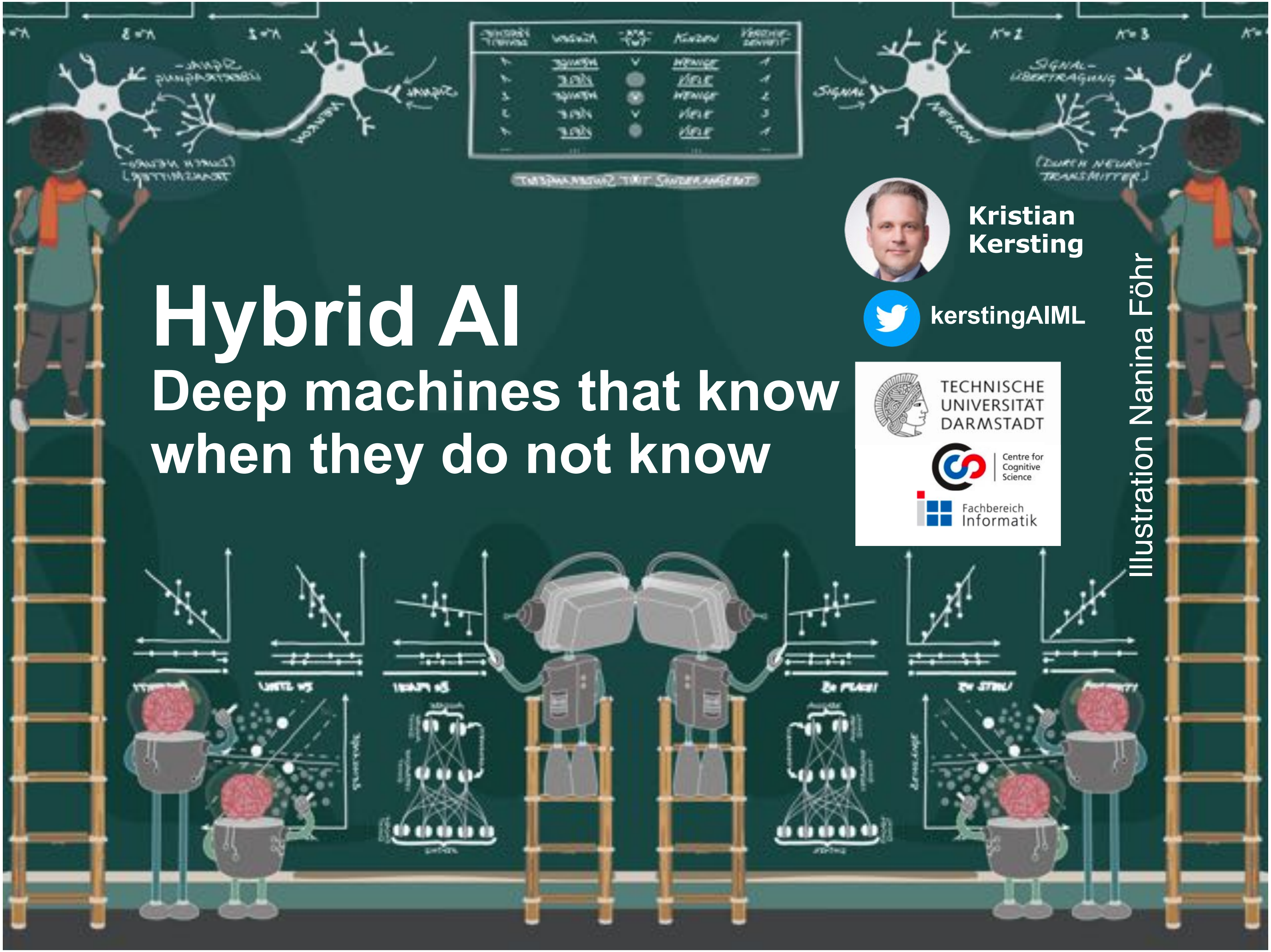


Kristian Kersting

kerstingAIML

TECHNISCHE UNIVERSITÄT DARMSTADT

Centre for Cognitive Science

Fachbereich Informatik

Hybrid AI

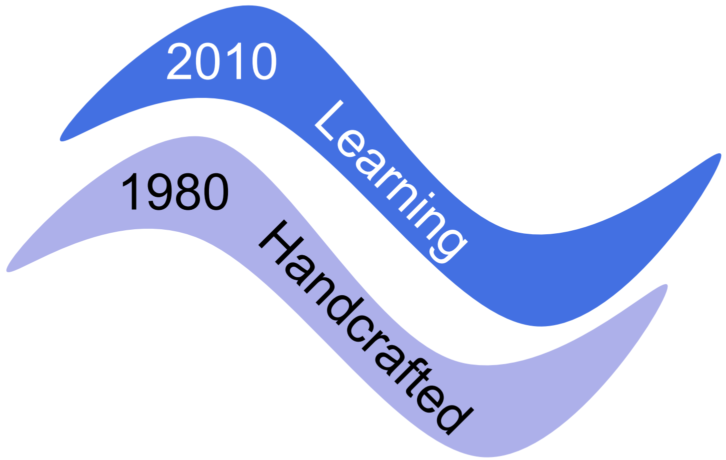
Deep machines that know when they do not know

Illustration Nanina Föhr

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



Third Wave of AI

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

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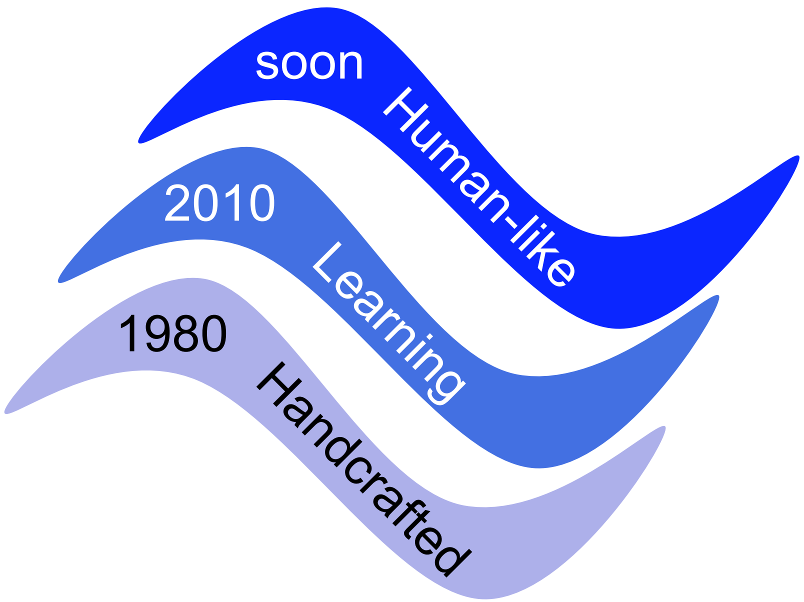
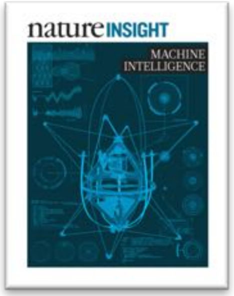


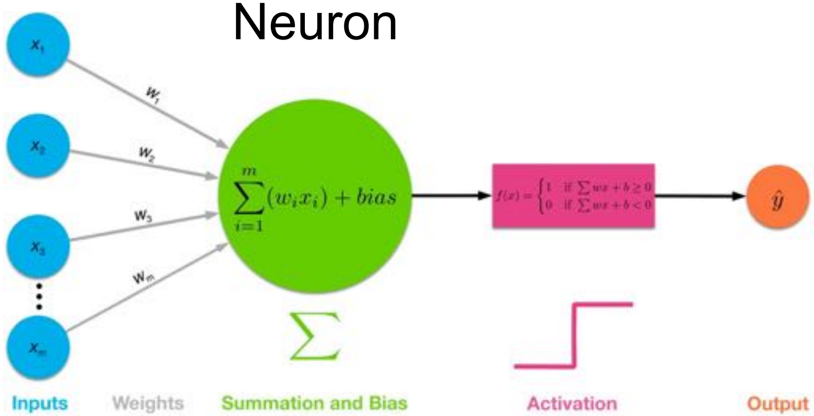
AI systems that can acquire human-like communication and reasoning capabilities, with the ability to recognise new situations and adapt to them.

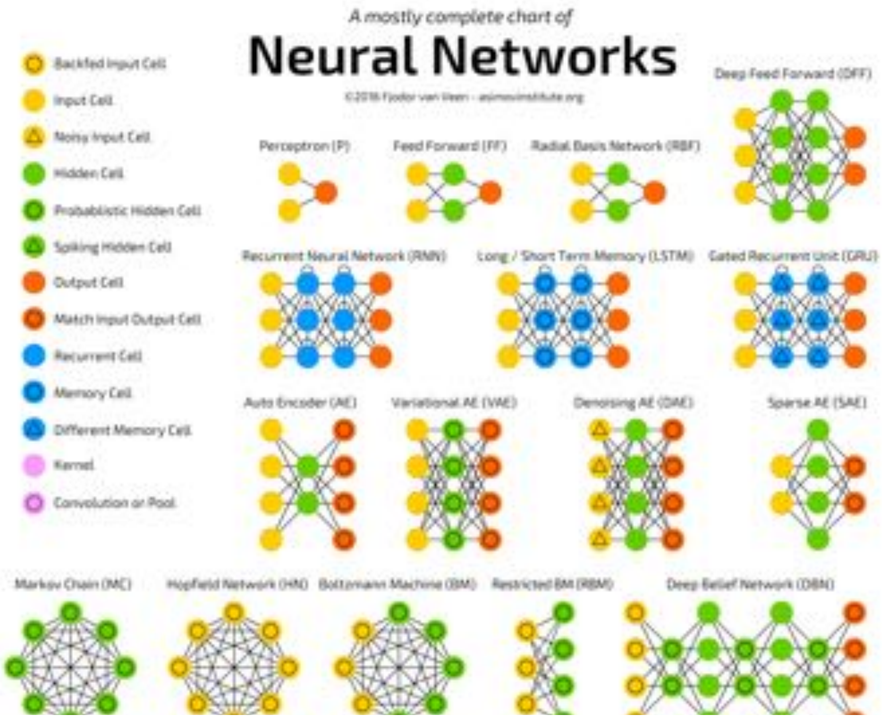
Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

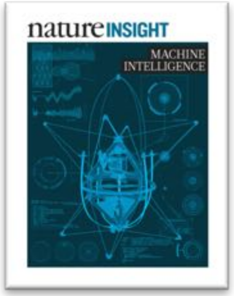
[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]





Differentiable Programming

Deep Neural Networks



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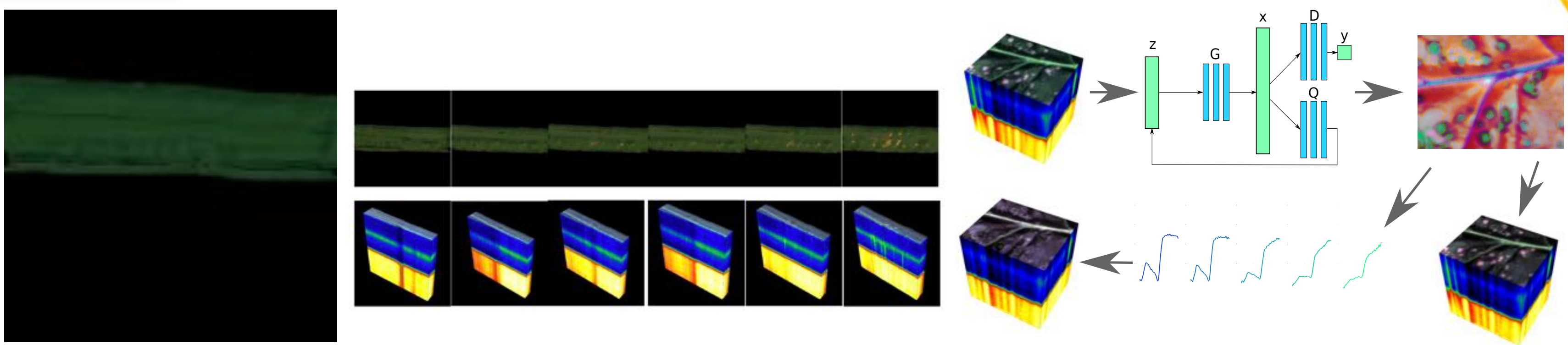
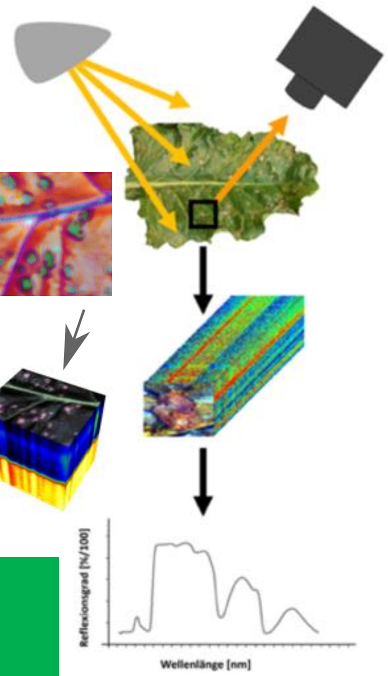




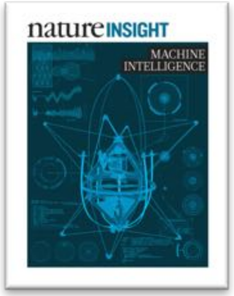
They “develop intuition” about complicated biological processes and generate scientific data

[Schramowski, Brugger, Mahlein, Kersting 2020]

