

Künstliche Intelligenz - Mythos und Realität

Wie wir die Zukunft mit Prescriptive Analytics gestalten

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HEAL

HEURISTIC AND EVOLUTIONARY
ALGORITHMS LABORATORY



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<https://dev.heuristiclab.com>



Softwarepark Hagenberg 1989

Softwarepark Hagenberg



Softwarepark Hagenberg 2018

- **Campus Hagenberg**

- Communication, Software, and Media
- 1700 students
- Research Center for Software Technologies and Applications



- **Softwarepark Hagenberg**

- Education, Research, Economy
- More than 3000 employees and students
- Around 30.000 m² floor space in buildings



10
Research
Institutions

24
Study
Programs

75
Companies



Softwarepark Hagenberg



Softwarepark Hagenberg 2020



What is AI

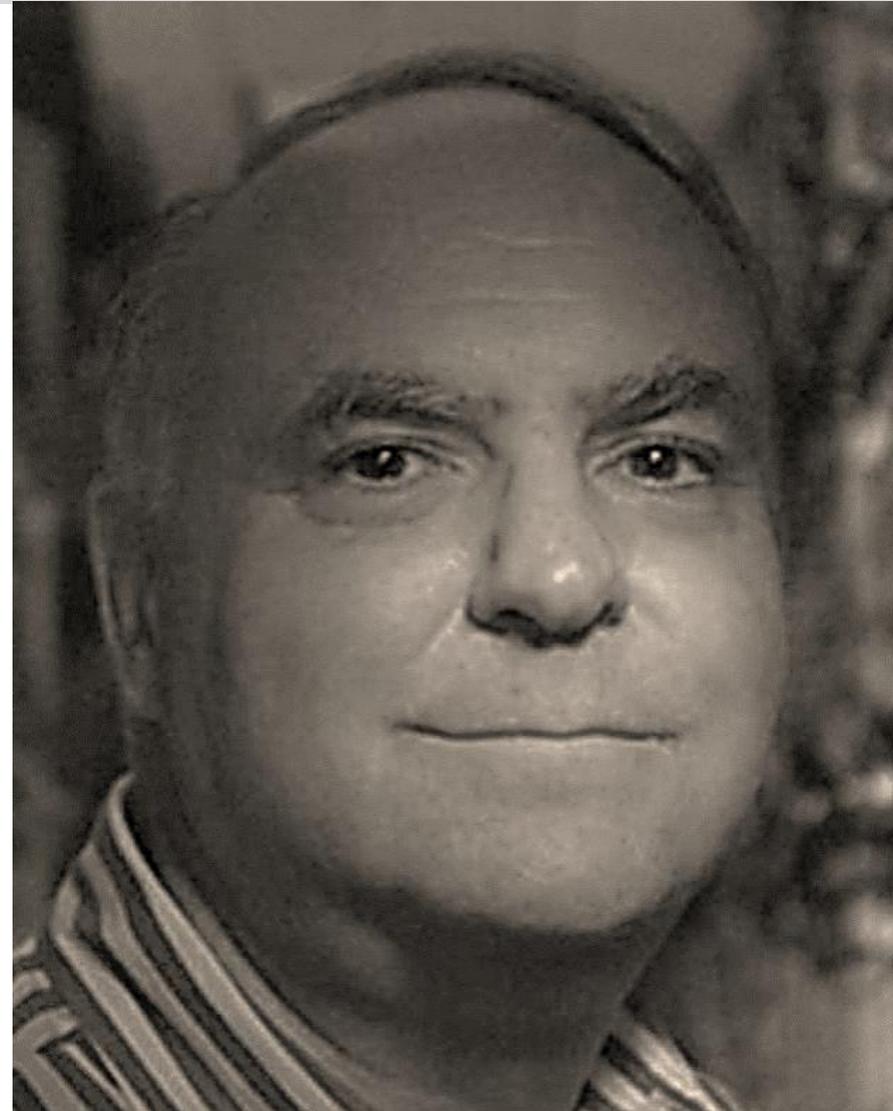
*“Artificial Intelligence
is the science and
engineering of making
intelligent machines”*

John McCarthy mid-1950



“The artificial to intelligence ratio is the ratio of that which is delivered by the automated operation of the artificial method to the amount of intelligence that is supplied by the human applying the method to a particular problem”

John Koza mid-1990

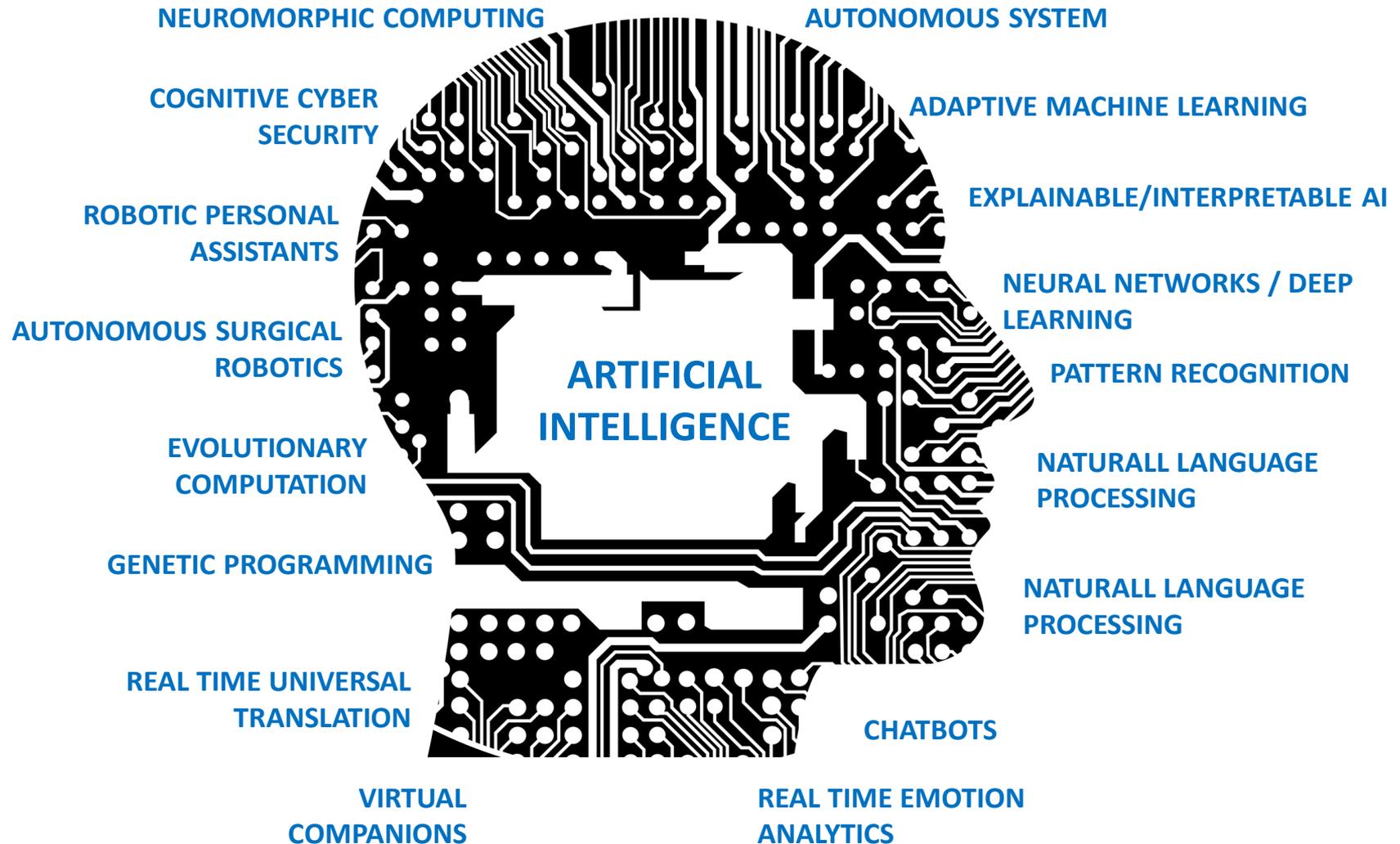




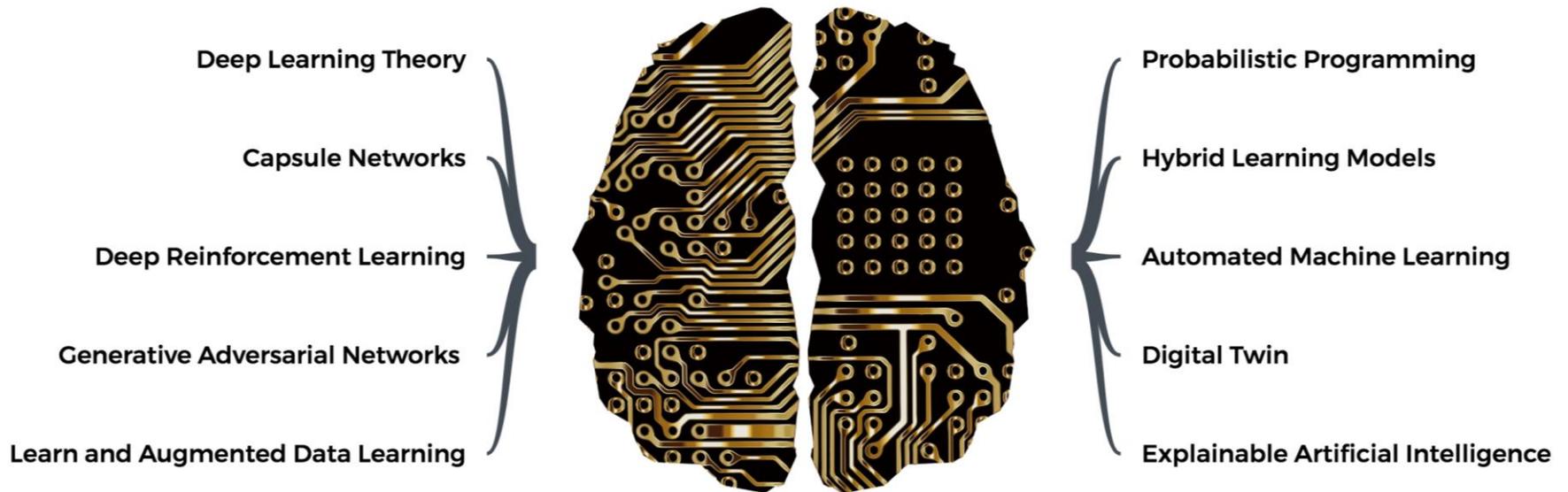
Why should we care about AI?

- **AI is an old friend in research and development...
...so why so much noise now?**
- **AI will add 14 thousand billions to global economy 2030**
- **AI is already in our house and our streets**
- **AI can impact in the transformation of jobs**

Technology Landscape in AI



The AI of the future



Top 10 AI tech trends for 2018 (source: pwc)

Do we need any strategy?



