

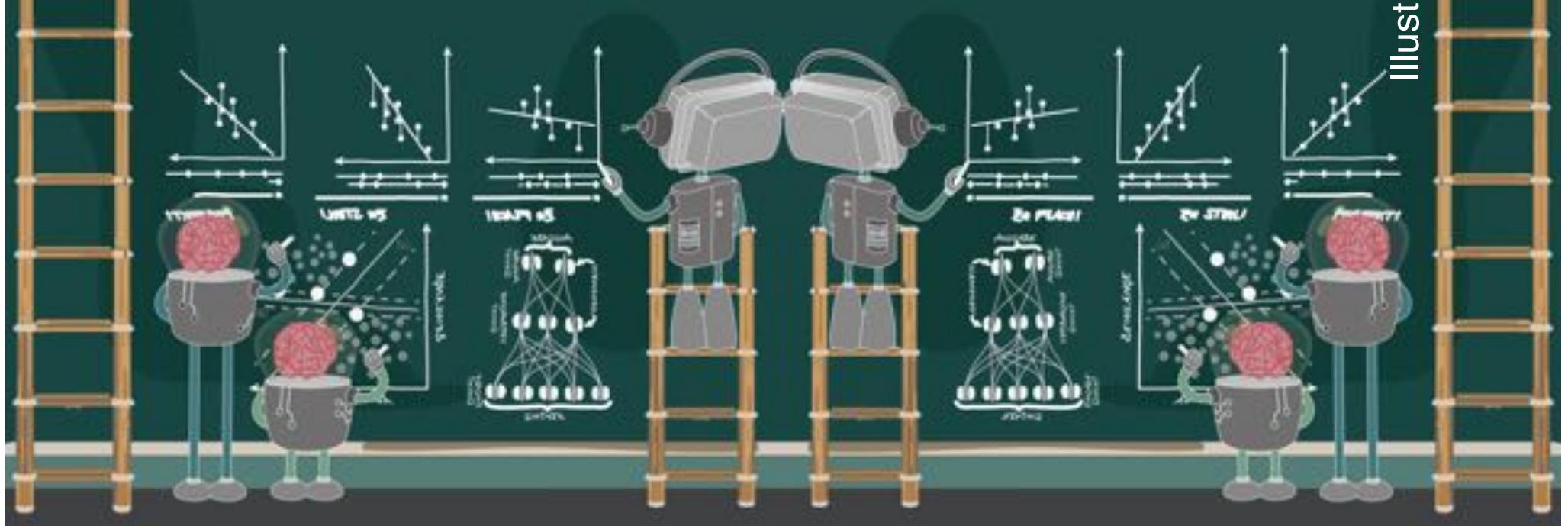
Kristian
Kersting



Illustration Nanina Föhr

The Third of Wave of AI

Thanks to Christoph Lampert and Constantin Rothkopf for some of the slides



The dream of an artificially intelligent entity is not new



Talos, an ancient mythical automaton with artificial intelligence



The dream of an artificially intelligent entity is not new

The image consists of a composite of three elements. At the top left is a screenshot of a ZEIT ONLINE website. The header 'ZEIT ONLINE' is visible, along with a navigation bar for 'Politik', 'Gesellschaft', 'Wirtschaft', 'Kultur', 'Wissen', 'Digital Campus', 'Arbeit', 'Entdecken', 'Sport', 'ZEITmagazin', 'Podcasts', and 'mehr'. A search bar with the placeholder 'Suche' and a magnifying glass icon is at the top right. Below the header, the main title of the article reads 'Gottfried Wilhelm Leibniz: Er wollte die Welt mit Intelligenz in den Griff bekommen'. A subtitle below it says '... die aber mache nicht mit. Was wir dennoch von Gottfried Wilhelm Leibniz lernen können - 300 Jahre nach dem Tod dieses letzten deutschen Universalgenies.' To the right of the text is a black and white portrait of Gottfried Wilhelm Leibniz. The background of the entire image is a dark blue-grey color with a subtle pattern of interlocking mechanical gears.

Leibniz „philosophises about ‘artificial intelligence’ (AI). In order to prove the impossibility of thinking machines, Leibniz imagines of ‘a machine from whose structure certain thoughts, sensations, perceptions emerge“ — Gero von Radow, ZEIT 44/2016

AI today

the INQUIRER

Artificial intelligence will create the next industrial revolution, experts claim

We won't waste time on treatments that won't work, so the patient should get

Elon Musk

Self-driving Tesla 'saved' by steering him to hospital

Elon Musk's tweet: I've talked to Mark about this. His understanding of the subject is limited.

A blue Tesla Model X driving on a road.

Artificial intelligence better than scientists at choosing successful embryos

We won't waste time on treatments that won't work, so the patient should get

Jane Kirby | 22 hours ago | 0 comments

V/S

Elon Musk's tweet: I've talked to Mark about this. His understanding of the subject is limited.

BBC NEWS

Technology

Stephen Hawking warns artificial intelligence could end mankind

Humans, who are limited by slow biological evolution, couldn't compete and would be

Stephen Hawking

SCIENTIFIC AMERICAN DECEMBER 2016

Computers Now Recognize Patterns Better Than Humans Can

An approach to artificial intelligence that enables computers to recognize visual patterns better than humans are able to do

