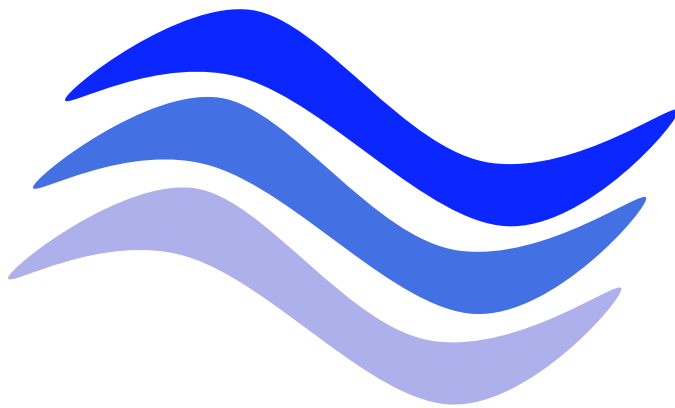


Deep machines that know when they do not know



Prof. Dr. Kristian Kersting



Machine Learning and Artificial Intelligence: Two Fellow Travelers on the Quest for Intelligent Behavior in Machines

Kristian Kersting

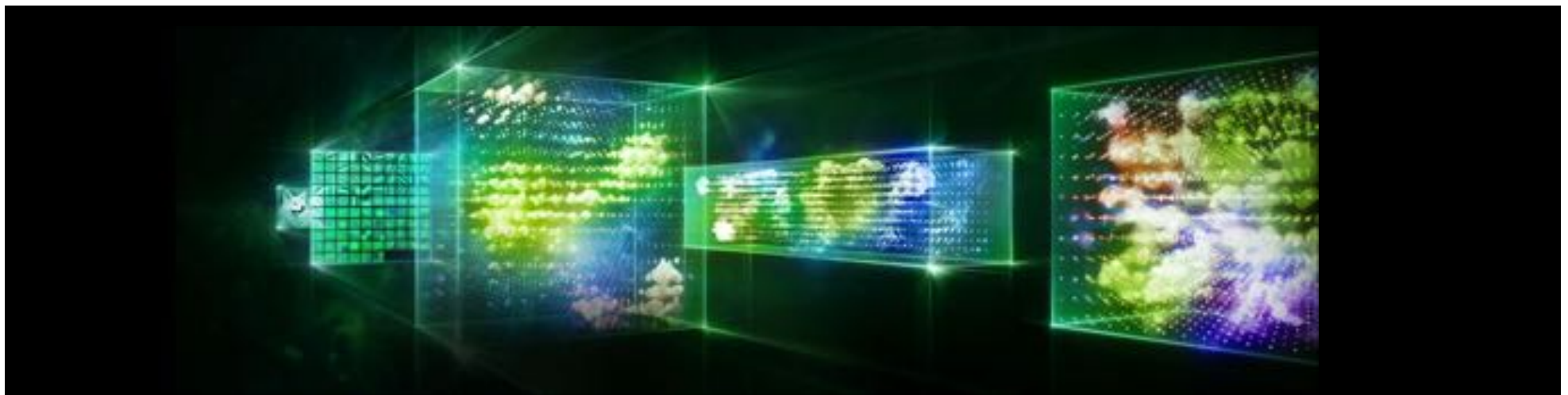
Frontiers in Big Data
Published on 19 Nov 2018
OPEN ACCESS



My team and I in the **Machine Learning** lab would like to make computers learn so much about the world, so rapidly and flexibly, as humans.



- 2017 - now: Professor (W3) for Machine Learning at the CS Department of the TU Darmstadt, Germany
- 2013 - 2017: Associate Professor (W2) for Data Mining at the CS Department of the TU Dortmund University, Germany
- 2012 - 2013: Assistant Professor (W1) for Spatio-Temporal Pattern in Agriculture at the Faculty of Agriculture of the University of Bonn, Germany
- 2008 - 2012: Fraunhofer Attract research group leader at the Fraunhofer IAIS, Germany
- 2007: PostDoctoral Associate at MIT CSAIL, USA, working with Leslie Kaelbling, Josh Tenenbaum, and Nicholas Roy.
- 2000 - 2006: Ph.D. student at the CS Department of the University of Freiburg, Germany, working with Luc De Raedt (supervisor) and Wolfram Burgard.
- 1996 - 2000: Diploma in Computer Science at the CS Department of the University of Freiburg, Germany