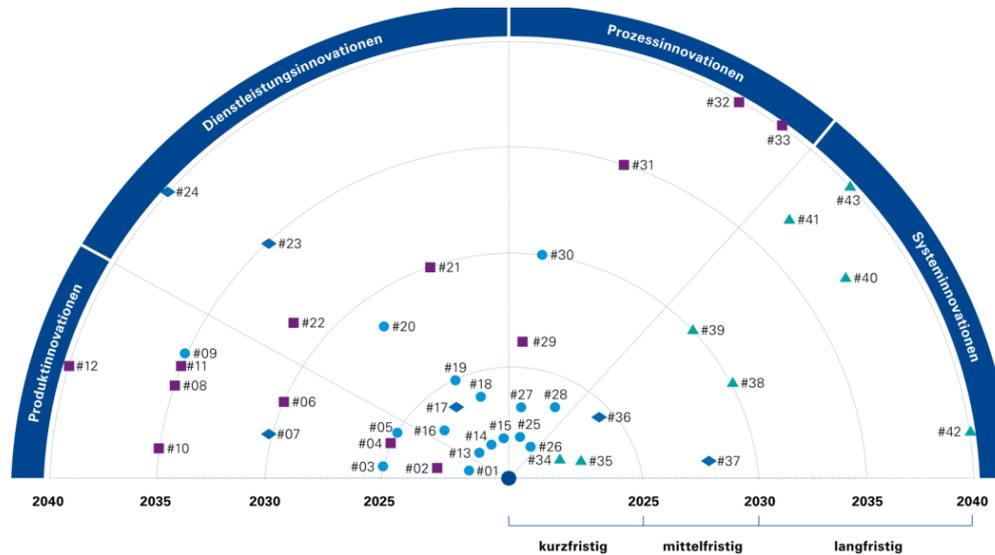


Prozessinnovationen

- #25 Robotic Process Automation (2018)
- #26 Präskriptive Analytik (2019)
- #27 AutoML (2020)
- #28 Frugale KI-Innovation (2022)
- #29 KI-Mentor (2027)
- #30 Digitale Medizinrevolution (2035)
- #31 Brain-Machine-Interface (2035)
- #32 Digitale „Telepathie“ (2040)
- #33 Telepathisches KI-Autocomplete (2040)

Systeminnovationen

- #34 Der Daten-See (2021)
- #35 Das KI-Universum (2022)
- #36 Die Robotersteuer (2024)
- #37 Die progressive Konsumsteuer (2028)
- #38 Phänomenales KI-Lernen (2030)
- #39 Community of Things (2030)
- #40 Quanten-Internet (2038)
- #41 Web of Thoughts (2038)
- #42 Technologische Singularität (2040)
- #43 Die Sensorik-Eruption (2040)



Quelle: KPMG in Deutschland / TRENDONE, 2018

Produktinnovationen

- #01 Die Lifos (2018)
- #02 Kumpel Cobot (2022)
- #03 KI Fake News-Agent (2025)
- #04 Das Exo-Skelett (2025)
- #05 Autonomes Fahren (2025)
- #06 Die eigene KI-Kopie (2030)
- #07 Militär-Roboter (2030)
- #08 Der Android (2035)
- #09 Escort Bots (2035)
- #10 Neuro-Staub (2035)
- #11 Virtuelle Verkörperung (2035)
- #12 Der Cyborg (2040)

Dienstleistungsinnovationen

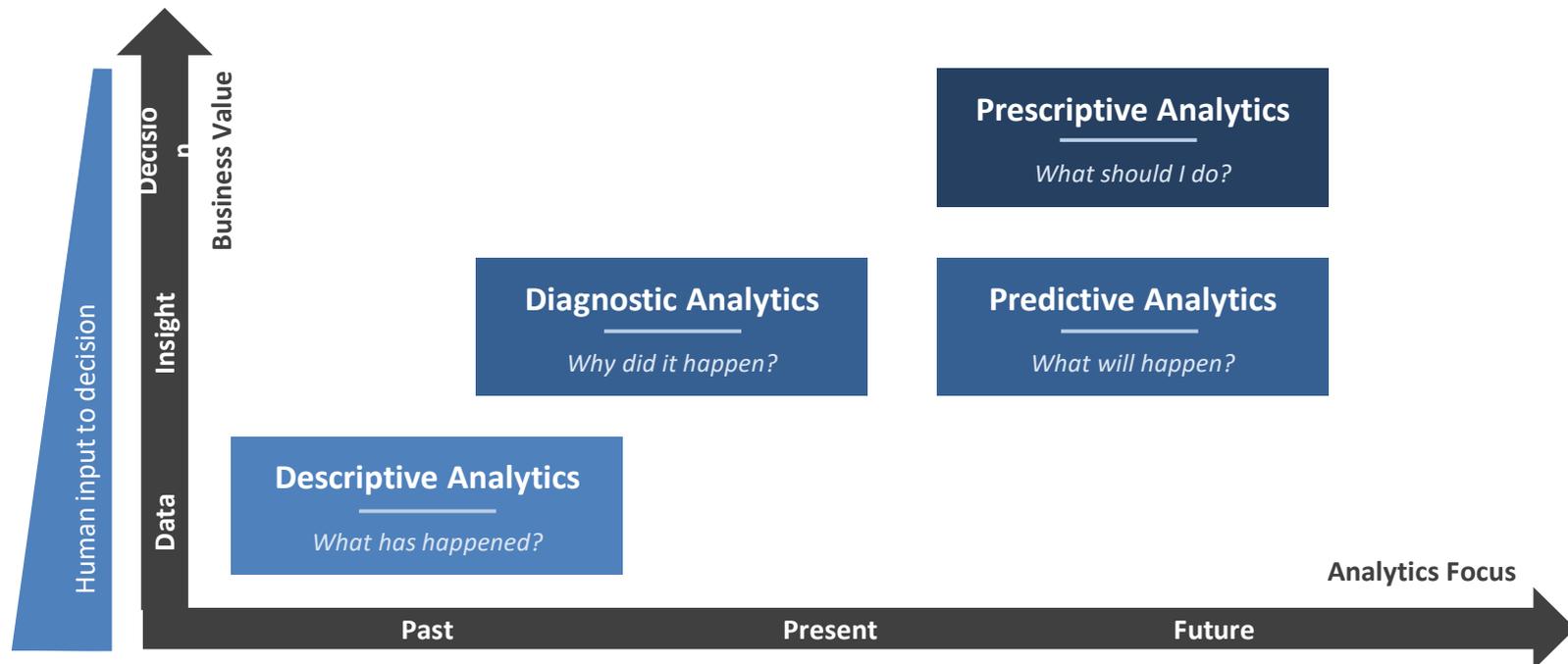
- #13 Der KI-Kundendienst (2018)
- #14 Cash Recovery mit KI (2018)
- #15 KI-Forensik (2018)
- #16 Smart Contracting (2021)
- #17 Der KI-TÜV (2022)
- #18 KI-Chatbots (2022)
- #19 Algorithm Audit (2025)
- #20 Präemptive Sicherheit (2028)
- #21 Der Pflege-Bot (2030)
- #22 KI-basiertes Lernen (2032)
- #23 Robot Lawyer (2035)
- #24 Die Robo-Polizei (2040)

Legende

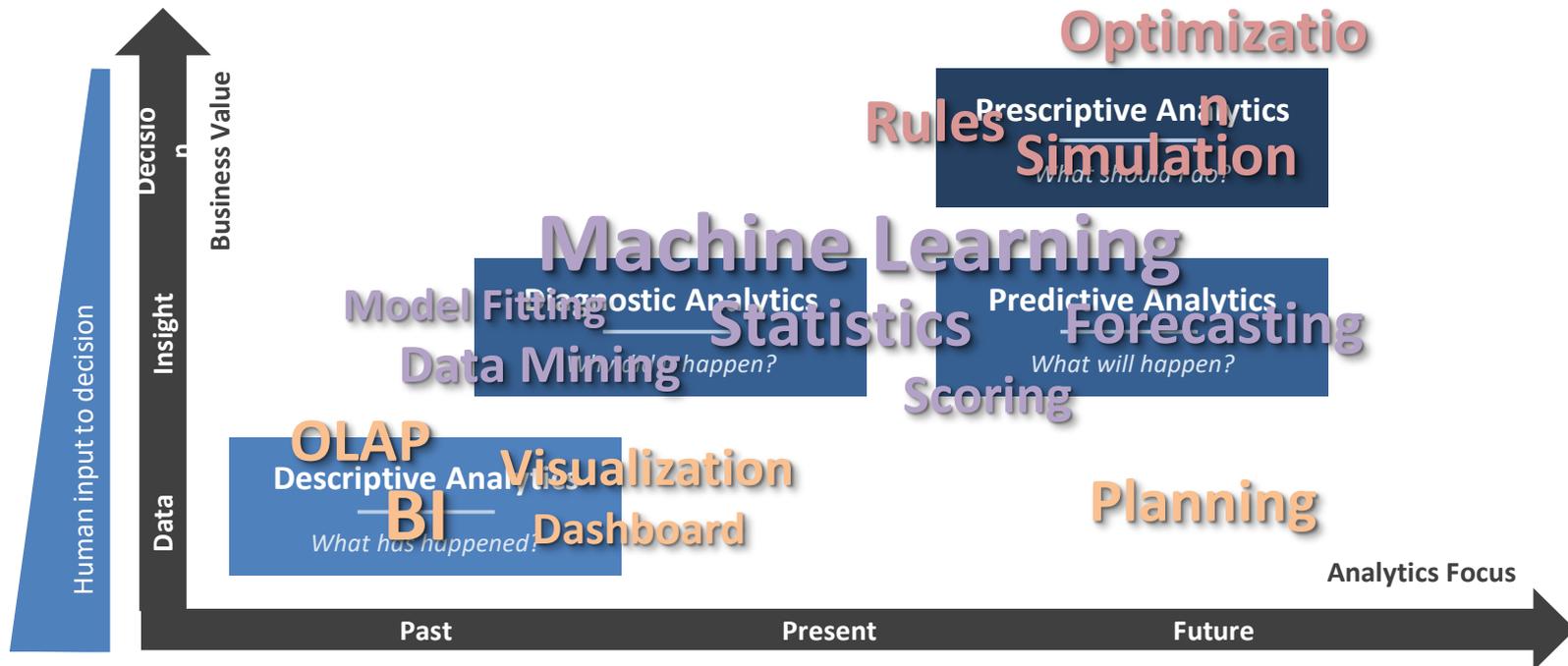
Hinweis: Form und Farbe der Icons kennzeichnen den Bereich, in dem die Chancen primär anwendbar sind:

- ▲ Universal (Ganzheitlicher Einsatz)
- Wirtschaft (Unternehmenswelt)
- ◆ Öffentlicher Sektor
- Mitarbeiter (Persönliche Anwendung)

Prescriptive Analytics



Prescriptive Analytics





WAS BEDEUTET DAS PRAKTISCH?



1. NOVEMBER

Start of compulsory winter tires.
High season for garages.
Strong sales for tire dealers.



❄️	★ ★ ★ ★ ★
🛢️	★ ★ ★ ★ ★
🔊	★ ★ ★

❄️	★ ★ ★ ★ ★
🛢️	★ ★ ★
🔊	★ ★ ★

❄️	★ ★ ★
🛢️	★ ★ ★ ★ ★
🔊	★ ★ ★ ★ ★

Reifen Auswahl?

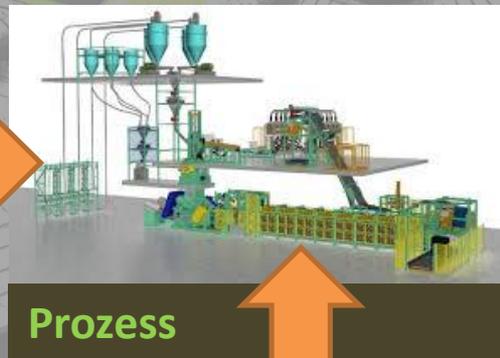
Unterschiedliche und widersprüchliche Produkteigenschaften beeinflussen die Auswahl von neuen Reifen.



Reifen Produktionsprozess



Input – Rohstoffe



Prozess

Rezeptur
... für die richtige
Gummimischung



Output

Merkmale des Reifens:

1. Temperaturverhalten
2. Abrollverhalten
3. Bremsverhalten
4. Trockene Fahrbahn
5. Eis, Schnee und Nässe
6. Energieverbrauch
7. Geräusentwicklung
8. Verschleiss
9. Fahrkomfort
10. etc.



Lösungsansätze:

a. Experimentell:

Mit hohem Aufwand verbunden, teuer und langsam

b. Simulation:

Modellbildung wegen der hohen Komplexität nur eingeschränkt möglich
Aussagekraft nur in Teilbereichen vorhanden

c. Hybrid:

Machine Learning → Modelle für Qualitätsmerkmale
Inverse Modellierung
Optimierung

→ **Prescriptive Analytics!**



Problemstellung invers ...

Die gewünschten Produktmerkmale werden an ein AI-basiertes System übertragen. Das Ergebnis ist ein passendes Produktionsrezept.

