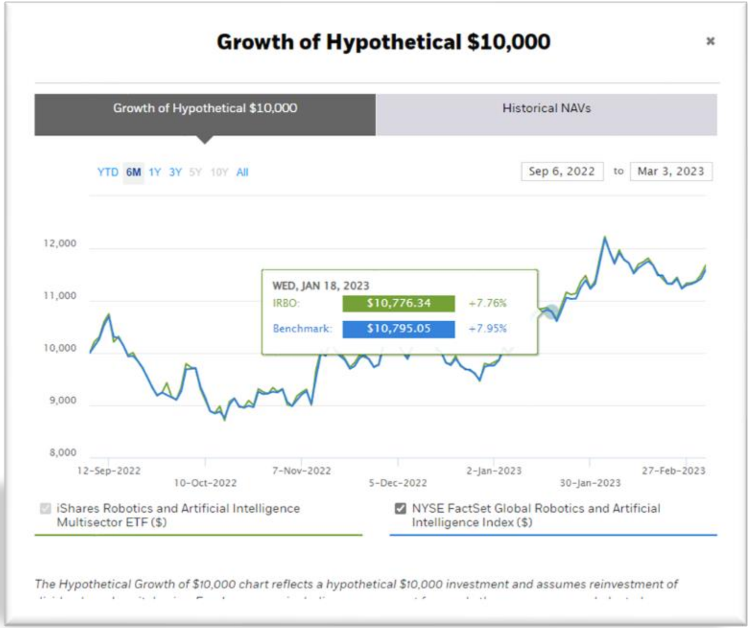
04. WRAP UP, DISCUSSION, Q&A

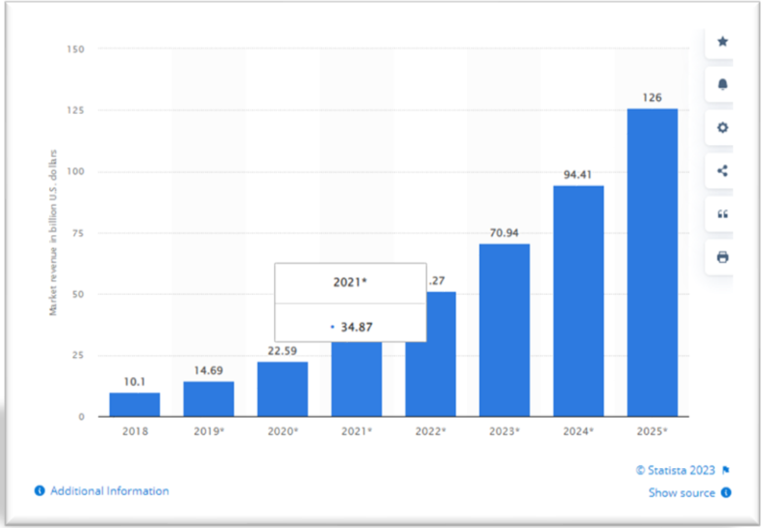
MOTIVATION

01

WE ARE SURROUNDED BY MACHINE LEARNING & ARTIFICAL INTELLIGENCE

MARKETS RECOGNIZE THE BENEFITS FROM AI

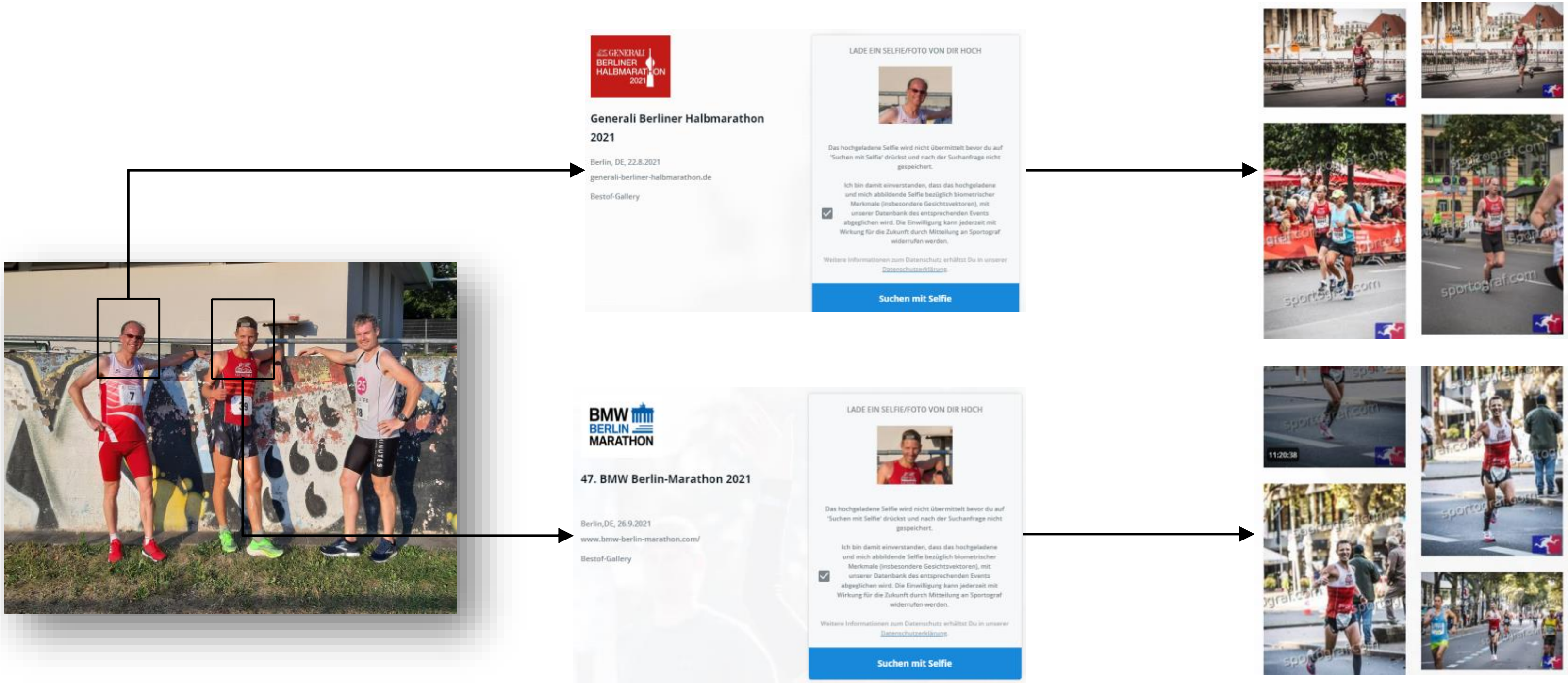




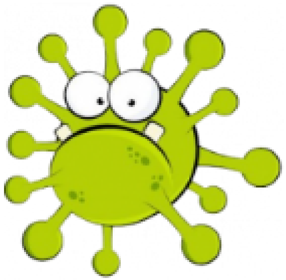
[iShares Automation & Robotics UCITS ETF | 2B76]

[Global AI software market size 2018-2025 | Statista]

IMAGE RECOGNITION WITH THE HELP OF DEEP LEARNING



DEVELOPING IMMUNOTHERAPIES BY LEVERAGING ARTIFICAL INTELLIGENCE AND MACHINE LEARNING



BIONTECH News | Events & Presentations | Financials | Corporate Governance | ESG | Stock Info | Annual General Meeting | Contact Us

Press Release

BioNTech to Acquire InstaDeep to Strengthen Pioneering Position in the Field of AI-powered Drug Discovery, Design and Development

10 January 2023

PDF Version

- *Acquisition to enable creation of a fully integrated, enterprise-wide capability to discover, design and develop next-generation immunotherapies at scale by leveraging artificial intelligence and machine learning technologies across BioNTech's therapeutic platforms and operations*
- *Builds on multi-year strategic collaboration between BioNTech and InstaDeep which included the formation of an AI Innovation Lab in 2020 and completion of dozens of joint projects*
- *Acquisition expected to add approximately 240 highly skilled professionals and a global network of research partners in the fields of artificial intelligence, machine learning and data science based in the world's leading global technology hubs*
- *BioNTech to pay an upfront consideration of approximately £362 million in cash and BioNTech shares, to acquire 100% of remaining InstaDeep shares following BioNTech's Series B investment in 2022*
- *InstaDeep to operate globally from London headquarters as a BioNTech company post-closing, which is expected in the first half of 2023, subject to regulatory approval*

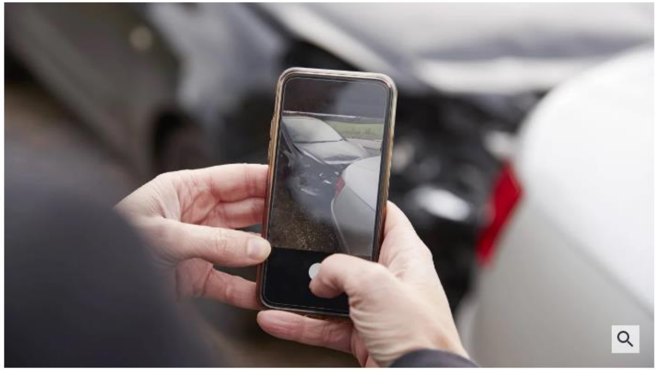
BioNTech to Acquire InstaDeep to Strengthen Pioneering Position in the Field of AI-powered Drug Discovery, Design and Development | BioNTech

DATA DRIVEN INSURANCE AND ARTIFICAL INTELLIGENCE

Künstliche Intelligenz

Wenn die Versicherung alles weiß

29. Juni 2022, 19:36 Uhr | Lesezeit: 3 min



Wer war schuld? Manche Versicherungsfälle lassen sich einfach mit künstlicher Intelligenz klären, bei anderen muss ein Sachverständiger ran. (Foto: imago images)

Wie Versicherungen mit künstlicher Intelligenz arbeiten - Wirtschaft - SZ.de (sueddeutsche.de)

Künstliche Intelligenz: So heben Versicherungen ihr Potenzial

Künstliche Intelligenz (KI) hat ein großes Potenzial für Versicherungen. So können KI-Lösungen Betrugsversuche aufdecken, Dialoge führen oder Dokumente automatisch weiterleiten.

Foto: geralt/Pixabay

Künstliche Intelligenz: So heben Versicherungen ihr Potenzial - Netzwelten - Versicherungsbote.de

APPLICATIONS IN INSURANCE

- Claims management by using AI techniques, e.g. image recognition
- Risk management, e.g. SCR calculation by an internal model based on Machine Learning techniques
- Fraud detection
- High data quality by anomaly detection
- Classification of documents and extraction of data from documents
- Prediction of purchasing probabilities and price sensitivity models
- Customer communication via chat bots
- Robo-adviser for sales & distribution
- Churn prediction to monitor customers
- etc.