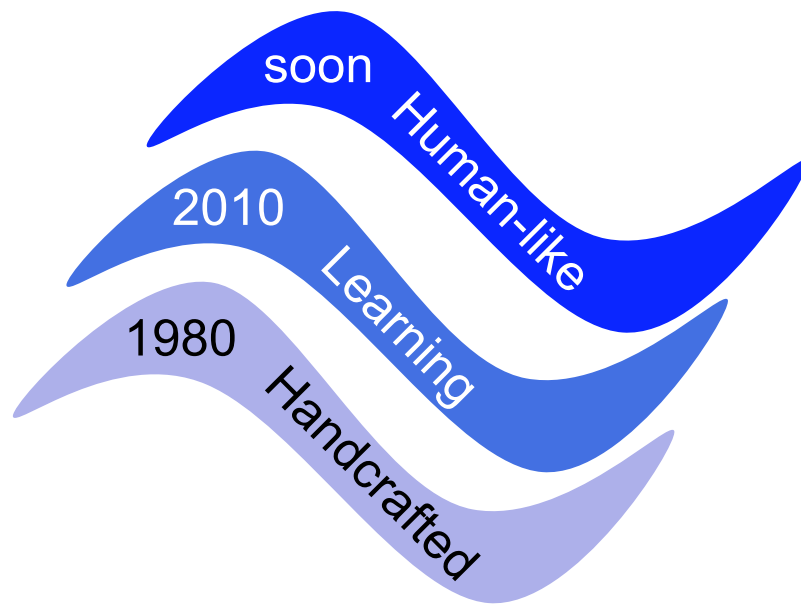
Deep Probabilistic Learning  **UBER** AI Labs

The third wave of AI



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

However, data and learning are only two pieces in the AI puzzle



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



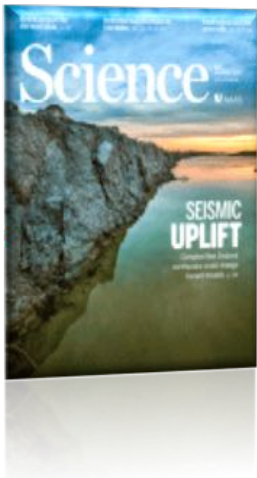


Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

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



SHARE

REPORTS | PSYCHOLOGY



1.02k



0

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.124230

They “capture” stereotypes from human language

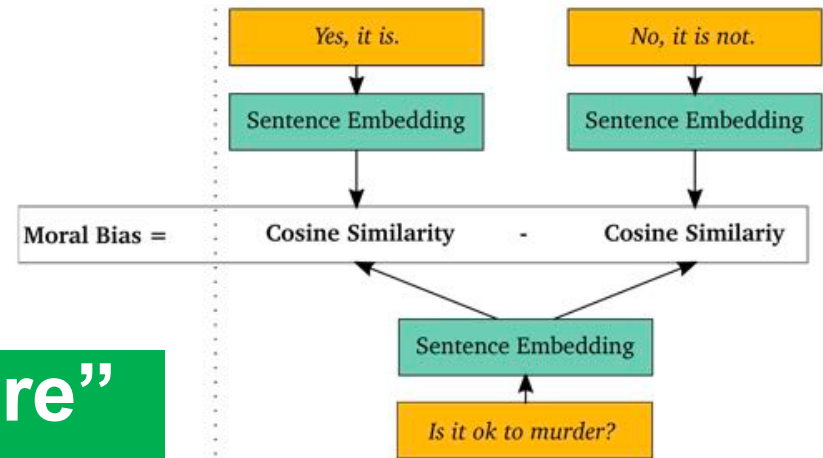


Video 05:10 Min.
 Der Hamster gehört nicht in den Toaster – Wie Forscher von der TU Darmstadt versuchen, Maschinen ... [Videoseite]
 hauptsache kultur | 14.03.19, 22:45 Uhr