Input – Reifens



Merkmale des Reifens:

1. Temperaturverhalten
2. Abrollverhalten
3. Bremsverhalten
4. Trockene Fahrbahn
5. Eis, Schnee und Nässe
6. Energieverbrauch
7. Geräuscentwicklung
8. Verschleiss
9. Fahrkomfort
10. etc.



Prescriptive
Analytics
System

Input:
Prozessparameter
Modelldaten
Ursache-Wirkung-Daten
u.a.

Output

**Die optimale
Rezeptur?**

... für die "richtige"
Gummimischung



Prescriptive Analytics – Tire Production

Sources

Data

Model

Benefits



x1	x2	x3	x4	x5	y
28.07845	13.93902	87.63394	20.07777	63.00267	250.4028
27.95657	12.75236	87.05083	19.95878	63.00894	440.0825
25.43135	23.03532	88.32881	21.98374	74.99575	292.6644
28.5034	36.71041	87.59461	20.55528	75.01106	100.8683
23.03413	46.5804	79.38985	18.67402	80.31421	435.7738
20.97957	41.52231	73.32074	21.49193	79.98517	288.5032
28.07431	28.49076	106.4166	27.38095	79.97826	?
28.00494	36.33813	104.7173	27.99428	75.00266	?
28.0274	31.84306	102.277	28.81878	78.1752	?
26.503	27.67078	93.81539	21.29002	62.99904	?
23.869	27.25298	93.67531	24.54099	80.00291	?

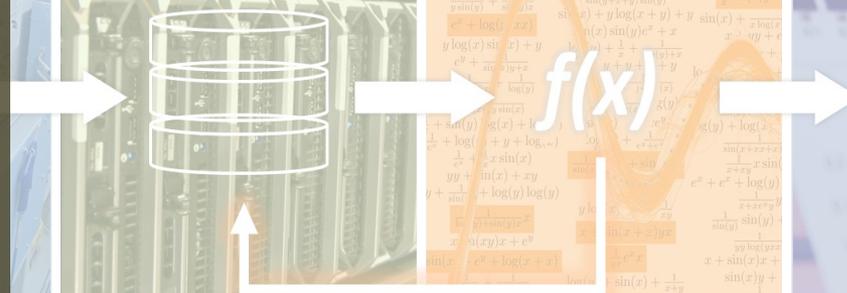
AI guided Simulation Experiments
e.g. What-If, ParamOpt, ...
= Speed-up = more experiments possible

$f(x)$

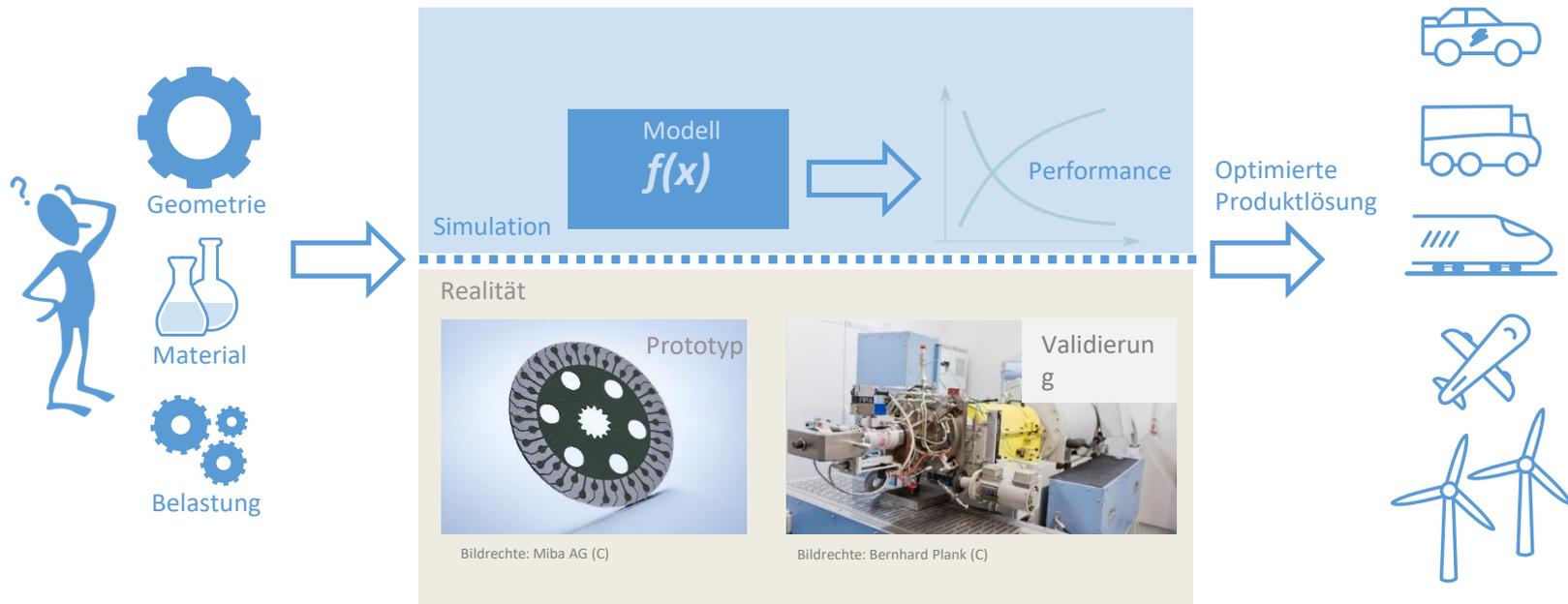
optimale Rezeptur:
erfüllt gegebene Eigenschaften

Materialeigenschaften:

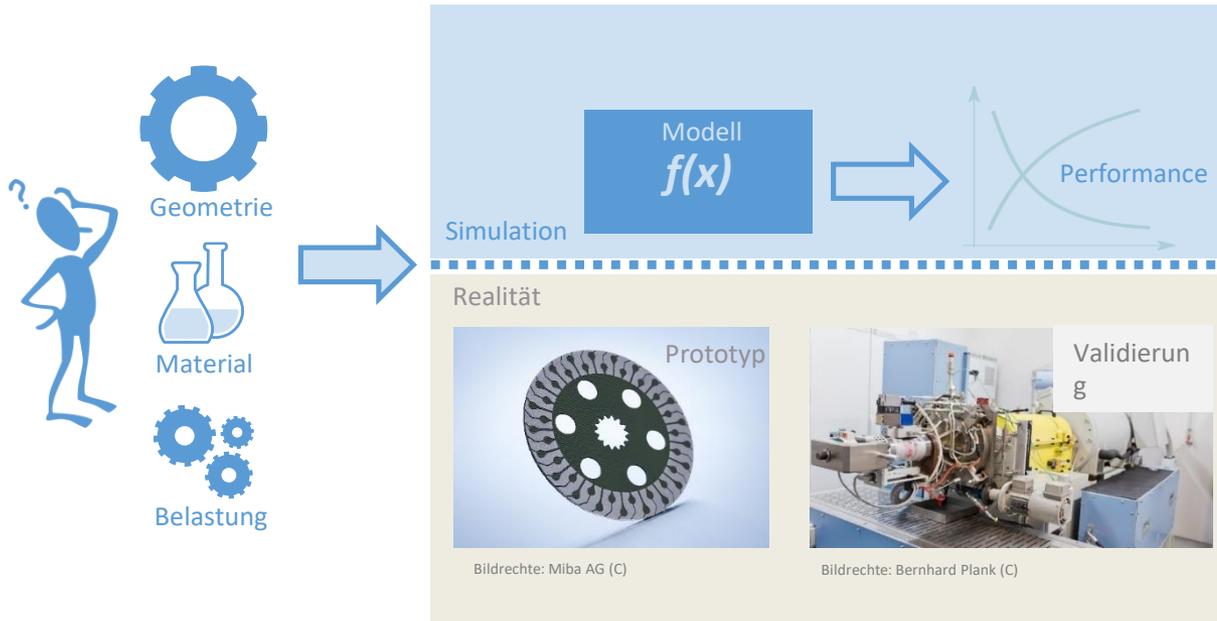
1. Temperaturverhalten
2. Abrollverhalten
3. Bremsverhalten
4. Trockene Fahrbahn
5. Eis, Schnee und Nässe
6. Energieverbrauch
7. Geräuschentwicklung
8. Verschleiss
9. Fahrkomfort
10. etc.



Prescriptive Analytics: Smart Engineering



Prescriptive Analytics: Smart Engineering

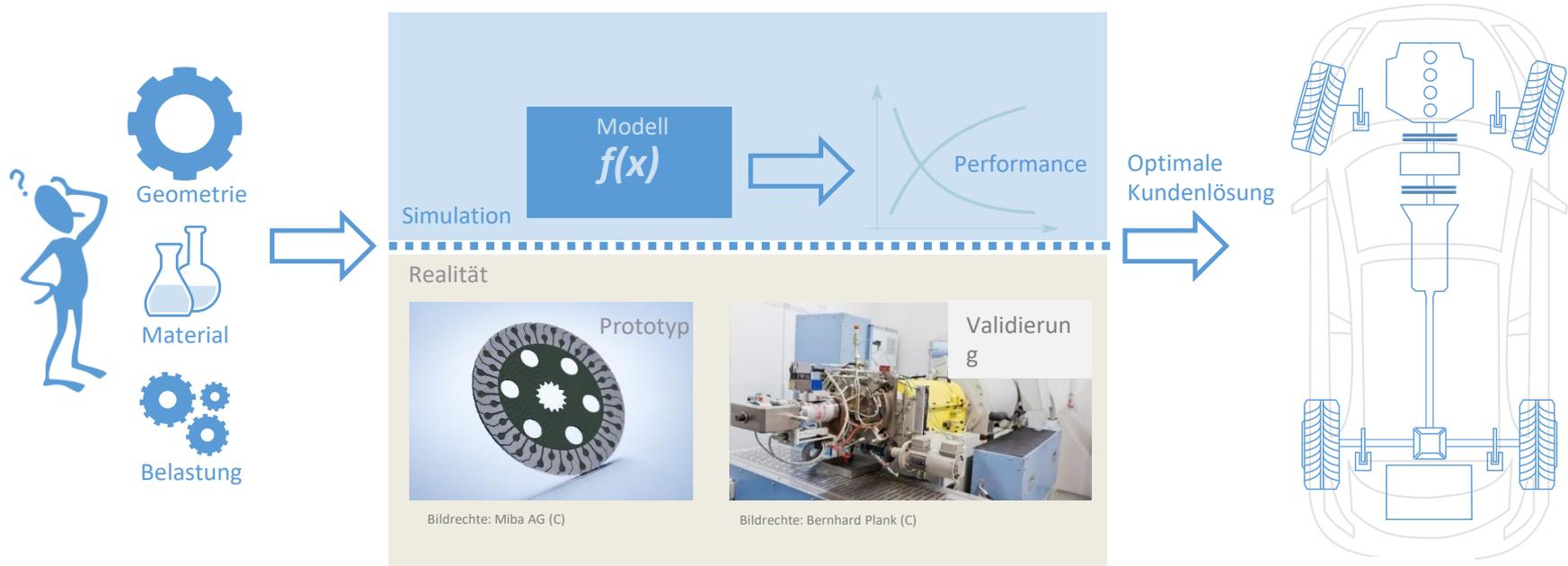


Reibwertprognose
bisher 10% Fehler
jetzt 2% Fehler

le
lösung



Prescriptive Analytics: Smart Engineering



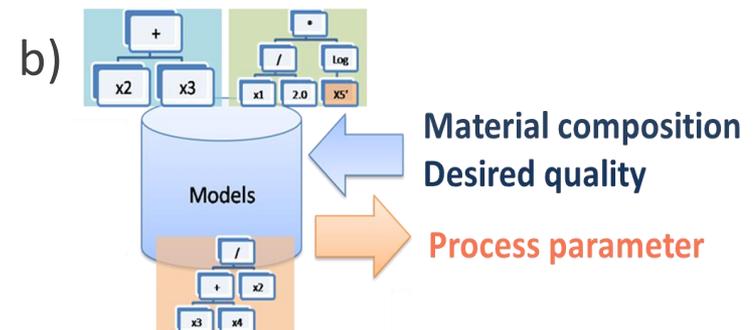
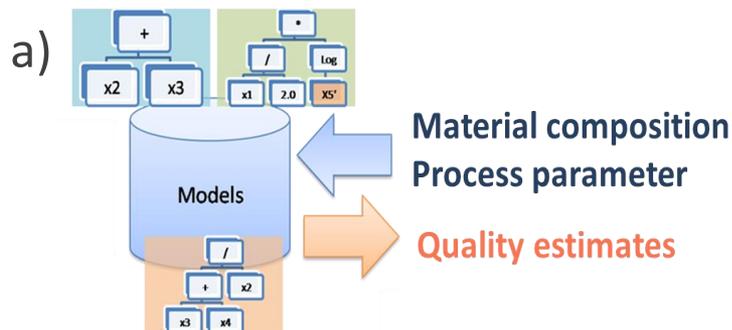
Example: Plasma Nitriding Modeling