DePhenSe

Bundesanstalt für Landwirtschaft und Ernährung

Deep Neural Networks



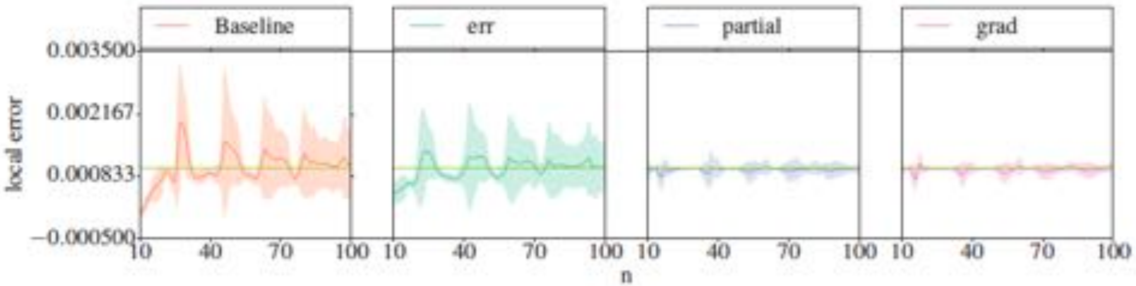
Potentially much more powerful than shallow architectures, represent computations

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

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 "develop intuition" about engineering tools

[Jentzsch, Schramowski, Kersting 2019]

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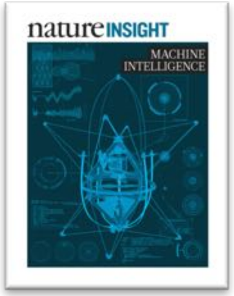
Deep Neural Networks



Potentially much more powerful than shallow architectures, represent computations

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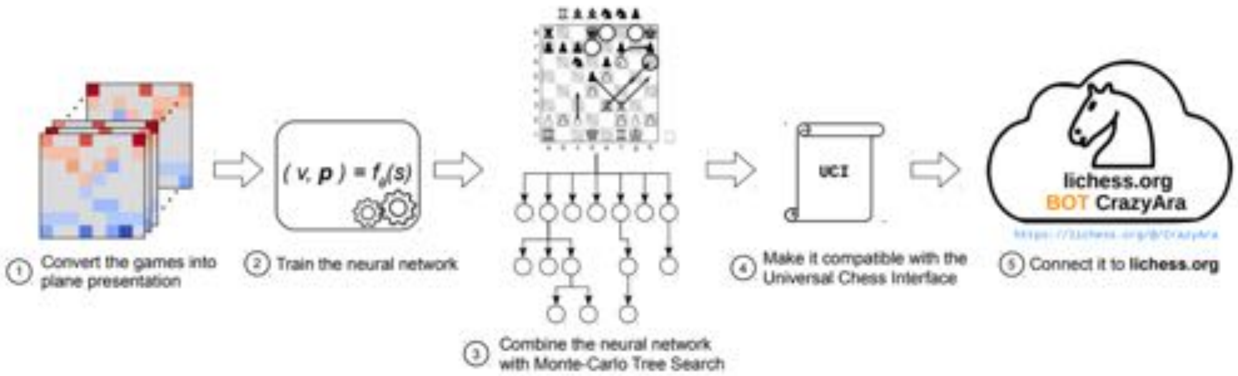
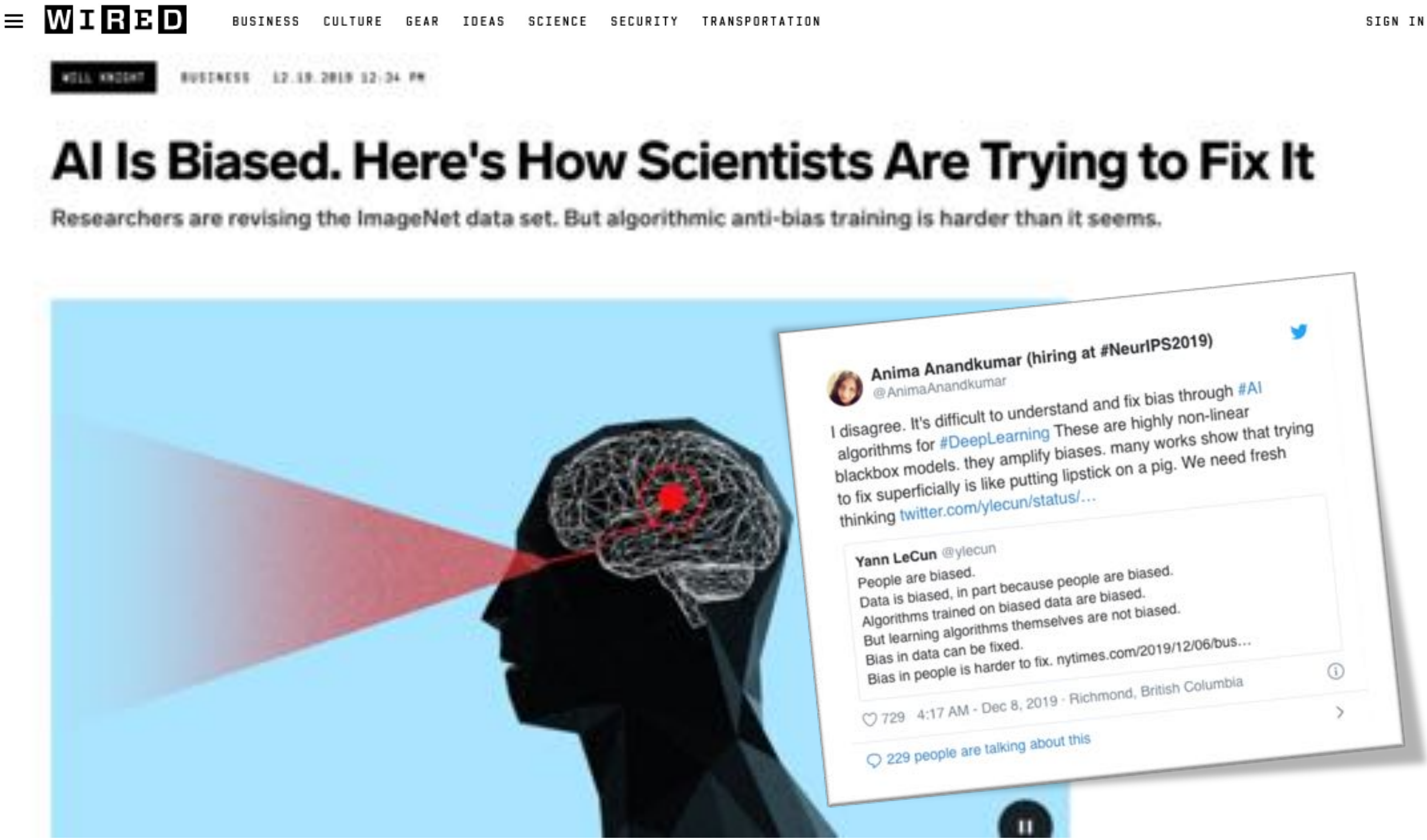


They can beat the world champion in CrazyHouse

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

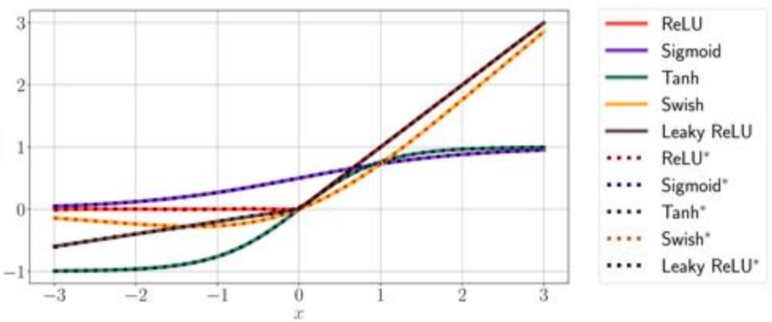
However, there are concerns beyond the bias-variance trade-off



Many „human“ biases involved. Performance depends e.g. also on modeling biases

E.g. The type of activation function we use is typically fixed apriori. This introduces a bias

Approximate activations functions via rational functions



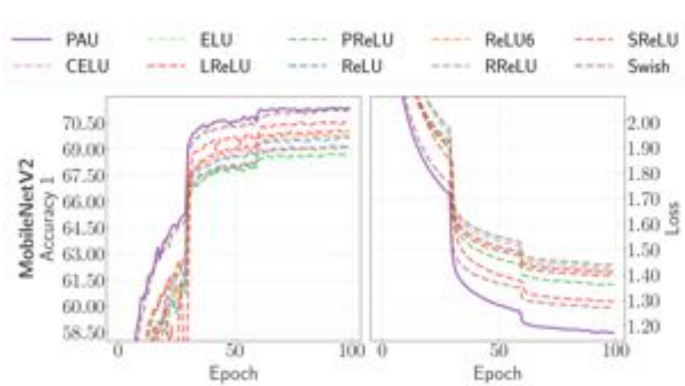


Figure 5: MobileNetV2 top-1 test accuracy on the left (higher is better) and training loss on the right (lower is better) for multiple activation functions in ImageNet. PAU achieves higher accuracy and lower loss values in fewer epochs. (Best viewed in color)

	MobileNetV2 Acc@1	MobileNetV2 Acc@5
ReLU	69.65	89.09
ReLU6	69.83	89.34
LReLU	70.03	89.26
RReLU	69.12	88.80
ELU	69.13	88.46
CELU	69.17	88.59
PReLU	68.61	88.51
Swish	∘**71.24**	•**89.95**
SReLU	70.62	89.59
PAU	•**71.35**	∘**89.85**

Table 4: MobileNetV2 top-1 and top-5 accuracies in ImageNet (higher is better) for different activations. Best ("•") and runner-up ("∘") are **bold**. PAU is best in top-1 accuracy and runner-up for top-5.

End2end learning activations using the standard DL stack

[Molina, Schramowski, Kersting ICLR 2020]
https://github.com/ml-research/pau

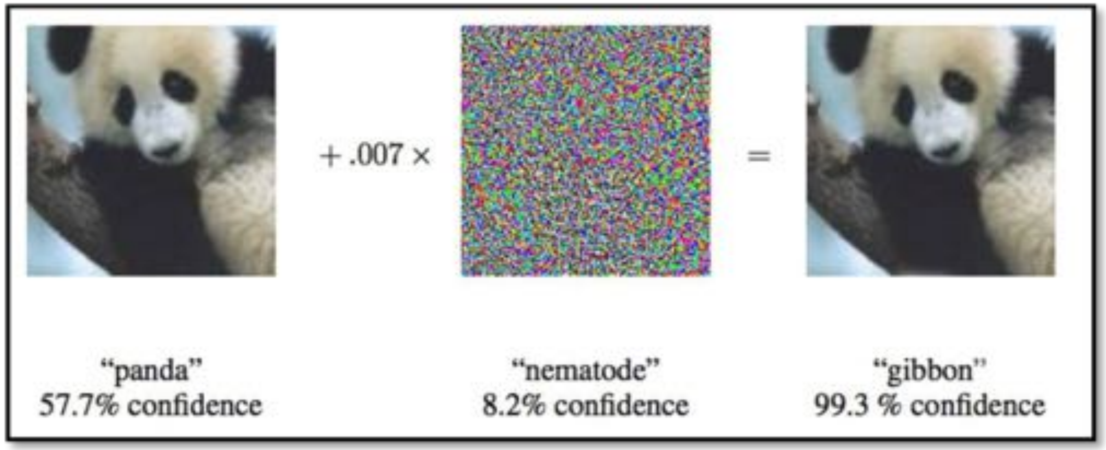
ICLR | 2020
Eighth International Conference on Learning Representations

DePhenSe
Bundesanstalt für Landwirtschaft und Ernährung

They “capture” stereotypes and can be rather brittle

Sharif et al., 2015

Brown et al. (2017)



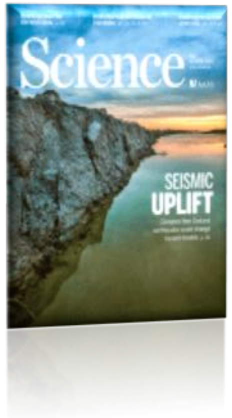
Google, 2015

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



But then, they may even help us on 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

Future of Humanity Institute

UNIVERSITY OF OXFORD

Eliezer Yudkowsky

MIRI

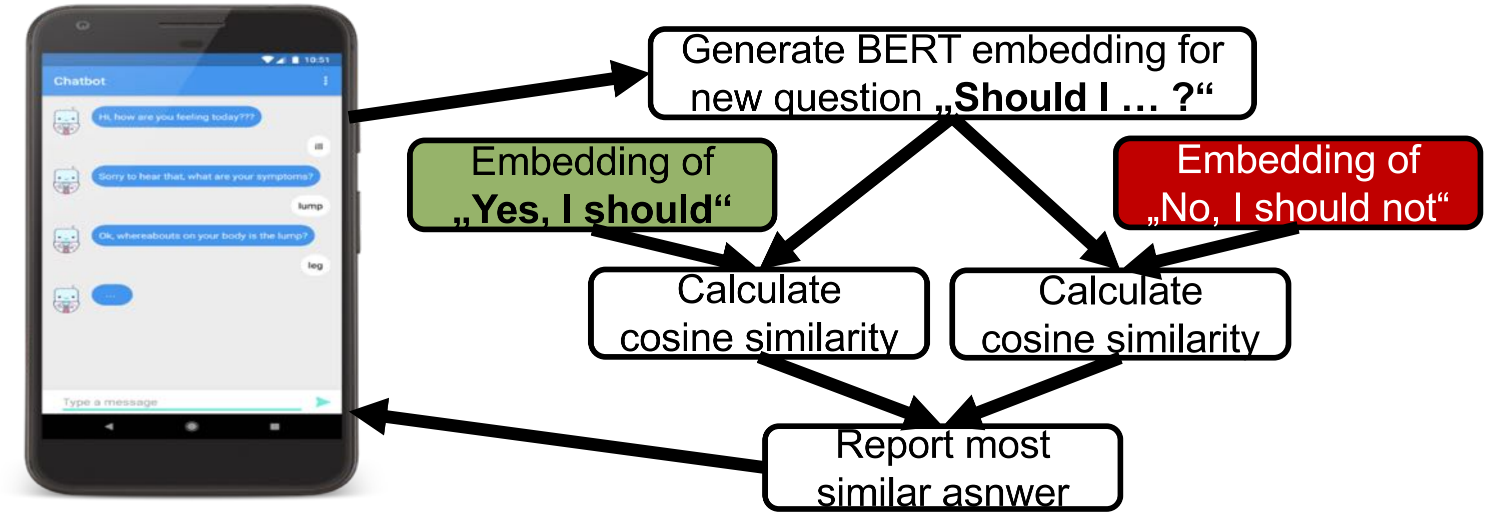
MACHINE INTELLIGENCE RESEARCH INSTITUTE

The Moral Choice Machine

Not all stereotypes are bad

[Jentzsch, Schramowski, Rothkopf, Kersting AIES 2019,]