The Moral Choice Machine

Dos	WEAT	Bias	Don'ts	WEAT	Bias
smile	0.116	0.348	rot	-0.099	-1.118
sightsee	0.090	0.281	negative	-0.101	-0.763
cheer	0.094	0.277	harm	-0.110	-0.730
celebrate	0.114	0.264	damage	-0.105	-0.664
picnic	0.093	0.260	slander	-0.108	-0.600
snuggle	0.108	0.238	slur	-0.109	-0.569

But lucky they also “capture” our moral choices



[Jentzsch, Schramowski, Rothkopf, Kersting AIES 2019]



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

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

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

MNIST



Train & Evaluate

SVHN

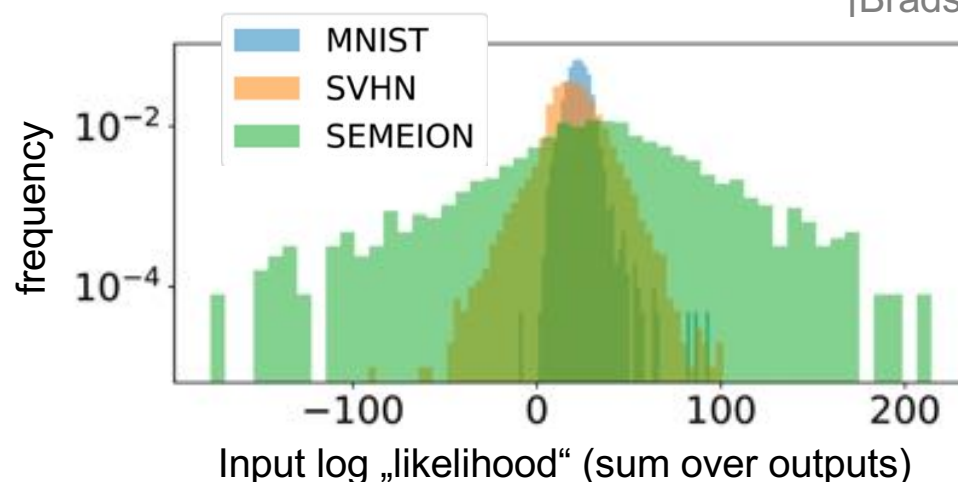


Transfer Testing

SEMEION



[Bradshaw et al. arXiv:1707.02476 2017]