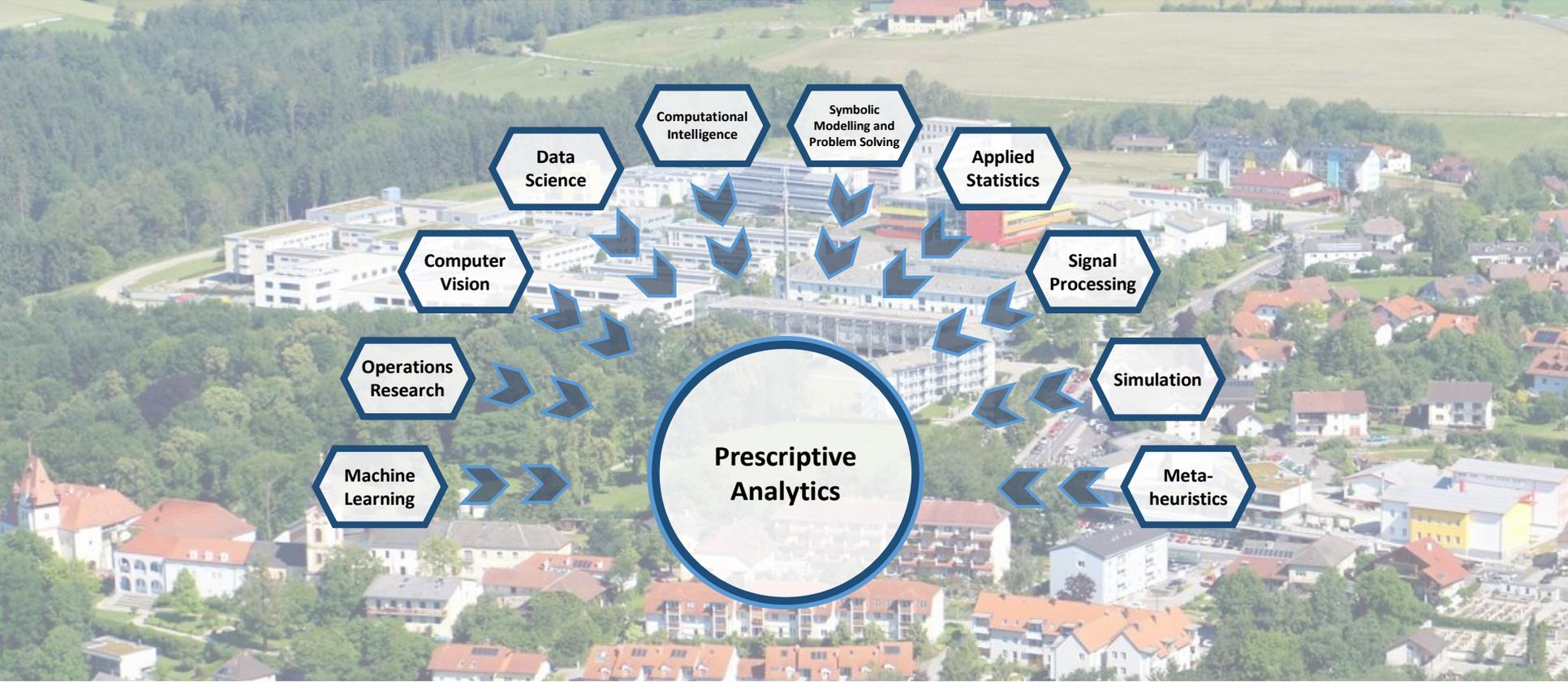
- **Motivation**

- hardening of materials (e.g. transmission parts)
- process parameter settings based on expert knowledge

- **Modeling Scenarios**

- a) prediction of quality values based on process parameters and material composition
- b) propose process parameter settings to reach the desired material characteristics





- **Research Group HEAL**

- established at FH Upper Austria since 2005
- 5 professors
- 17 research associates
- Interns, Students (Bachelor, Master)

- **Research Output**

- > 25 research projects, > 5 mio. EUR funding
- > 200 publications (peer-reviewed)
- > 10 dissertations
- > 60 thesis (Master and Bachelor)

- **Scientific and Industrial Partners**

- <https://heal.heuristiclab.com/patners>

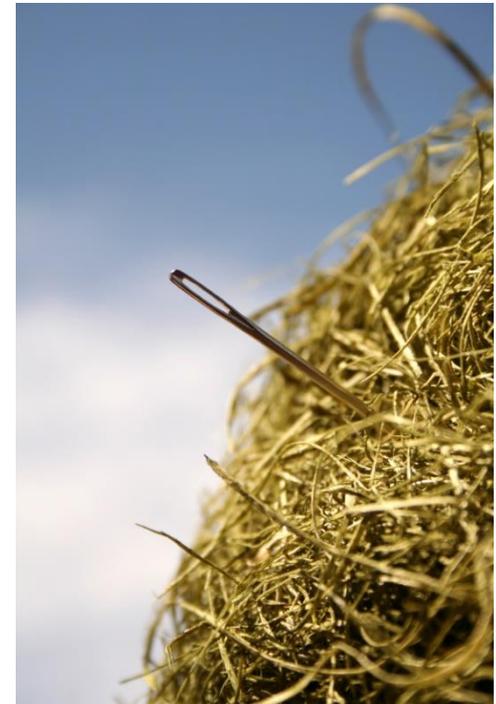
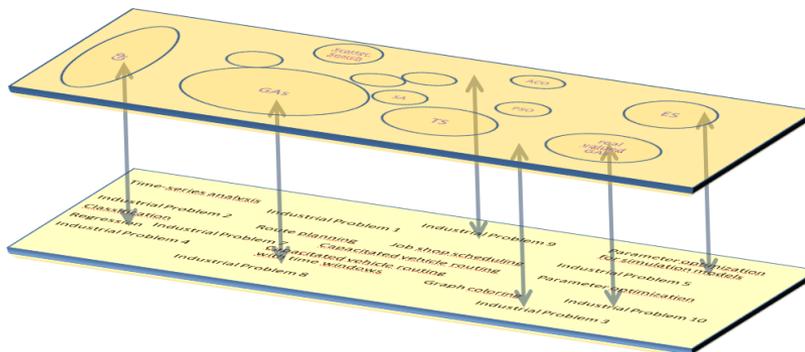


- **Metaheuristics**

- intelligent search strategies
- can be applied to different problems
- explore interesting regions of the search space (parameter)
- tradeoff: computation vs. quality
 - good solutions for very complex problems
- must be tuned to applications

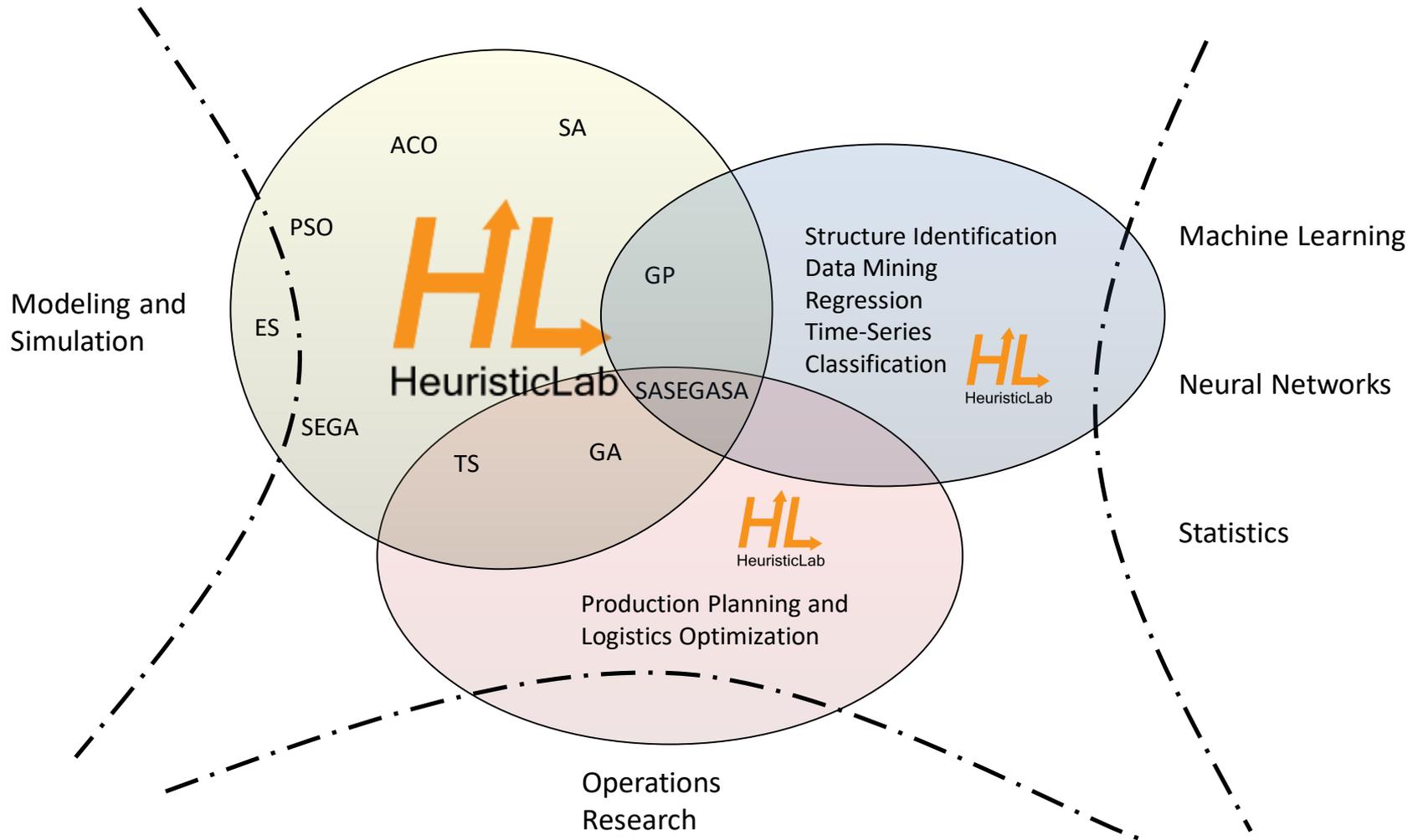
- **Challenges**

- choice of appropriate metaheuristics
- hybridization



Finding needles in haystacks

Research Focus



- **Open Source Optimization Environment HeuristicLab**

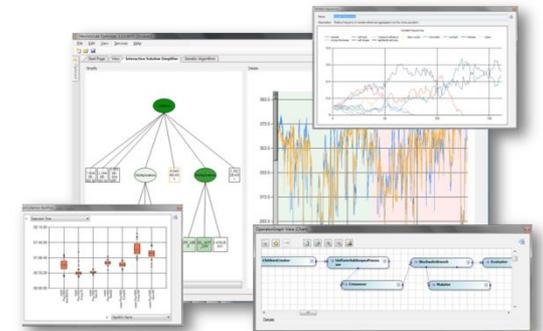
- developed since 2002
- basis of many research projects and publications
- 2nd place at *Microsoft Innovation Award 2009*
- HeuristicLab 3.3.x since May 2010 under GNU GPL