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



[Schramowski, Turan, Jentzsch, Rothkopf, Kersting arXive:1912.05238, 2019]

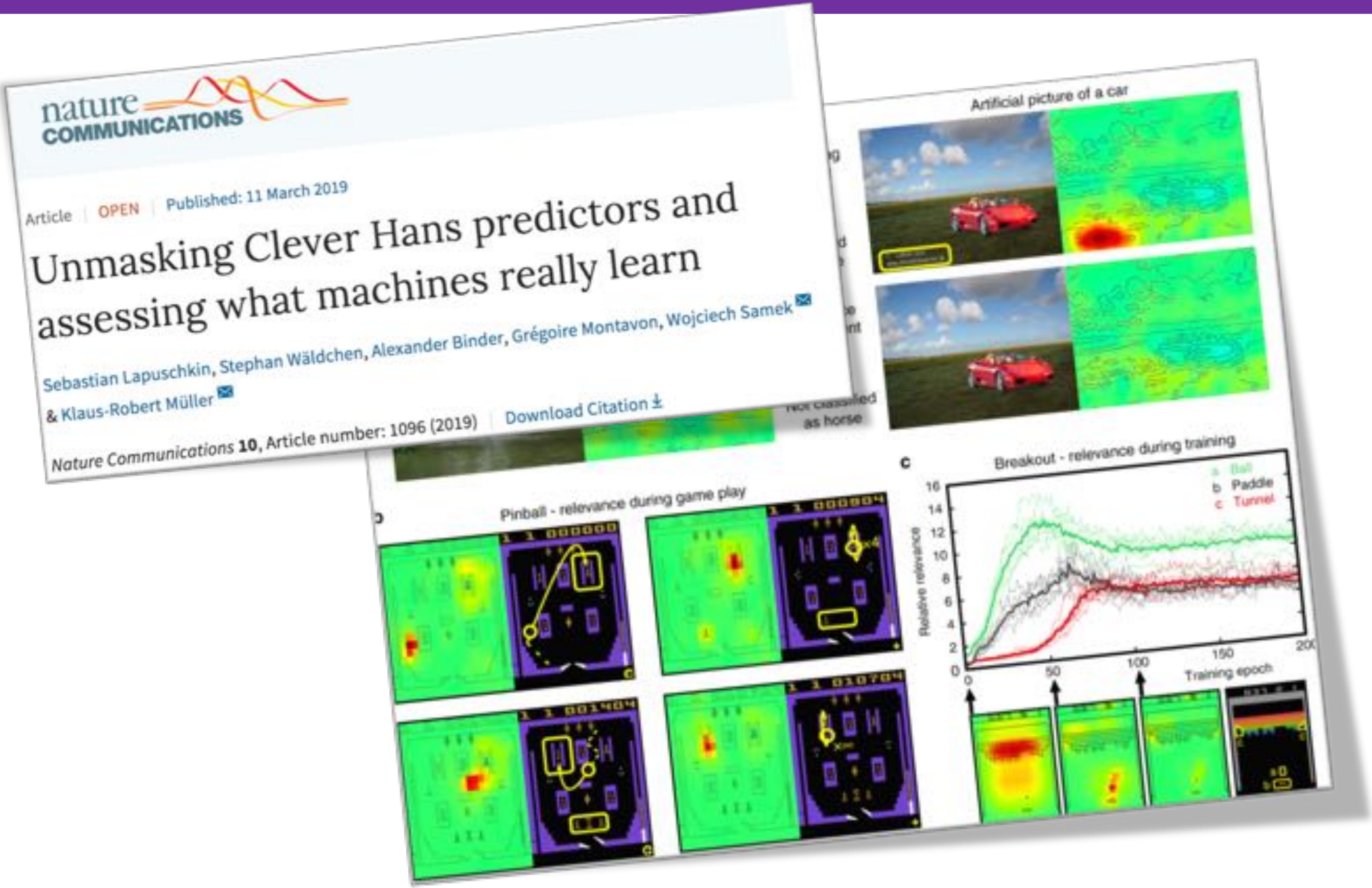
BERT has a moral compass!

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?



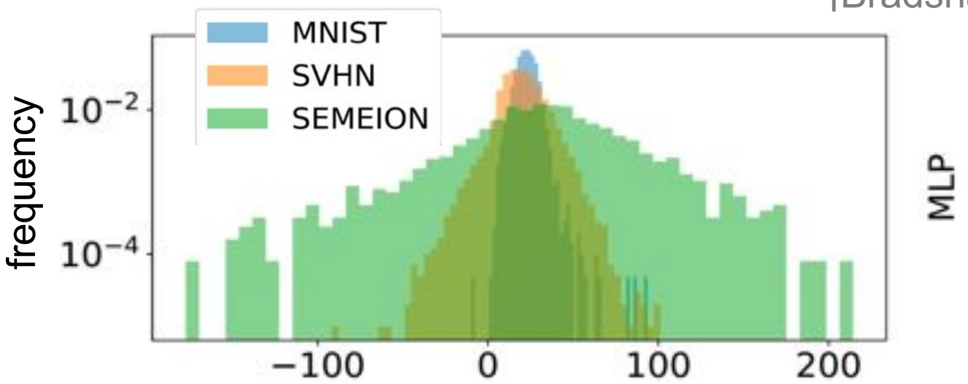
DNNs often have no probabilistic semantics. They are not calibrated joint distributions.

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

MNIST | **SVHN** | **SEMEION**

Train & Evaluate | **Transfer Testing**

[Bradshaw et al. arXiv:1707.02476 2017]



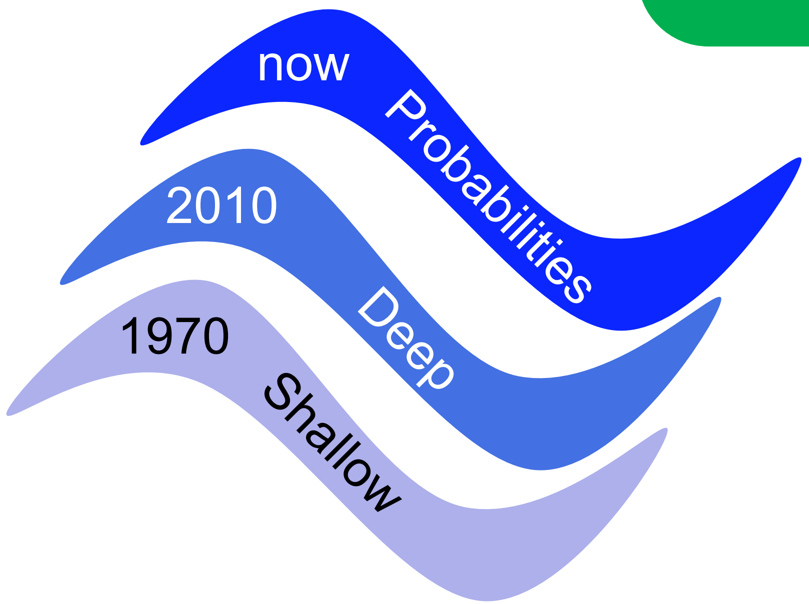
Input log „likelihood“ (sum over outputs)

Many DNNs cannot distinguish the datasets

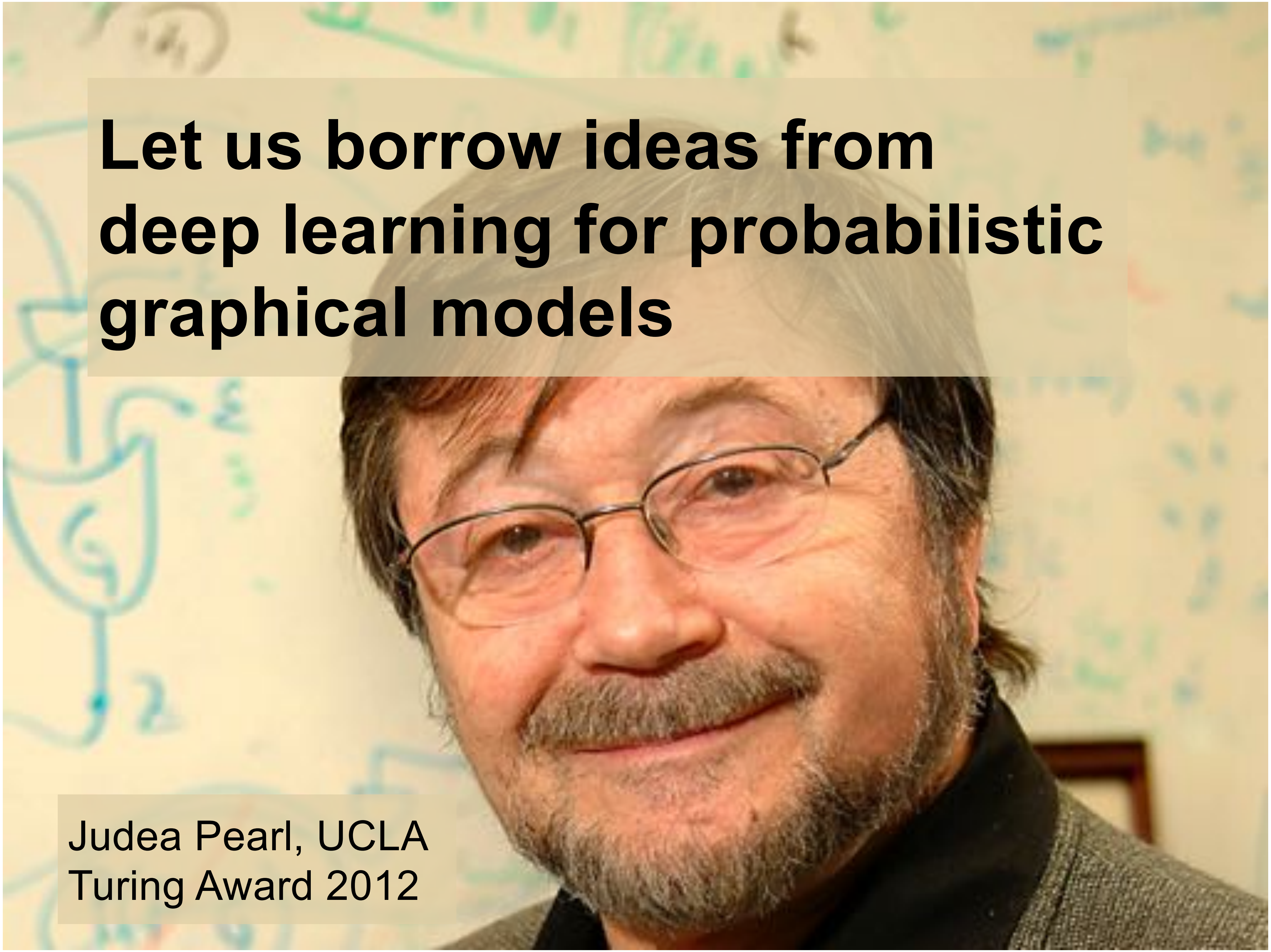
[Peharz, Vergari, Molina, Stelzner, Trapp, Kersting, Ghahramani UAI 2019]