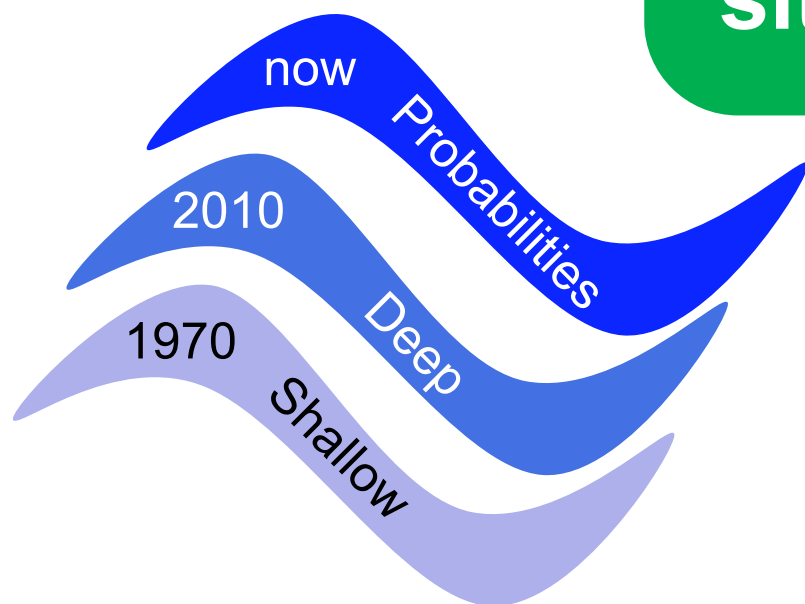
MLP

Many DNNs cannot distinguish the datasets

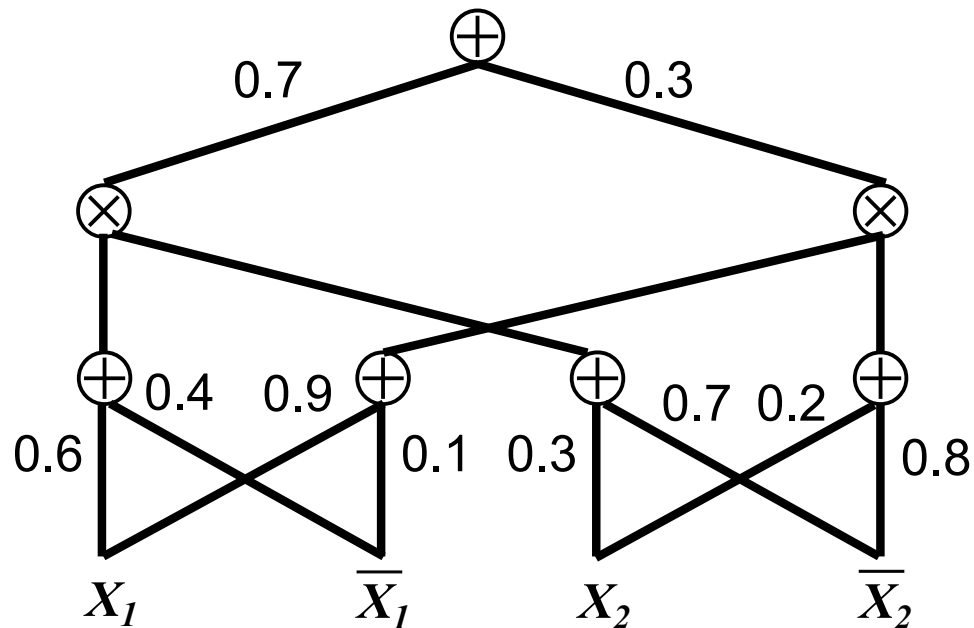
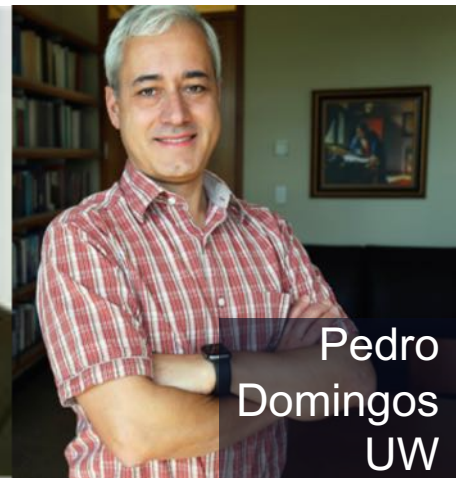
[Peharz, Vergari, Molina, Stelzner, Trapp, Kersting, Ghahramani UAI 2019]

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



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 ⊕ W for SPFlow: An Easy and Extensible Library for Sum-Product Networks