- **Motivation and Goals**

- graphical user interface for interactive development, analysis and application of optimizations methods
- numerous optimization algorithms and optimization problems
- support for extensive experiments and analysis
- distribution through parallel execution of algorithms
- extensibility and flexibility (plug-in architecture)

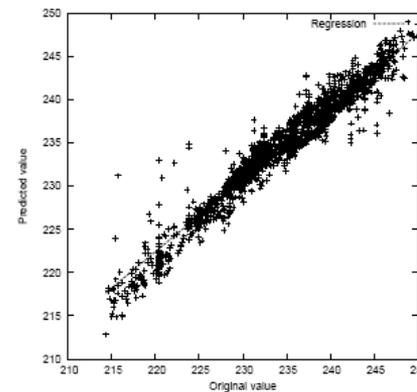
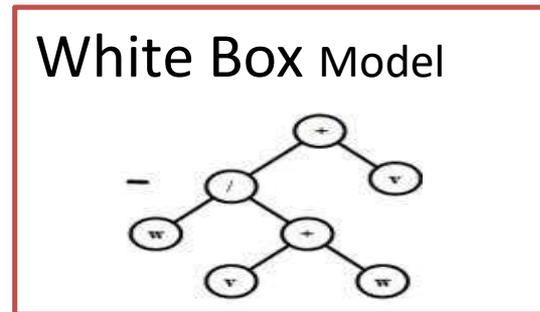
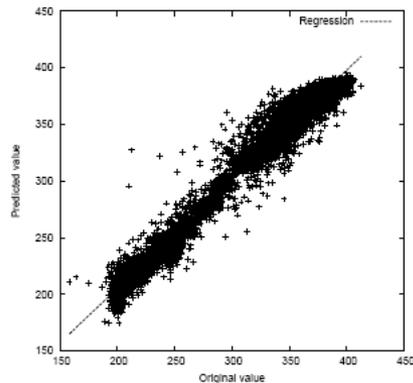
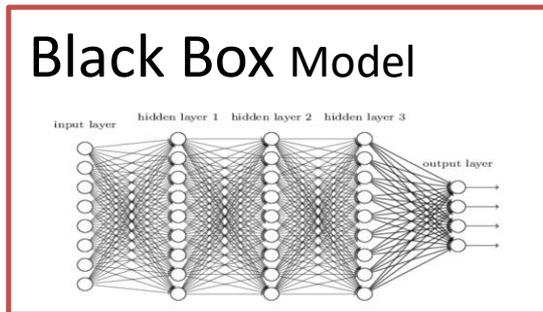
- **Distributed Computing with HeuristicLab Hive**

- framework for distribution and parallel execution of HeuristicLab algorithms
- compute resources at Campus Hagenberg
 - 2006 – 2011: research cluster 1 (14 cores)
 - since 2009: research cluster 2 (112 cores, 448GB RAM)
 - since 2011: lab computers (100 PCs, on demand in the night)
 - since 2017: research cluster 3 (448 cores, 4TB RAM)



Black-Box vs. White-Box Modeling

- Instead of **black box models** (ANN, SVM, etc.) identification of model structure, i.e. **white box models** (symbolic regression/classification with Genetic Programming)

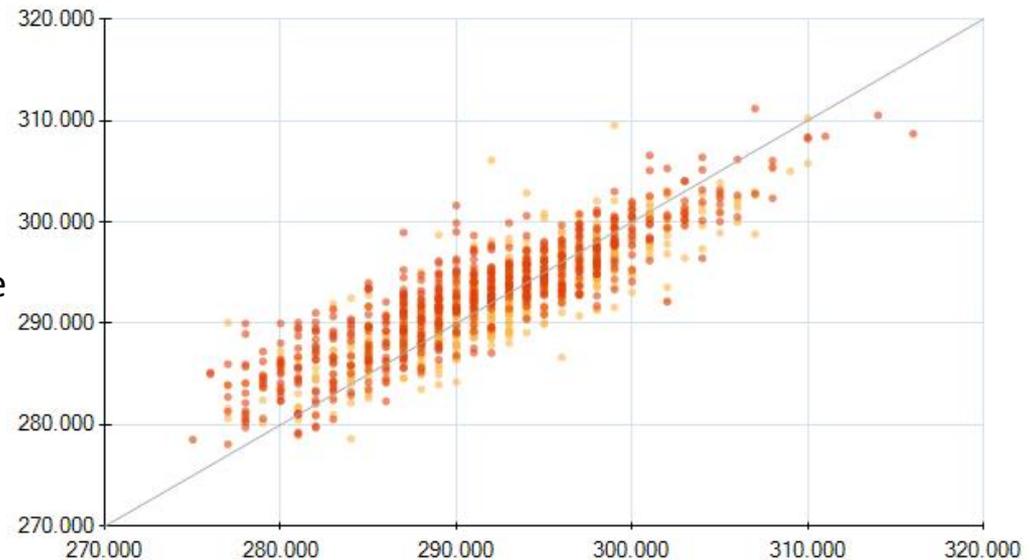


Learning of models as mathematical expressions

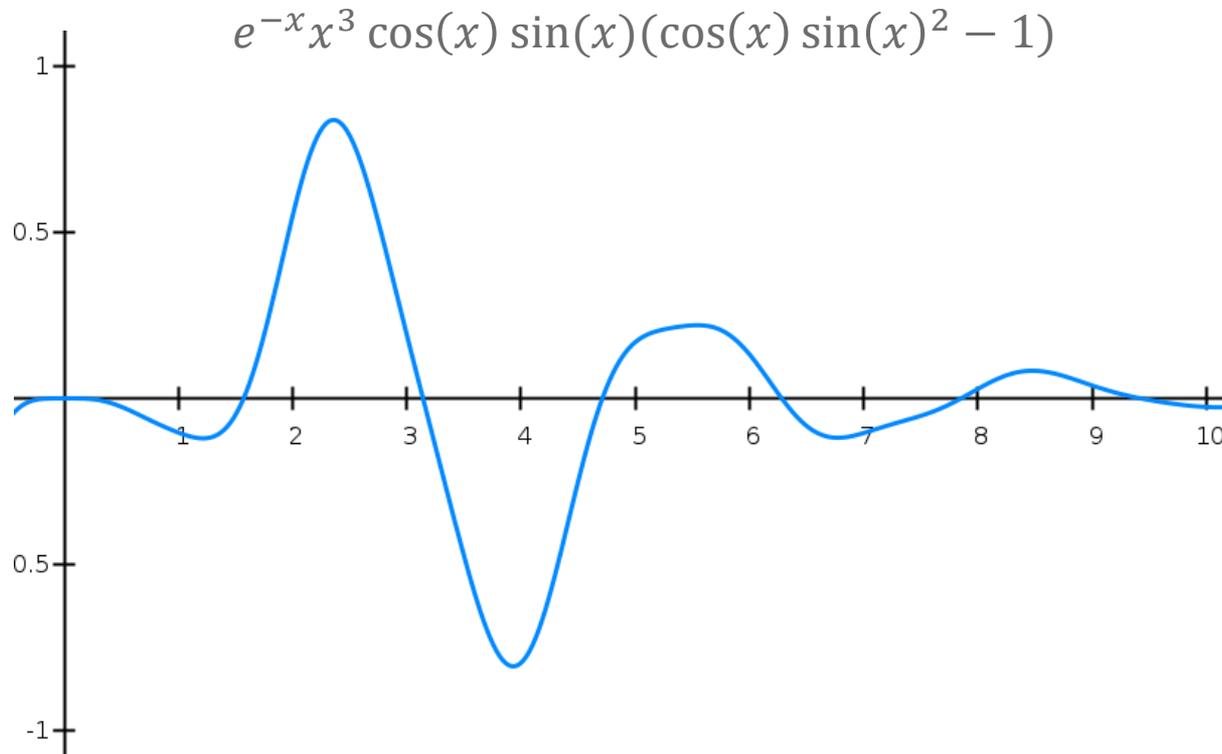
Properties

- Nonlinear Models
- Smooth Response Functions
- Integration of Prior Knowledge

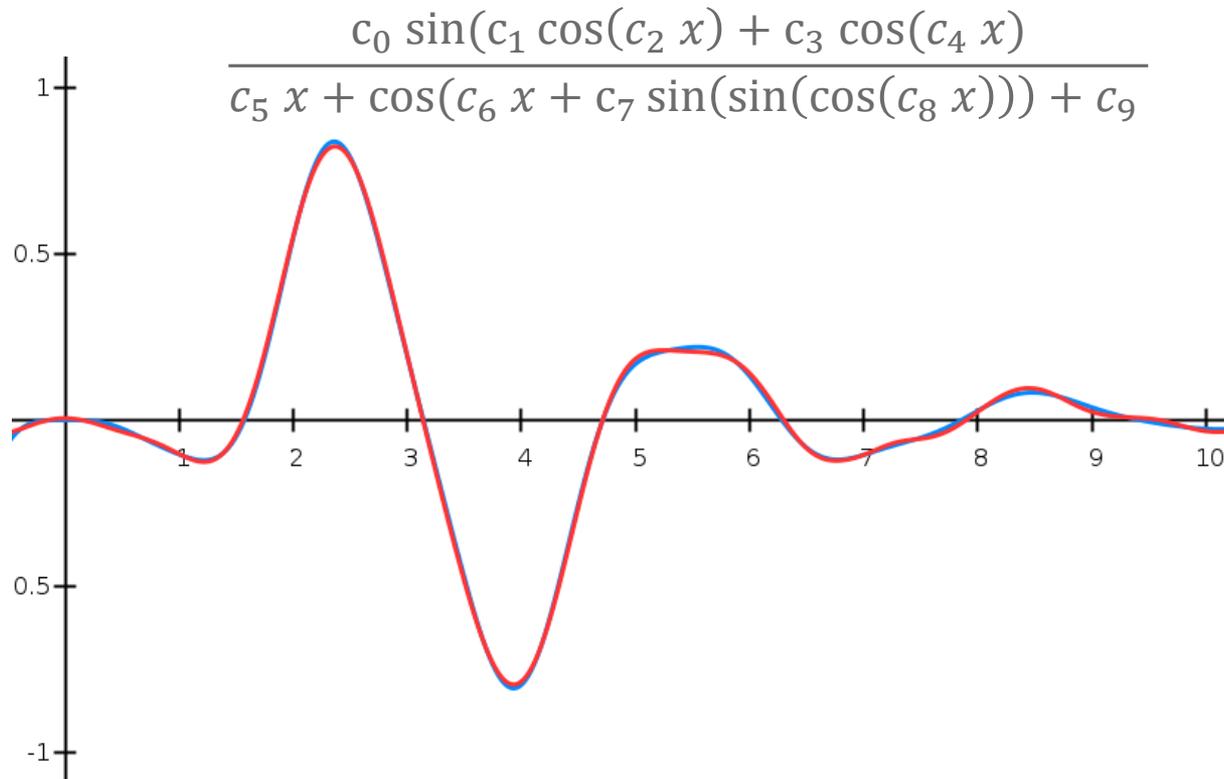
$$f(x_1, x_2) = \frac{0.0651 x_2 + 1.316}{1.5156 x_1 + 17.619}$$