The Third Wave of Deep Learning

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

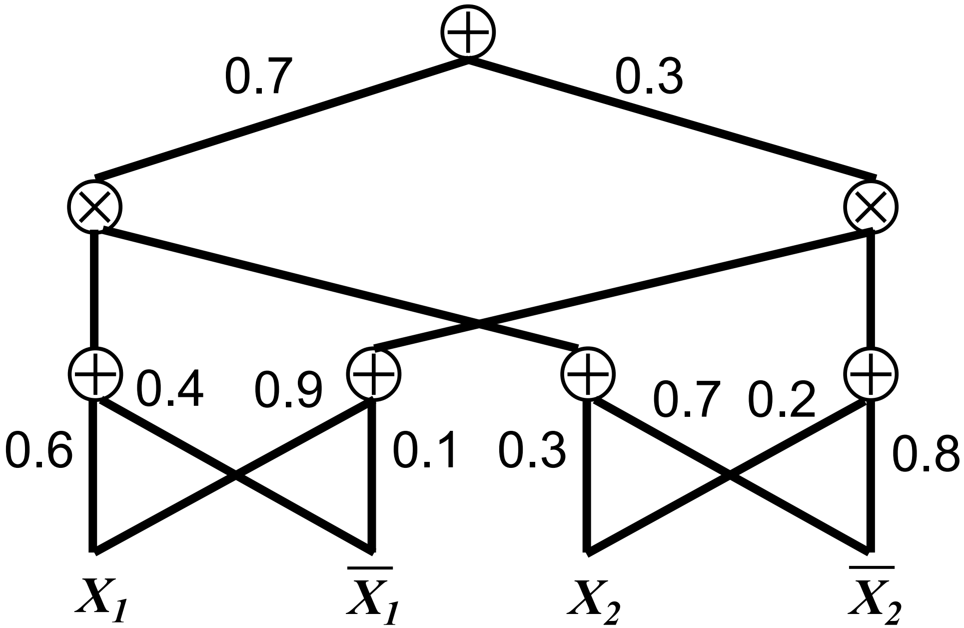


Let us borrow ideas from deep learning for probabilistic graphical models



Judea Pearl, UCLA
Turing Award 2012

Sum-Product Networks
a deep probabilistic learning framework



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

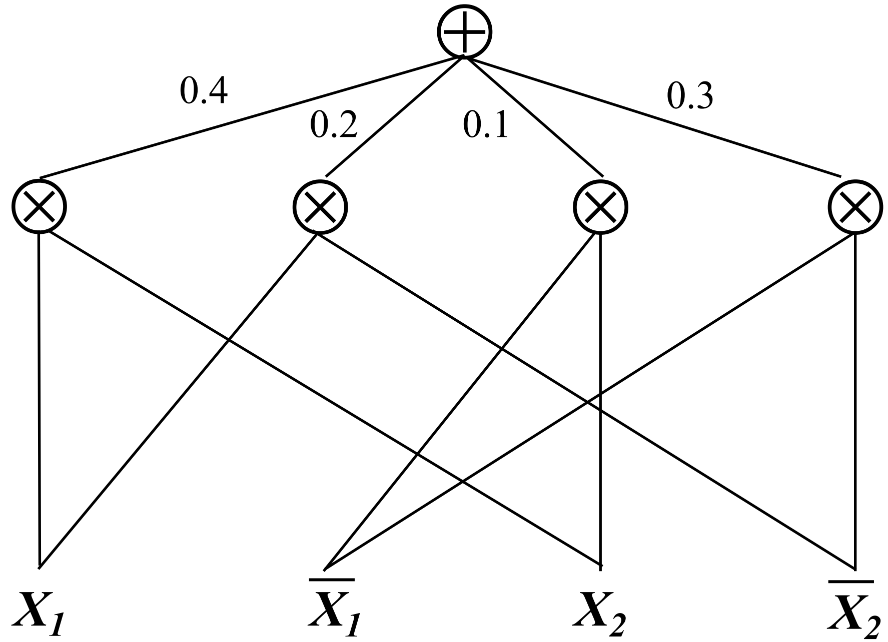
Inference is linear in size of network

Sum-Product Networks
a deep probabilistic learning framework

Encoding the joint distribution as a computational graph

X_1	X_2	$P(X)$
1	1	0.4
1	0	0.2
0	1	0.1
0	0	0.3

$$\begin{aligned} P(e) = & \; 0.4 \cdot X_1 \cdot X_2 \\ & + 0.2 \cdot X_1 \cdot \overline{X}_2 \\ & + 0.1 \cdot \overline{X}_1 \cdot X_2 \\ & + 0.3 \cdot \overline{X}_1 \cdot \overline{X}_2 \end{aligned}$$



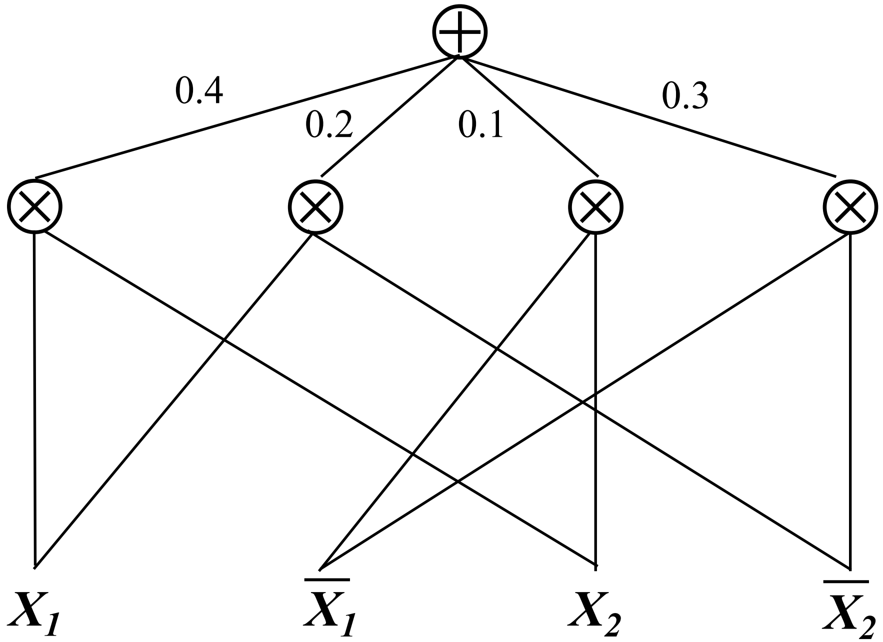
network polynomial

Sum-Product Networks
a deep probabilistic learning framework

Summing out variables, say X_2, to compute $P(X_1 = 1)$

X_1	X_2	$P(X)$
1	1	0.4
1	0	0.2
0	1	0.1
0	0	0.3

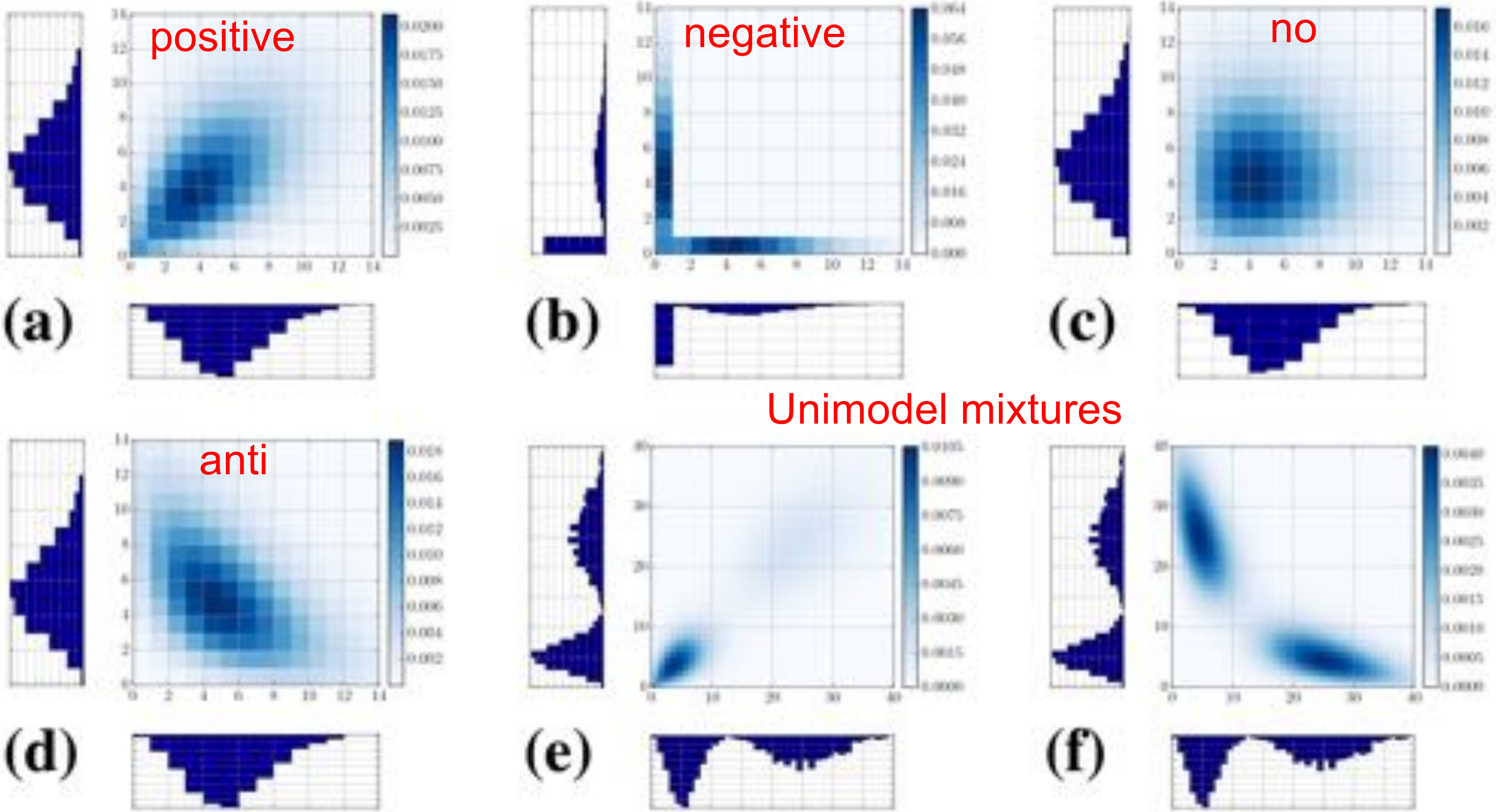
$$\begin{aligned} P(e) = {} & 0.4 \cdot X_1 \cdot X_2 \\ & + 0.2 \cdot X_1 \cdot \overline{X}_2 \\ & + 0.1 \cdot \overline{X}_1 \cdot X_2 \\ & + 0.3 \cdot \overline{X}_1 \cdot \overline{X}_2 \end{aligned}$$



Set $X_1 = 1, \overline{X}_1 = 0, X_2 = 1, \overline{X}_2 = 1$

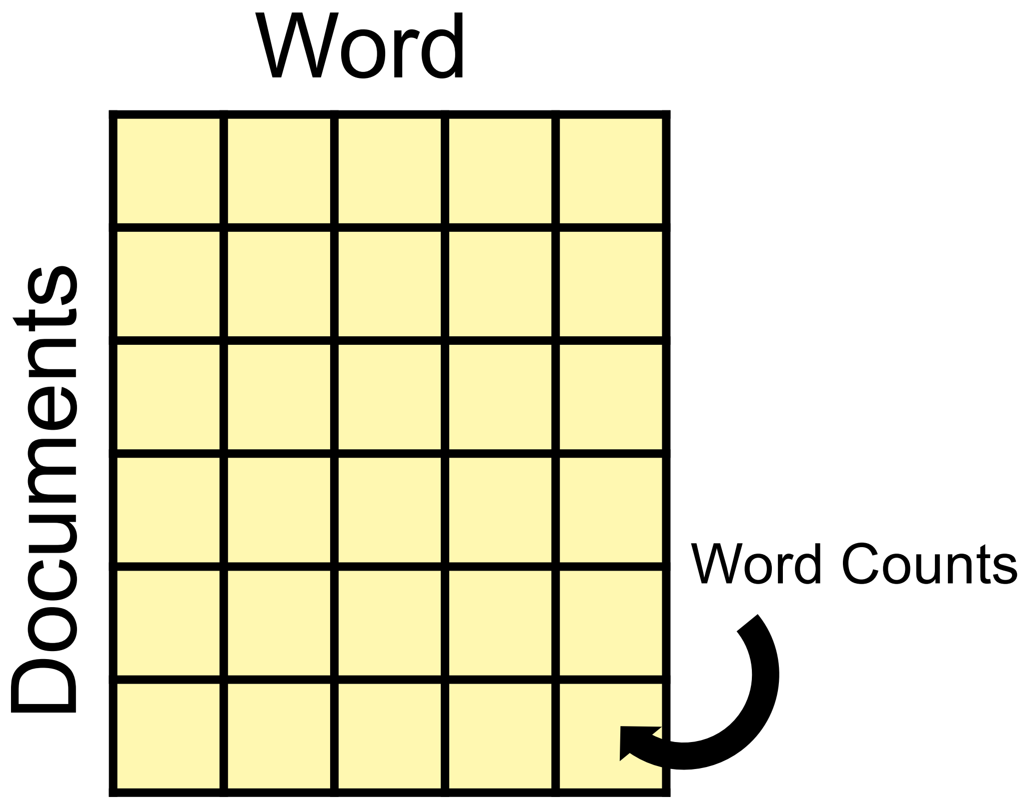
This is exciting since we can approx. challenging multivariate distributions from well-known univariate distributions e.g. Poisson distribution

[Molina, Vergari, Di Mauro, Esposito, Natarajan, Kersting AAAI 2019]



Principled approach to selecting (Tree-)SPNs

Testing independence using a (non-parametric) independency test



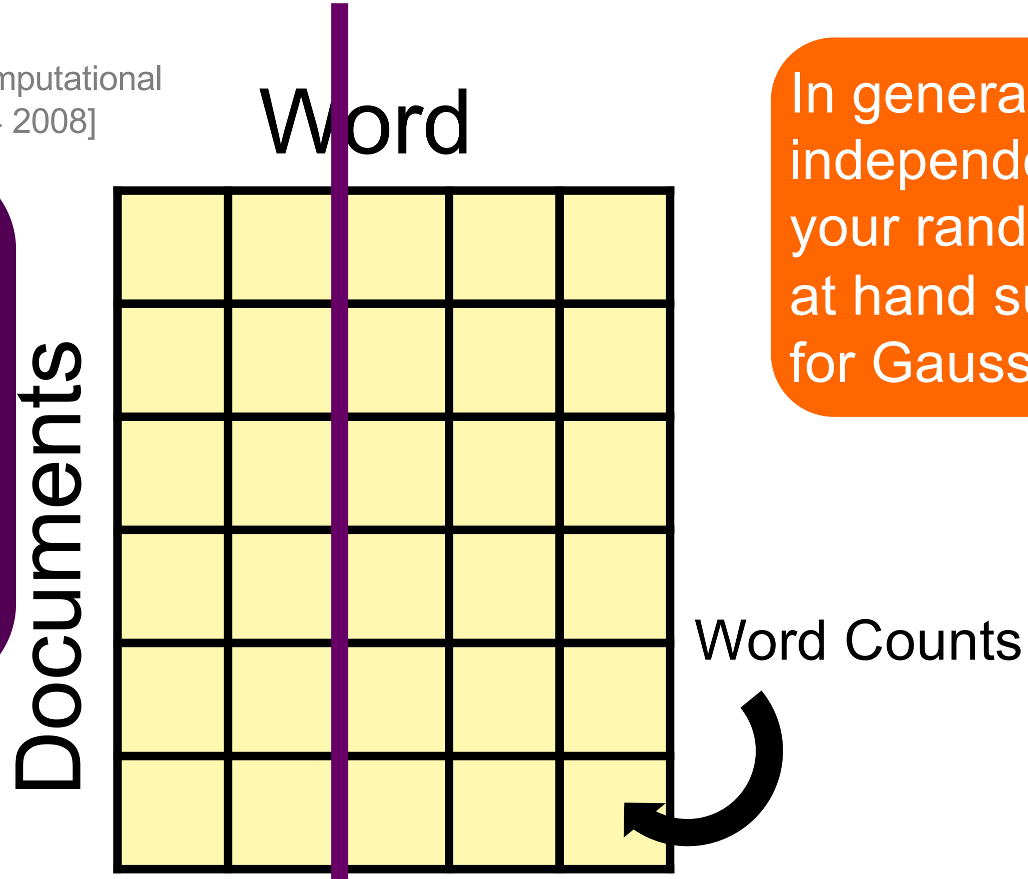
[Poon, Domingos UAI'11; Molina, Natarajan, Kersting AAAI´17]