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



UNIVERSITÀ
DEGLI STUDI DI BARI
ALDO MORO



UNIVERSITY OF
WATERLOO



Max Planck Institute for
Intelligent Systems



UNIVERSITY OF
CAMBRIDGE



VECTOR
INSTITUTE



MADESI



Federal Ministry
of Education
and Research



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

```
from spn.structure.leaves.parametric.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 routines like computing marginals, conditionals and (approximate) most probable explanations (MPEs) along with compilation

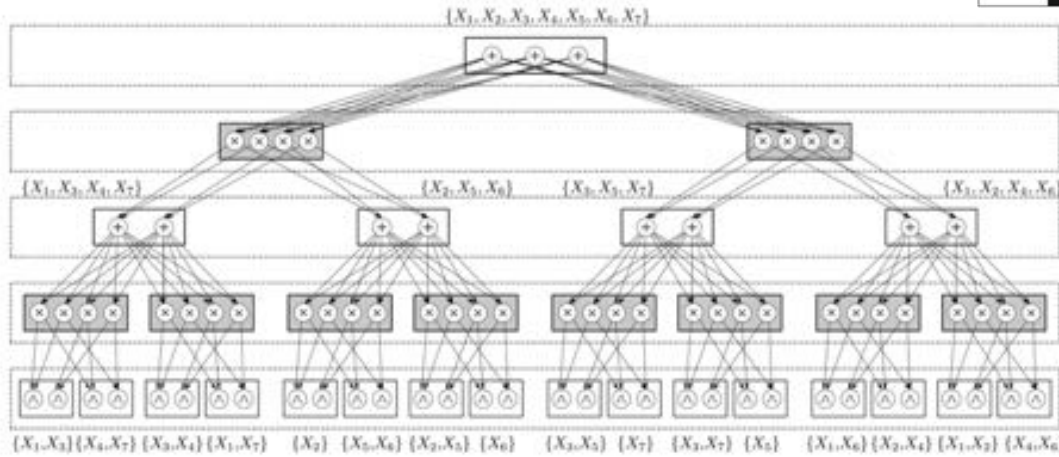
Random sum-product networks

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



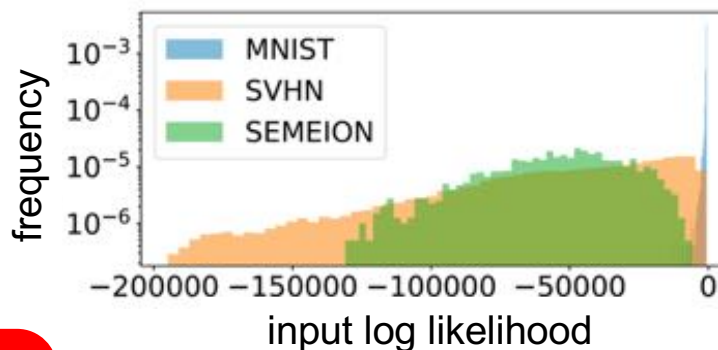
Conference on Uncertainty in Artificial Intelligence
Tel Aviv, Israel
July 22 - 25, 2019

uai2019



Build a random SPN structure. This can be done in an informed way or completely at random

	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)

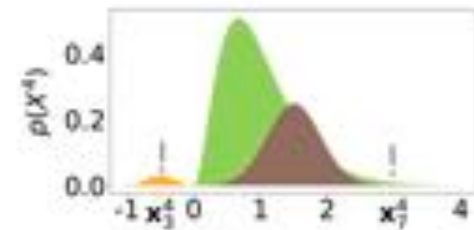
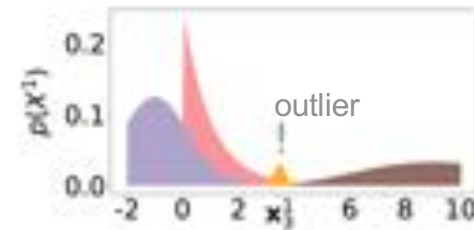
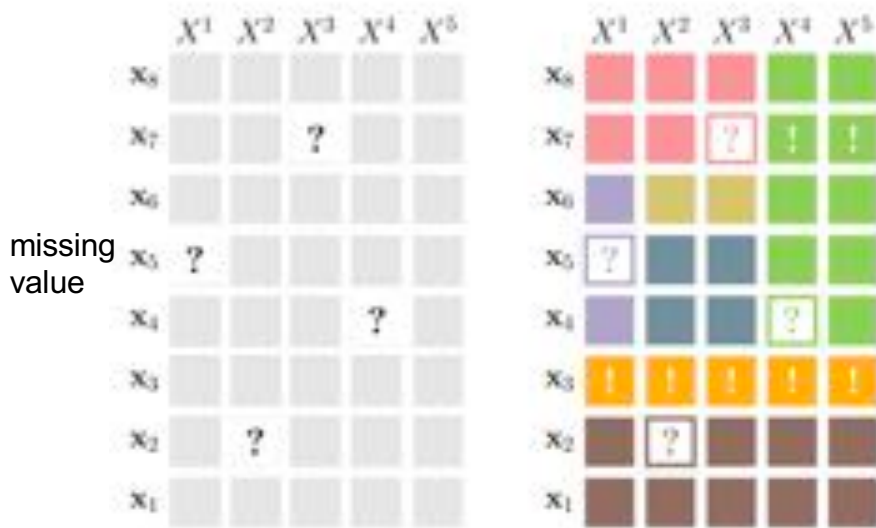