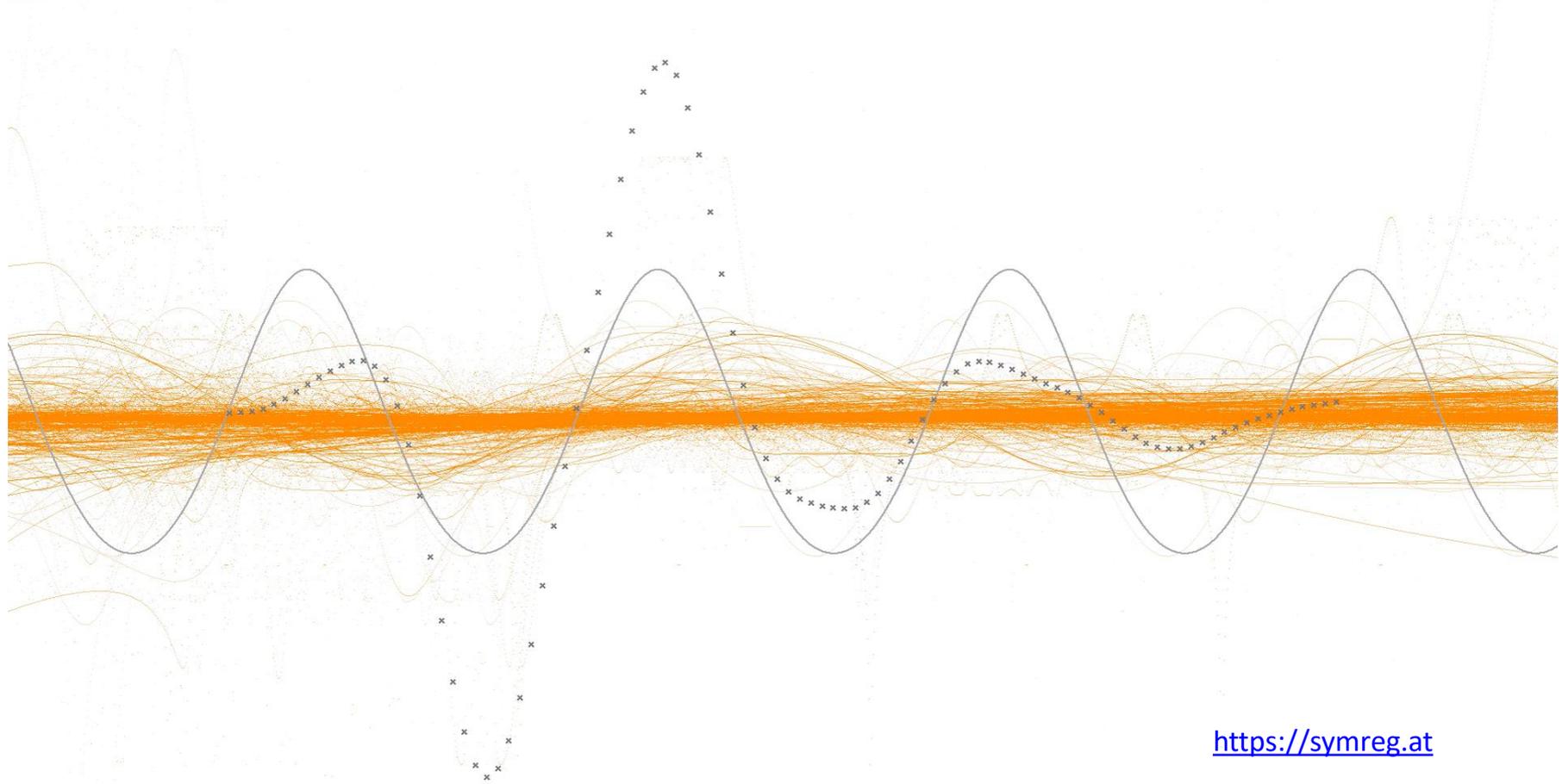
Symbolic regression



Symbolic regression



Symbolic regression

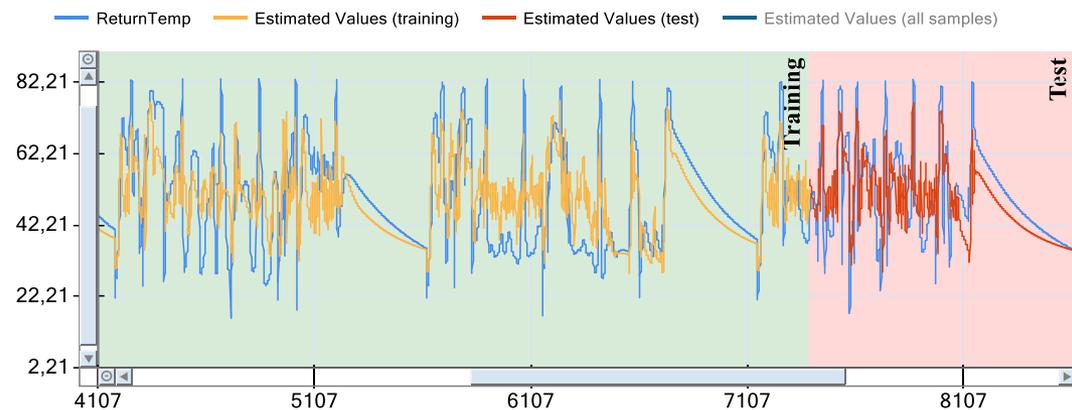
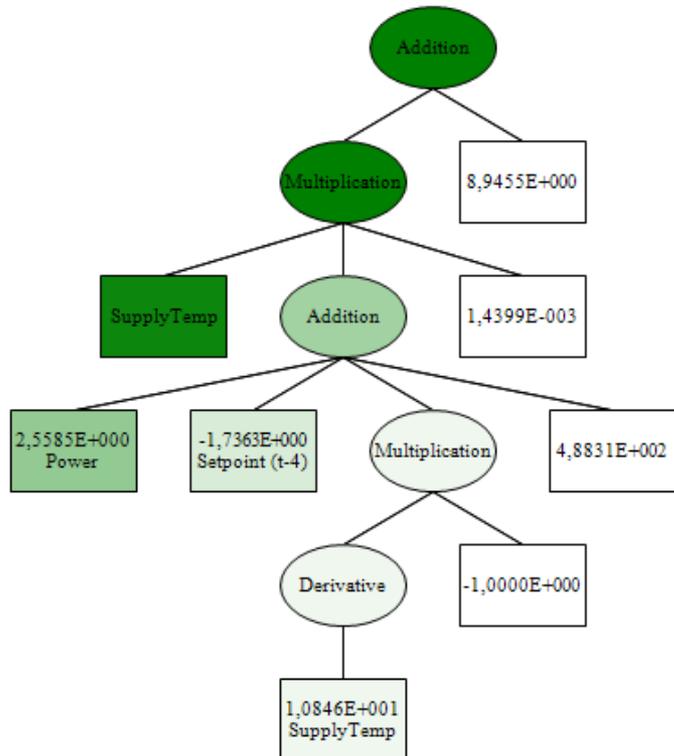


<https://symreg.at>

```
EXP(COS(SIN(((1*X) + COS(COS(SIN(SIN(COS(LOG((((NaN*X) + (NaN) / ((-1*X) + 6.3))))))))))))))
```

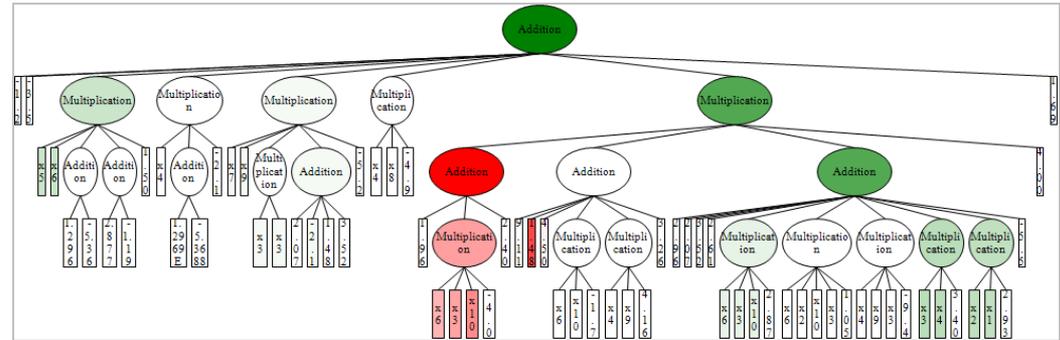
$$\text{ReturnTemp}(t) = \text{SupplyTemp} \cdot \left(c_0 \cdot \text{Power} + c_1 \cdot \text{Setpoint}(t - 4) + \frac{d(c_2 \cdot \text{SupplyTemp})}{dt} \cdot c_3 + c_4 \right) \cdot c_5 + c_6$$

$c_0 = 2.5585$
 $c_1 = -1.7363$
 $c_2 = 10.846$
 $c_3 = -1.0$
 $c_4 = 488.31$
 $c_5 = 0.0014399$
 $c_6 = 8.9455$



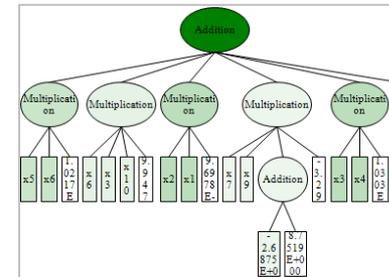
- **Simplification Methods**

- mathematical transformation
- remove nodes
- constant optimization
- external optimization



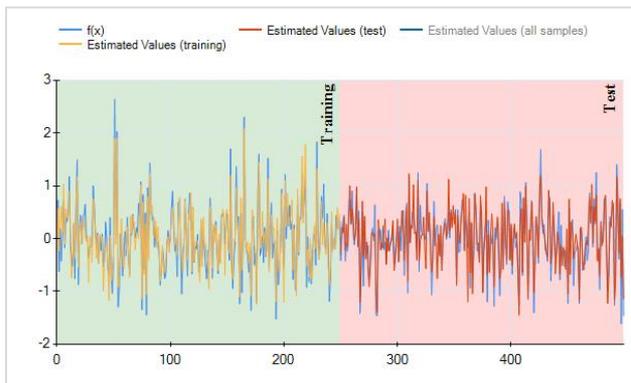
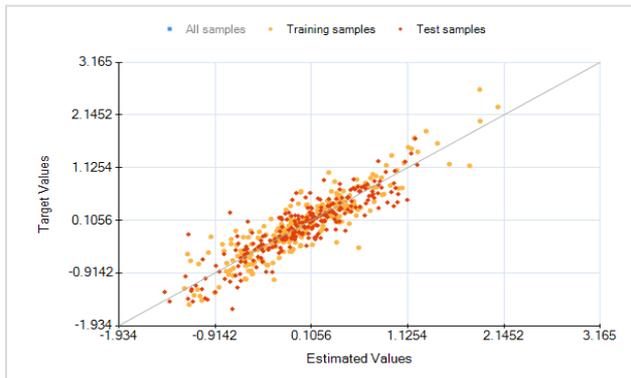
- **Export**

- textual export
- LaTeX, MatLab
- graphical export



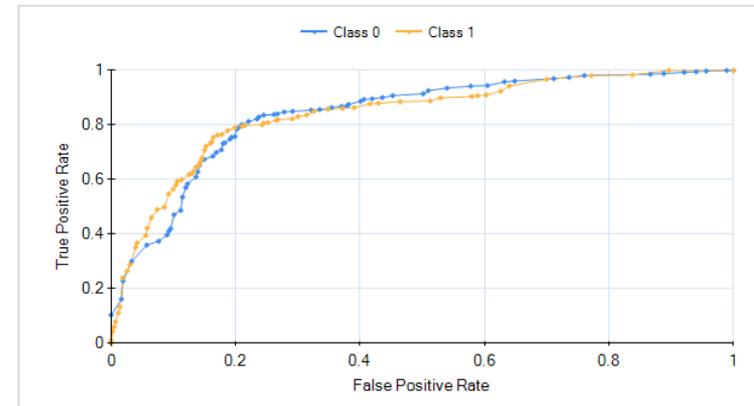
$$y = x_1 \cdot x_2 + x_3 \cdot x_4 + x_5 \cdot x_6 + x_1 \cdot x_7 \cdot x_9 + x_3 \cdot x_6 \cdot x_{10}$$