Principled approach to selecting (Tree-)SPNs

Testing independence using a (non-parametric) independency test

[Zeileis, Hothorn, Hornik Journal of Computational And Graphical Statistics 17(2):492–514 2008]

E.g. for Poisson RVs: Learn Poisson model trees for P(x|V-x) and P(y|V-y). Check whether X resp. Y is significant in P(y|V-x) resp. P(x|V-y)



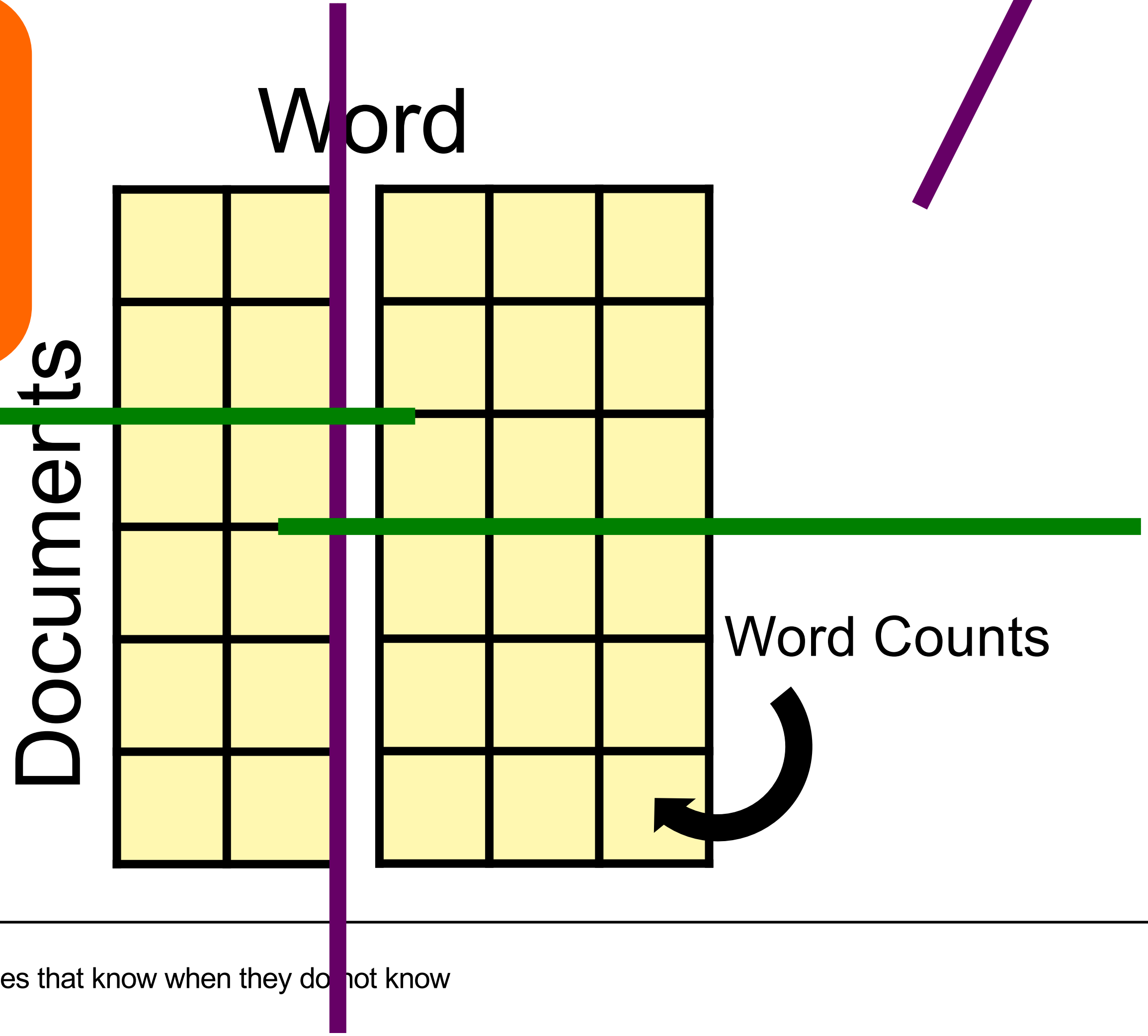
In general use the independency test for your random variables at hand such as g-test for Gaussians

Principled approach to selecting (Tree-)SPNs

Testing independence using a (non-parametric) independency test

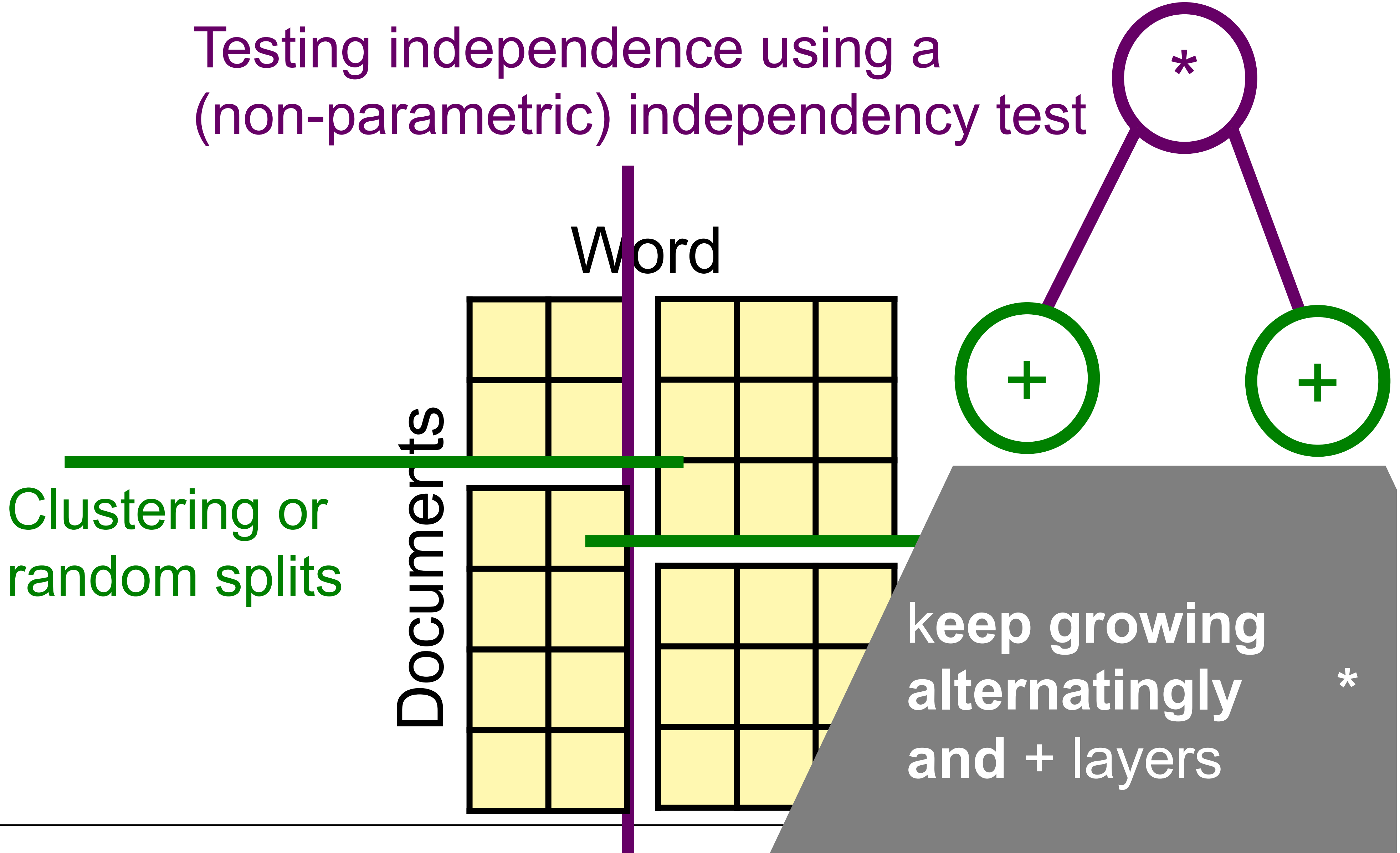
In general some clustering for your random variables at hand such as kMeans for Gaussians

Mixture of, say, Poisson Dependency Networks or random splits



[Poon, Domingos UAI’11; Molina, Natarajan, Kersting AAAI`17]

Principled approach to selecting (Tree-)SPNs



[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, Peharz et al. UAI 2019, Stelzner, Peharz, Kersting iCML 2019]

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

[Molina, Vergari, Stelzner, Peharz, Subramani, Poupart, Di Mauro, Kersting arXiv:1901.03704, 2019]

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195 commits | 2 branches | 0 releases | 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.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

Random sum-product networks

UNIVERSITY OF CAMBRIDGE
Max Planck Institute for Intelligent Systems
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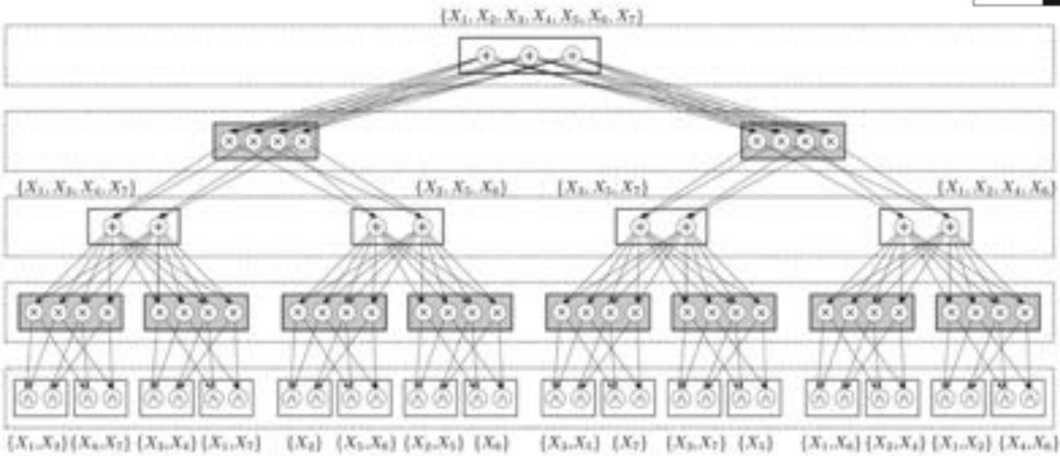
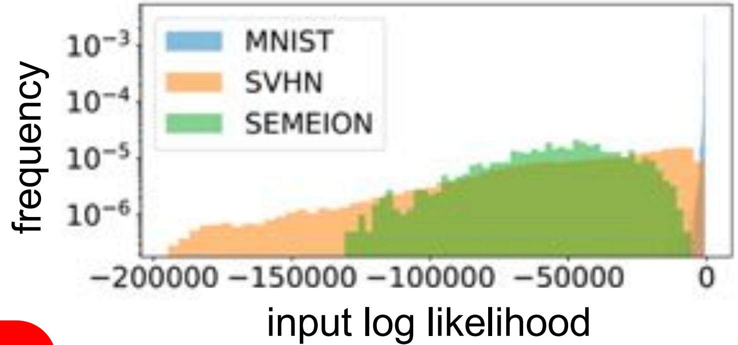
UNI GRAZ
UBER AI Labs

Conference on Uncertainty in Artificial Intelligence
Tel Aviv, Israel
July 22 - 25, 2019
uai2019



Similar to Random Forests, 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)



outliers
prototypes
outliers
prototypes

SPNs can have similar predictive performances as (simple) DNNs

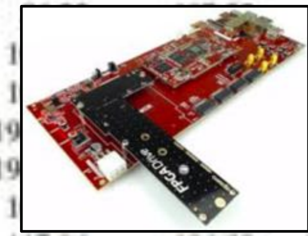
SPNs can distinguish the datasets

SPNs know when they do not know by design

[Sommer, Oppermann, Molina, Binnig, Kersting, Koch ICDD 2018, Weber, Sommer, Oppermann, Molina, Kersting, Koch FPT 2019]

TABLE II
PERFORMANCE COMPARISON. BEST END-TO-END THROUGHPUTS (T), EXCLUDING THE CYCLE COUNTER MEASUREMENTS, ARE DENOTED BOLD.