STRATEGY AT GENERALI

GENERALI Lifetime Partner 24
Driving Growth

3 STRATEGIC PILLARS

DRIVE SUSTAINABLE GROWTH
Boost P&C revenues and maintain best-in-class technical margins
Grow capital light business, technical profits and ESG product range
Underpin growth with effective cost management

ENHANCE EARNINGS PROFILE
Improve Life business profile and profitability
Redeploy capital to profitable growth initiatives
Develop Asset Management franchise further

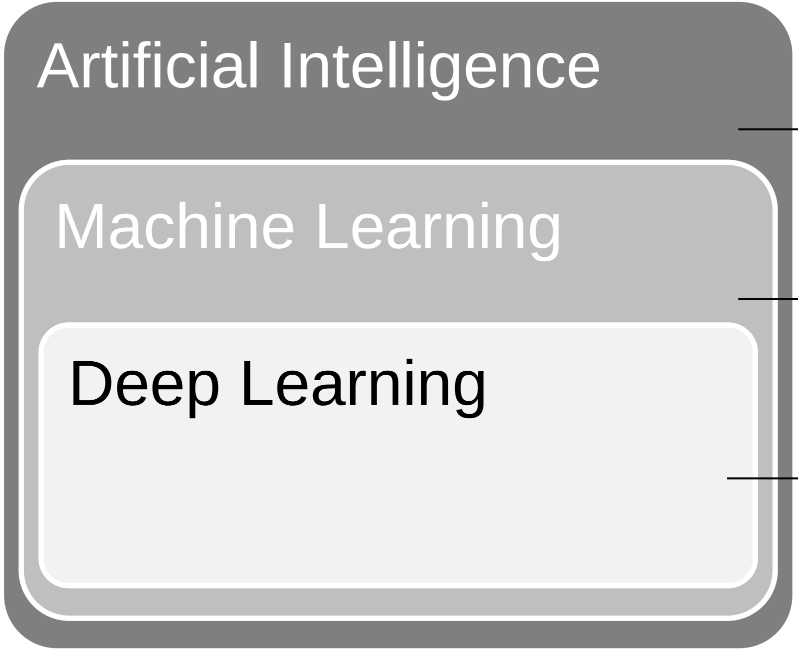
LEAD INNOVATION
Increase customer value through Lifetime Partner advisory model
Accelerate innovation as a data-driven company
Achieve additional operating efficiency by scaling automation and technology

DELIVER STRONG FINANCIAL PERFORMANCE, BEST-IN-CLASS CUSTOMER EXPERIENCE AND AN EVEN GREATER SOCIAL AND ENVIRONMENTAL IMPACT THANKS TO OUR EMPOWERED PEOPLE

WHY ARE MACHINE LEARNING, ARTIFICAL INTELLIGENCE AND BIG DATA ANALYTICS SO IMPORTANT?

- Implementation costs are relatively cheap
- Knowledge transfer is very high (open source and well-connected community); with some quantitative background techniques can be learned in short time
- Lead to competetive advantages
- Data is the lifeblood of all business (abundant resource)
- Many powerful & successful applications in several domains
- …

ARTIFICIAL INTELLIGENCE VS. MACHINE LEARNING VS. DEEP LEARNING



Artificial Intelligence

- Founded in 1956
- Getting a computer to mimic human behavior
- “Computer is doing something intelligent“

Machine Learning

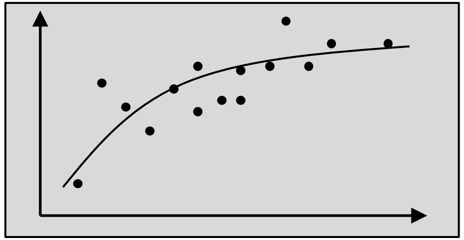
- Subset of artificial intelligence (AI)
- Techniques that enable computers to figure things out from the data and deliver AI applications
- Ability to learn without being explicitly programmed

Deep Learning

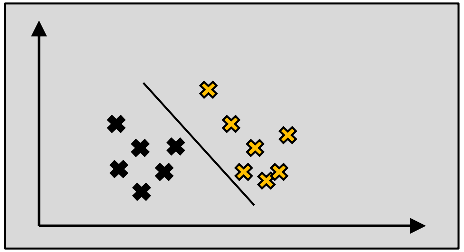
- Subset of machine learning
- Enables computers to solve more complex problems
- Based on artifical neural networks

MAIN TYPES OF PROBLEMS IN MACHINE LEARNING

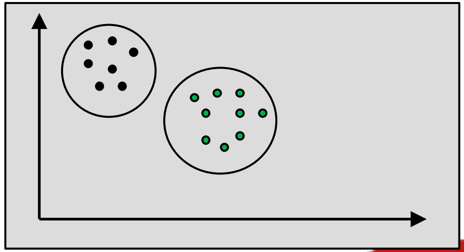
Regression



Classification



Clustering



OVERVIEW OF METHODS

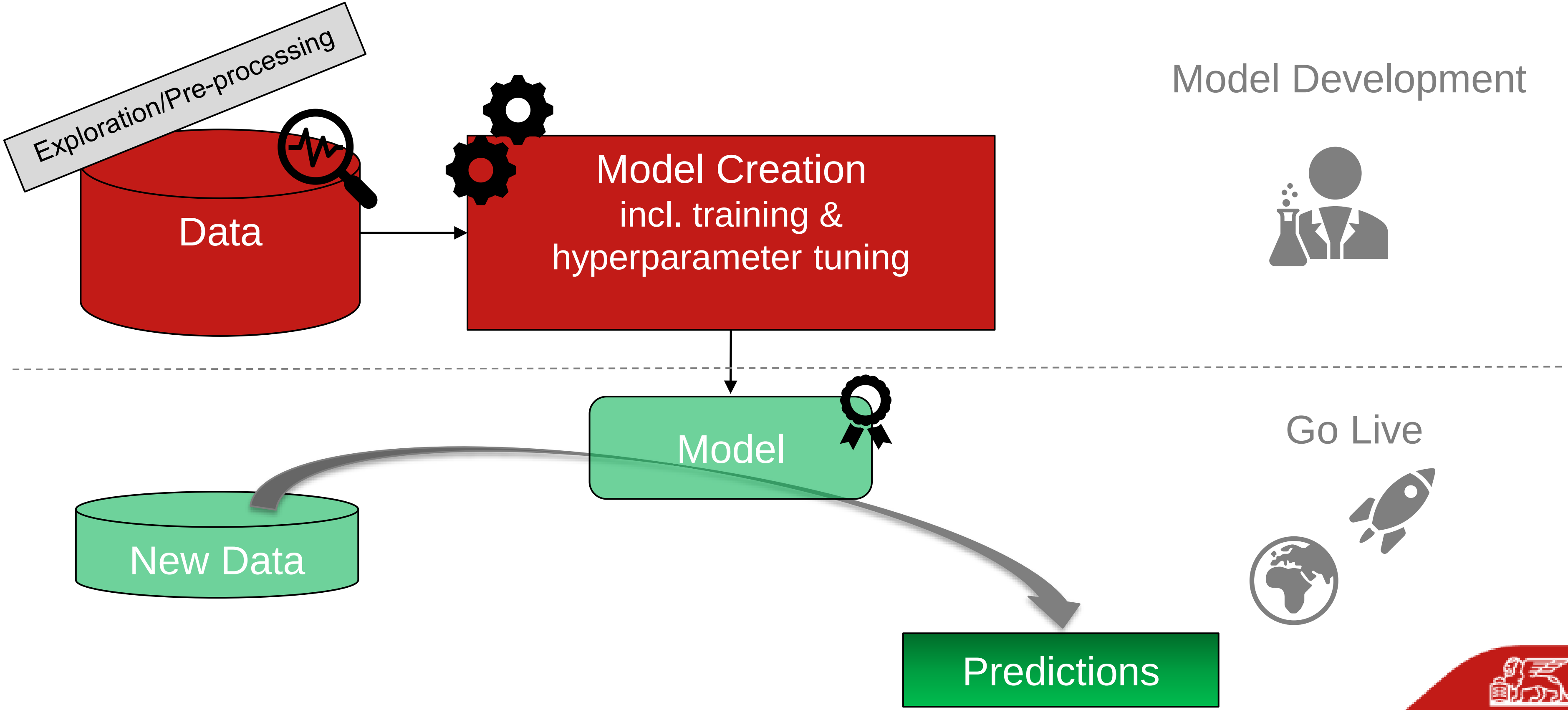
Classification:

- K-Nearest Neighbors
- Decision Tree
- Naive Bayes
- Logistic Regression
- Support Vector Machines
- Neural Networks
- Random Forest
- …

Regression:

- Ordinary Least Squares
- Ridge/Lasso Regression
- K-nearest Neighbor
- Decision Tree Regressor
- Random Forest
- Support Vector Machines
- Neural Networks
- …