Regression

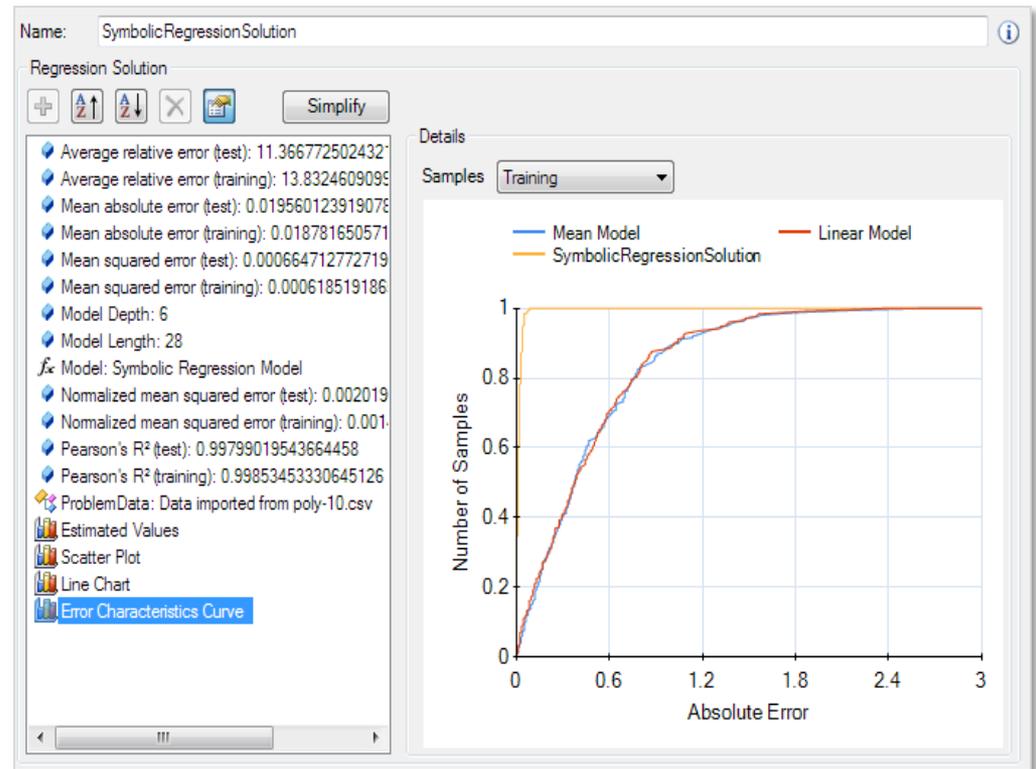
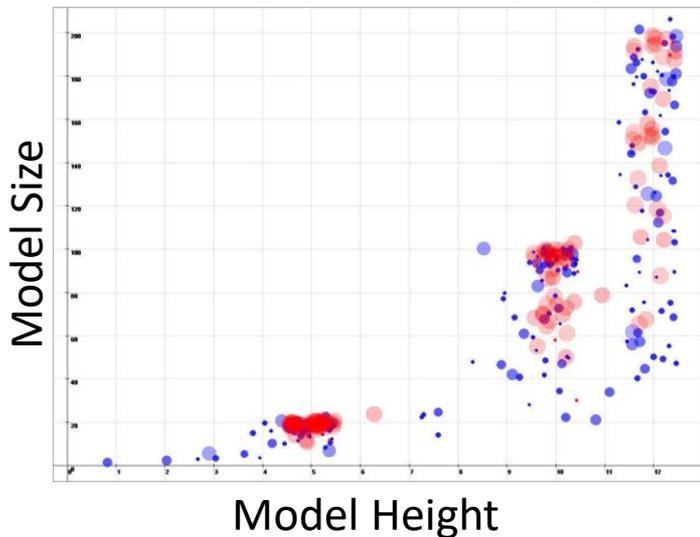
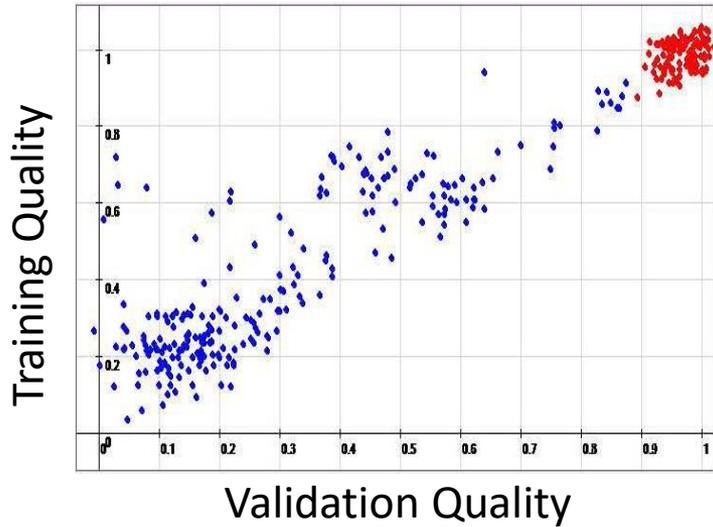


Classification

	Id	Target Variable	Estimated Values (all)	Absolute Error (all)	Relative Error (all)
Row 1	0	-0.051247964	-0.244931259696236	0.193683295696236	0.790765931373734
Row 2	1	0.727691161	0.566948971537046	0.160742189462954	0.283521441139877
▶ Row 3	2	-0.623794992	-0.235158714563106	0.388636277436894	1.65265522121487
Row 4	3	0.184169363	0.312577120202989	0.128407757202989	0.410803443065828
Row 5	4	-0.425409255	0.607464911486624	1.03287416648662	1.70030259683463
Row 6	5	0.13440877	0.135008413403134	0.000599643403133...	0.00444152618358...
Row 7	6	0.723969158	1.02967884646345	0.305709688463453	0.296898095472629
Row 8	7	-0.175618484	-0.096476538290749	0.079141945709251	0.820323232066462
Row 9	8	0.412736644	0.559935700149158	0.147199056149158	0.262885642244183
Row 10	9	0.321465414	0.391061335521024	0.0695959215210236	0.177966766845663
Row 11	10	0.492008676	0.412907348968929	0.0791013270310709	0.191571613410599



Visual Model Exploration

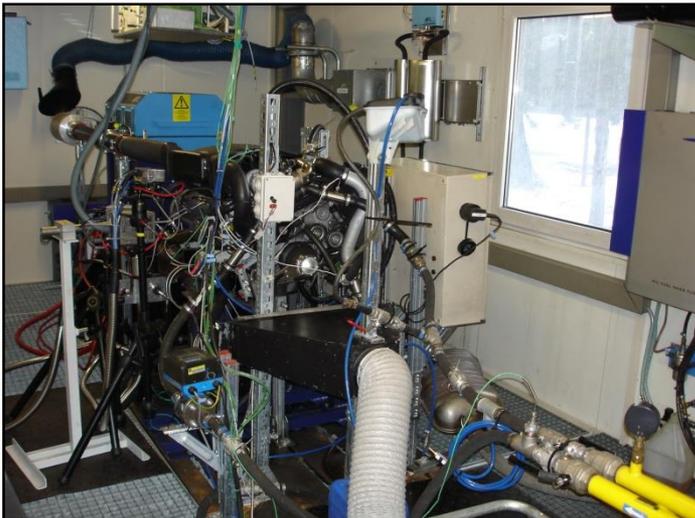


Selected Model

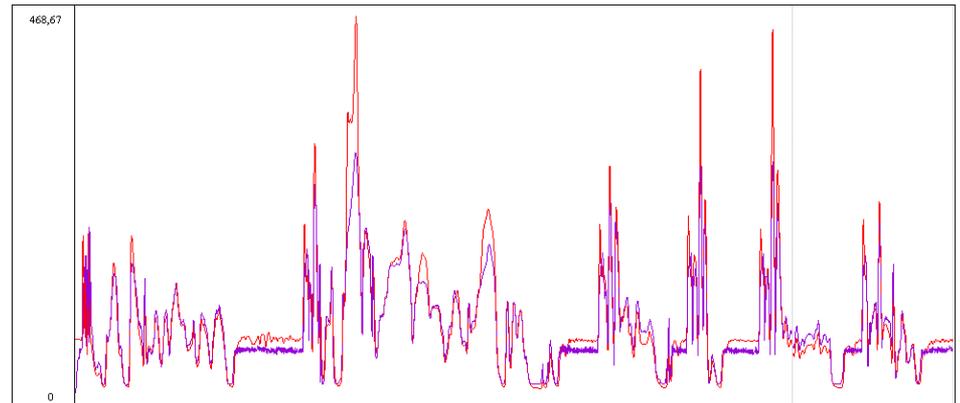
Example: Virtual Sensors for Modeling Exhaust Gases

- **Motivation**

- high quality modeling of emissions (NO_x and soot) of a diesel engine
- **virtual sensors:** (mathematical) models that mimic the behavior of physical sensors
- advantages: low cost and non-intrusive
- identify variable impacts:
 - injected fuel, engine frequency, manifold air pressure, concentration of O₂ in exhaustion etc.



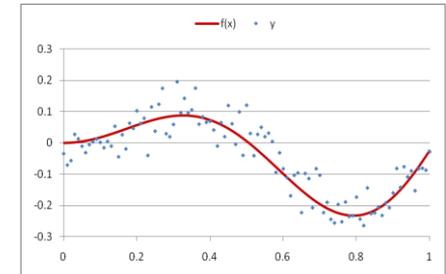
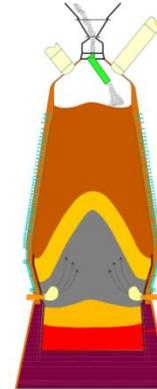
$$NO_x(t) = f(x1_{(t-7)}, x2_{(t-2)}, \dots)$$



Example: Blast Furnace Modeling



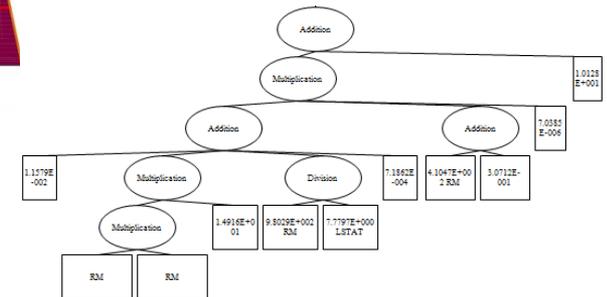
x1	x2	x3	x4	x5	y
28.07845	13.93902	87.63394	20.07777	63.00267	250.4028
27.95657	12.75236	87.05083	19.95878	63.00894	440.0825
25.43135	23.03532	88.32881	21.98374	74.99575	292.6644
28.5034	36.71041	87.59461	20.55528	75.01106	100.8683
23.03413	46.5804	79.38985	18.67402	80.31421	435.7738
20.97957	41.52231	73.32074	21.49193	79.98517	288.5032
28.07431	28.49076	106.4166	27.38095	79.97826	?
28.00494	36.33813	104.7173	27.99428	75.00266	?
28.0274	31.84306	102.277	28.81878	78.1752	?
26.503	27.67078	93.81539	21.29002	62.99904	?
23.869	27.25298	93.67531	24.54099	80.00291	?