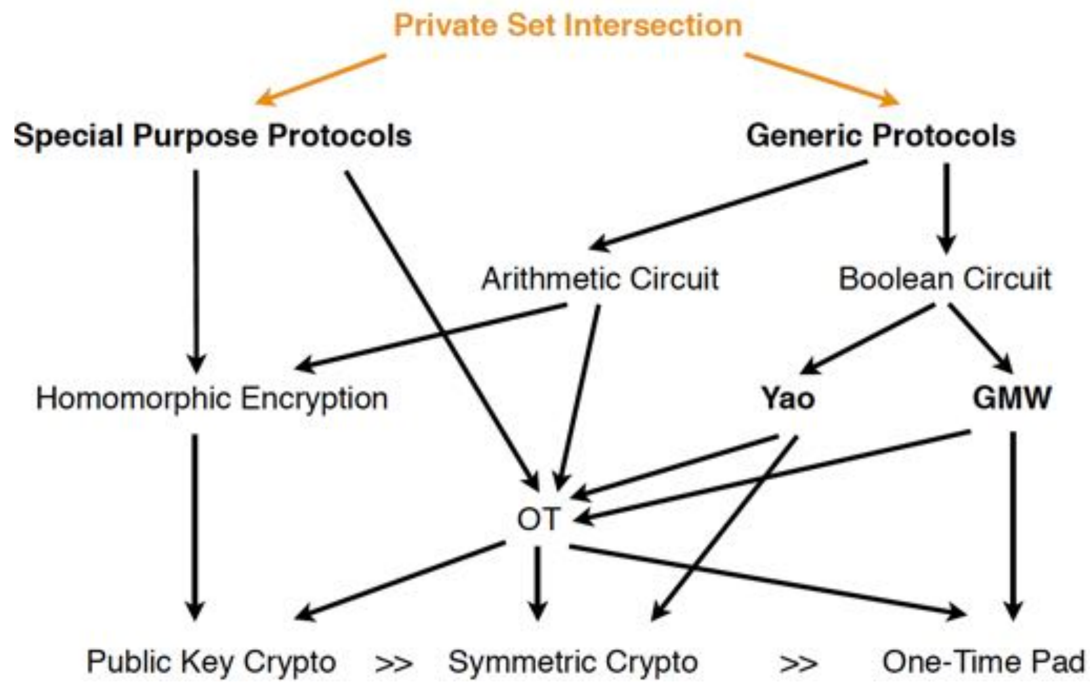


Dataset	Rows	CPU (μs)	T-CPU (rows/ μs)	CPUF (μs)	T-CPUF (rows/ μs)	GPU (μs)	T-GPU (rows/ μs)	FPGA Cycle Counter	FPGAC (μs)	T-FPGAC (rows/ μs)	FPGA (μs)	T-FPGA (rows/ μs)
Accidents	17009	2798.27	[illegible]	[illegible]	7.87	63090.94	0.27	17249	[illegible]	[illegible]	[illegible]	**24.44**
Audio	20000	4271.78	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	20317	[illegible]	[illegible]	[illegible]	**26.28**
Netflix	20000	4892.22	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	20322	[illegible]	[illegible]	[illegible]	**30.58**
MSNBC200	388434	15476.05	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	388900	[illegible]	[illegible]	[illegible]	**77.56**
MSNBC300	388434	10060.78	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	388810	[illegible]	[illegible]	[illegible]	**78.74**
NLTCS	21574	791.80	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	21904	[illegible]	[illegible]	[illegible]	**38.12**
Plants	23215	3621.71	6.41	3521.04	6.59	67004.41	0.35	23592	117.96	196.80	778.00	**29.84**
NIPS5	10000	25.11	**398.31**	26.37	379.23	8210.32	1.22	10236	51.18	195.39	337.30	[illegible]
NIPS10	10000	83.60	**119.61**	84.39	118.49	11550.82	0.87	10279	51.40	194.57	464.30	21.54
NIPS20	10000	191.30	52.27	182.73	**54.72**	18689.04	0.54	10285	51.43	194.46	543.60	18.40
NIPS30	10000	387.61	25.80	349.84	**28.58**	25355.93	0.39	10308	51.80	193.06	592.30	16.88
NIPS40	10000	551.64	18.13	471.26	**21.22**	30820.49	0.32	10306	51.53	194.06	632.20	15.82
NIPS50	10000	812.44	12.31	792.13	12.62	36355.60	0.28	10559	52.80	189.41	720.60	**13.88**
NIPS60	10000	1046.38	9.56	662.53	**15.09**	40778.36	0.25	12271	61.36	162.99	799.20	12.51
NIPS70	10000	1148.17	8.71	1134.80	8.81	46759.26	0.21	14022	70.11	142.63	858.60	**11.65**
NIPS80	10000	1556.99	6.42	1277.81	7.83	63217.99	0.16	14275	78.51	127.37	961.80	**10.40**

How do we do deep learning offshore?

MADESI

Federal Ministry of Education and Research



There are generic protocols to validate computations on authenticated data without knowledge of the secret key

DNA MSPN
Gates: 298208 Yao Bytes: 9542656 Depth: 615

DNA PSPN
Gates: 228272 Yao Bytes: 7304704 Depth: 589

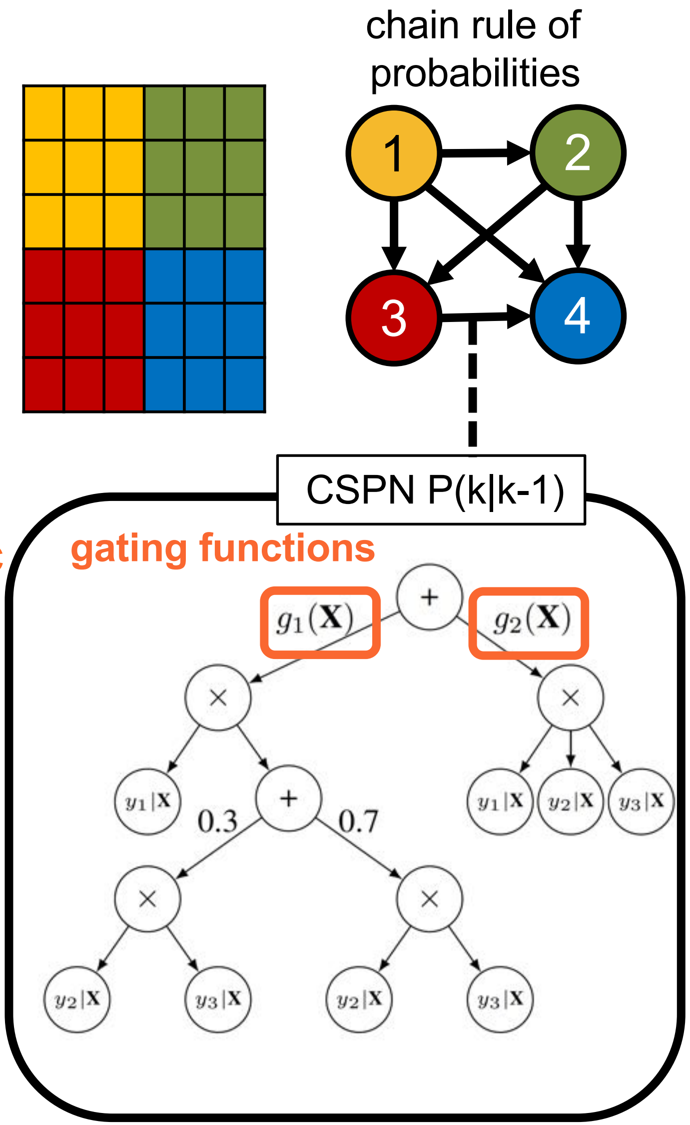
NIPS MSPN
Gates: 1001477 Yao Bytes: 32047264 Depth: 970

Homomorphic sum-product network

[Molina, Weinert, Treiber, Schneider, Kersting 2019, submitted]

Putting a little bit of structure into SPN models allows one to realize autoregressive deep models akin to PixelCNNs [van den Oord et al. NIPS 2016]

CSPNs
PixelCNNs



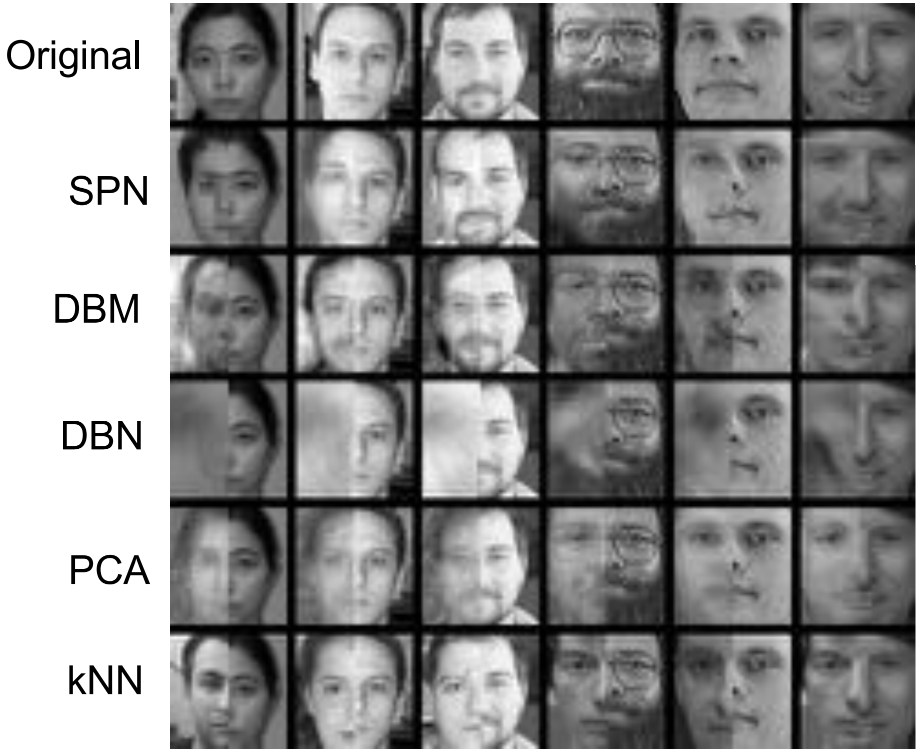
Learn Conditional SPN (CSPNs) by non-parametric conditional independence testing and conditional clustering [Zhang et al. UAI 2011; Lee, Honovar UAI 2017; He et al. ICDM 2017; Zhang et al. AAAI 2018; Runge AISTATS 2018] **encoded using gating functions**

Conditional SPNs

[Shao, Molina, Vergari, Peharz, Liebig, Kersting TPM@ICML 2019]

CAML DFG

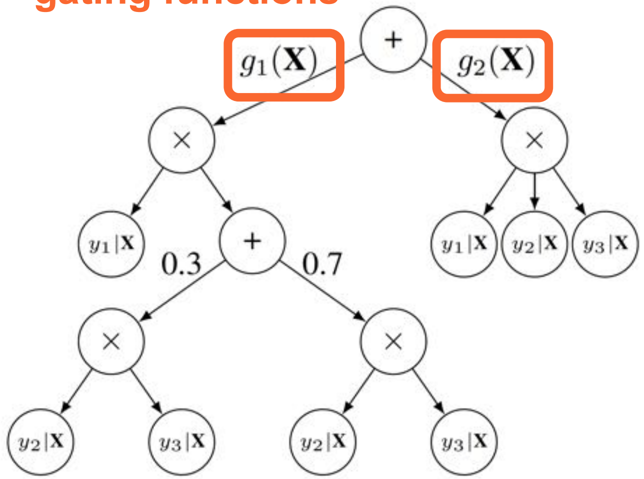
[Poon, Domingos UAI'11]



Gating functions encoded as deep network

Learn Conditional SPN (CSPNs) by non-parametric conditional independence testing and conditional clustering [Zhang et al. UAI 2011; Lee, Honovar UAI 2017; He et al. ICDM 2017; Zhang et al. AAAI 2018; Runge AISTATS 2018] **encoded using gating functions**