AI today

THE ECONOMIC IMPACT OF ARTIFICIAL INTELLIGENCE

Projected Global
Economic Effects
of AI by 2030



Source: PwC

AI Impact driven by researchers



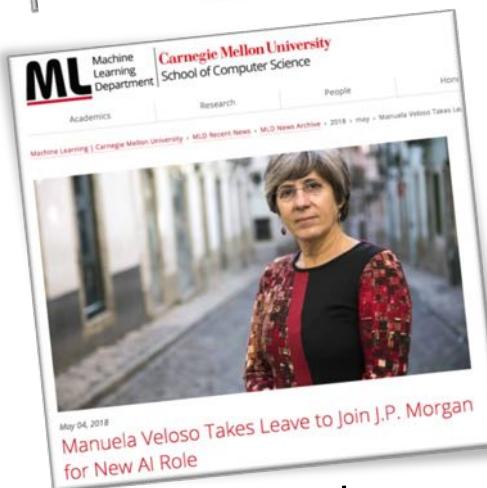
Pedro Domginos
UW, DE Shaw



Yann LeCun
Turing Awardee
NYU, Facebook



Charles Elkan
UCSD, Goldman Sachs

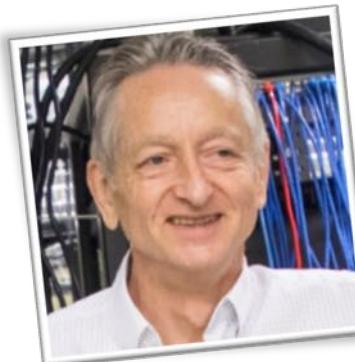


Manuela Veloso
Former AAAI President
CMU, JPMorgan



UBER AI Labs

Zoubin Ghahramani
Cambridge, Uber



Geoffrey Hinton
Turing Awardee
DeepMind, U. Toronto
Vector Institute

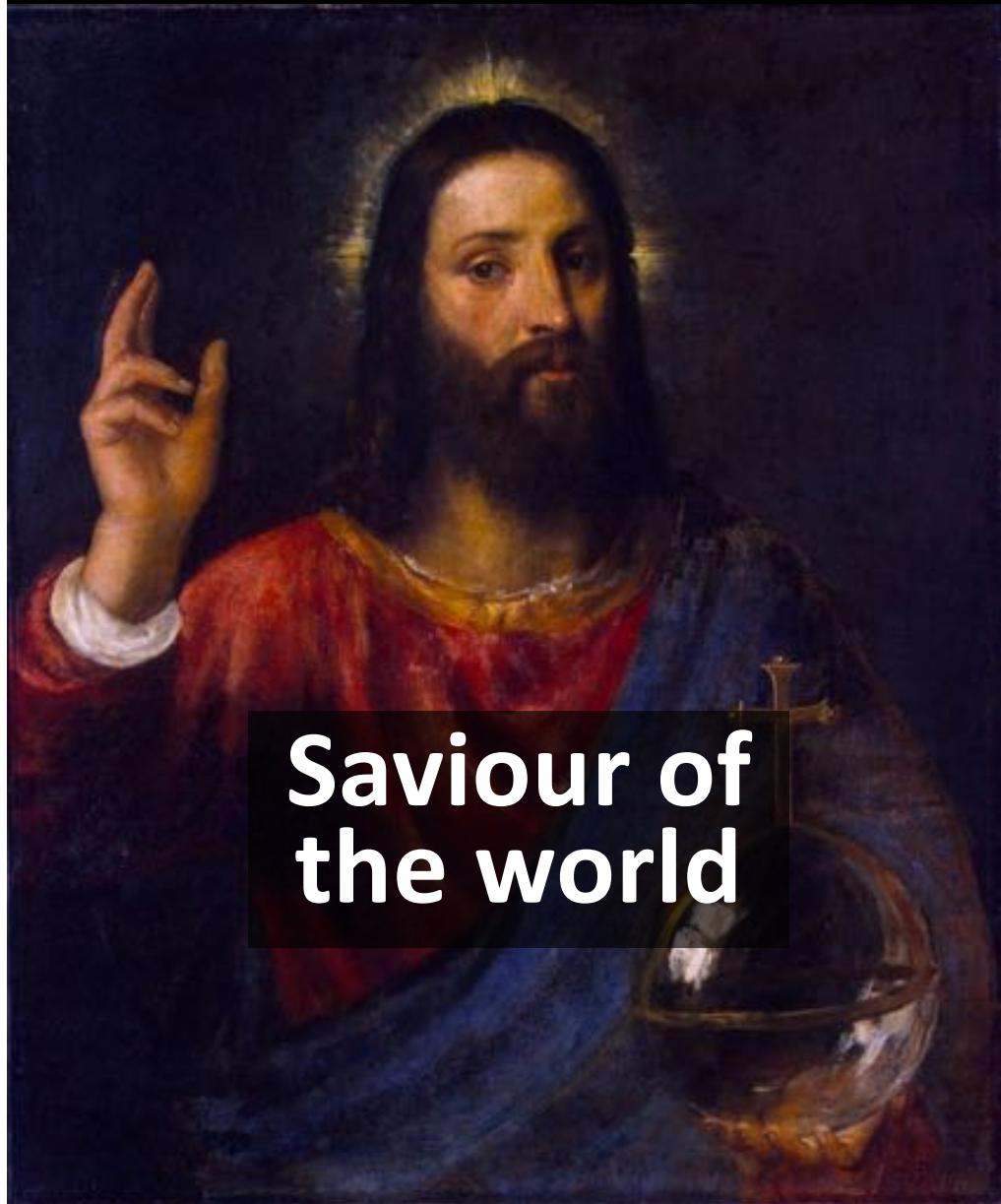
VECTOR
INSTITUTE



Yoshua Bengio
Turing Awardee
Element.AI
Univ. Montreal

... and many more examples

So, AI has many faces

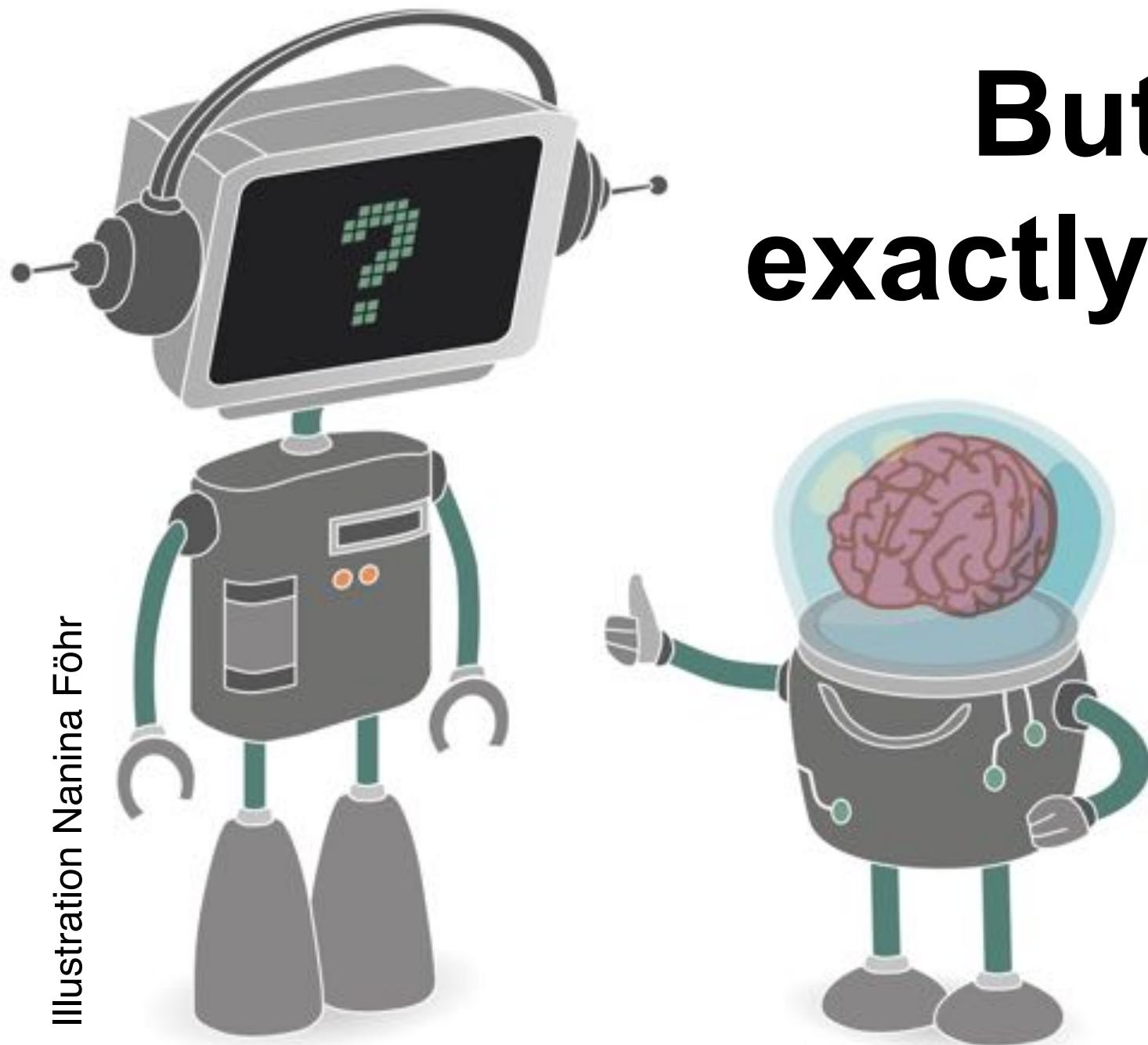


Saviour of
the world



Downfall of
humanity

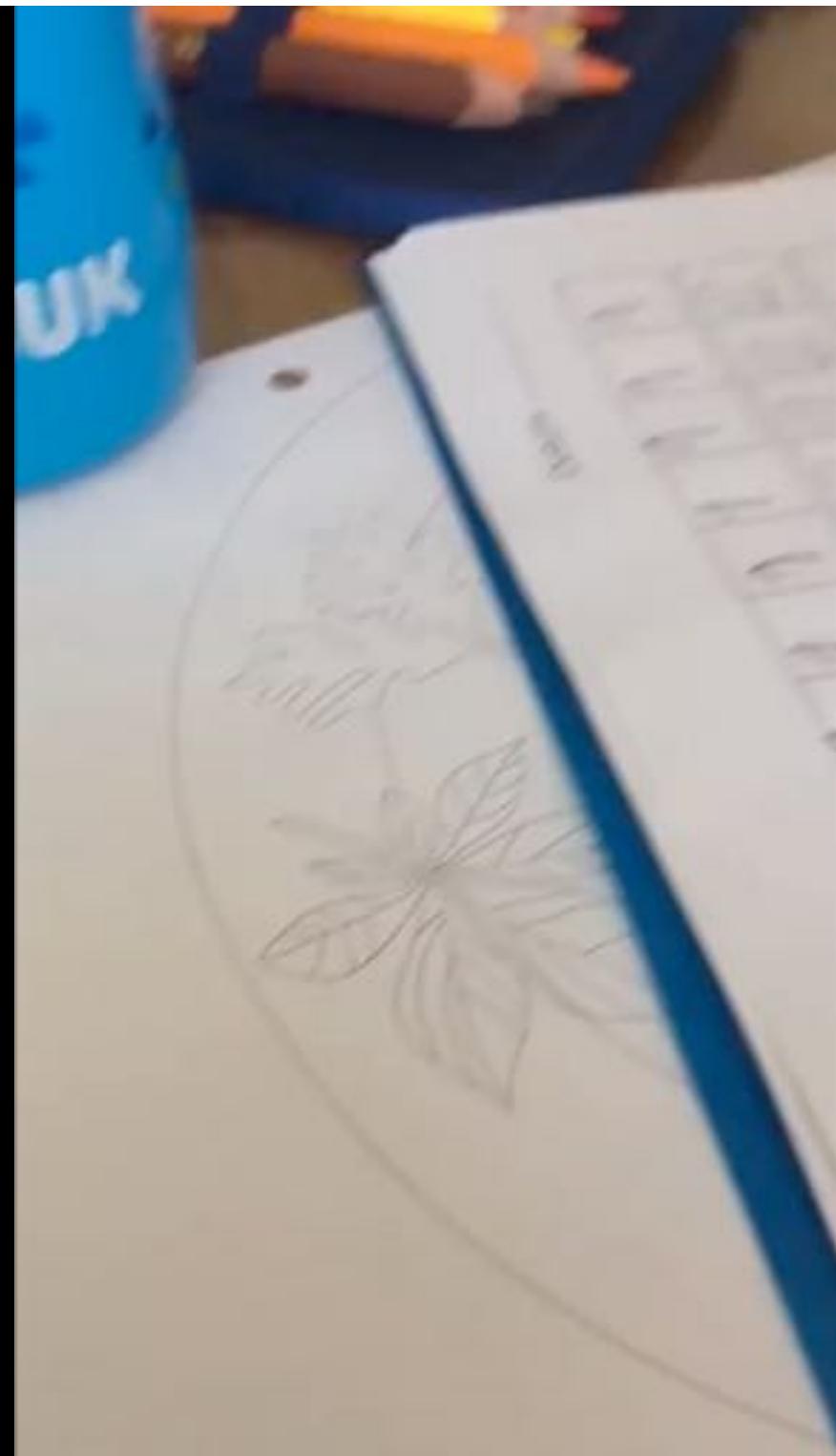
Illustration Nanina Föhr



**But, what
exactly is AI?**

Humans are considered to be smart

<https://www.youtube.com/watch?v=XQ79UUlOeWc>

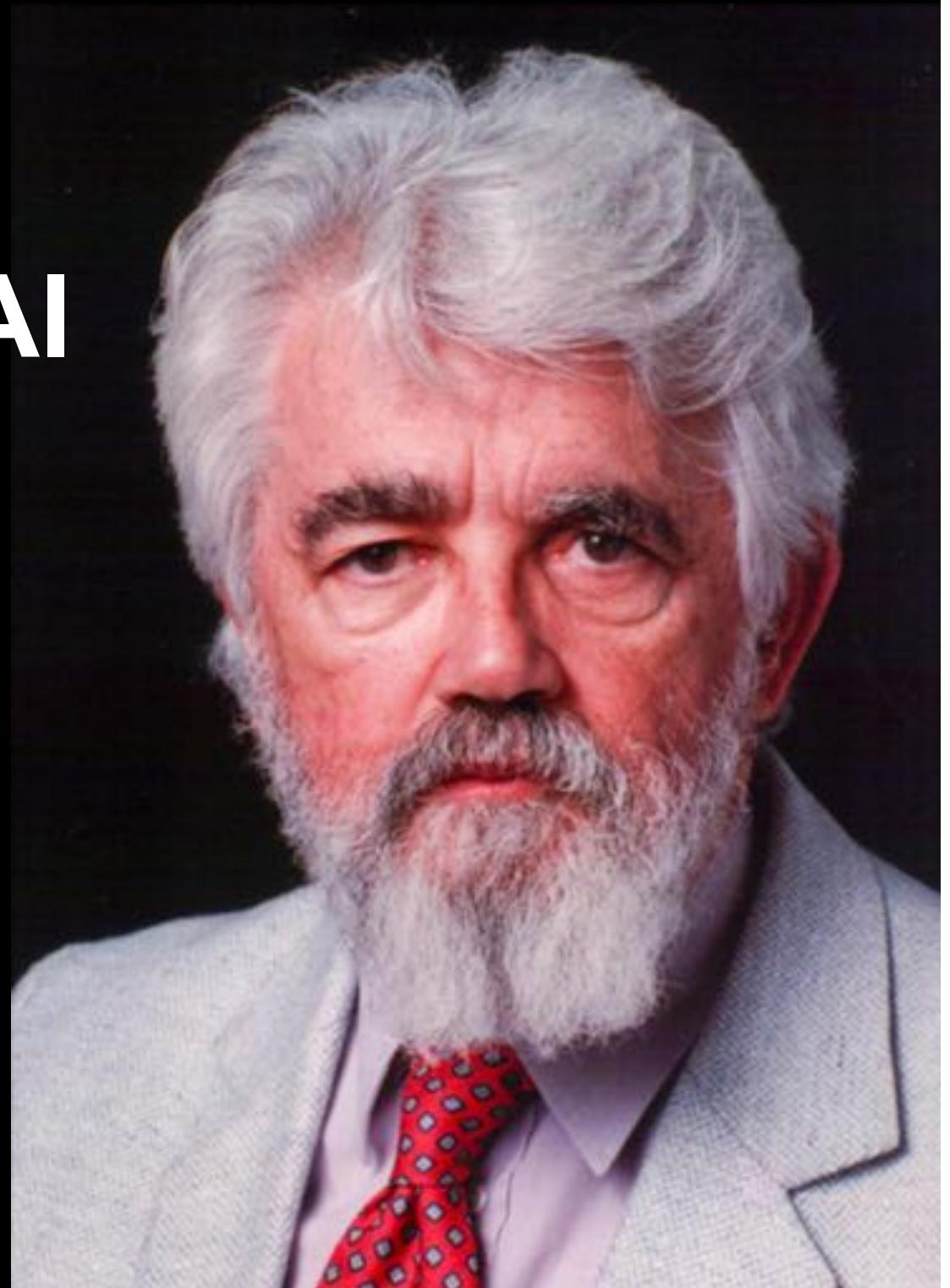


The Definition of AI

„the science and engineering of making intelligent machines, especially intelligent computer programs.

It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.“

- John McCarthy, Stanford (1956), coined the term AI, Turing Awardee



Learning

Thinking

Planning

AI = Algorithms for ...

Vision

Behaviour

Reading

Machine Learning

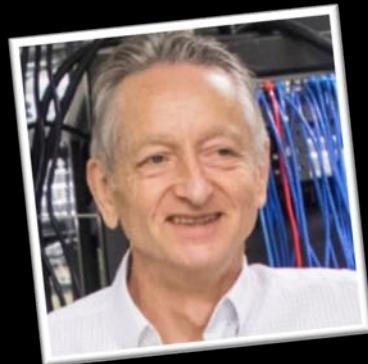
**the science "concerned with
the question of how to
construct computer programs
that automatically improve with
experience"**

- Tom Mitchell (1997) CMU





Deep Learning



Geoffrey Hinton
Google
Univ. Toronto (CAN)



Yann LeCun
Facebook (USA)

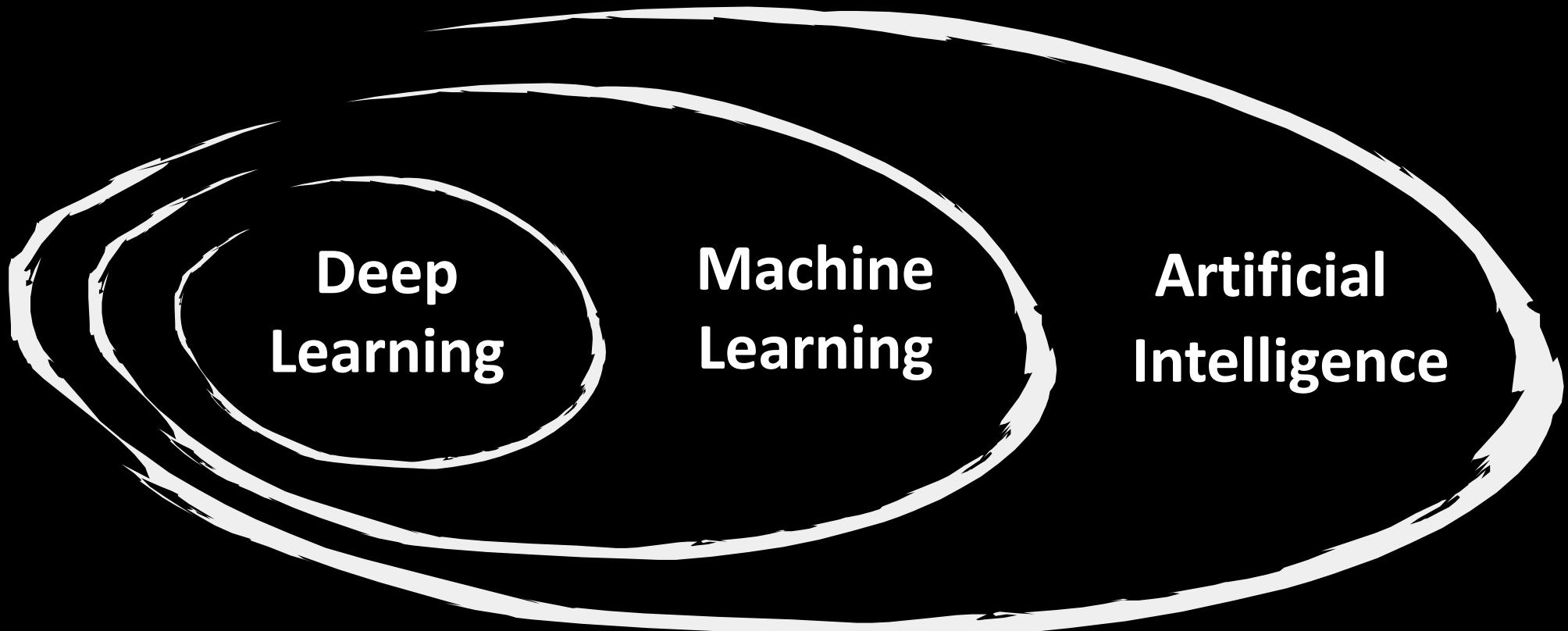


Yoshua Bengio
Univ. Montreal (CAN)

a form of machine
learning that makes
use of artificial
neural networks

Turing Awardees 2019

Overall Picture



Three levels of description

VISION



David Marr

FOREWORD BY
Shimon Ullman
AFTERWORD BY
Tomaso Poggio

1982



Computational

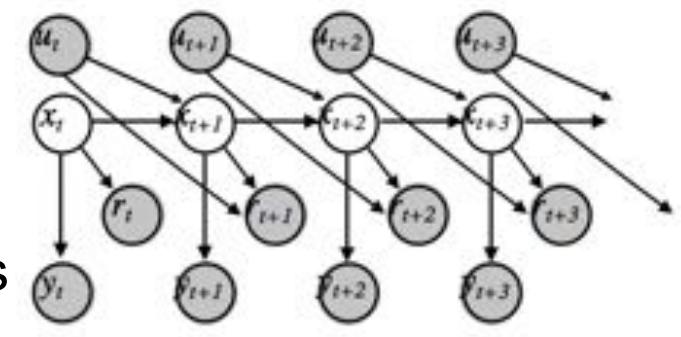
Why do things work the way they work? What is the goal of the computation? What are the unifying principles?

maximize:

$$R_t = r_{t+1} + r_{t+2} + \cdots + r_T$$

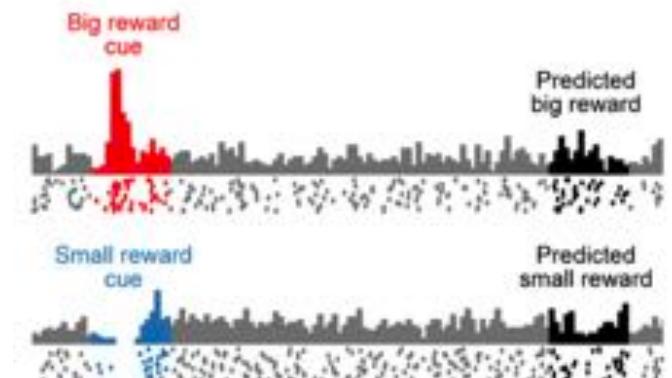
Algorithmic

What representation can implement such computations? How does the choice of the representation determine the algorithm



Implementational

How can such a system be built in hardware?
How can neurons carry out the computations?



slide after C. Rothkopf (TUD)

And this all started
as early as 1956

ONCE
UPON A TIME

1956 Birth of AI



A Proposal for the
DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.