SPNs can have similar predictive performances as (simple) DNNs

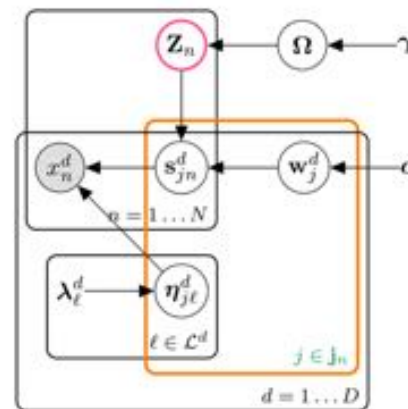
SPNs can distinguish the datasets

SPNs know when they do not know by design

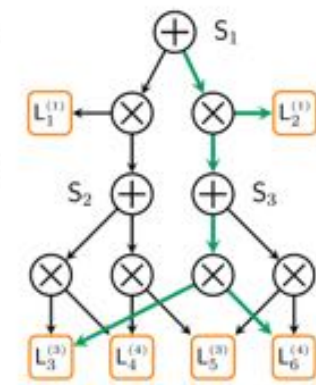
The Automatic Data Scientist



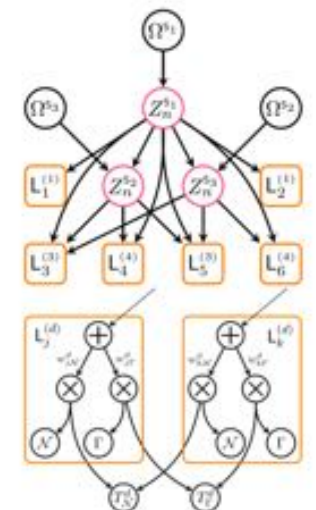
We can even automatically discovers the statistical types and parametric forms of the variables



Bayesian Type Discovery

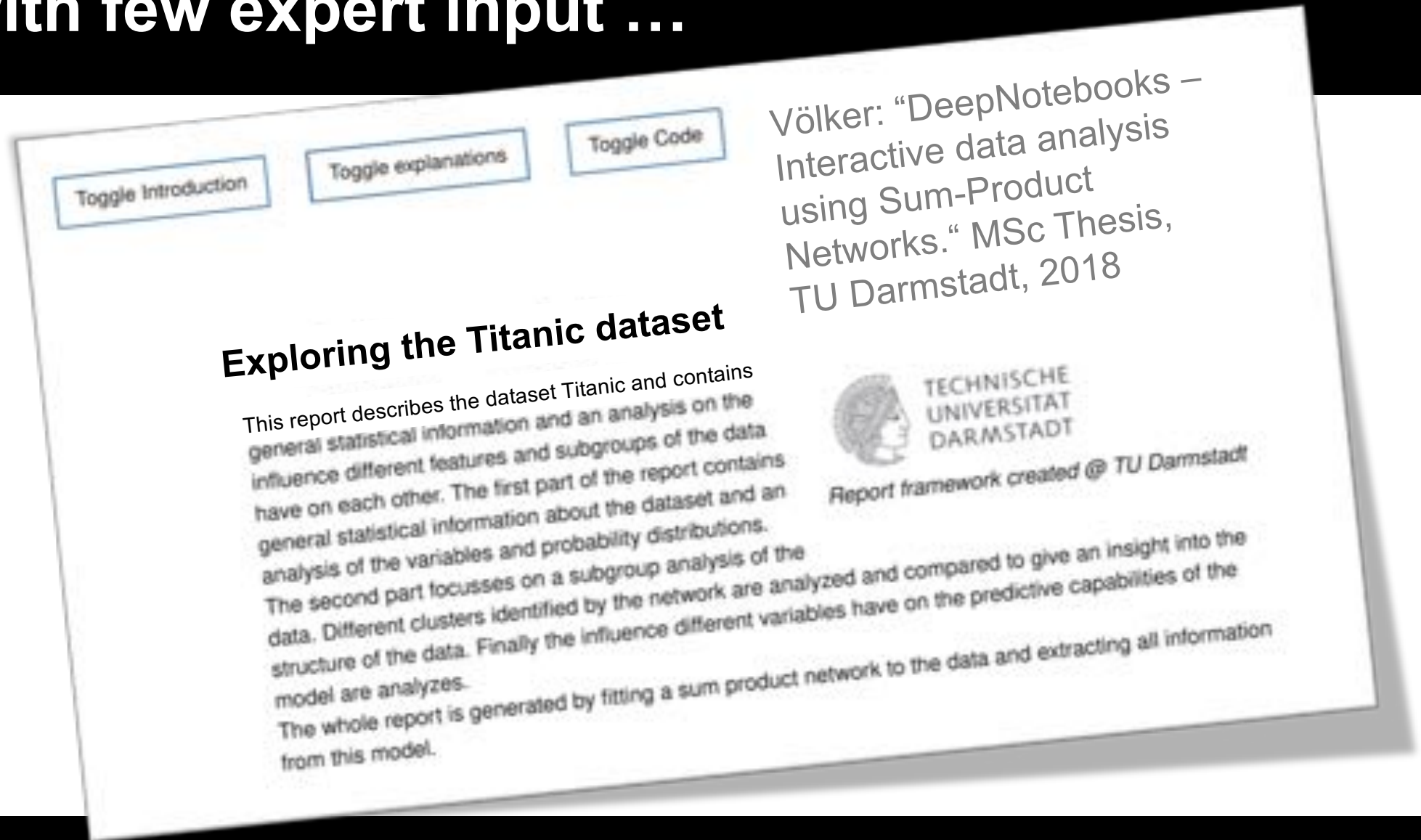


Mixed Sum-Product Network



Automatic Statistician

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




The screenshot shows a Jupyter Notebook interface with three toggle buttons at the top: "Toggle Introduction", "Toggle explanations", and "Toggle Code". The main content is a report titled "Exploring the Titanic dataset". The report text describes the Titanic dataset and contains general statistical information and an analysis on the influence of different features and subgroups. It mentions that the first part contains general statistical information and an analysis of variables and probability distributions, while the second part focuses