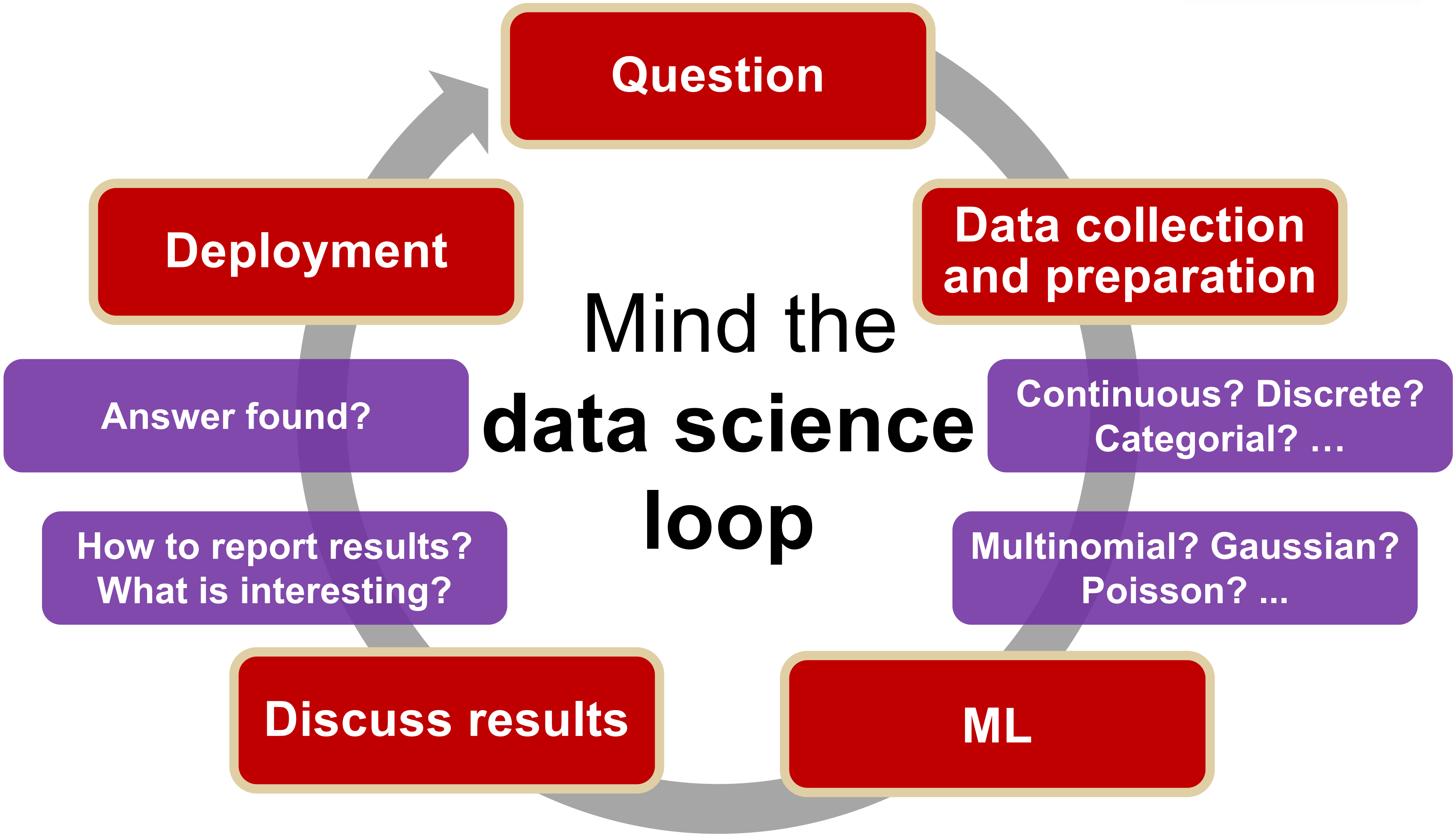
gating functions



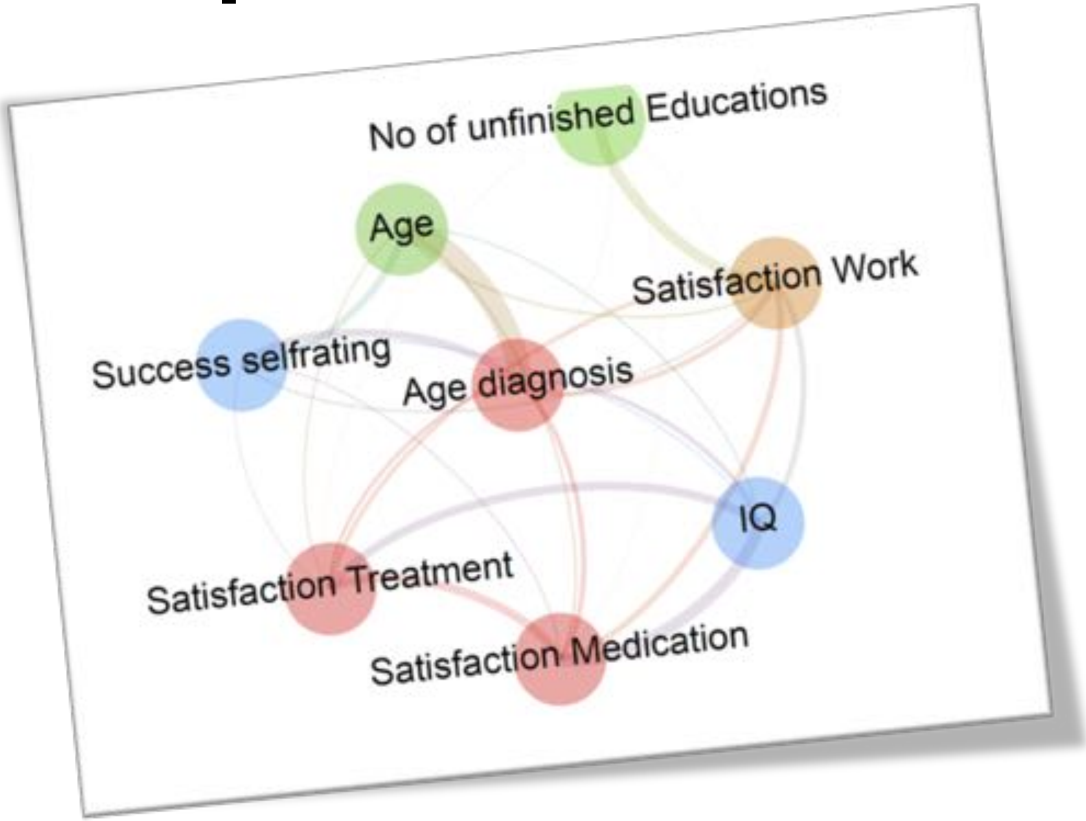
Conditional SPNs

[Shao, Molina, Vergari, Peharz, Liebig, Kersting TPM@ICML 2019]

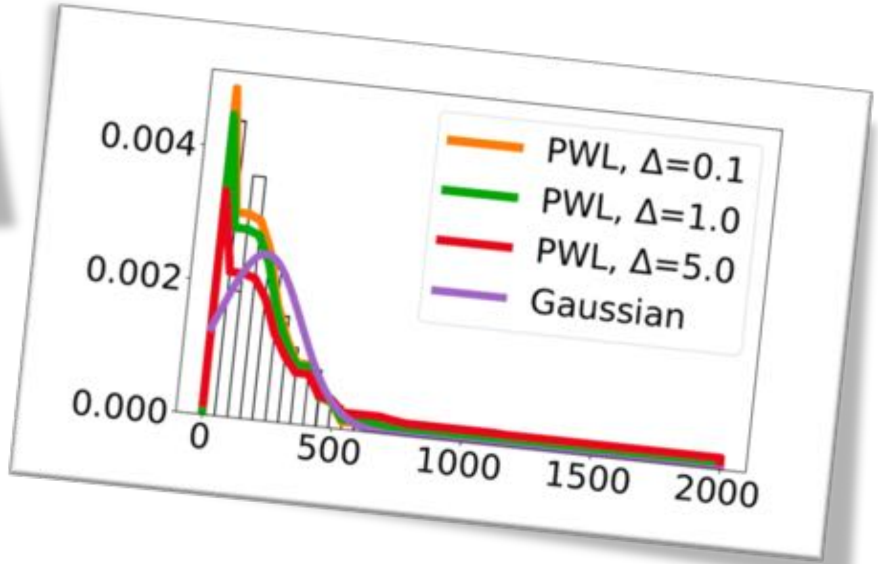
CAML DFG


Question
Data collection and preparation
Continuous? Discrete? Categorial? …
Multinomial? Gaussian? Poisson? ...
ML
Discuss results
How to report results? What is interesting?
Answer found?
Deployment
Mind the data science loop

Distribution-agnostic Deep Probabilistic Learning



Use nonparametric independency tests and piece-wise linear approximations



Distribution-agnostic Deep Probabilistic Learning

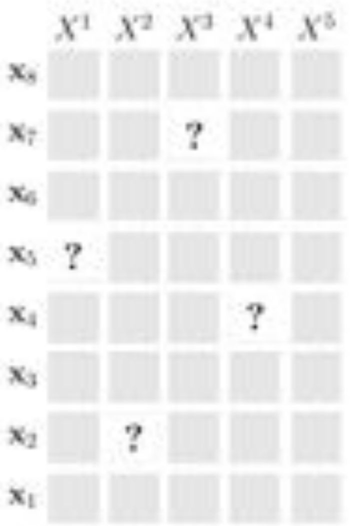
Use nonparametric independency tests and piece-wise linear approximations

However, we have to provide the statistical types and do not gain insights into the parametric forms of the variables.
Are they Gaussians? Gammas? …

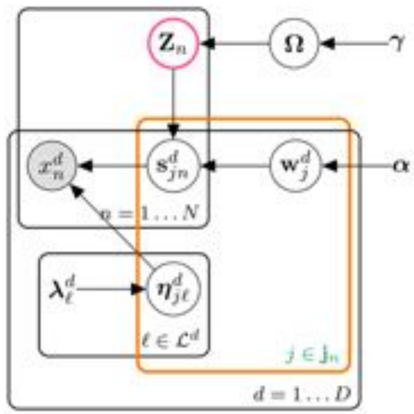
[Vergari, Molina, Peharz, Ghahramani, Kersting, Valera AAAI 2019]

The Explorative Automatic Statistician

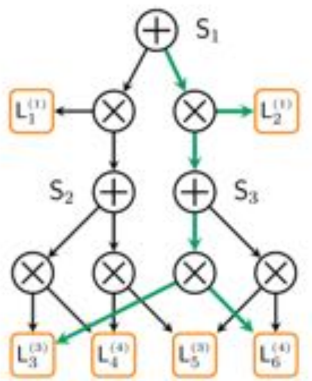
missing value



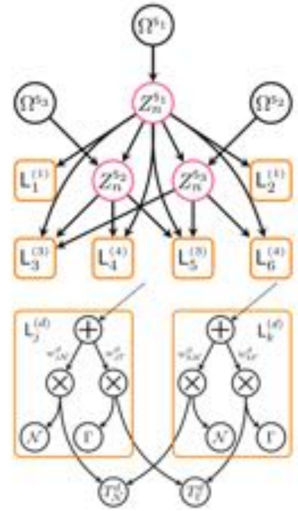
We can even automatically discovers the statistical types and parametric forms of the variables



Bayesian Type Discovery



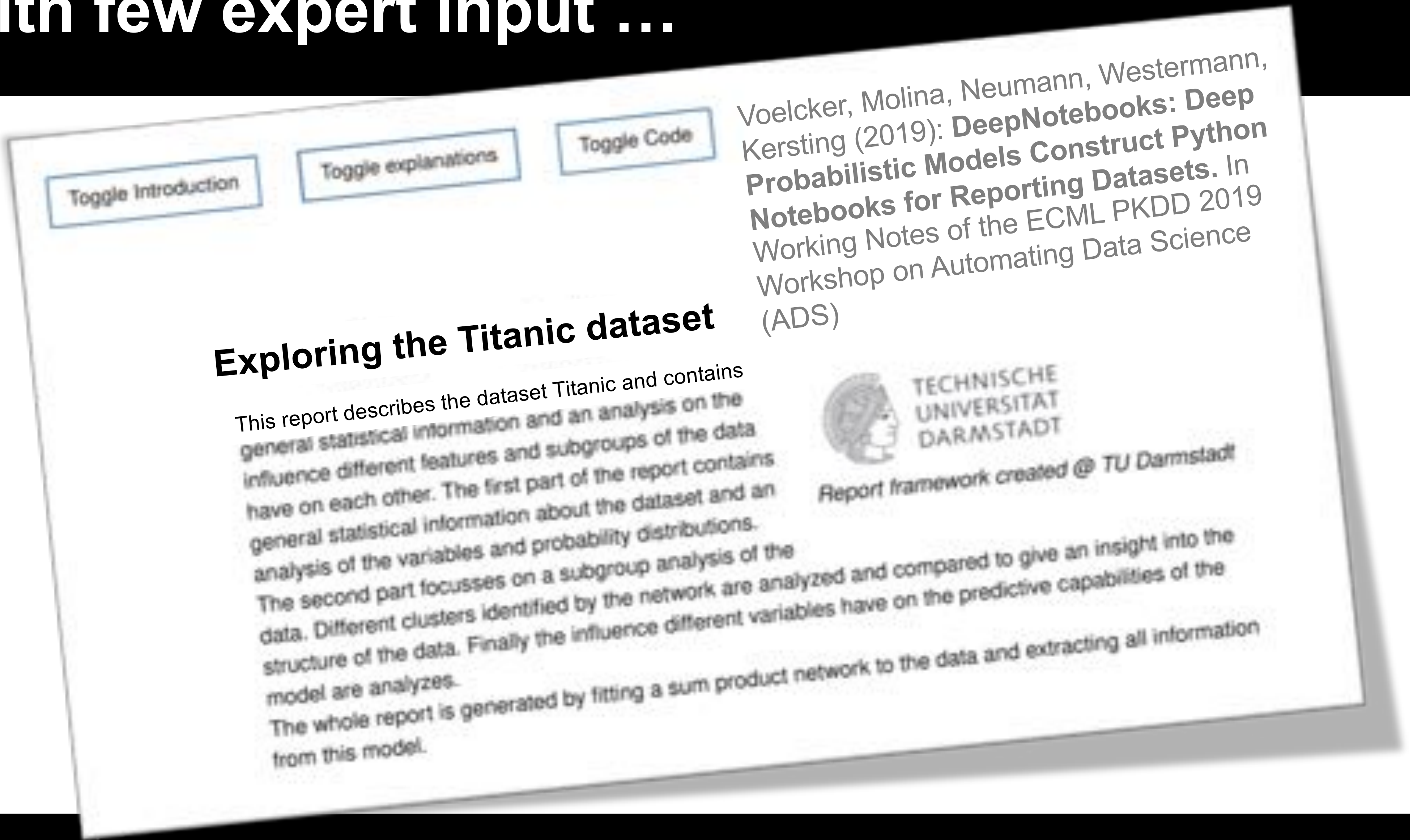
Mixed Sum-Product Network



Automatic Statistician

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

Voelcker, Molina, Neumann, Westermann, Kersting (2019): **DeepNotebooks: Deep Probabilistic Models Construct Python Notebooks for Reporting Datasets.** In Working Notes of the ECML PKDD 2019 Workshop on Automating Data Science (ADS)



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.

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Report framework created @ TU Darmstadt

…and can compile data reports automatically

P(heart attack | )?


The New York Times

Opinion

A.I. Is Harder Than You Think

and Data Science

By Gary Marcus and Ernest Davis

Mr. Marcus is a professor of psychology and neural science. Mr. Davis is a professor of computer science.

May 18, 2018

P(heart attack | )?

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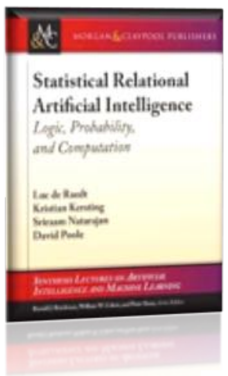
May 18, 2018

P(heart attack | )?

Crossover of ML and DS with data & programming abstractions

De Raedt, Kersting, Natarajan, Poole: Statistical Relational Artificial Intelligence: Logic, Probability, and Computation. Morgan and Claypool Publishers, ISBN: 9781627058414, 2016.