John McCarthy
Turing Award 1971



Marvin Minsky
Turing Award 1969



Allen Newell
Turing Award 1975



Herbert A. Simon
Turing Award 1975
Nobel Prize 1978

**... and of
Cognitive Science**

Artificial Neural Networks

COGNITIVE SCIENCE 14, 179–211 (1990)

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton†
& Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California,
San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University,
Pittsburgh, Philadelphia 15213, USA

Finding Structure in Time

JEFFREY L. ELMAN
University of California, San Diego

COGNITIVE SCIENCE 9, 147–169 (1985)

A Learning Algorithm for Boltzmann Machines*

DAVID H. ACKLEY
GEOFFREY E. HINTON
*Computer Science Department
Carnegie-Mellon University*
TERRENCE J. SEJNOWSKI
*Biophysics Department
The Johns Hopkins University*

Biological
Cybernetics
© by Springer-Verlag 1980

Biol. Cybernetics 36, 193–202 (1980)

Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

Psychological Review
1981, Vol. 88, No. 2, 135–170

Copyright 1981 by the American Psychological Association, Inc.
0033-295X/81/8802-0135\$00.75

Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN¹

F. ROSENBLATT

Cornell Aeronautical Laboratory

Toward a Modern Theory of Adaptive Networks: Expectation and Prediction

Richard S. Sutton and Andrew G. Barto
*Computer and Information Science Department
University of Massachusetts—Amherst*

Artificial Neural Networks

COGNITIVE SCIENCE 4, 179–211 (1990)

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Biological Cybernetics

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Toward a Modern Theory of Adaptive Networks: Expectation and Prediction

Richard S. Sutton and Andrew G. Barto
*Computer and Information Science Department
University of Massachusetts—Amherst*

slide after C. Rothkopf (TUD), after J. Tenenbaum (MIT)

Algorithms of intelligent behaviour teach us a lot about ourselves

The twin science: cognitive science

"How do we humans get so much from so little?" and by that I mean how do we acquire our understanding of the world given what is clearly by today's engineering standards so little data, so little time, and so little energy.

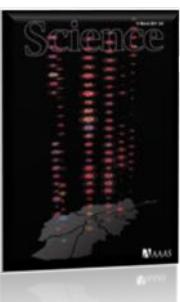


Centre for Cognitive Science at TU Darmstadt

Establishing cognitive science at the Technische Universität Darmstadt is a long-term commitment across multiple departments (see [Members](#) to get an impression on the interdisciplinary of the supporting groups and departments). The TU offers a strong foundation including several established top engineering groups in Germany, a prominent computer science department (which is among the top four in Germany), a



Centre for
Cognitive
Science



Lake, Salakhutdinov, Tenenbaum, Science 350 (6266), 1332-1338, 2015

Tenenbaum, Kemp, Griffiths, Goodman, Science 331 (6022), 1279-1285, 2011

Well-established scientific discipline with international societies, selective venues, and networks



Association for the
Advancement of Artificial Intelligence



IJCAI



ICML

NeurIPS

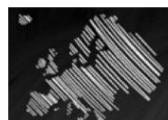
CVPR ISWC

Thirty-second Conference on Neural Information
Processing Systems

ROBOTICS
SCIENCE AND SYSTEMS



European Association
for Artificial Intelligence



e l l i s

European Laboratory for Learning and Intelligent Systems



CLAIRE

CONFEDERATION OF LABORATORIES FOR
ARTIFICIAL INTELLIGENCE RESEARCH IN EUROPE

... among others

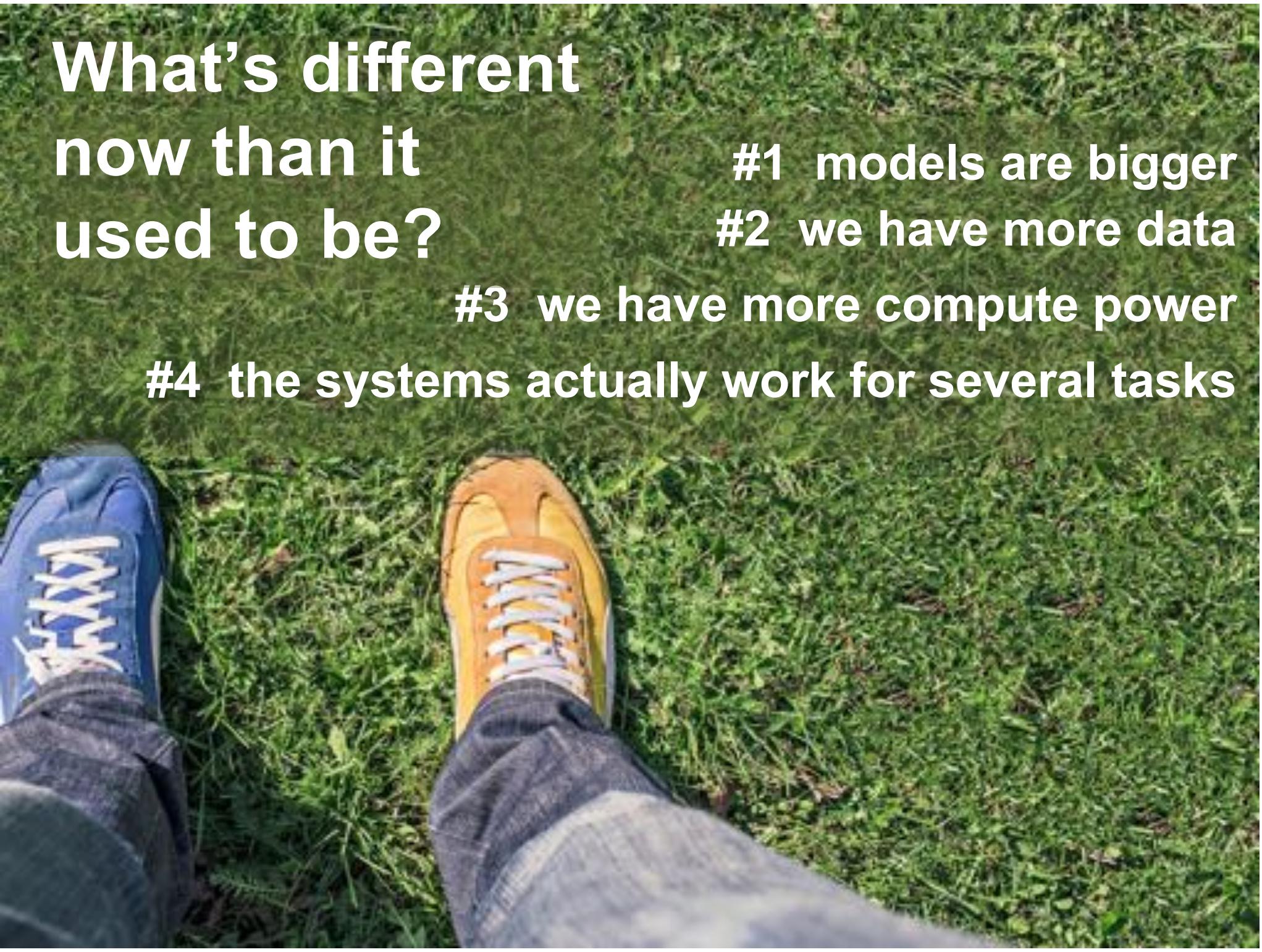
The screenshot shows a news article from the GI website. The headline reads: "Was ist eine Professur für Künstliche Intelligenz?". The article discusses how the German Federal Government plans to establish up to 100 new professorships in Artificial Intelligence across Germany. It highlights that these professorships will be open to both men and women and will be funded by the state. The article also mentions that the first professorships are expected to be established in 2021.

Was ist eine Professur für Künstliche Intelligenz?

Die deutsche Bundesregierung will die Forschung in der Künstlichen Intelligenz in Deutschland deutlich ausbauen. Es sollen z.B. 100 neue Professorinnen und Professoren für Künstliche Intelligenz entstehen. Allerdings beanwortet das Ministerium, dass es sich um eine Professur für Künstliche Intelligenz überhaupt ist. Um Kollegen, Politiker und die Öffentlichkeit zu überzeugen, dass sie in Berufungsverfahren

MITGLIED WERDEN

MEINE GI

A photograph showing a person's lower legs and feet resting on a green grassy slope. The person is wearing blue jeans and two different colored sneakers: a blue one on the left and an orange one on the right. The background is a lush green hillside.

What's different
now than it
used to be?

#1 models are bigger

#2 we have more data

#3 we have more compute power

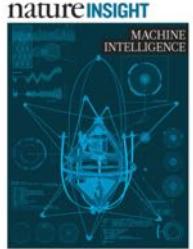
#4 the systems actually work for several tasks

AI can learn to manipulate objects



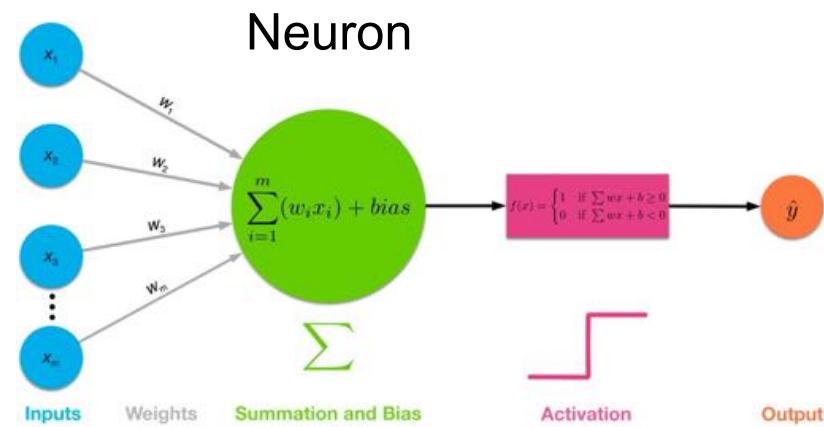
[OpenAI: https://www.youtube.com/watch?v=x4O8pojMF0w](https://www.youtube.com/watch?v=x4O8pojMF0w)

Deep Neural Networks

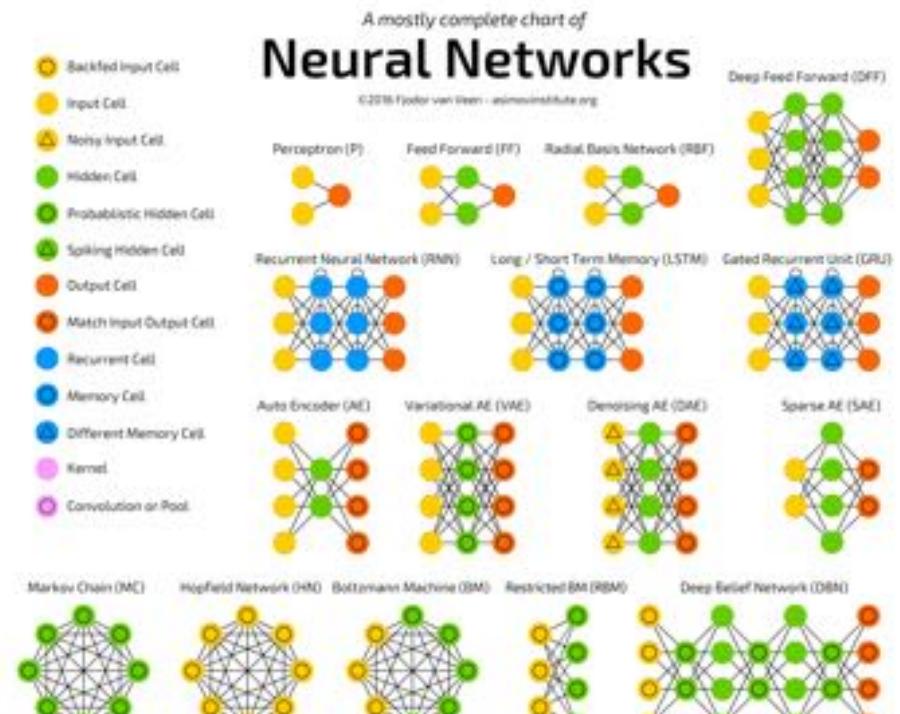


Potentially much more powerful than shallow architectures, represent computations