MACHINE LEARNING WORKFLOW



02

SOLVENCY II INTERNAL MODEL BASED ON NEURAL NETWORKS

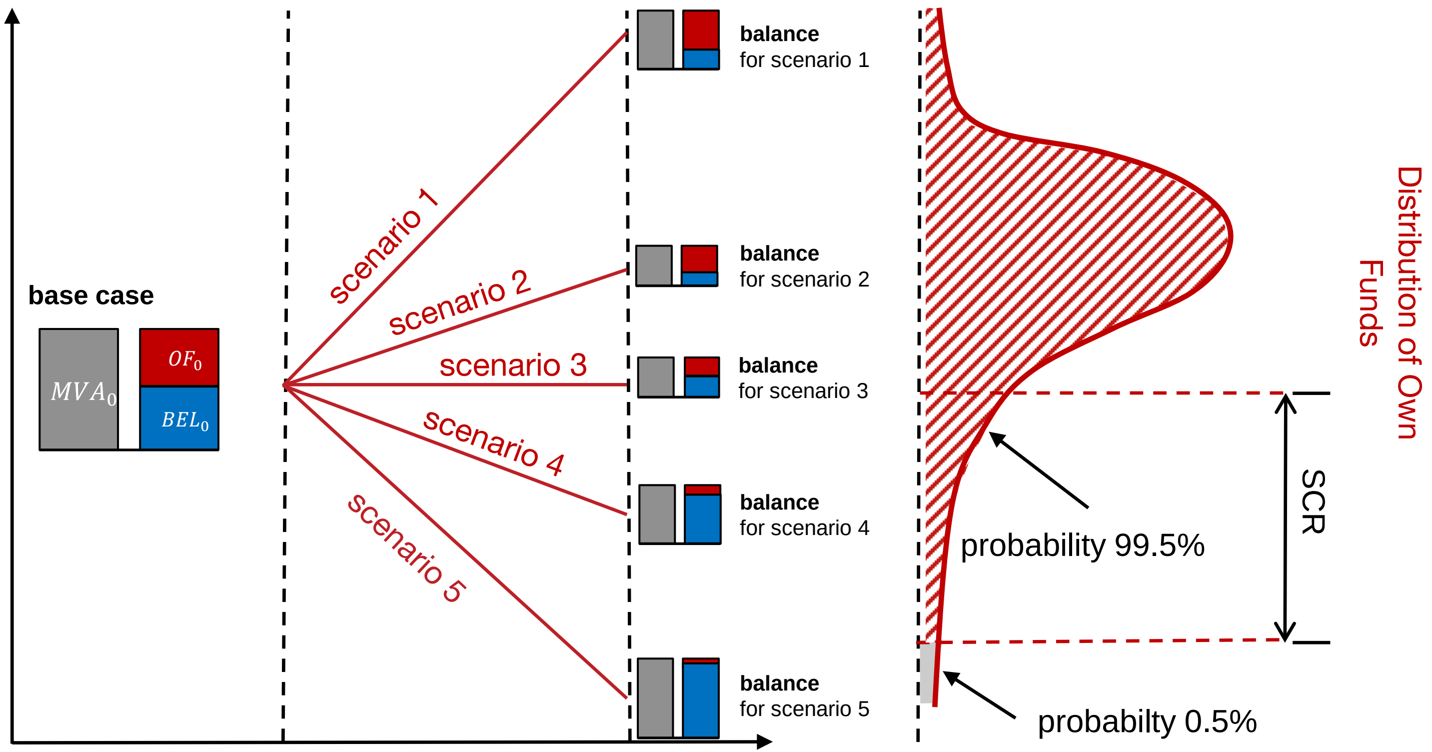
SOLVENCY II INTERNAL MODEL

- **Determination of solvency capital requirement (SCR)** for an insurance company by an internal model (*Solvency II*)

- In terms of **open science** we provide a **comprehensive data set** for the actuarial community, such that practitioners and researchers are able to apply modern data analytics methods for a realistic problem, namely the SCR calculation.

- Data set consists of comprehensive **evaluations of Own Funds** for three fictive but realistic insurance portfolios (life and health), which have been derived on the basis of advanced actuarial projection models (mapping of assets and liabilities, management rules, regulatory requirements, …) and well-defined scenarios.

DISTRIBUTION OF OWN FUNDS AT RISK HORIZON



➢ **Nested stochastic problem**

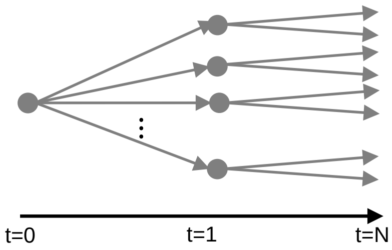
FURTHER DESCRIPTIONS

- Each **scenario** is the **realisation of D risk factors** $RF_1, \dots, RF_D$ (e.g. longevity, lapse, interest rate, equity, among others) and represents a possible development at the risk horizon (1 year); D=12 resp. D=13 in our data set
- The **calculation of the market value balance sheet items** (for base case and stress scenarios) requires comprehensive (stochastic) simulations by adequate projection models due to complex dependencies and asymmetries
  → ***Monte Carlo simulation***

- This leads to a **nested stochastic problem** with exploding computational effort (simulation in a simulation)
- Apply data analytics techniques to avoid massive run time issues

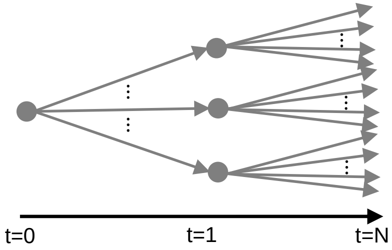
DATA SET

1. Training Set



2^{15} outer scenarios, each with 2 inner scenarios

2. Validation Set



2^{8} outer scenarios, each with 1k inner scenarios

3. Base Case and SCR region

- Base point with 16k simulations
- 129 resp. 50 outer scenarios around the 0.5% quantile scenario (SCR region), each with 4k simulations

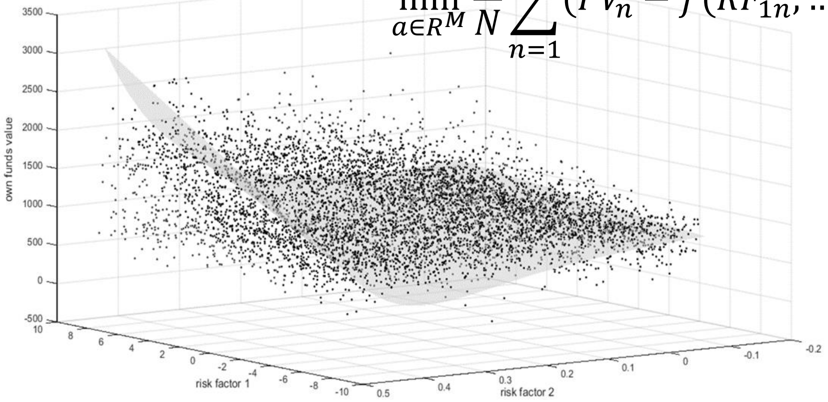
ORDINARY LEAST SQUARES METHOD

- **Practical model function** is given by a simple linear combination of basis functions $\{\varphi_m(\cdot)\}_{m=1}^{M}$ with coefficients a_m:

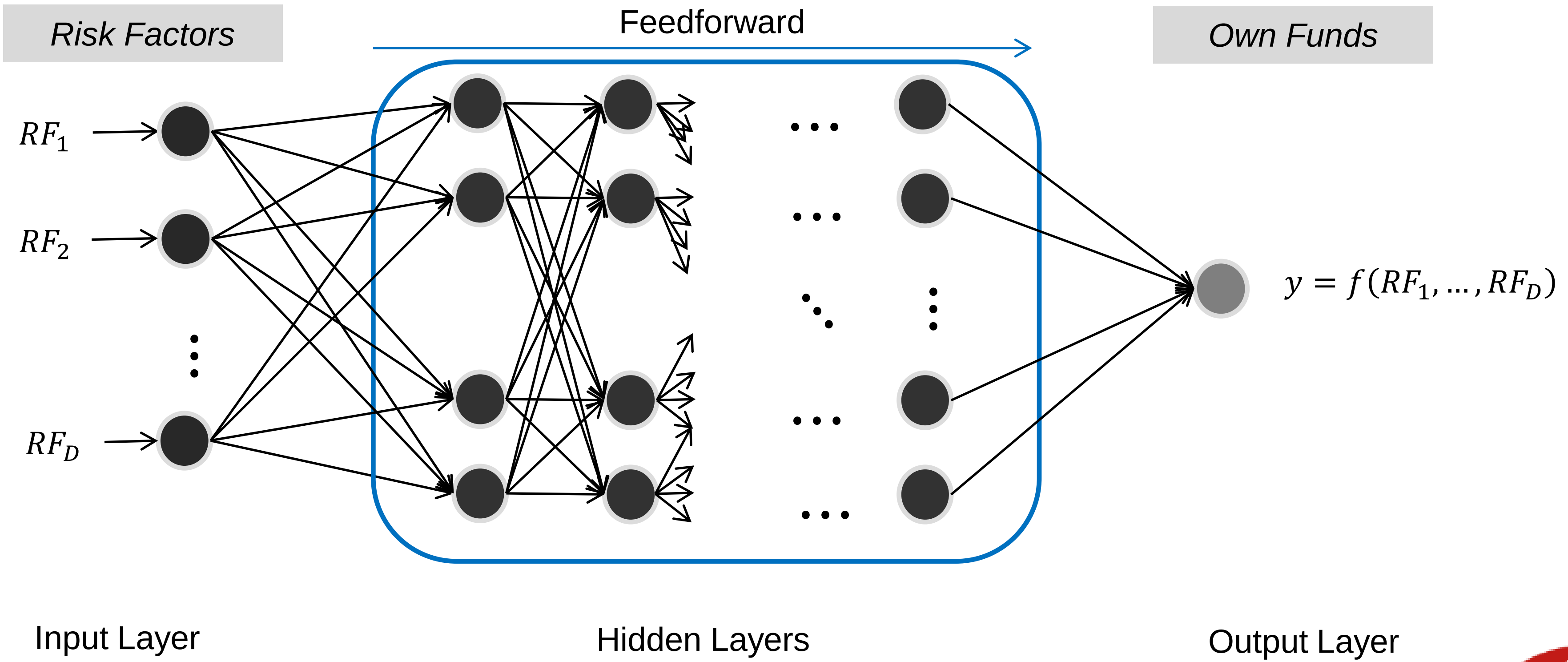
$$f(RF_1, \dots, RF_D) = \sum_{m=1}^{M} a_m \varphi_m(RF_1, \dots, RF_D)$$

- For $n = 1, \dots, N$, by denoting PV_n as Own Funds samples and $RF_{1n}, \dots, RF_{Dn}$ as N simulated vectors of risk factors (outer scenarios), we are able to determine the function f via **Least Squares**:

$$\min_{a \in R^M} \frac{1}{N} \sum_{n=1}^{N} (PV_n - f(RF_{1n}, \dots, RF_{Dn}))^2$$