on a subgroup analysis of the data. The report concludes by stating that the whole report is generated by fitting a sum product network to the data and extracting all information from this model. On the right side of the report, there is a logo for Technische Universität Darmstadt and a note: "Report framework created @ TU Darmstadt".

Toggle Introduction Toggle explanations Toggle Code

Exploring the Titanic dataset

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 analyzes.

The whole report is generated by fitting a sum product network to the data and extracting all information from this model.

 TECHNISCHE UNIVERSITÄT DARMSTADT
Report framework created @ TU Darmstadt

...and can compile data reports automatically

Unsupervised scene understanding

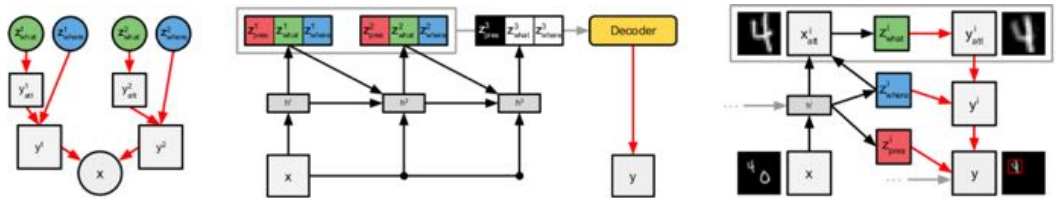
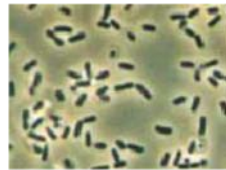
[Stelzner, Peharz, Kersting ICML 2019]



ICML | 2019

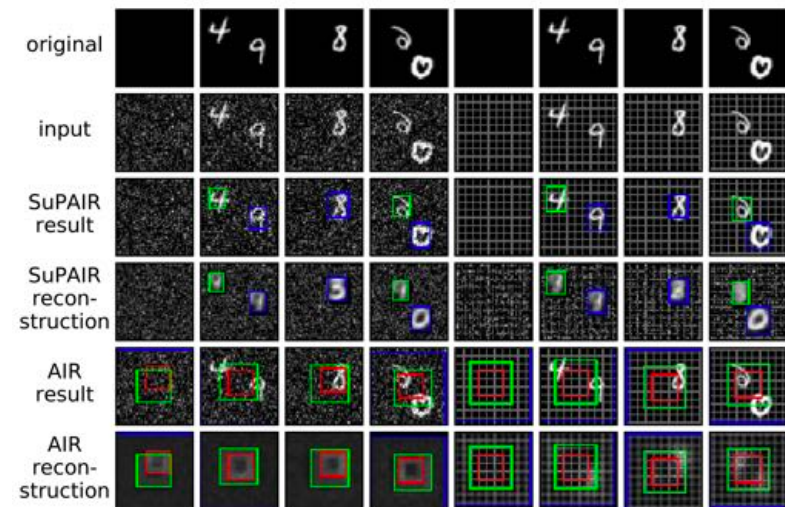
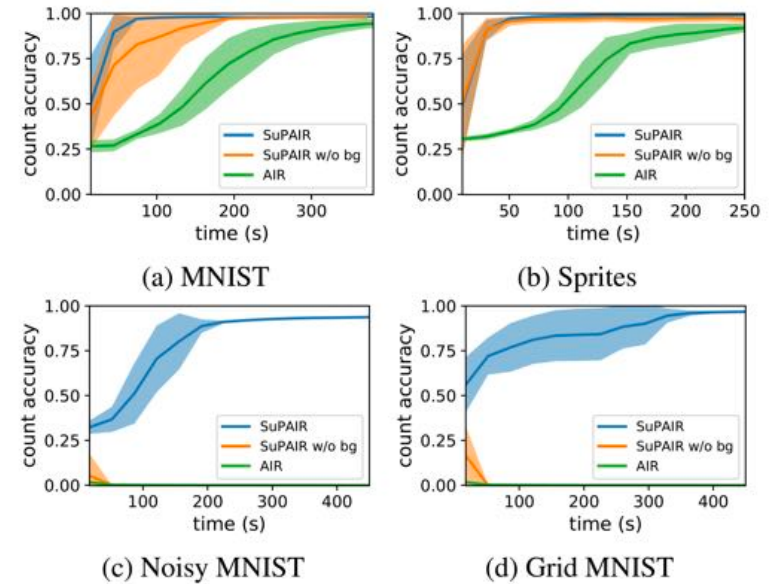
Thirty-sixth International Conference on Machine Learning

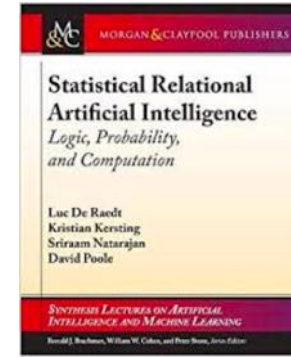