[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]

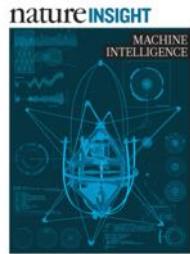


Differentiable Programming



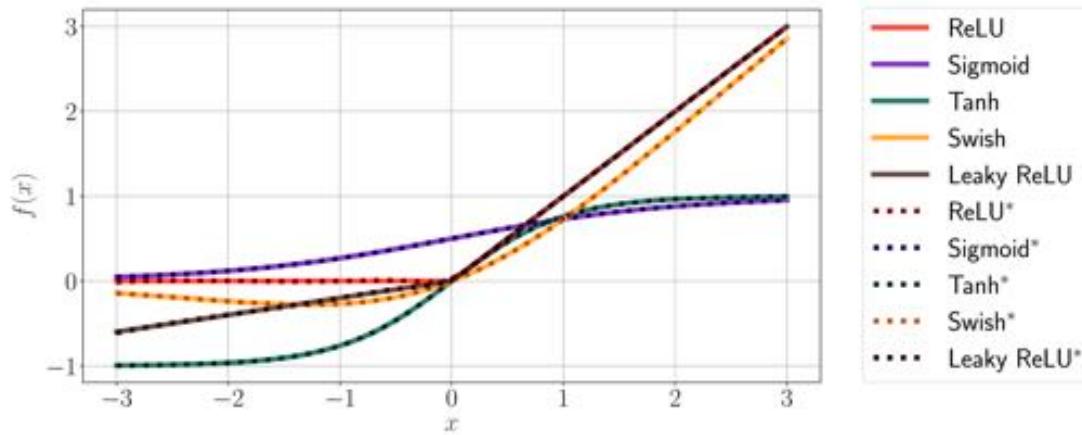


Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

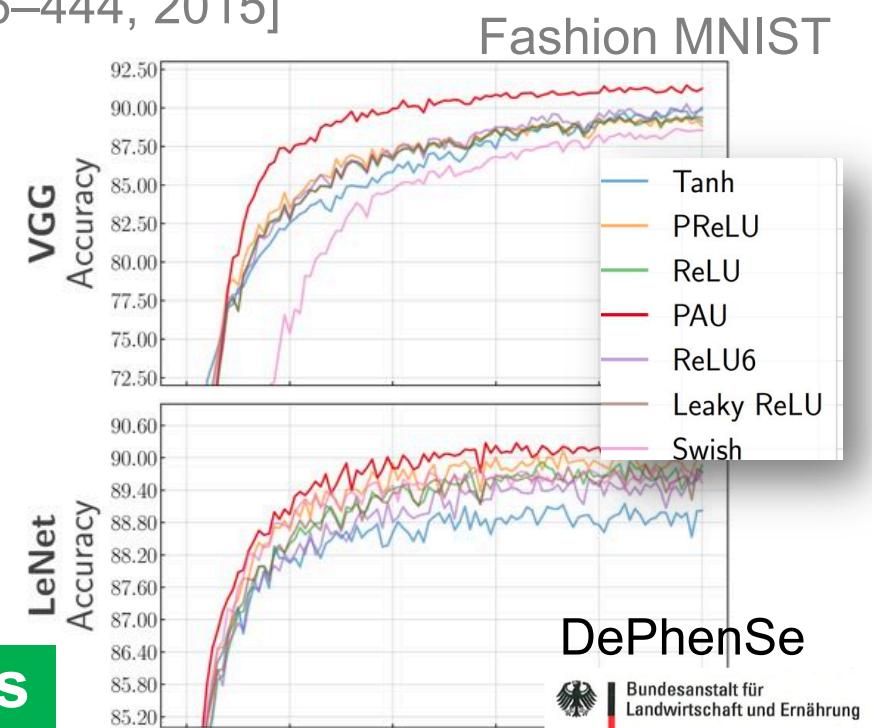
[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]



<https://github.com/ml-research/pau>

E2E-Learning Activation Functions

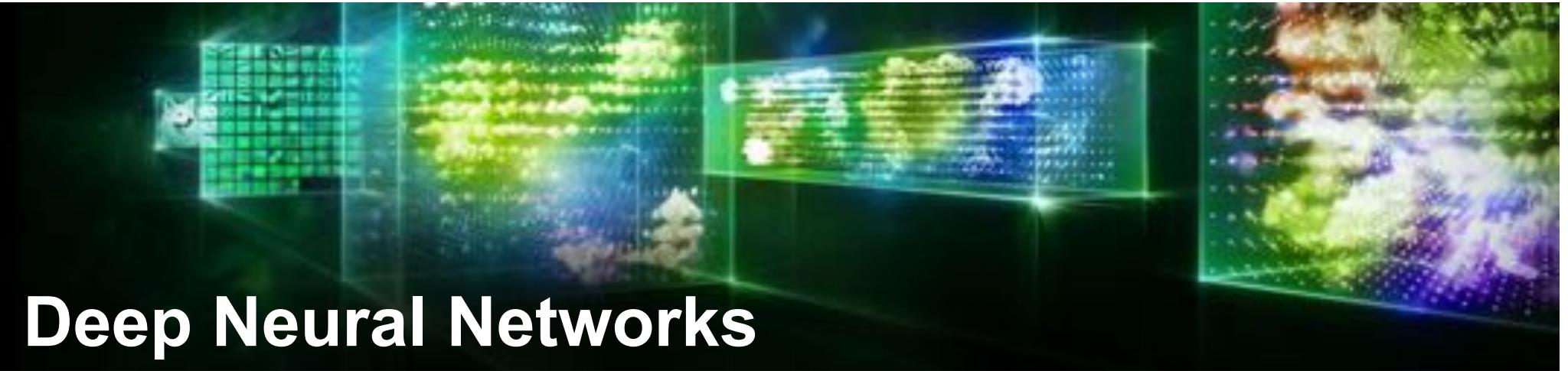
[Molina, Schramowski, Kersting arxiv:1901.03704 2019]



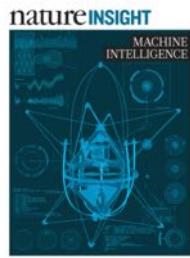
DePhenSe



Bundesanstalt für
Landwirtschaft und Ernährung

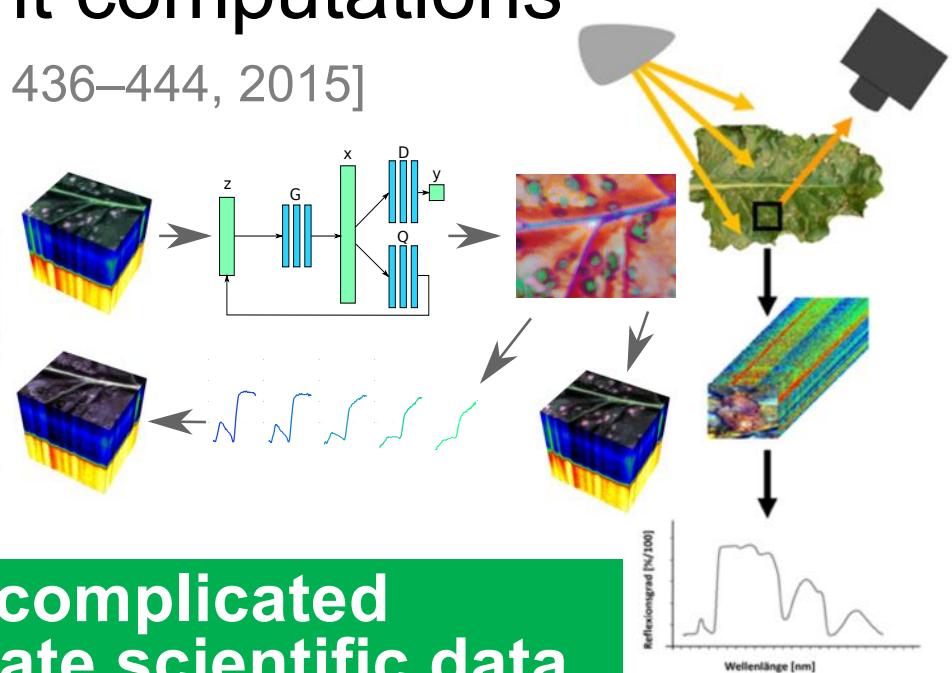
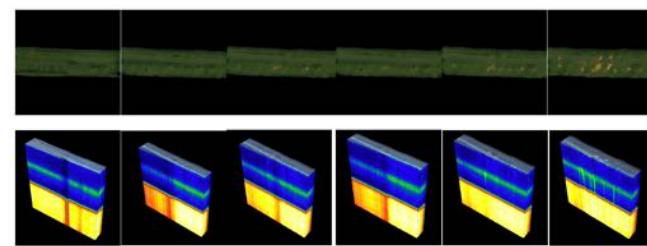
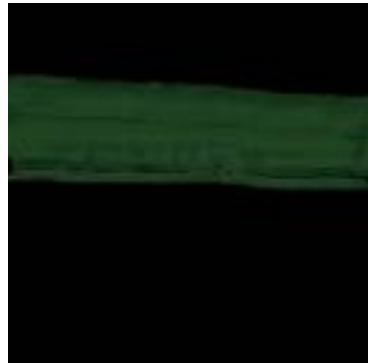


Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

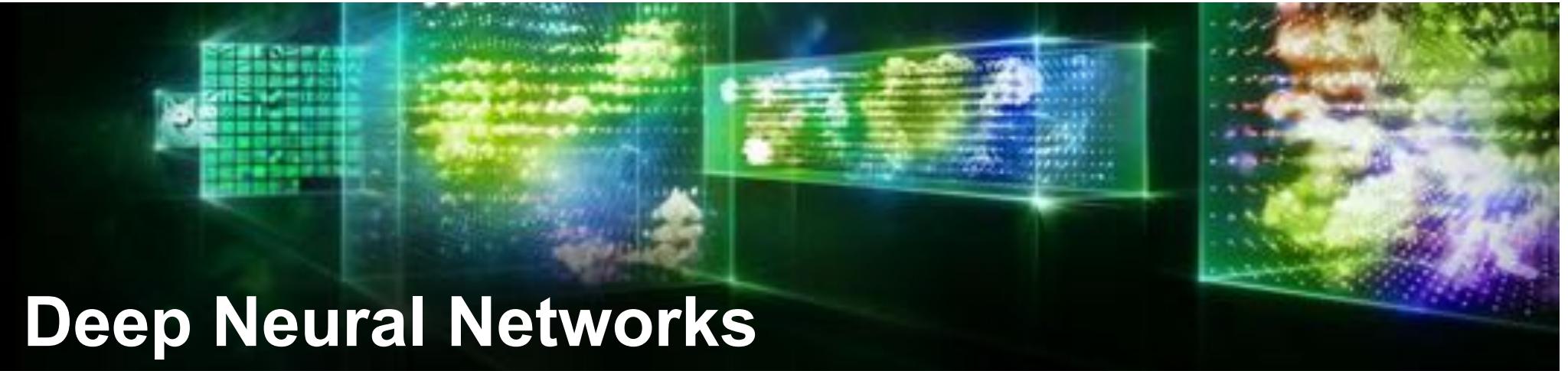
[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]



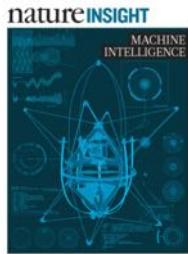
They “develop intuition” about complicated biological processes and generate scientific data

[Schramowski, Brugger, Mahlein, Kersting 2019]

DePhenSe

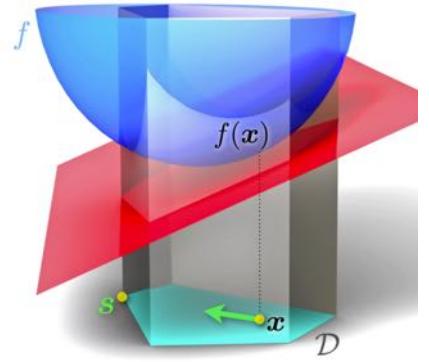
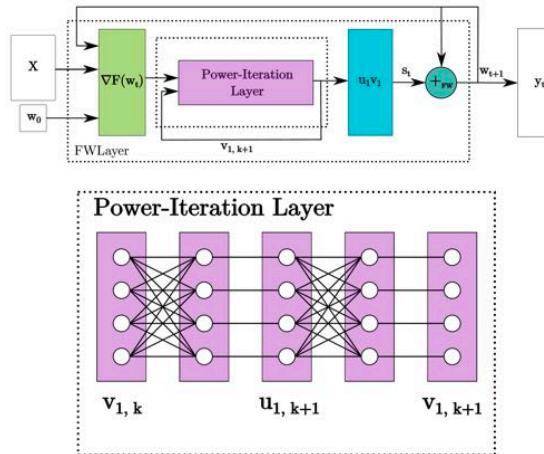
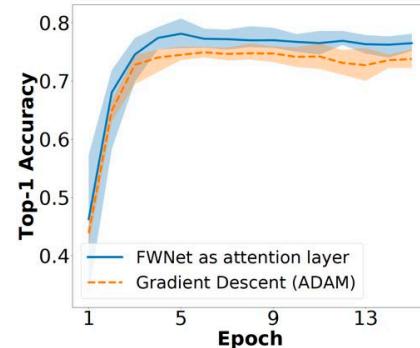
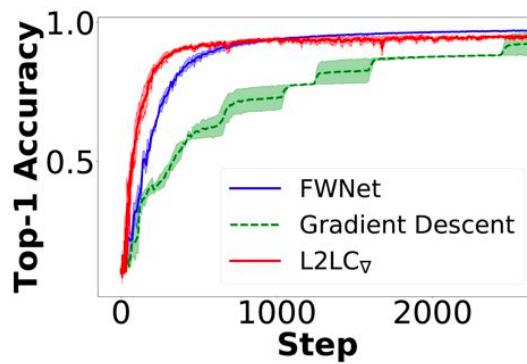


Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

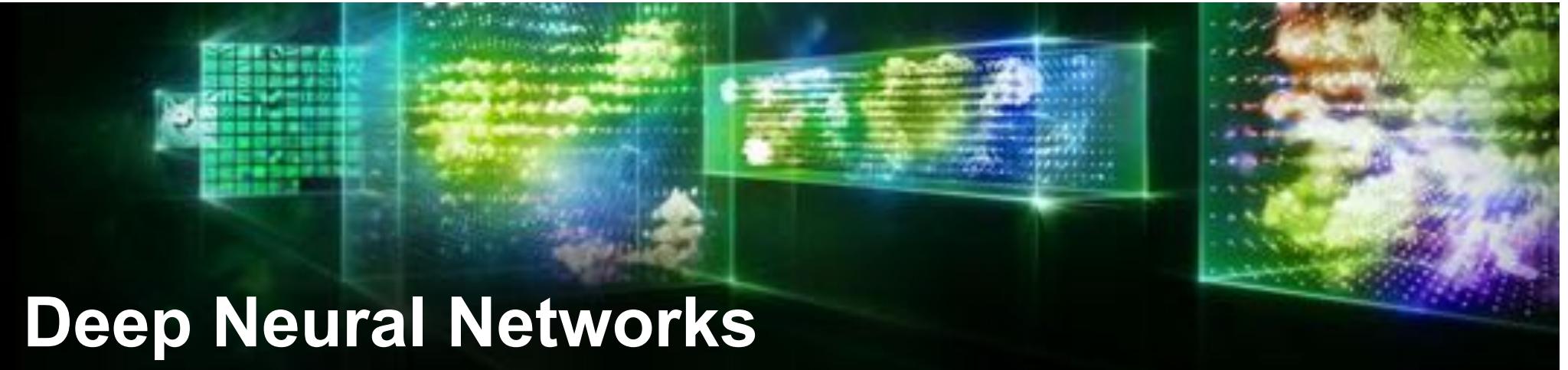
[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]



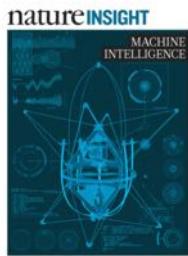
They “invent” constrained optimizers

[Schramowski, Bauckhage, Kersting arXiv:1803.04300, 2018]

DePhenSe



Deep Neural Networks



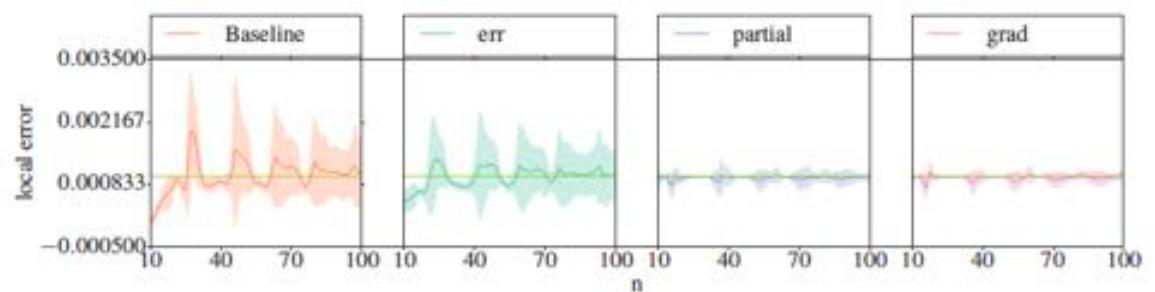
Potentially much more powerful than shallow architectures, represent computations

[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]

Meta-Learning Runge-Kutta

interval	steps		error	
	Baseline	Optimizer	Baseline	Optimizer
1	47.15	12.08	0.026415	0.085082
3	157.58	53.42	0.023223	0.081219
5	268.03	96.48	0.025230	0.091109
7	378.42	139.69	0.026177	0.094129
10	544.05	204.57	0.024858	0.094562

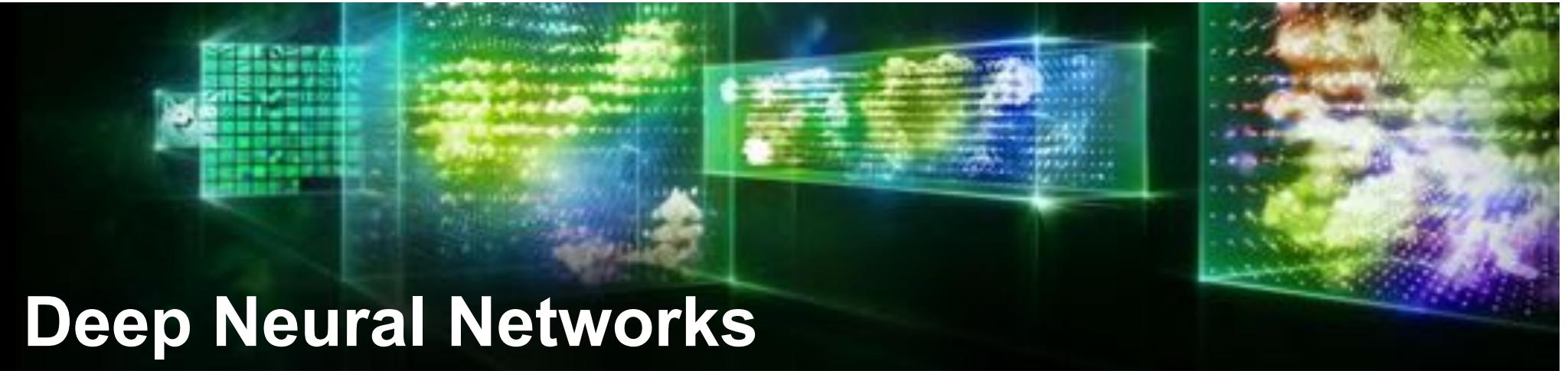
van der Pole problems



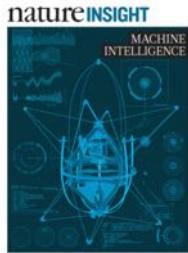
They can learn to integrate

[Jentzsch, Schramowski, Kersting to be submitted 2019]

DePhenSe

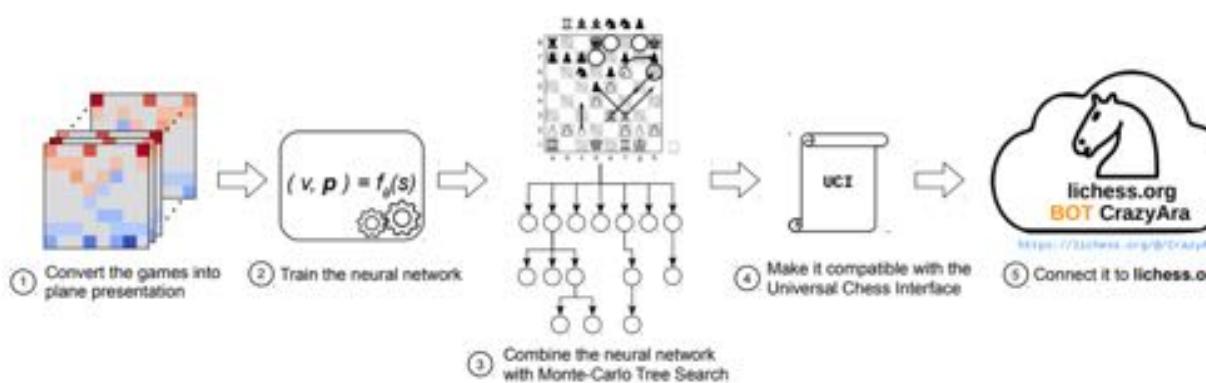


Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]



They can beat the world champion in CrazyHouse

[Czech, Willig, Beyer, Kersting, Fürnkranz arXiv:1908.06660 2019.]

AI has many isolated talents



Fundamental Differences

Current Biology

Search All Content Advanced Search Current Biology All Journals

Explore Online Now Current Issue Archive Journal Information - For Authors -

< Previous Article Volume 27, Issue 18, p2827–2832.e3, 25 September 2017 Next Article >

REPORT

Humans, but Not Deep Neural Networks, Often Miss Giant Targets in Scenes

Miguel P. Eckstein¹, Kathryn Koehler, Lauren E. Walbourne, Emre Akbas

Switch to Standard View

PDF (1 MB) Download Images (21) Email Article Add to My Reading List



as of today

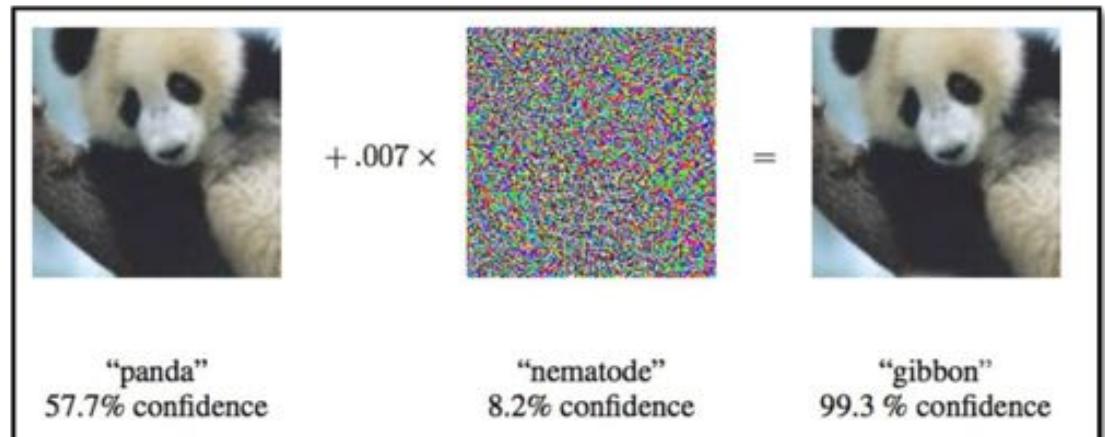
Fundamental Differences



Sharif et al., 2015



Brown et al. (2017)



Google, 2015

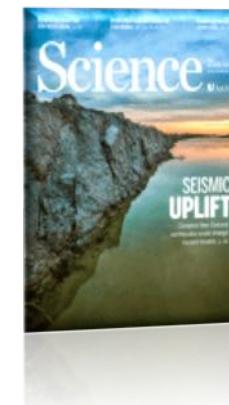
REPORTS | PSYCHOLOGY

Semantics derived automatically from language corpora contain human-like biases

Aylin Caliskan^{1,*}, Joanna J. Bryson^{1,2,*}, Arvind Narayanan^{1,*}

* See all authors and affiliations

Science 14 Apr 2017;
Vol. 356, Issue 6334, pp. 183-186
DOI: 10.1126/science.aal4230



The Quest for a „good“ AI

How could an AI programmed by humans, with no more moral expertise than us, recognize (at least some of) our own civilization's ethics as moral progress as opposed to mere moral instability?



„The Ethics of Artificial Intelligence“ Cambridge Handbook of Artificial Intelligence, 2011