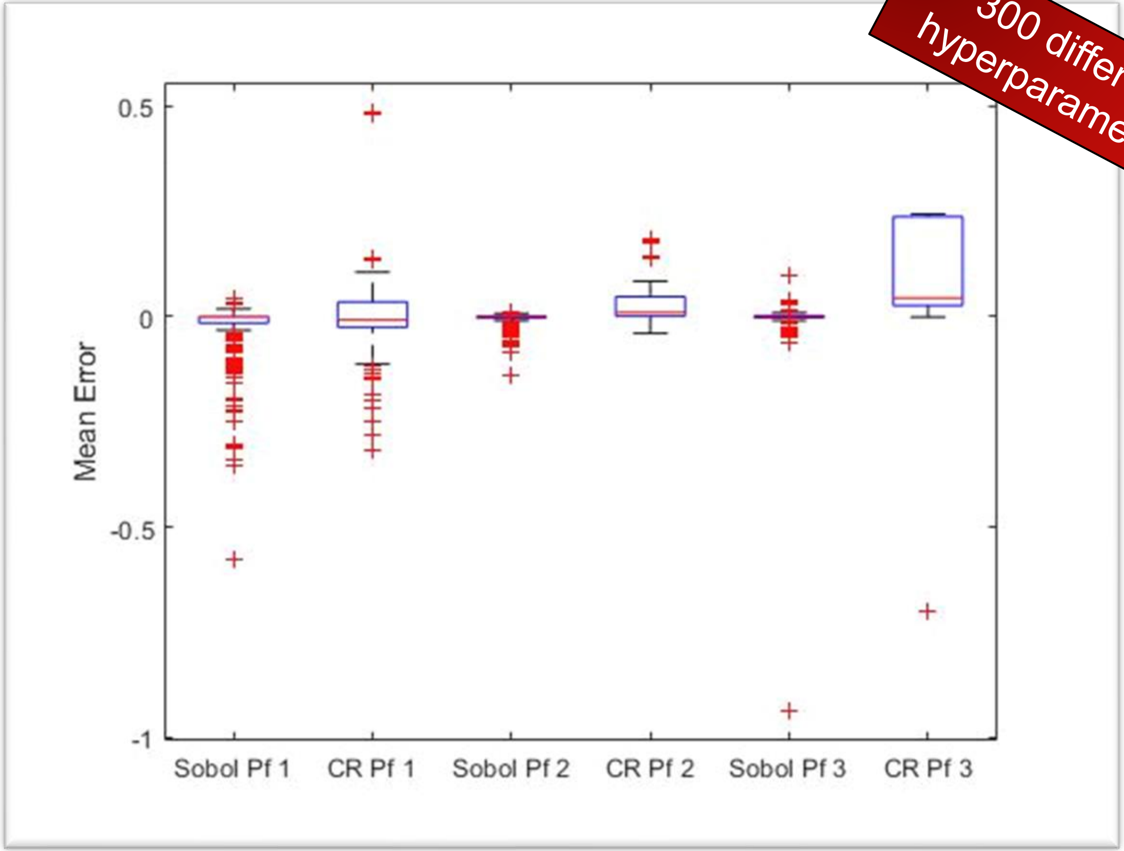
STRUCTURE OF NEURAL NETWORKS



LET‘S GO

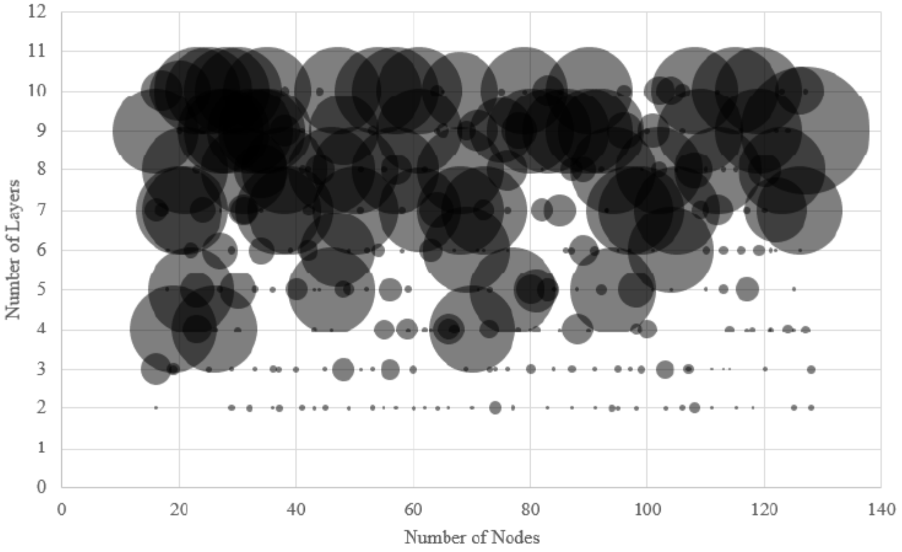
- **Architecture:**
  - Number of hidden layers: 2-10
  - Number of nodes for each hidden layer: 16-128
  - Activation functions (inner nodes): Sigmoid, Rectified Linear Unit (ReLU), Leaky ReLU with α values between 0 and 0.1
  - Activation function (output): Linear, Sigmoid
- **Optimization:**
  - Algorithm: Adam, Adamax, Nadam
  - Learning rate: 0.0005 – 0.005
  - Dropout rate: 0 – 0.4
  - Batch size: 100 – 1600
  - Initialisation weights: random Normal, random Uniform, Glorot Uniform

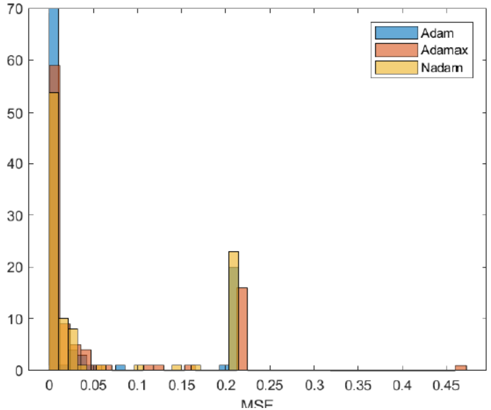
THE PROOF IS IN THE PUDDING

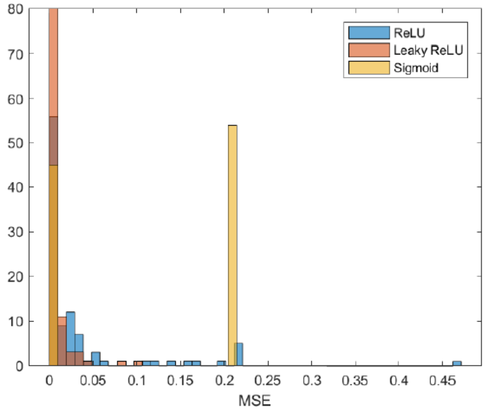


300 different hyperparameters

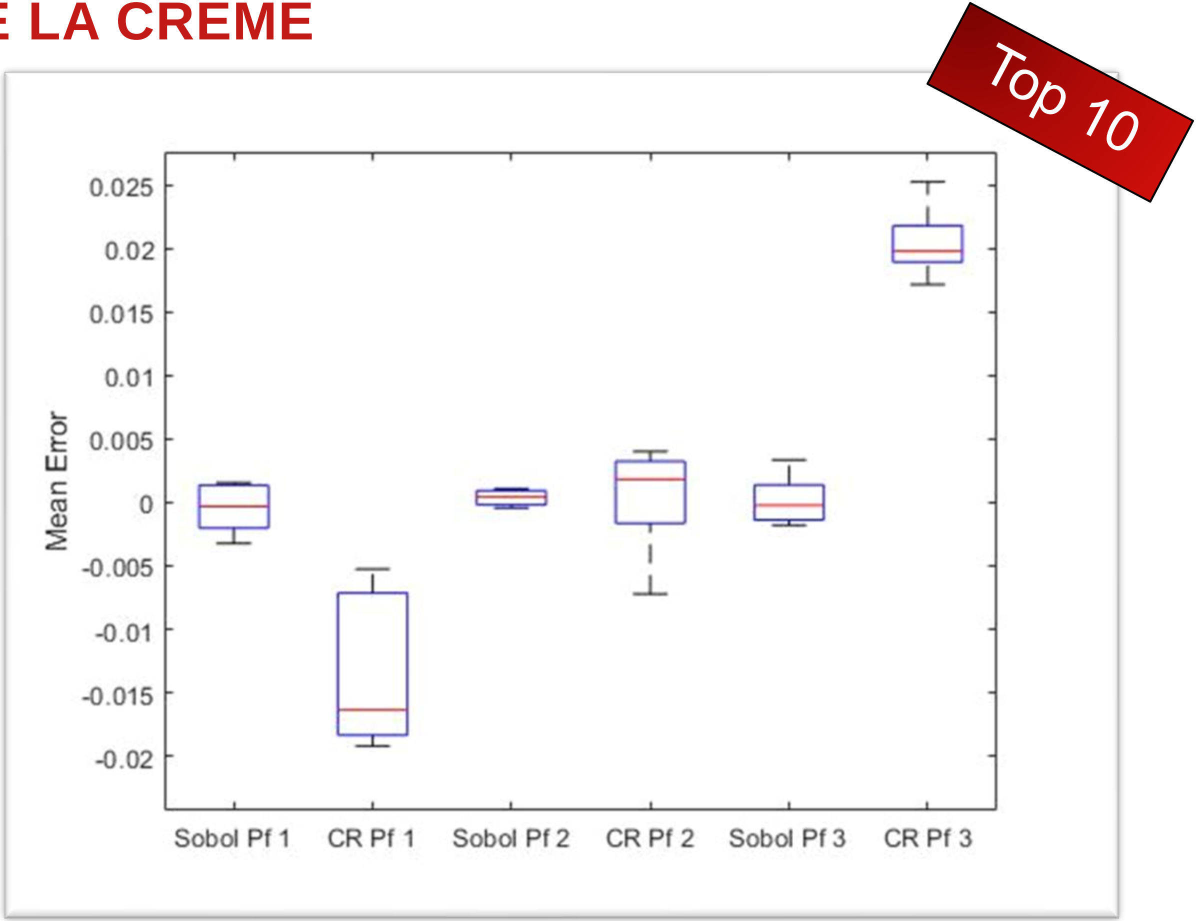
CREATING EFFICIENT NEURAL NETWORKS



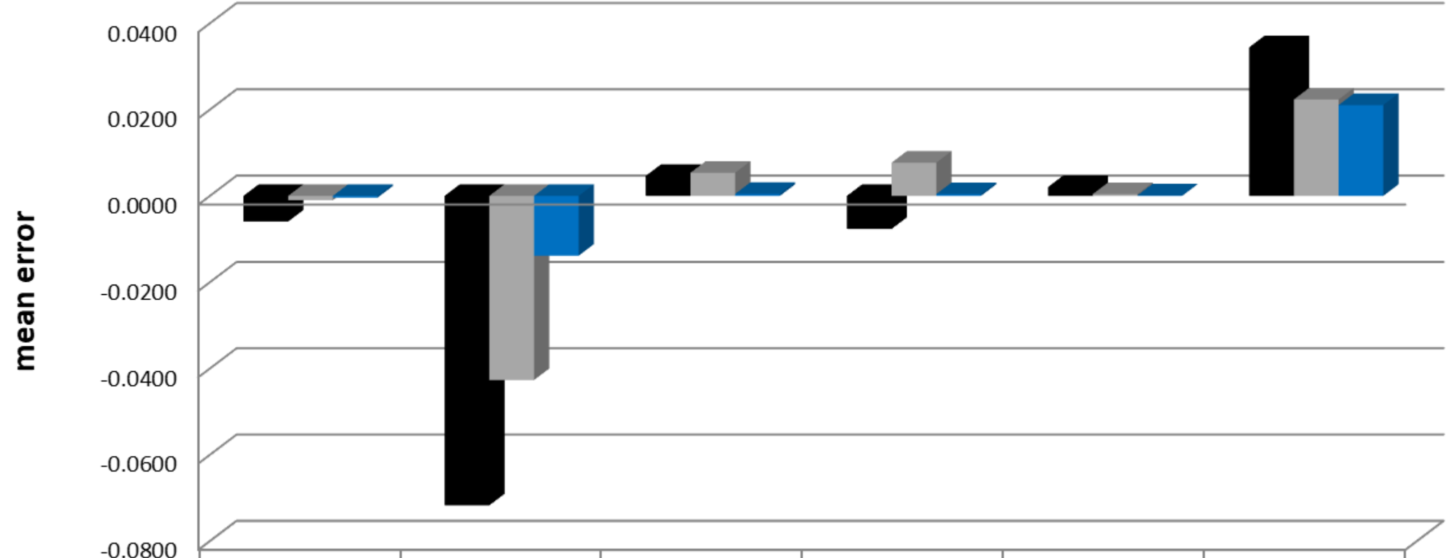




CRÈME DE LA CRÈME



#TEAMWORK



	Validation PF1	Nested PF1	Validation PF2	Nested PF2	Validation PF3	Nested PF3
	Portfolio 1		Portfolio 2		Portfolio 3	
OLS P1	-0.0059	-0.0717	0.0046	-0.0077	0.0021	0.0344
OLS P2	-0.0010	-0.0427	0.0054	0.0077	0.0004	0.0223
NN Ensemble	-0.0004	-0.0139	0.0005	0.0004	0.0001	0.0211

USE (THIS SOLVENCY II) CASE!