Model

$f(x)$

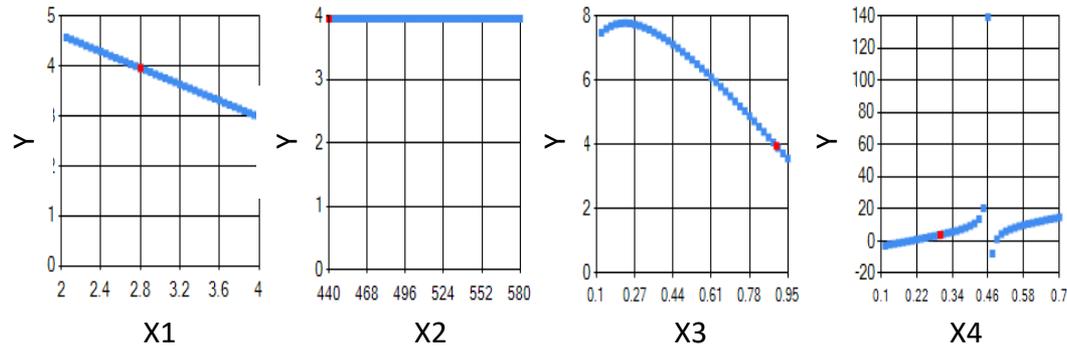
Prognosis



• Innovations

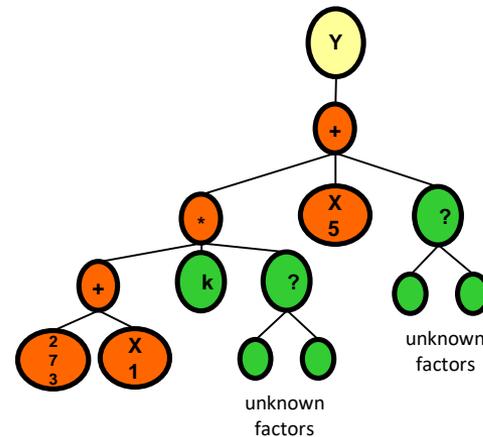
- results as formulas → domain experts can analyze, simplify and refine the models
- integration of prior physical knowledge into modeling process
- powerful data analysis tools: model simplification and variable impact analysis

- Model Analysis

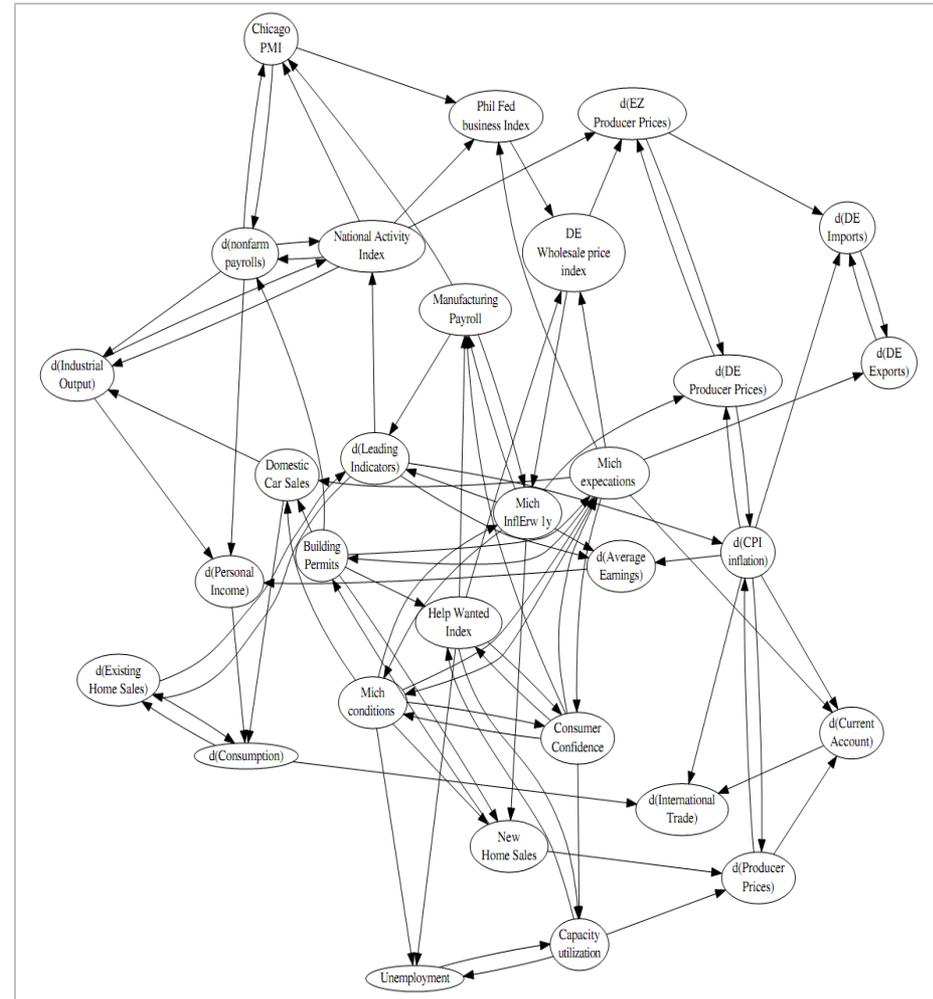
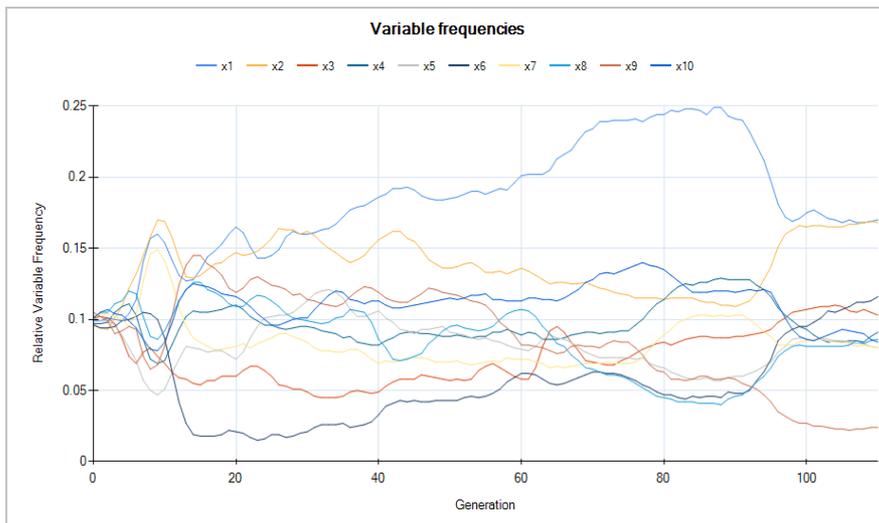


- Knowledge Integration

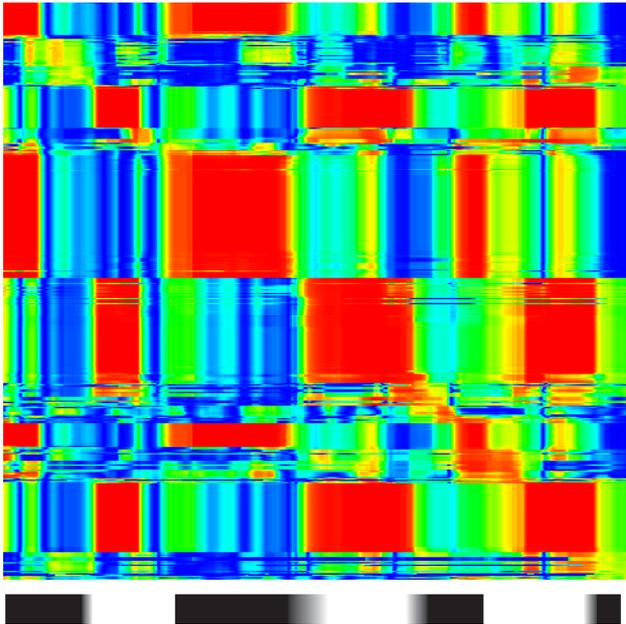
- specification of known correlations
- model extension through algorithm



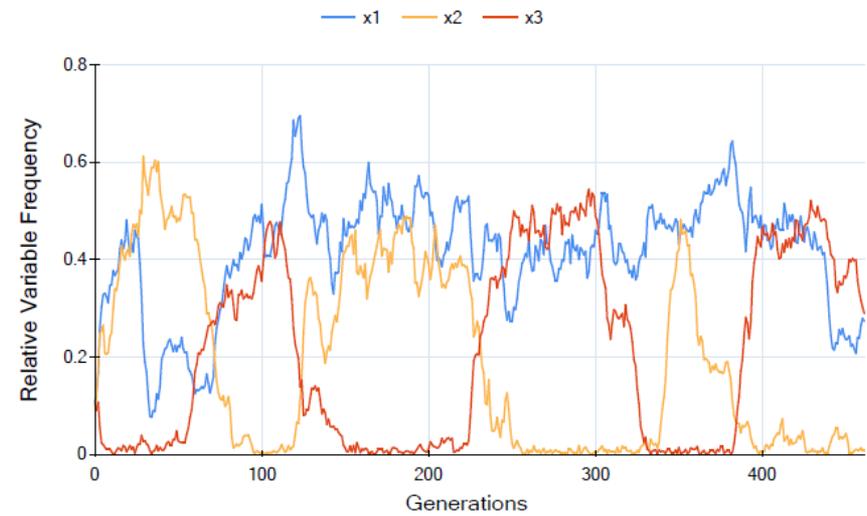
- **Variable interaction networks**
 - reveals non-linear correlations
- **Variable frequencies**
 - analyzed during the algorithm run

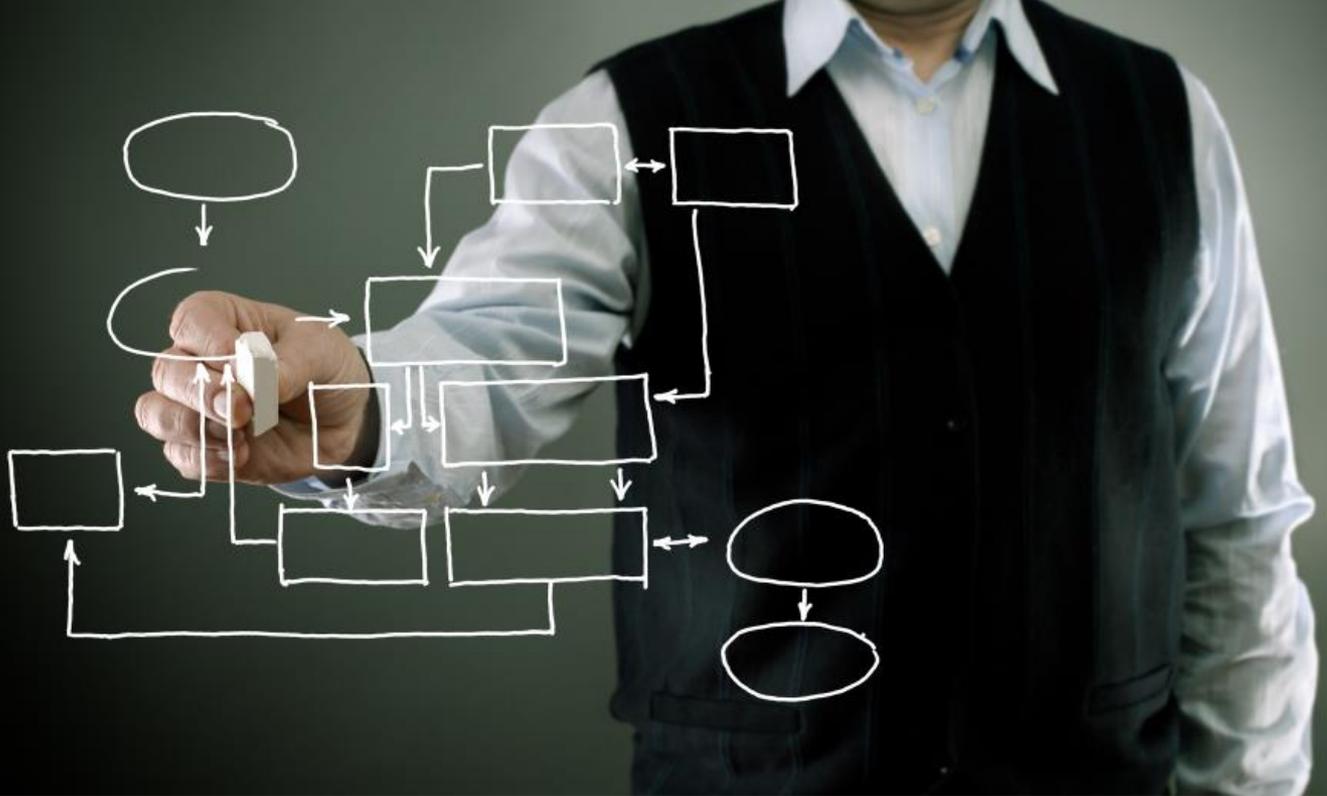


- Real-time Analytics (Streaming Data)
- Analysis of Variable Frequencies
 - clearly shows that algorithm is able to detect which variables are relevant



$$f_1(x, h) = x_1 * (h * x_2 + (1 - h) * x_3)$$





Künstliche Intelligenz - Mythos und Realität

Wie wir die Zukunft mit Prescriptive Analytics gestalten

Michael Affenzeller
November 12th 2020



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