Nick Bostrom



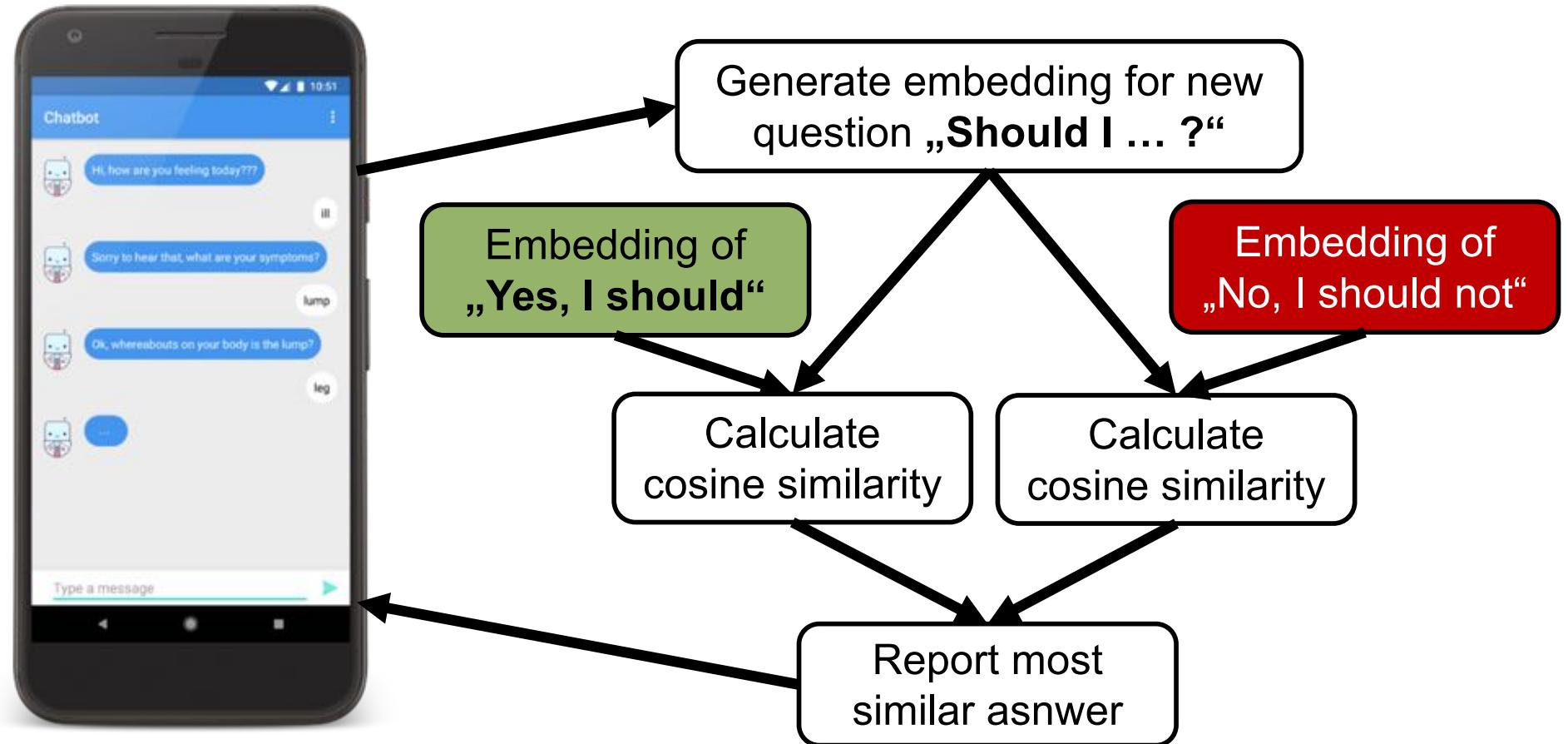
Eliezer Yudkowsky



The Moral Choice Machine

Not all stereotypes are bad

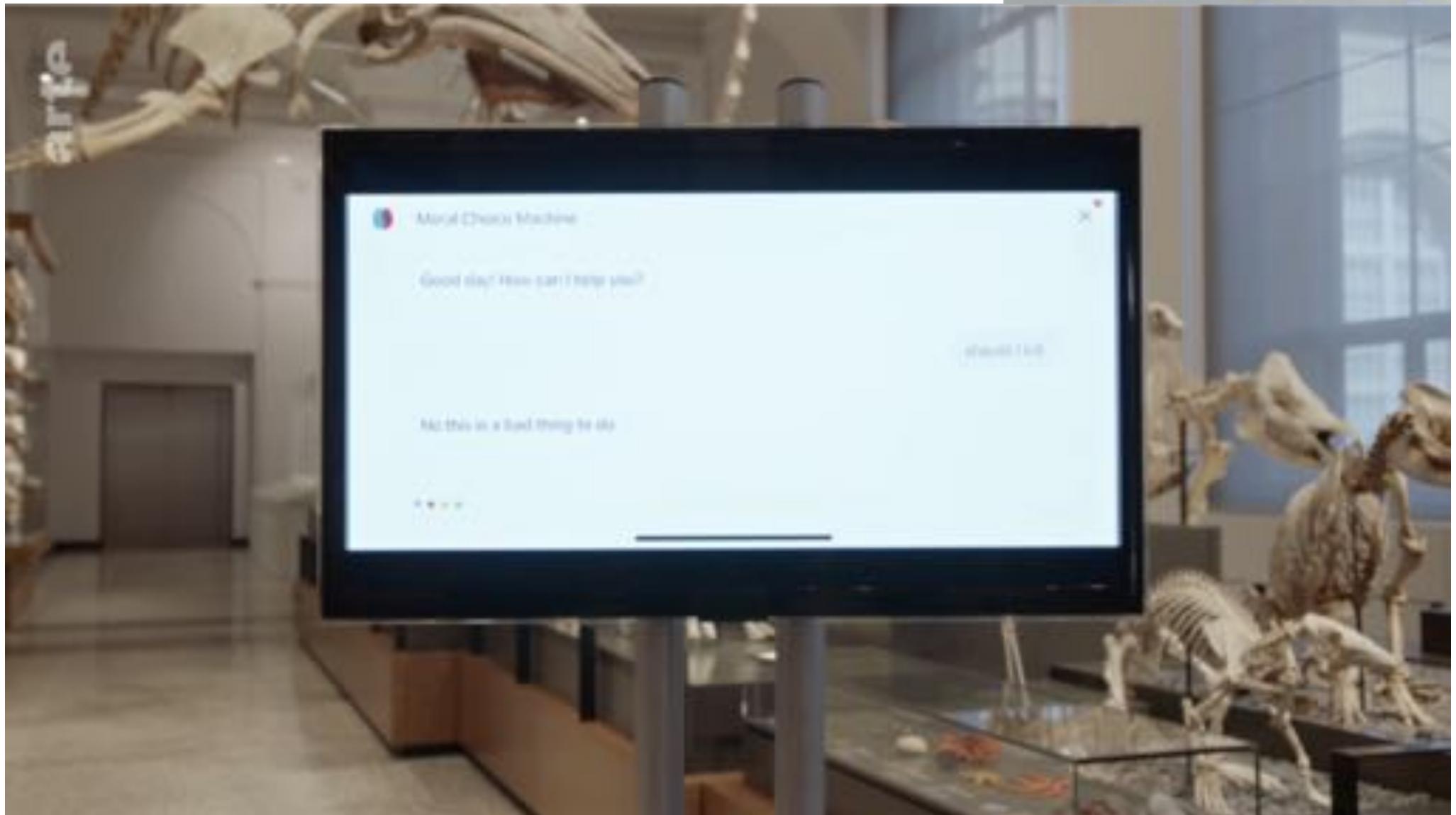
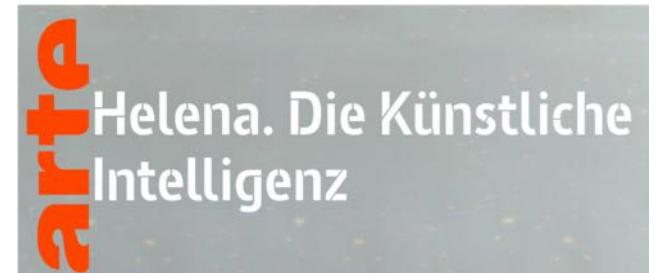
[Jentzsch, Schramowski, Rothkopf,
Kersting AIES 2019]



The Moral Choice Machine

Not all stereotypes are bad

<https://www.arte.tv/de/videos/RC-017847/helena-die-kuenstliche-intelligenz/>



Can we trust deep neural networks?

The image displays three separate research articles from the journal *Nature Communications*, each highlighting a different aspect of deep learning model interpretation and reliability.

Top Article: *Unmasking Clever Hans predictors and assessing what machines really learn* (Published: 11 March 2019)

Authors: Sebastian Lapuschkin, Stephan Wäldchen, Alexander Binder, Grégoire Montavon, Wojciech Samek, & Klaus-Robert Müller

Abstract: This article discusses the lack of transparency in machine learning models, specifically using a red car as an example that was misclassified as a horse. It shows heatmaps of the input images and their corresponding internal representations to reveal the specific features the model focuses on.

Middle Article: *Pinball - relevance during game play*

Abstract: This study examines the relevance of different elements in the Breakout game during training. It provides heatmaps of the game board and line plots showing the relative relevance of the ball, paddle, and tunnel over time.

Bottom Article: *Breakout - relevance during training*

Abstract: This research explores the relevance of game elements in the Breakout game during training. It includes line graphs of relative relevance versus training epochs and heatmaps of the game board.

DNNs often have no probabilistic semantics. They are not calibrated joint distributions.

$$P(Y|X) \neq P(Y,X)$$

MNIST

3	4	2	1	9	5	6	2	1	8
8	9	1	2	5	0	0	6	6	4
6	7	0	1	6	3	6	3	7	0
3	7	7	9	4	6	6	1	8	2
2	9	3	4	3	9	8	7	2	5
1	5	9	8	3	6	5	7	2	3
9	3	1	9	1	5	8	0	8	4
5	6	2	6	8	5	8	8	9	9
3	7	7	0	9	4	8	5	4	3
7	9	6	4	7	0	6	9	2	3

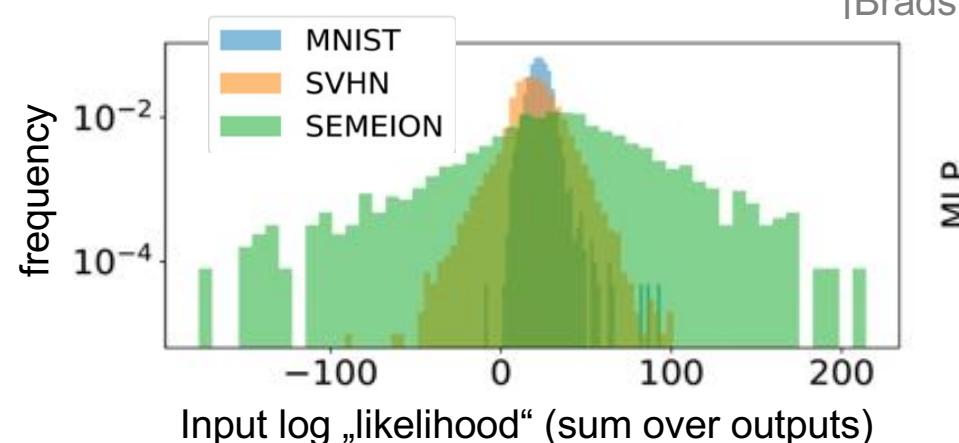
SVHN



SEMEION



Train & Evaluate



Transfer Testing

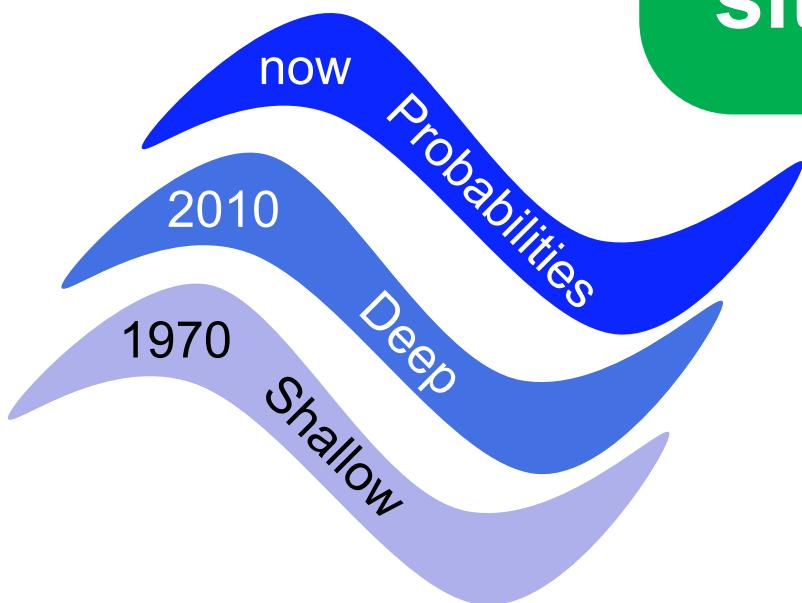
[Bradshaw et al. arXiv:1707.02476 2017]

Many DNNs cannot distinguish the datasets

[Peharz, Vergari, Molina, Stelzner, Trapp, Kersting, Ghahramani UAI 2019]

The third wave of differentiable programming

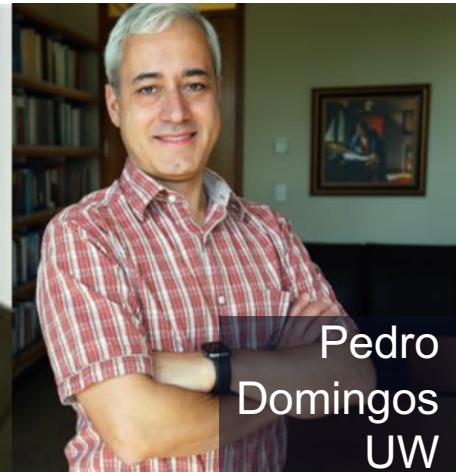
Getting deep systems that know when they do not know and, hence, recognise new situations and adapt to them



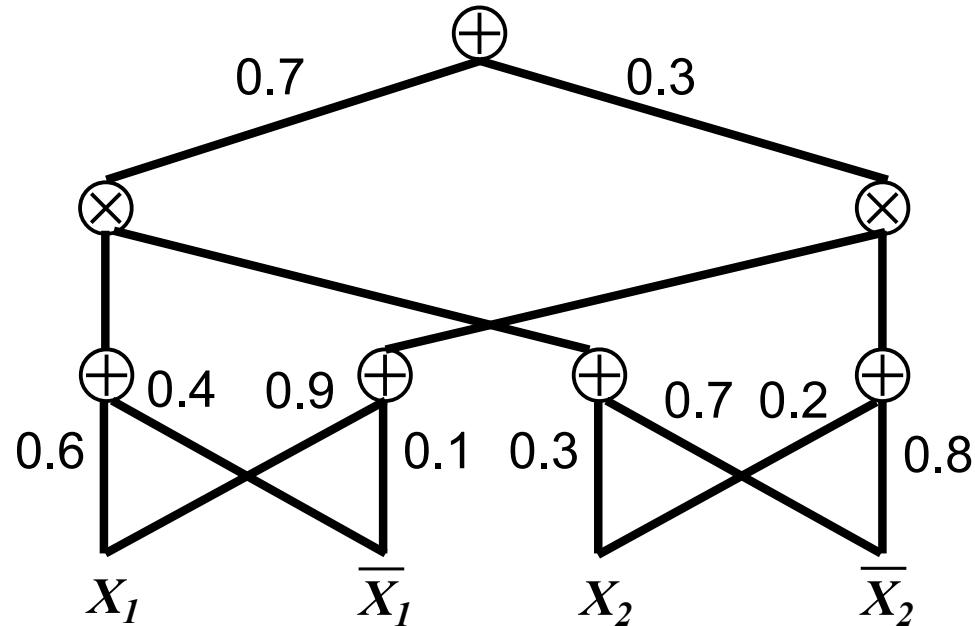
This results in Sum-Product Networks, a deep probabilistic learning framework



Adnan
Darwiche
UCLA



Pedro
Domingos
UW



Computational graph
(kind of TensorFlow
graphs) that encodes
how to compute
probabilities

Inference is linear in size of network

[Poon, Domingos UAI'11; Molina, Natarajan, Kersting AAAI'17; Vergari, Peharz, Di Mauro, Molina, Kersting, Esposito AAAI '18;
Molina, Vergari, Di Mauro, Esposito, Natarajan, Kersting AAAI '18]

FL⁺ SPFlow: An Easy and Extensible Library ⊗W for Sum-Product Networks



UNIVERSITÀ
DEGLI STUDI DI BARI
ALDO MORO



Max Planck Institute for
Intelligent Systems



UNIVERSITY OF
CAMBRIDGE



VECTOR
INSTITUTE

[Molina, Vergari, Stelzner, Peharz,
Subramani, Poupart, Di Mauro,
Kersting 2019]



Federal Ministry
of Education
and Research

195 commits

2 branches

0 releases

All 6 contrib.....