- Lebensversicherung
- Altersvorsorge
- Krankenversicherung
- Schadenversicherung/HUK
- ERM/Solvency II
- Investment
- Rechnungslegung und Regulierung
- Verbraucherschutz
- Actuarial Data Science
  - Anwendungsfälle
  - Data Science Challenge
- Aktuarielles Glossar

Use (this Solvency II) case! Neuronale Netze treffen auf Least Squares Monte Carlo

Das Thema künstliche Intelligenz ist gerade in aller Munde und die Anwendungsgebiete erfreuen sich immer größerer Beliebtheit. In dieser Fallstudie wollen wir uns der Risikokapitalermittlung von Versicherungsunternehmen im Solvency II-Kontext widmen und wir werden den klassischen Least Squares Monte Carlo-Ansatz mit neuronalen Netzen herausfordern.

Die speziell für diesen Zweck erzeugten, realistischen Projektionsdaten von drei im Rahmen dieses Use Case aufbereiteten Lebensversicherungs- und Krankenversicherungsportfolien bilden den zentralen Bestandteil dieses Use Case.

Risikokapitalberechnung unter Solvency II

Solvency II zielt auf die Implementierung einer robusten Solvenzregelung für Versicherungen ab, die in angemessener Weise die tatsächlichen Risiken berücksichtigt. Eines der Kernkonzepte ist dabei die Berechnung der Solvenzkapitalanforderung (SCR). Gemäß Artikel 101 (3) der Richtlinie des europäischen Parlaments und des Rates *„wird das SCR so kalibriert, dass gewährleistet wird, dass alle quantifizierbaren Risiken, denen ein Versicherungs- oder Rückversicherungsunternehmen ausgesetzt ist, berücksichtigt werden. Sie deckt sowohl die laufende Geschäftstätigkeit als auch die in den folgenden zwölf Monaten erwarteten neuen Geschäfte ab. In Bezug auf die laufende Geschäftstätigkeit deckt sie nur unerwartete Verluste ab. Sie entspricht dem Value-at-Risk der Basiseigenmittel eines Versicherungs- oder Rückversicherungsunternehmens zu einem Konfidenzniveau von 99,5 % über den Zeitraum eines Jahres."*

Demzufolge müssen die ökonomische Bilanz basierend auf einer marktkonsistenten Bewertung zum heutigen Zeitpunkt (Basisfall) sowie mittels einer geeigneten Approximationsmethode die erwarteten zukünftigen Cash-Flows zwischen dem Versicherungsunternehmen und den Versicherungsnehmern (versicherungstechnische Rückstellungen bzw. Technical Provisions) bzw. den

Login

Adressnr.:

Passwort:

Passwort vergessen? Login

Weitere Informationen

Ihre Ansprechpartner aus der Arbeitsgruppe *Statistische Methoden zum Anwendungsfall:*

Christian Jonen, Tamino Meyhöfer, Zoran Nikolić

Kontakt über:

Vivien Heidemann
vivien.heidemann@aktuar.de
0221/912 554-226

GitHub-Account

Den Code und die Daten zu diesem Anwendungsfall finden Sie auf dem GitHub-Account der DAV.

Python code and data

[Seiten - Anwendungsfall 2 (aktuar.de)]

CASE STUDY – EUROPEAN ACTUARIAL JOURNAL

Case Study | Open Access | Published: 08 July 2022

Neural networks meet least squares Monte Carlo at internal model data

Christian Jonen, Tamino Meyhöfer & Zoran Nikolić

European Actuarial Journal (2022) | Cite this article

Abstract

In August 2020 we published “Comprehensive Internal Model Data for Three Portfolios” as an outcome of our work for the committee “Actuarial Data Science” of the German Actuarial Association. The data sets include realistic cash-flow models outputs used for proxy modelling of life and health insurers. Using these data, we implement the hitherto most promising model in proxy modeling consisting of ensembles of feed-forward neural networks and compare the results with the *least squares Monte Carlo (LSMC)* polynomial regression. To date, the latter represents—to our best knowledge—the most accurate proxy function productively in use by insurance companies. An additional goal of this publication is a more precise description of “Comprehensive Internal Model Data for Three Portfolios” for other researchers, practitioners and regulators interested in developing *solvency capital requirement (SCR)* proxy models.

[Neural networks meet least squares Monte Carlo at internal model data | SpringerLink]()

PRICING AMERICAN OPTIONS WITH NEURAL NETWORKS

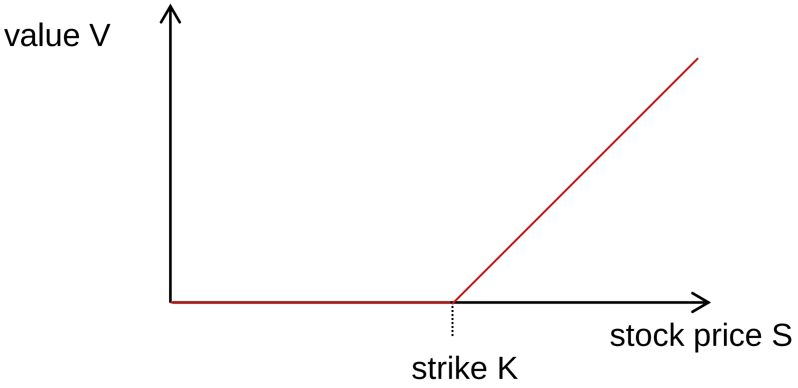
03

GENERALI

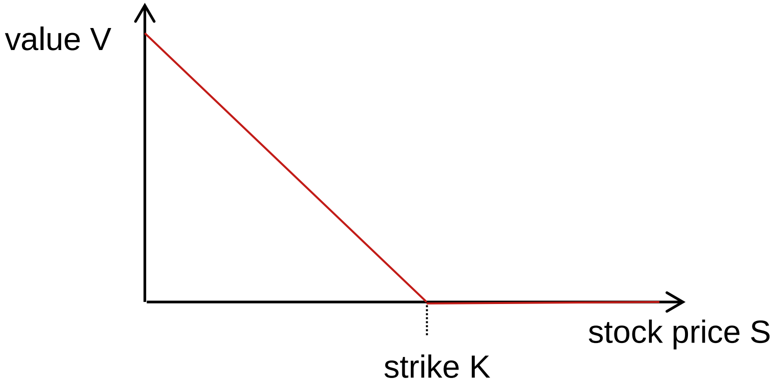
PLAIN VANILLA OPTIONS

An **option** is a contract giving the buyer the right (but not the obligation) to buy or sell an underlying asset at a specific price (*strike*) on a certain time point T (*European*) or before a certain time point t $\leq T$ (*American/Bermudan*)

$$\max(S_T - K, 0)$$



$$\max(K - S_T, 0)$$

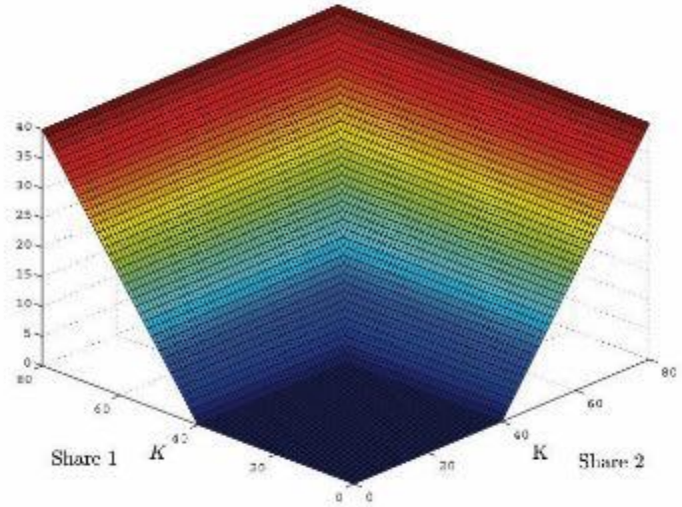


- Options are used for trading strategies as **hedging** or **speculation**

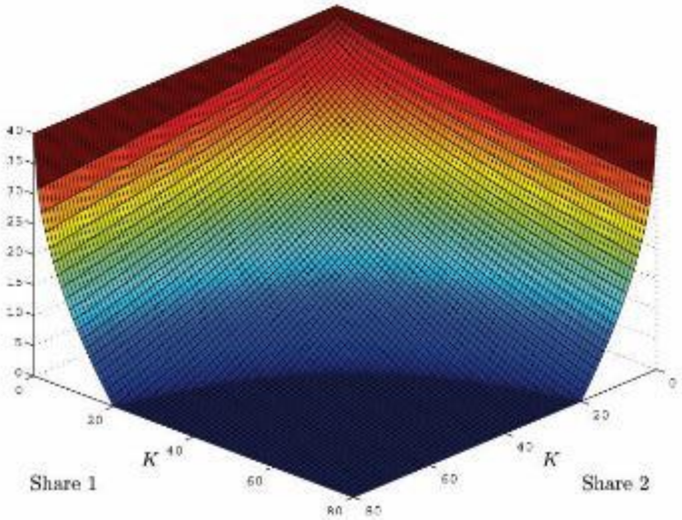
EXOTIC OPTIONS

Non-standard options belong to the class of **exotic options** such as barrier options, lookback options, options on several stocks, among others.