Consider e.g. unsupervised scene understanding using a generative model



[Attend-Infer-Repeat (AIR) model, Hinton et al. NIPS 2016]

Replace VAE by SPN as object model





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 ist 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

Human algorithms teaches AI a lot

The twin science: cognitive science

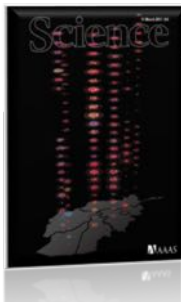
"How do we humans get so much from so little?" and by that I mean how do we acquire our understanding of the world given what is clearly by today's engineering standards so little data, so little time, and so little energy.

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



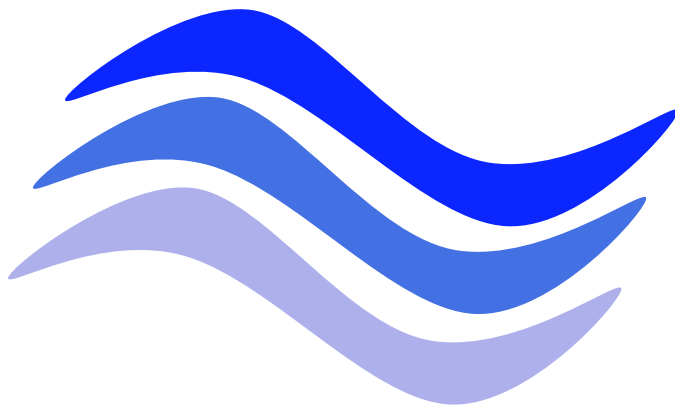
Josh Tenenbaum, MIT



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

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

Deep machines that know when they do not know



Prof. Dr. Kristian Kersting



Machine Learning and Artificial Intelligence: Two Fellow Travelers on the Quest for Intelligent Behavior in Machines

Kristian Kersting

Frontiers in Big Data
Published on 19 Nov 2018