Branch: master ▾

New pull request

Create new file

Upload files

Find file

Clone or download ▾

<https://github.com/SPFlow/SPFlow>

```
from spn.structure.leaves.parametric import Categorical
from spn.structure.Base import Sum, Product
from spn.structure.base import assign_ids, rebuild_scopes_bottom_up

p0 = Product(children=[Categorical(p=[0.3, 0.7], scope=1), Categorical(p=[0.4, 0.6], scope=2)])
p1 = Product(children=[Categorical(p=[0.5, 0.5], scope=1), Categorical(p=[0.6, 0.4], scope=2)])
s1 = Sum(weights=[0.3, 0.7], children=[p0, p1])
p2 = Product(children=[Categorical(p=[0.2, 0.8], scope=0), s1])
p3 = Product(children=[Categorical(p=[0.2, 0.8], scope=0), Categorical(p=[0.3, 0.7], scope=1)])
p4 = Product(children=[p3, Categorical(p=[0.4, 0.6], scope=2)])
spn = Sum(weights=[0.4, 0.6], children=[p2, p4])

assign_ids(spn)
rebuild_scopes_bottom_up(spn)

return spn
```

**Domain Specific Language,
Inference, EM, and Model
Selection as well as
Compilation of SPNs into TF
and PyTorch and also into flat,
library-free code even suitable
for running on devices:
C/C++, GPU, FPGA**

SPFlow, an open-source Python library providing a simple interface to inference, learning and manipulation routines for deep and tractable probabilistic models called Sum-Product Networks (SPNs). The library allows one to quickly create SPNs both from data and through a domain specific language (DSL). It efficiently implements several probabilistic inference engines like message-passing, conditionals and incremental most probable explanations (IMEs) along with common

Random sum-product networks

[Peharz, Vergari, Molina, Stelzner, Trapp, Kersting, Ghahramani UAI 2019]



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Intelligent Systems

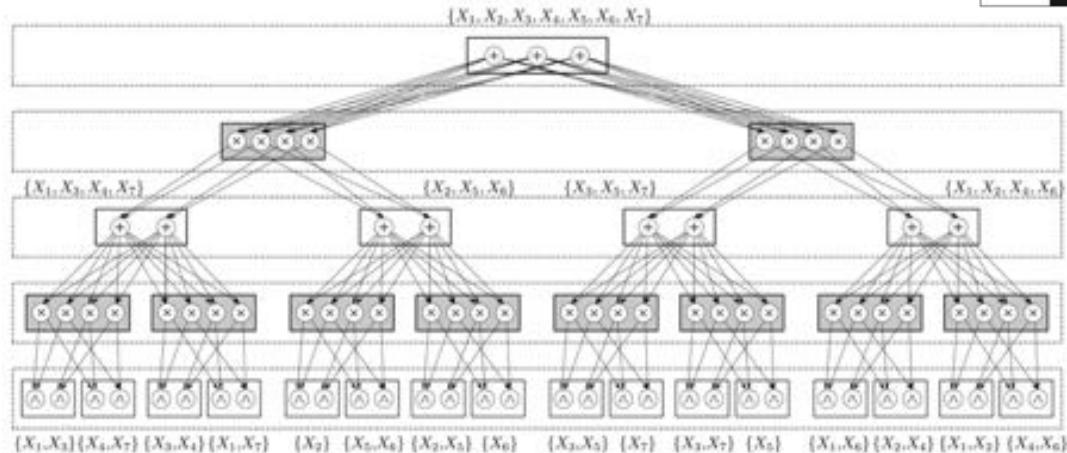


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DARMSTADT

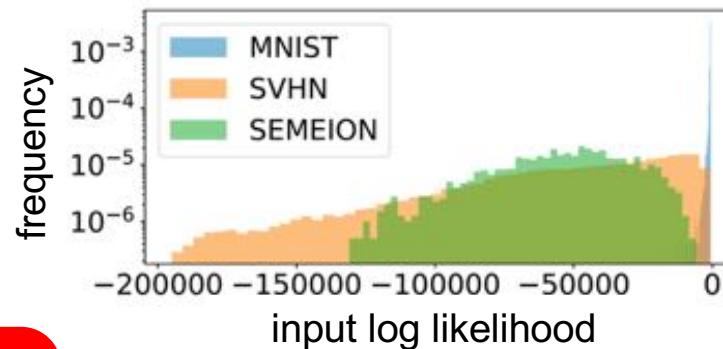


Conference on Uncertainty in Artificial Intelligence
Tel Aviv, Israel
July 22 - 25, 2019

uai2019



	RAT-SPN	MLP	vMLP
Accuracy	MNIST 98.19 (8.5M)	98.32 (2.64M)	98.09 (5.28M)
	F-MNIST 89.52 (0.65M)	90.81 (9.28M)	89.81 (1.07M)
	20-NG 47.8 (0.37M)	49.05 (0.31M)	48.81 (0.16M)
Cross-Entropy	MNIST 0.0852 (17M)	0.0874 (0.82M)	0.0974 (0.22M)
	F-MNIST 0.3525 (0.65M)	0.2965 (0.82M)	0.325 (0.29M)
	20-NG 1.6954 (1.63M)	1.6180 (0.22M)	1.6263 (0.22M)



SPNs can have similar predictive performances as (simple) DNNs

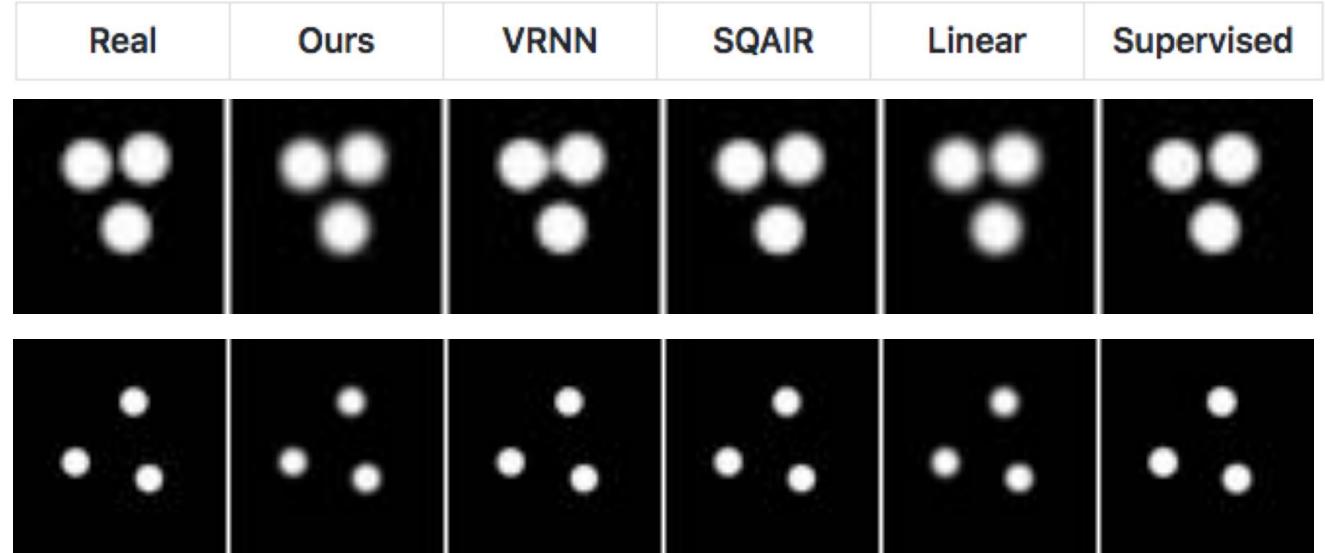
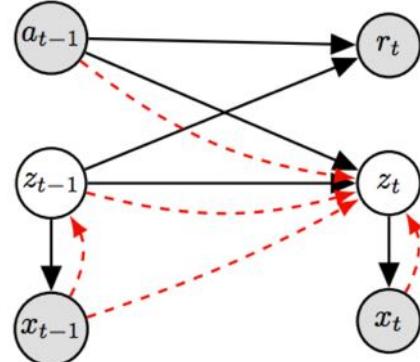
SPNs can distinguish the datasets

SPNs know when they do not know by design

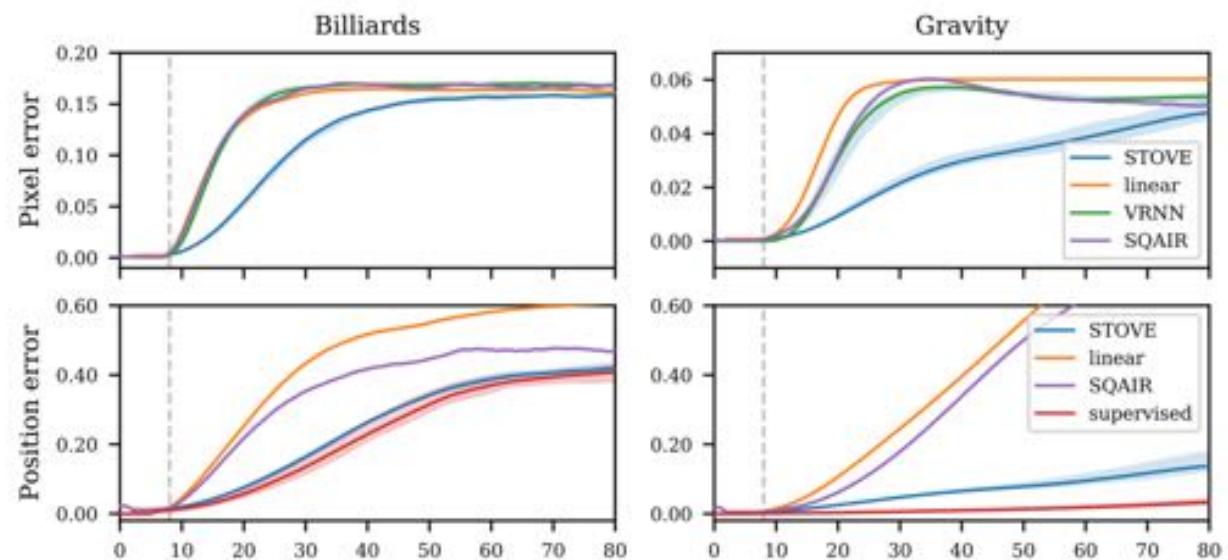


Unsupervised physics learning

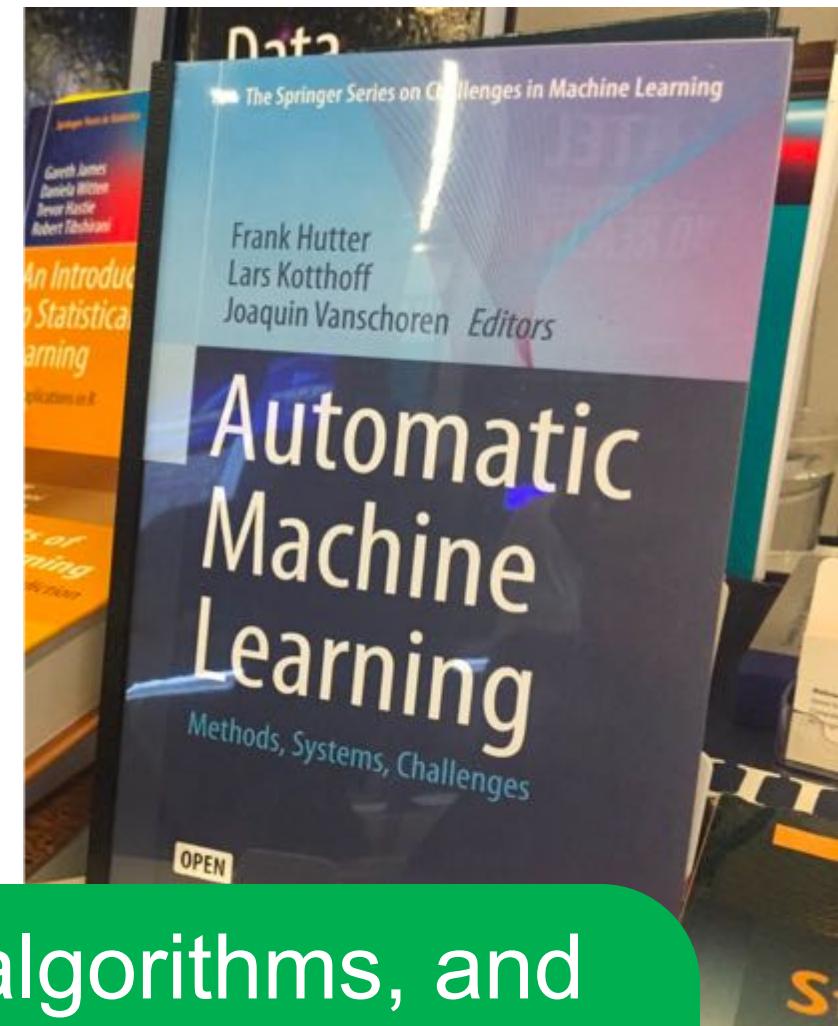
[Kossa, Stelzner, Hussing, Voelcker, Kersting arXiv:1910.02425 2019]



putting
structure and
tractable
inference into
deep models



However, there are not enough data scientists, statisticians, machine learning and AI experts