$\max(0, \max(S^1, S^2) - K)$



$\max(0, \sqrt{S^1 S^2} - K)$



OPTIMAL STOPPING PROBLEM

The **fair value of an American or Bermudan option** time t_0 is given by

$$\sup_{\tau \in \mathrm{T}_{0,L}} E_0\left[D_{0,\tau} Z_\tau\right]$$

where $\mathrm{T}_{0,L}$ is the set of all stoppping times with values in $\{0, \dots, L\}$, $(Z_l)_{0 \le l \le L}$ is an adapted payoff process, $E_t = E[\cdot \,|S_t] = E[\cdot \,|F_t]$ is the expectation conditional on the information available until time date t, $(S_t)_{0 \le t \le T}$ is a Markov process, $F = \{F_t | 0 \le t \le T\}$ is the filtration with the σ-Algebra F_t at time date t, $D_{s,t}$ is the discount factor ($D_{s,t} = e^{-r(t-s)}$ in the special case of a constant risk-free rate r).

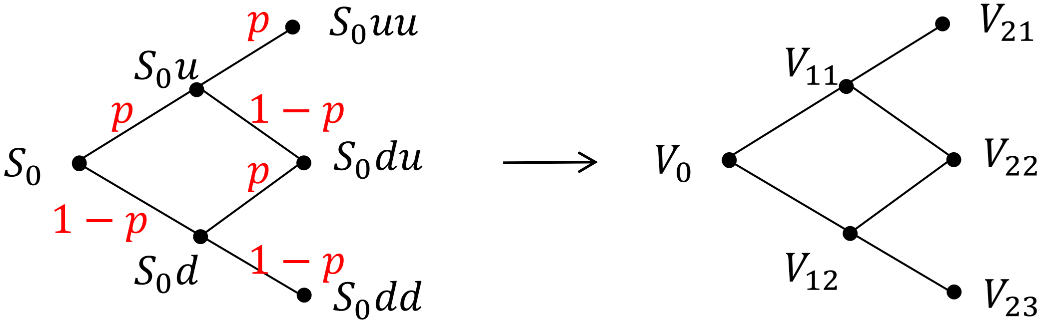
DYNAMICAL PROGRAMMING PRINCIPLE

Solution:

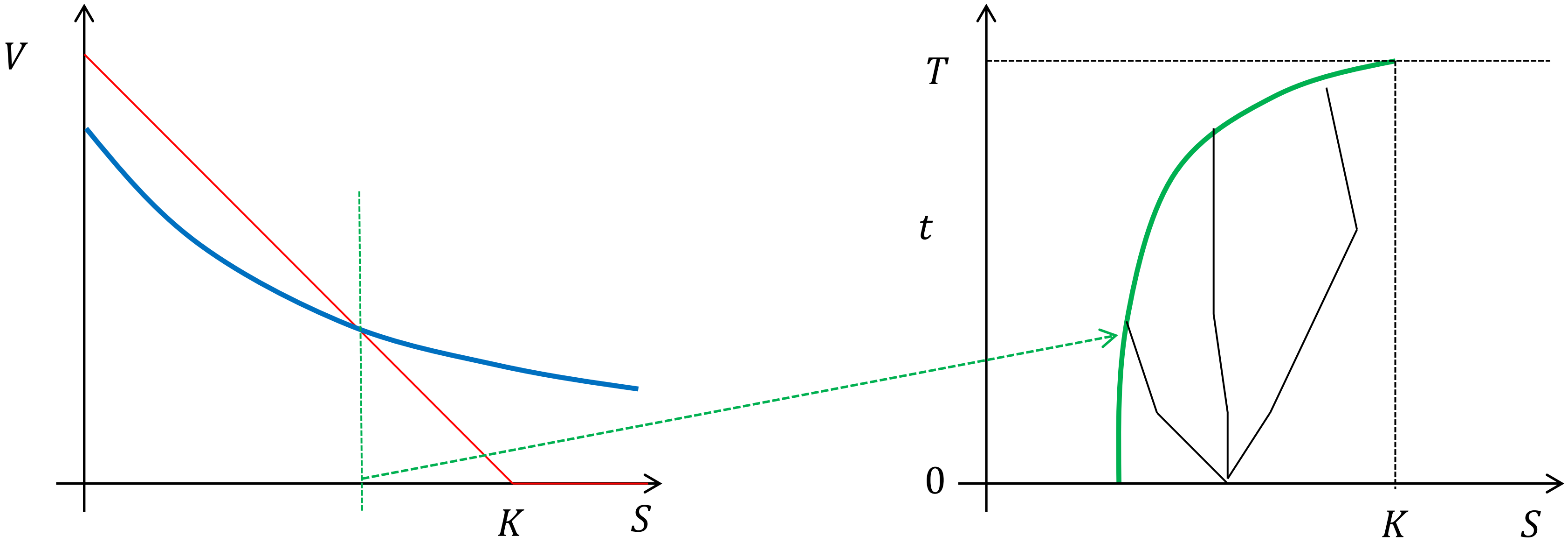
This **optimal stopping problem** can be solved via the **dynamical programming principle (DPP)** for the value process $(V_l)_{0\leq l\leq L}$:

$$V_L = Z_L$$
$$V_l = max\{Z_l, E_l[D_{l,l+1}V_{l+1}]\}, l = L-1, \ldots, 0$$

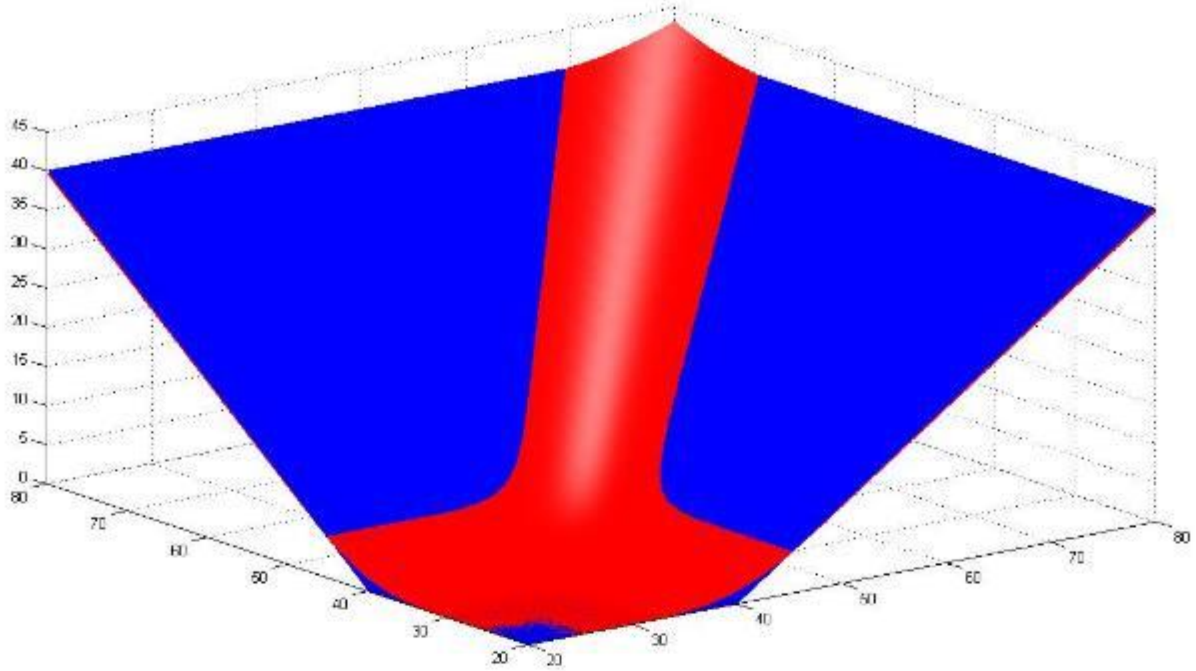
Many algorithms for calculating option prices are based on this DPP, e.g. the **binomial tree**



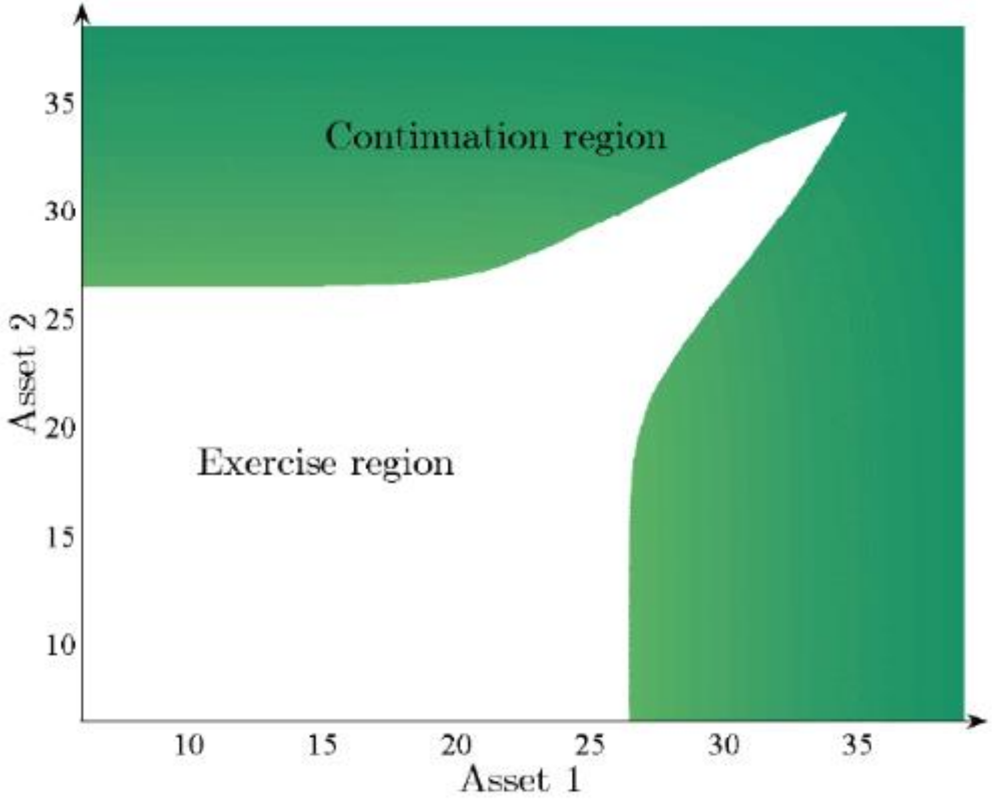
EARLY EXERCISE CURVE



EARLY EXERCISE REGIONS – MAX CALL OPTIONS



EARLY EXERCISE REGIONS – MAX PUT OPTIONS



DYNAMICAL PROGRAMMING PRINCIPLE – OPTIMAL STOPPING TIMES

Alternative Solution:

Alternatively, the **DPP** can be formulated in terms of the optimal stopping times:

$$\tau_L = L$$
$$\tau_l = \begin{cases} l & , Z_l, \geq E_l[D_{l,\tau_{l+1}} Z_{\tau_{l+1}}] \\ \tau_{l+1} & , sonst \end{cases} , l = L-1, \dots, 0$$

Then, the continutation value at time point t_l is given by

$$C_l := E_l[D_{l,\tau_{l+1}} Z_{\tau_{l+1}}]$$

and we get the fair option value by

$$V_0 = E_0[D_{l,\tau_0} Z_{\tau_0}]$$

For any stopping time we receive a lower bound

LONGSTAFF SCHWARTZ METHOD

- Approximation of continuation value

$$C_l := E_Q\left[e^{-r(\tau_{l+1}-l)\Delta t} Z_{\tau_{l+1}} | S_l\right] \approx \sum_{m=1}^{M} \omega_m \phi_m(S_l) =: \tilde{C}_l$$

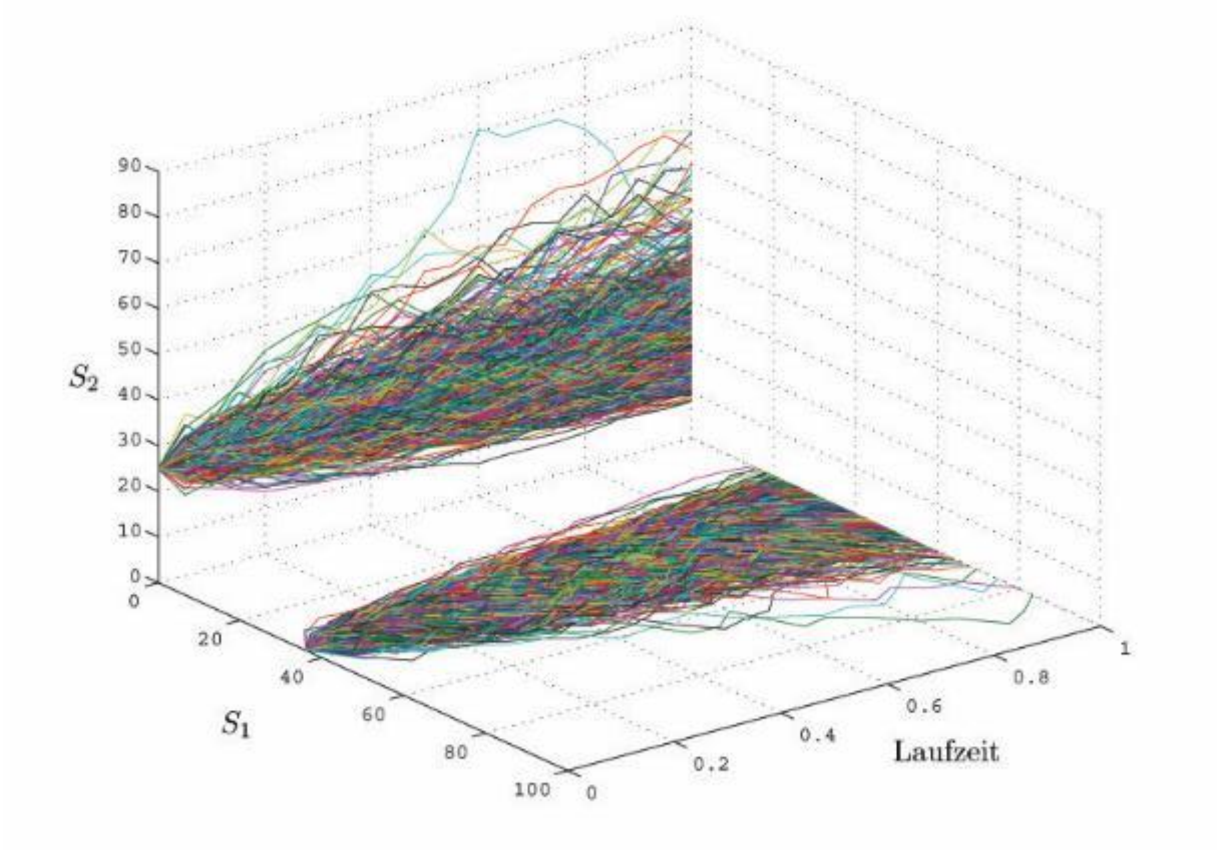
- Ordinary Least Squares

$$\min_{\omega \in R^M} E_Q\left[\left(C_l - \tilde{C}_l\right)^2\right] \approx \min_{\bar{\omega} \in R^M} \frac{1}{N} \sum_{n=1}^{N} \left(C_{l,n} - \bar{C}_{l,n}\right)^2$$

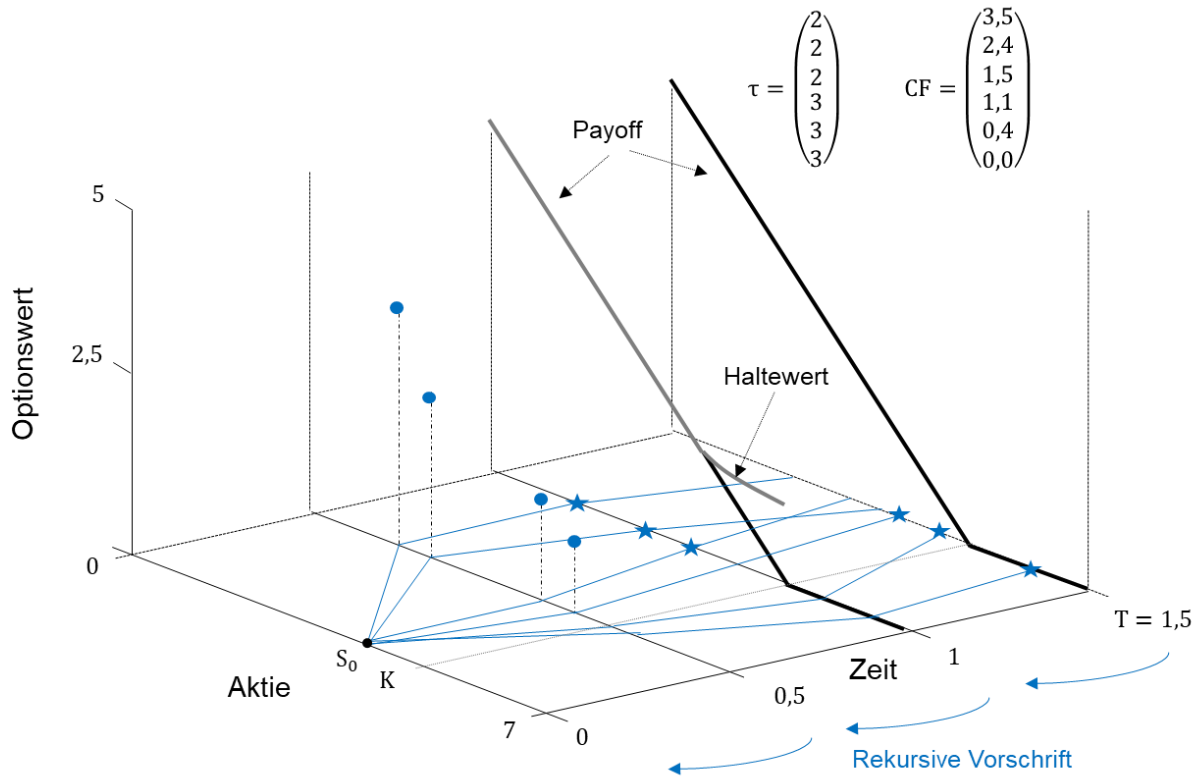
- Option price today at t_0

$$\hat{V}_0 = max\left(Z_0, \frac{1}{N} \sum_{n=1}^{N} e^{-r\tau_{1,n}\Delta t} Z_{\tau_{1,n}}\right)$$

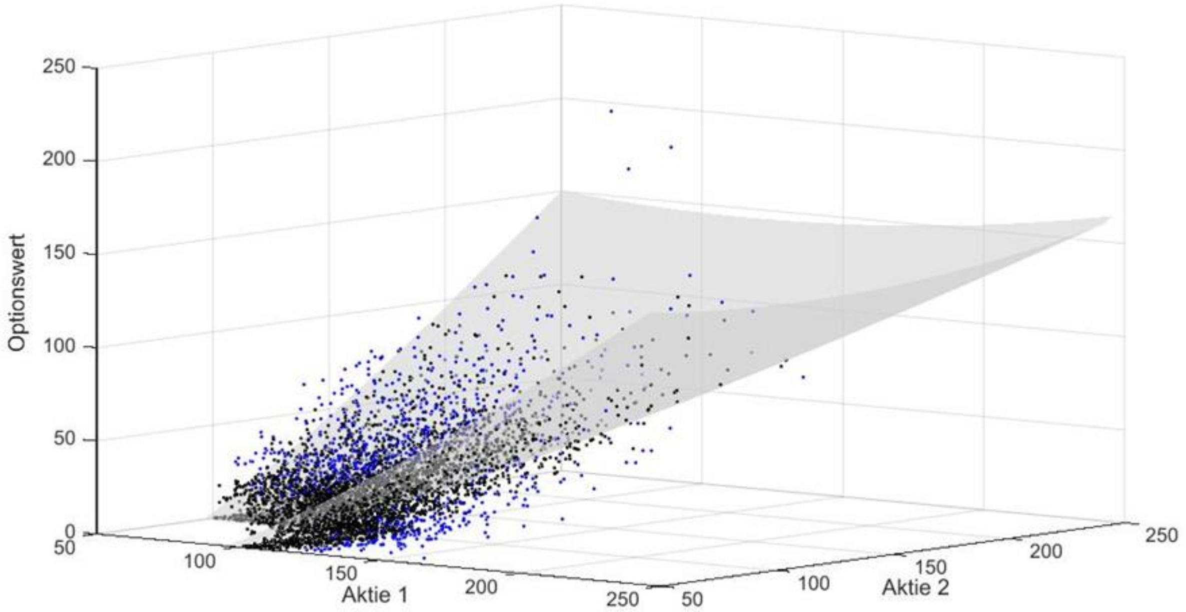
MONTE CARLO SIMULATION FOR TWO STOCKS



FUNCTIONALITY OF REGRESSION-BASED APPROACH

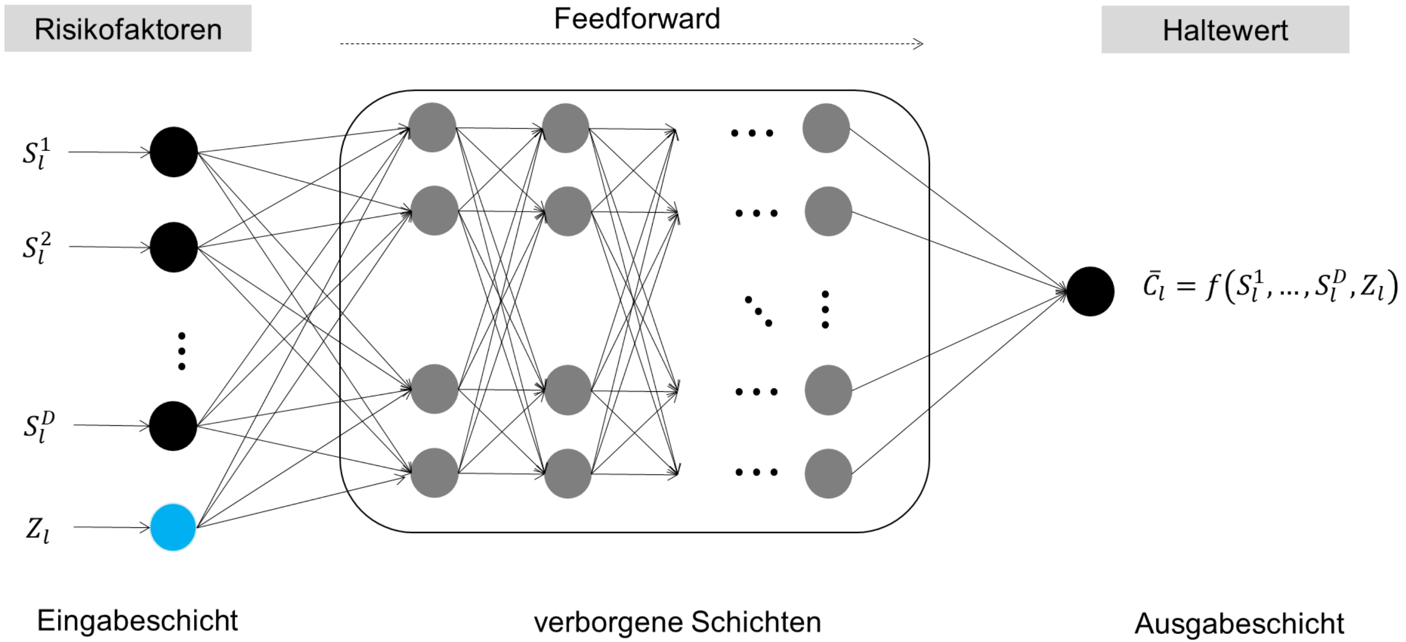


APPROXIMATION OF CONTINUATION VALUE FOR MAX CALL OPTION

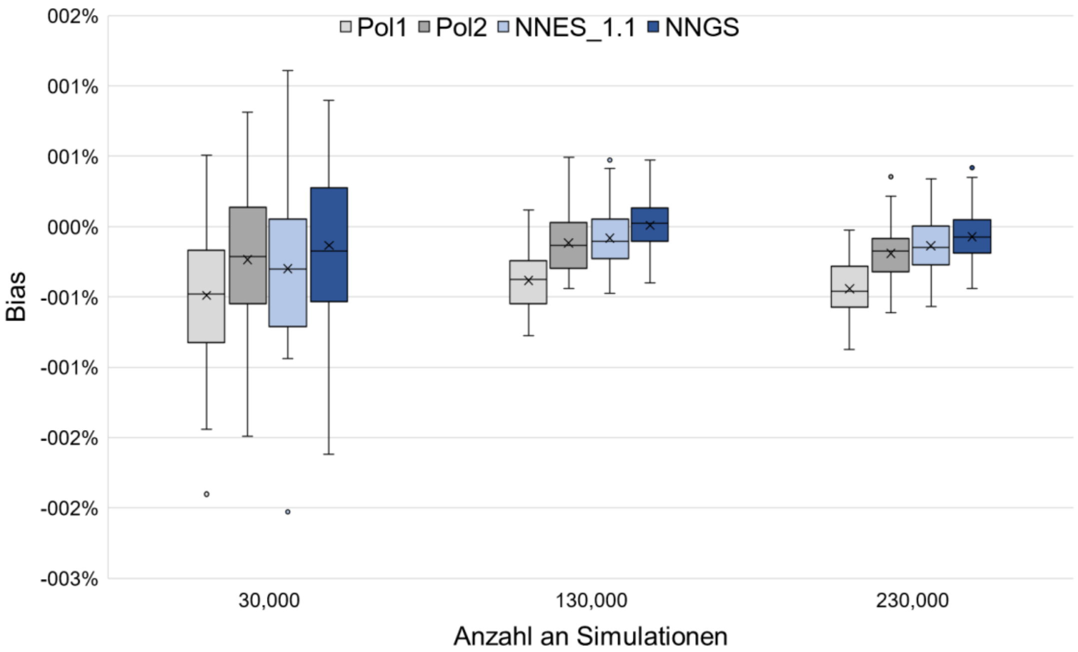


Idea: Determine continuation value by **neural networks**!

STRUCTURE OF NEURAL NETWORK FOR OPTION PRICING



CONVERGENCE ANALYSIS FOR BERMUDAN MAX CALL OPTION ON 2 ASSETS



- Underlying-Modell & Optionscharakteristika: Geometrisch-Brownsche-Bewegung mit $\mathrm{T} = 3, \Delta\mathrm{t} = \frac{1}{3}, \mathrm{K} = 100, \mathrm{r} = 0{,}05, \delta_1 = \delta_2 = 0{,}1,\ \sigma_1 = \sigma_2 = 0{,}2, \mathrm{S}_0^1 = \mathrm{S}_0^2 = 100$.
- Pol1: Polynom mit Basis $\{1, s_1, s_2, (s_1)^2, (s_2)^2, s_1 s_2, (s_1)^3, (s_2)^3\}$, wobei s_d der realisierte Wert der Aktie d ist, Pol2: Polynom mit Basis $\{1, x_1, x_2, (x_1)^2, (x_2)^2, x_1 x_2, (x_1)^3, (x_2)^3\}$, wobei x_d der d-höchste Aktienkurs ist.
- NNES_1.1: Neuronales Netz mit einer Schicht (16 Neuronen), Payoff zusätzlicher Input, Early Stopping, ReLU Aktivierungsfunktion, NNGS: Neuronales Netz mittels Grid-Search-Ansatz mit k-fold Cross Validation und verschiedenen Hyperparameter-Kombinationen, sh. Artikel

LOWER BOUNDS FOR MAX CALL OPTION ON 5 ASSETS

S_0	Methode	Untere Schranke $\hat{L}_0$	Untere Schranken des 95%-CI
90	Pol3	38,420 (0,047)	38,329
	Pol4	38,752 (0,050)	38,653
	NNGS	38,792 (0,051)	38,692
100	Pol3	49,481 (0,052)	49,378
	Pol4	49,952 (0,057)	49,841
	NNGS	50,063 (0,057)	49,952
110	Pol3	61,524 (0,057)	61,411
	Pol4	62,143 (0,063)	62,019
	NNGS	62,267 (0,063)	62,143

- Underlying-Modell & Optionscharakteristika: Geometrisch-Brownsche-Bewegung mit $T = 3, \Delta t = \frac{1}{3}, K = 100, r = 0{,}05, \delta_d = 0{,}1$,

$$\Sigma = \begin{pmatrix} 0{,}2^2 & 0{,}2 \cdot 0{,}35 \cdot (-0{,}1) & 0{,}2 \cdot 0{,}08 \cdot (-0{,}2) & 0{,}2 \cdot 0{,}5 \cdot 0{,}05 & 0{,}2 \cdot 0{,}4 \cdot 0{,}0 \\ 0{,}2 \cdot 0{,}35 \cdot (-0{,}1) & 0{,}35^2 & 0{,}35 \cdot 0{,}08 \cdot 0{,}4 & 0{,}35 \cdot 0{,}5 \cdot 0{,}1 & 0{,}35 \cdot 0{,}4 \cdot 0{,}25 \\ 0{,}2 \cdot 0{,}08 \cdot (-0{,}2) & 0{,}35 \cdot 0{,}08 \cdot 0{,}4 & 0{,}08^2 & 0{,}08 \cdot 0{,}5 \cdot 0{,}2 & 0{,}08 \cdot 0{,}4 \cdot 0{,}25 \\ 0{,}2 \cdot 0{,}5 \cdot 0{,}05 & 0{,}35 \cdot 0{,}5 \cdot 0{,}1 & 0{,}08 \cdot 0{,}5 \cdot 0{,}2 & 0{,}5^2 & 0{,}5 \cdot 0{,}4 \cdot 0{,}15 \\ 0{,}2 \cdot 0{,}4 \cdot 0{,}0 & 0{,}35 \cdot 0{,}4 \cdot 0{,}25 & 0{,}08 \cdot 0{,}4 \cdot 0{,}25 & 0{,}5 \cdot 0{,}4 \cdot 0{,}15 & 0{,}4^2 \end{pmatrix}$$

- Pol3: $\left\{1, \{s_d\}_{d=1}^5, \{(s_d)^2\}_{d=1}^5\right\}$, Pol4: $\left\{1, \{x_d\}_{d=1}^5, \{(x_d)^2\}_{d=1}^5, \{(x_d)^3\}_{d=1}^5, x_1x_2, x_1x_3, x_2x_3, (x_1)^2\ x_2, x_1(x_2)^2\right\}$, NNGS: Neuronales Netz mit Grid-Search-Ansatz, sh. Artikel

FURTHER MATERIAL

Fachartikel

Rudolf Born und Dr. Christian Jonen

Bewertung von amerikanischen Optionen mittels neuronaler Netze

WRAP UP, DISCUSSION, Q&A

04

WRAP UP

- **Neural networks** are powerful for modelling and prediction tasks
- **Architecture, parameter choice and learning method** are essential for successful applications
- **Neural networks** might be very complex and the training might take long (be computationally intensive) such that common approaches are more efficient (this highly depends on the underlying problem to be solved)
- **Machine Learning** has been used for a long time in industry and the development is ongoing
- **Data Science is an important field**, also for financial engineering, and more and more companies apply these techniques to improve processes and predictions
- **Actuaries** should learn these techniques and build up knowledge
- **Feel free and be motivated** to apply Machine Learning techniques for your own applications
- **Python, R and Matlab** provide very good development environments for neural networks (in general for Machine Learning)

DISCUSSION, Q&A

MANY THANKS AND STAY HEALTHY

GENERALI