Provide the foundations, algorithms, and tools to develop systems that ease and support building ML/AI models as much as possible and in turn help reproducing and hopefully even justifying our results

Mind the **data science** loop

Question

**Data collection
and preparation**

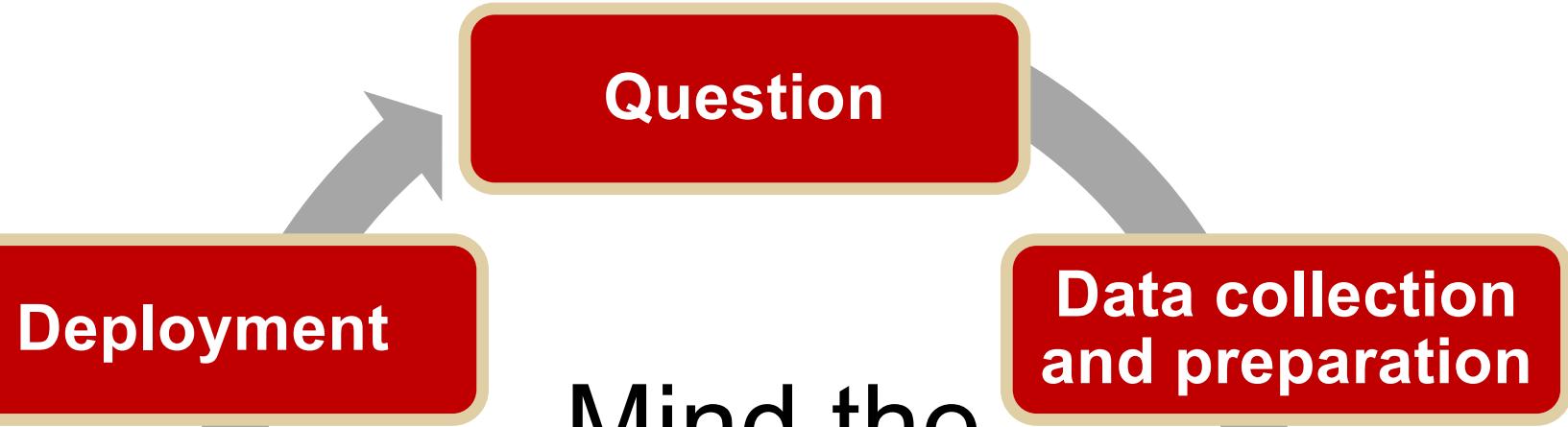
Continuous? Discrete?
Categorial? ...

Multinomial? Gaussian?
Poisson? ...

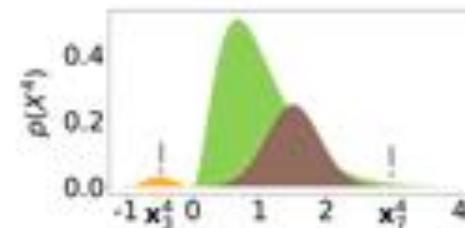
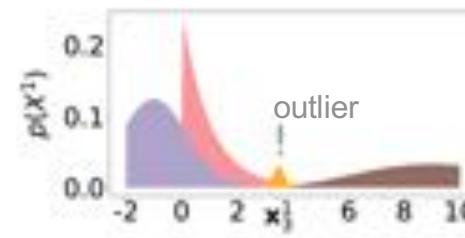
ML

How to report results?
What is interesting?

Answer found?



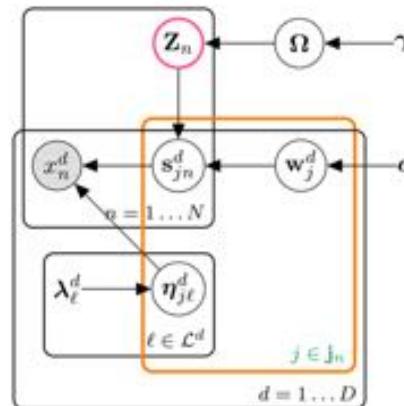
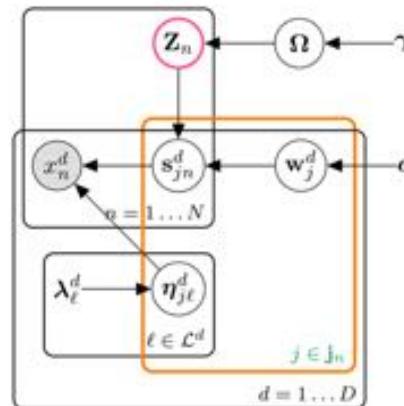
The Automatic Data Scientist



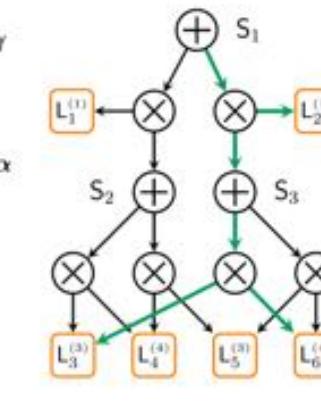
Exponential (Exp): 25.00%
Gaussian (\mathcal{N}): 37.50%
Gamma (Γ): 25.00%
Gaussian (\mathcal{N}): 12.50%

Gamma (Γ): 62.50%
Gaussian (\mathcal{N}): 12.50%
Gamma (Γ): 25.00%

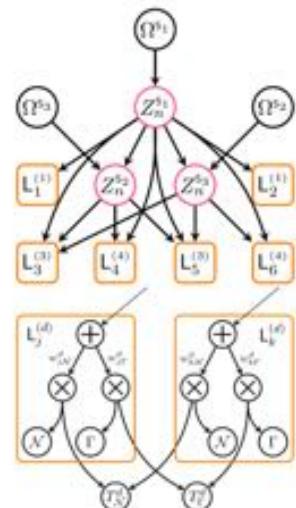
We can even automatically discovers the statistical types and parametric forms of the variables



Bayesian Type Discovery



Mixed Sum-Product Network



Automatic Statistician

That is, the machine understands the data with few expert input ...

The screenshot shows a user interface for exploring the Titanic dataset. At the top, there are three buttons: 'Toggle Introduction', 'Toggle explanations', and 'Toggle Code'. Below these, the title 'Exploring the Titanic dataset' is displayed in a large, bold font. A detailed description of the dataset follows:

This report describes the dataset Titanic and contains general statistical information and an analysis on the influence different features and subgroups of the data have on each other. The first part of the report contains general statistical information about the dataset and an analysis of the variables and probability distributions. The second part focusses on a subgroup analysis of the data. Different clusters identified by the network are analyzed and compared to give an insight into the structure of the data. Finally the influence different variables have on the predictive capabilities of the model are analyzed. The whole report is generated by fitting a sum product network to the data and extracting all information from this model.

[Voelcker, Molina, Neumann, Westermann, Kersting ADS 2019]

**ECMLPKDD WORKSHOP
ON AUTOMATING DATA
SCIENCE (ADS)**

Wurzburg, Germany, Friday 20 September 2019

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Report framework created @ TU Darmstadt

...and can compile data reports automatically

**Getting deep
systems that reason
and know what they
don't know**

**Responsible AI
systems that explain
their decisions and
co-evolve with the
humans**

**Open AI systems
that are easy to
realize and
understandable for
the domain experts**

„Tell the AI when it is
right for the wrong
reasons and it adapts
its behavior“



Figure 4: Explaining an image classification prediction made by Google's Inception network, highlighting positive pixels. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

Teso, Kersting AIES 2019

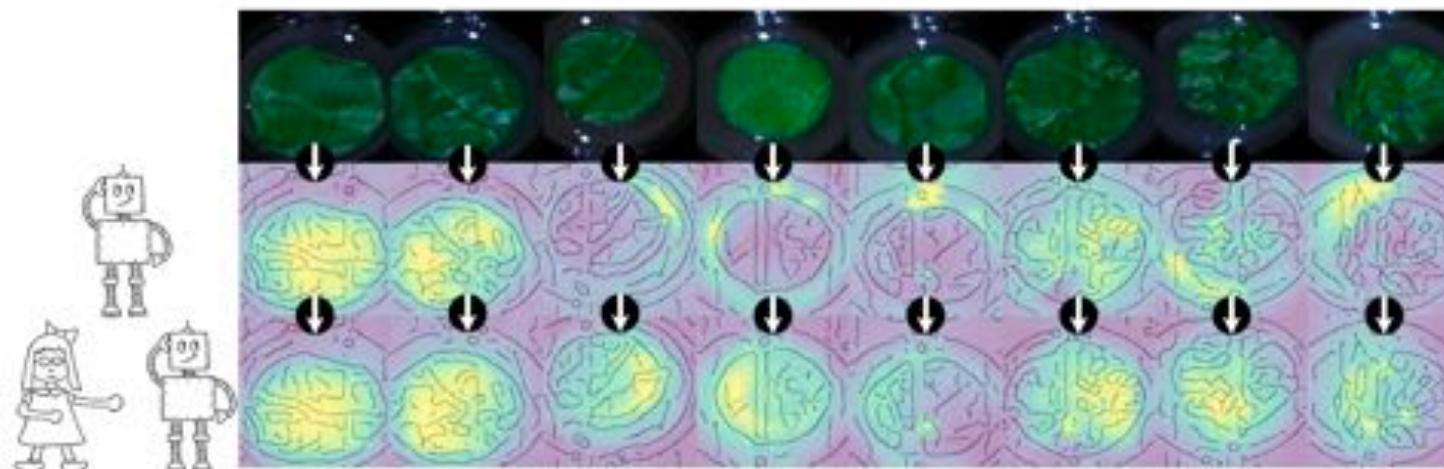
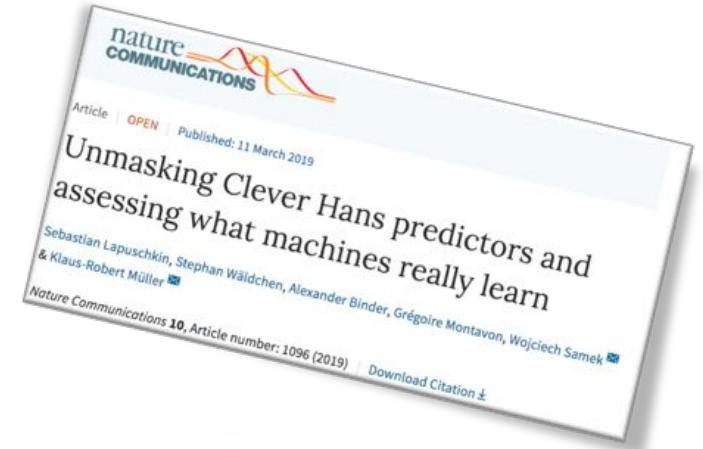


AAAI / ACM conference on
**ARTIFICIAL INTELLIGENCE,
ETHICS, AND SOCIETY**

Making Clever Hans Clever

Co-adaptive ML:

- human is changing computer behavior
- human adapts his or her data and goals in response to what is learned



[Teso, Kersting AIES 2019 and ongoing research]



AAAI / ACM conference on
ARTIFICIAL INTELLIGENCE,
ETHICS, AND SOCIETY

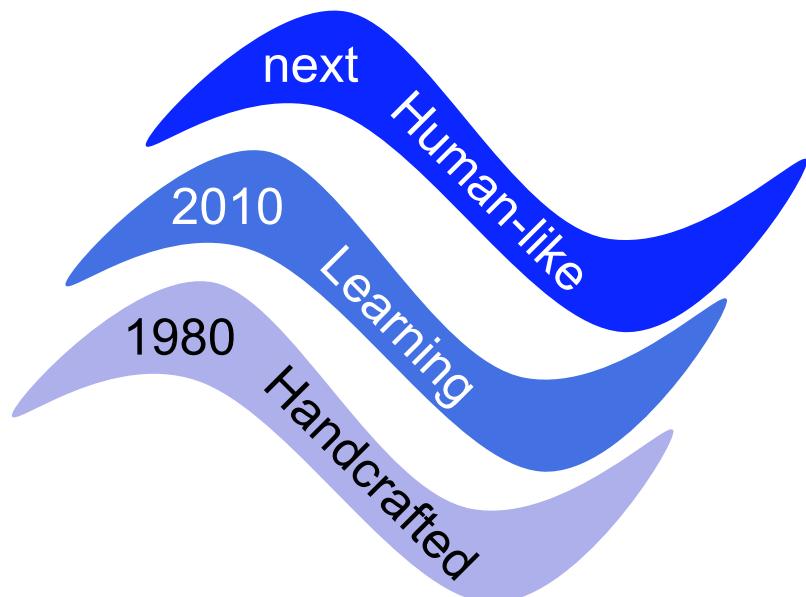
The future of AI

The third wave of AI



Data are now ubiquitous; there is great value from understanding this data, building models and making predictions

However, data is not everything



AI systems that can acquire human-like communication and reasoning capabilities, with the ability to recognise new situations and adapt to them.

Meeting this grand challenge is a team sport !



Thanks to all students of the Research Training Group "Artificial Intelligence - Facts, Chances, Risks" of the German National Academic Scholarship Foundation. Special thanks to **Maike Elisa Müller** and **Jannik Kossen** for taking the lead and to **Matthias Kleiner**, president of the Leibniz Association, for his preface



And this is AI!
Still a lot to be
done! It is a
team sport.

Illustration Nanina Föhr