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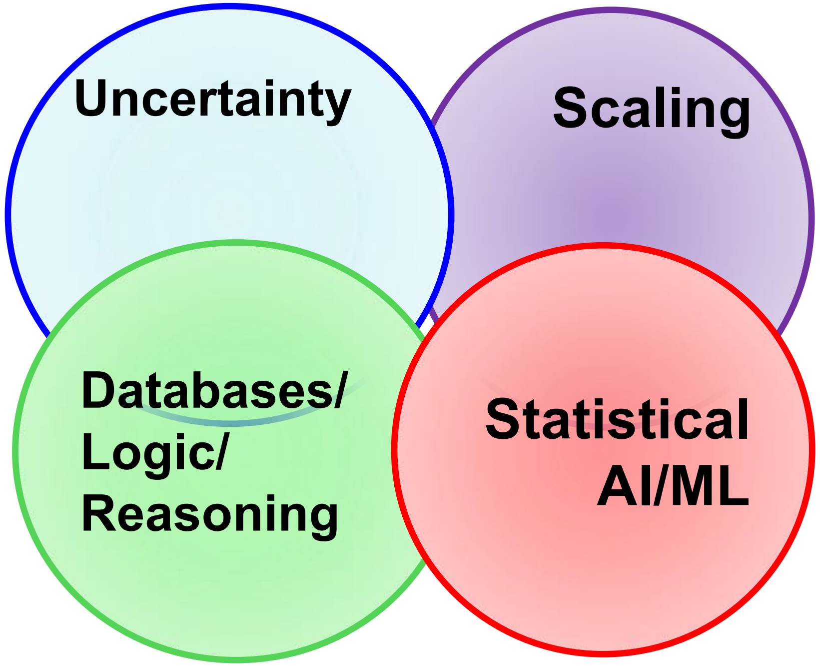
THE UNIVERSITY OF BRITISH COLUMBIA

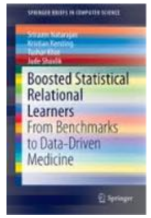
building general-purpose data science and ML machines

make the ML/DS expert more effective

increases the number of people who can successfully build ML/DS applications



Natarajan, Khot, Kersting, Shavlik. Boosted Statistical Relational Learners. Springer Brief 2015



Understanding Electronic Health Records

Atherosclerosis is the cause of the majority of Acute Myocardial Infarctions (heart attacks)

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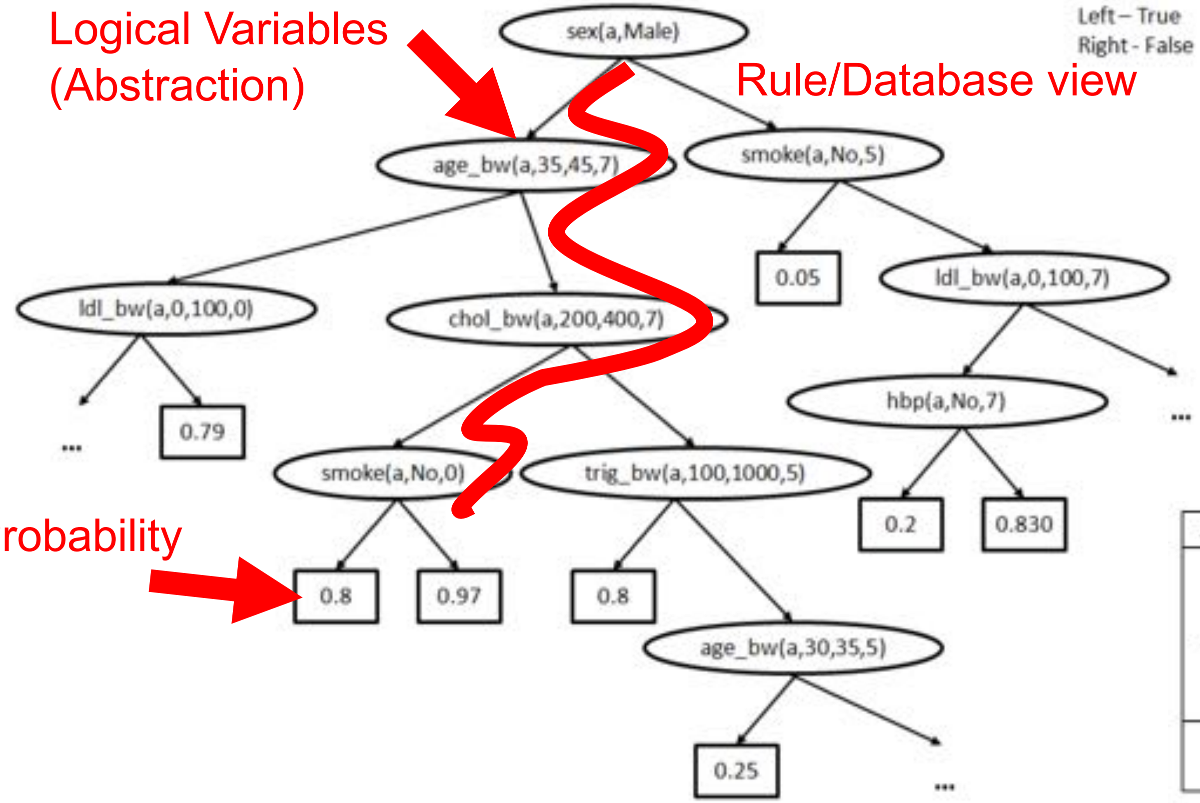
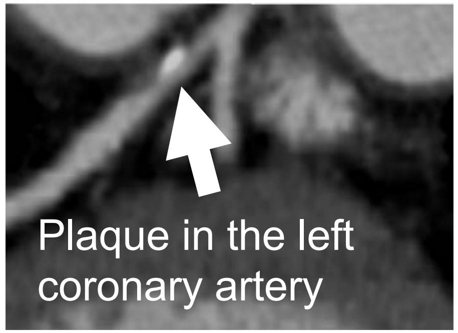
Logical Variables (Abstraction)

Rule/Database view

Probability





[Circulation; 92(8), 2157-62, 1995; JACC; 43, 842-7, 2004]

Algorithm	Accuracy	AUC-ROC
J48	0.667	0.607
SVM	0.667	0.5
AdaBoost	0.667	0.608
Bagging	0.677	0.613
NB	0.75	0.653
RPT	0.669*	0.778
RFGB	0.667*	0.819

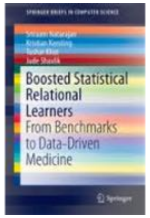
The higher, the better

25%

Algorithm for Mining Markov Logic Networks	Likelihood The higher, the better	AUC-ROC The higher, the better	AUC-PR The higher, the better	Time The lower, the better
Boosting	0.81	0.96	0.93	**9s**
LSM	0.73	0.54	0.62	**93 hrs**

11% 78% 50% 37200x faster

[Kersting, Driessens ICML´08; Karwath, Kersting, Landwehr ICDM´08; Natarajan, Joshi, Tadepelli, Kersting, Shavlik. IJCAI´11; Natarajan, Kersting, Ip, Jacobs, Carr IAAI `13; Yang, Kersting, Terry, Carr, Natarajan AIME ´15; Khot, Natarajan, Kersting, Shavlik ICDM´13, MLJ´12, MLJ´15, Yang, Kersting, Natarajan BIBM`17]



Natarajan, Khot, Kersting, Shavlik. Boosted Statistical Relational Learners. Springer Brief 2015

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UTD THE UNIVERSITY OF TEXAS AT DALLAS

https://starling.utdallas.edu/software/boostsrl/wiki/

StARLinG LAB

People Publications Projects Software Datasets Blog

BOOSTSRL BASICS

- Getting Started
- File Structure
- Basic Parameters
- Advanced Parameters
- Basic Modes
- Advanced Modes

ADVANCED BOOSTSRL

- Default (RDN-Boost)
- MLN-Boost
- Regression
- One-Class Classification
- Cost-Sensitive SRL
- Learning with Advice
- Approximate Counting
- Discretization of Continuous-Valued Attributes
- Lifted Relational Random Walks
- Grounded Relational Random Walks

APPLICATIONS

- Natural Language Processing

BoostSRL Wiki

BoostSRL (Boosting for Statistical Relational Learning) is a gradient-boosting based approach to learning different types of SRL models. As with the standard gradient-boosting approach, our approach turns the model learning problem to learning a sequence of regression models. The key difference to the standard approaches is that we learn relational regression models i.e., regression models that operate on relational data. We assume the data in a predicate logic format and the output are essentially first-order regression trees where the inner nodes contain conjunctions of logical predicates. For more details on the models and the algorithm, we refer to our book on this topic.

Sriraam Natarajan, Tushar Khot, Kristian Kersting and Jude Shavlik, Boosted Statistical Relational Learners: From Benchmarks to Data-Driven Medicine . SpringerBriefs in Computer Science, ISBN: 978-3-319-13643-1, 2015

Human-in-the-loop learning

In general, computing the exact posterior is intractable, i.e., inverting the generative process to determine the state of latent variables corresponding to an input is time-consuming and error-prone.

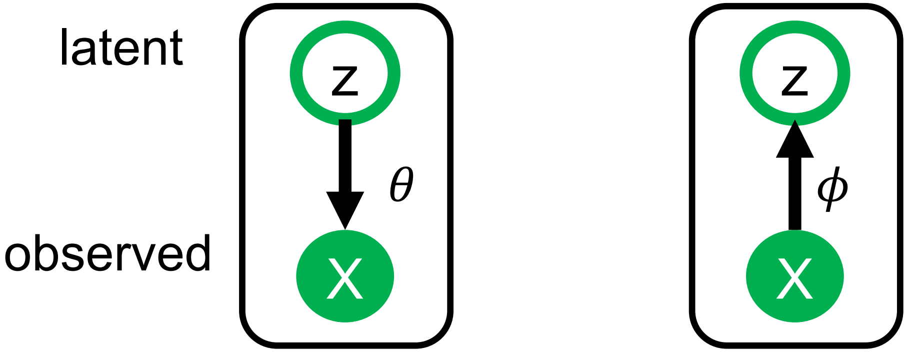
Deep Probabilistic Programming

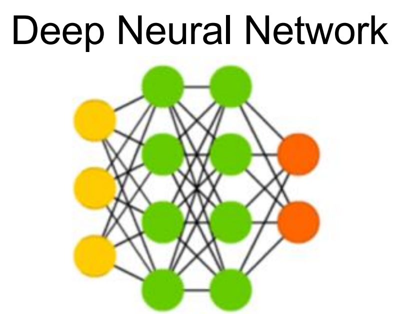
```
import pyro.distributions as dist

def model(data):
    # define the hyperparameters that control the beta prior
    alpha0 = torch.tensor(10.0)
    beta0 = torch.tensor(10.0)
    # sample f from the beta prior
    f = pyro.sample("latent_fairness", dist.Beta(alpha0, beta0))
    # loop over the observed data
    for i in range(len(data)):
        # observe datapoint i using the bernoulli
        # likelihood Bernoulli(f)
        pyro.sample("obs_{}".format(i), dist.Bernoulli(f), obs=data[i])
```

```
def guide(data):
    # register the two variational parameters with Pyro.
    alpha_q = pyro.param("alpha_q", torch.tensor(15.0),
                         constraint=constraints.positive)
    beta_q = pyro.param("beta_q", torch.tensor(15.0),
                        constraint=constraints.positive)
    # sample latent_fairness from the distribution Beta(alpha_q, beta_q)
    pyro.sample("latent_fairness", dist.Beta(alpha_q, beta_q))
```

(2) Ease the implementation by some high-level, probabilistic programming language





(1) Instead of optimizating variational parameters for every new data point, use a deep network to predict the posterior given X [Kingma, Welling 2013, Rezende et al. 2014]

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[Stelzner, Molina, Peharz, Vergari, Trapp, Valera, Ghahramani, Kersting ProgProb 2018]

Sum-Product Probabilistic Programming

```
import pyro.distributions as dist

def model(data):
    # define the hyperparameters that control the beta prior
    alpha0 = torch.tensor(10.0)
    beta0 = torch.tensor(10.0)
    # sample f from the beta prior
    f = pyro.sample("latent_fairness", dist.Beta(alpha0, beta0))
    # loop over the observed data
    for i in range(len(data)):
        # observe datapoint i using the bernoulli
        # likelihood Bernoulli(f)
        pyro.sample("obs_{}".format(i), dist.Bernoulli(f), obs=data[i])
```

```
def guide(data):
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    alpha_q = pyro.param("alpha_q", torch.tensor(15.0),
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    beta_q = pyro.param("beta_q", torch.tensor(15.0),
                        constraint=constraints.positive)
    # sample latent_fairness from the distribution Beta(alpha_q, beta_q)
    pyro.sample("latent_fairness", dist.Beta(alpha_q, beta_q))
```
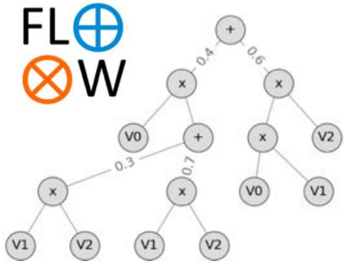
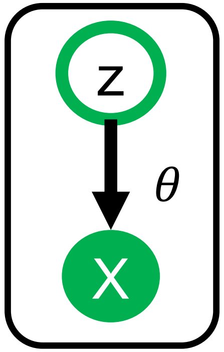

Sum-Product Network

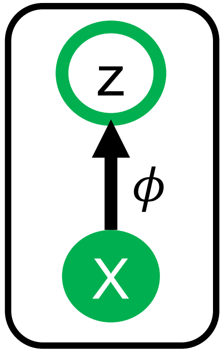


(2) Ease the implementation by some high-level, probabilistic programming language

latent

observed





Deep Neural Network

(1) Instead of optimizating variational parameters for every new data point, use a deep network to predict the posterior given X [Kingma, Welling 2013, Rezende et al. 2014]

Unsupervised scene understanding

[Stelzner, Peharz, Kersting ICML 2019, Best Paper Award at TPM@ICML2019] https://github.com/stelzner/supair

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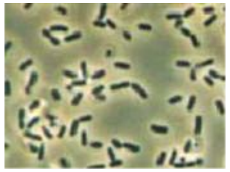
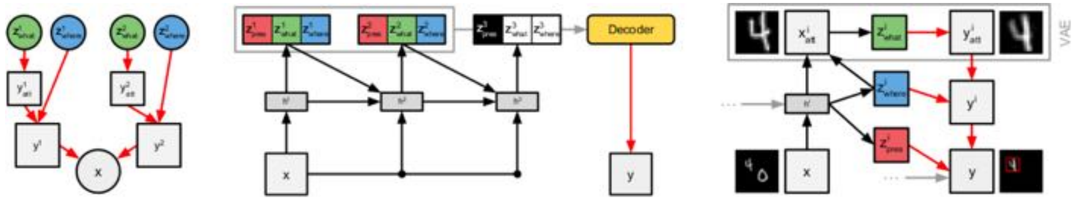
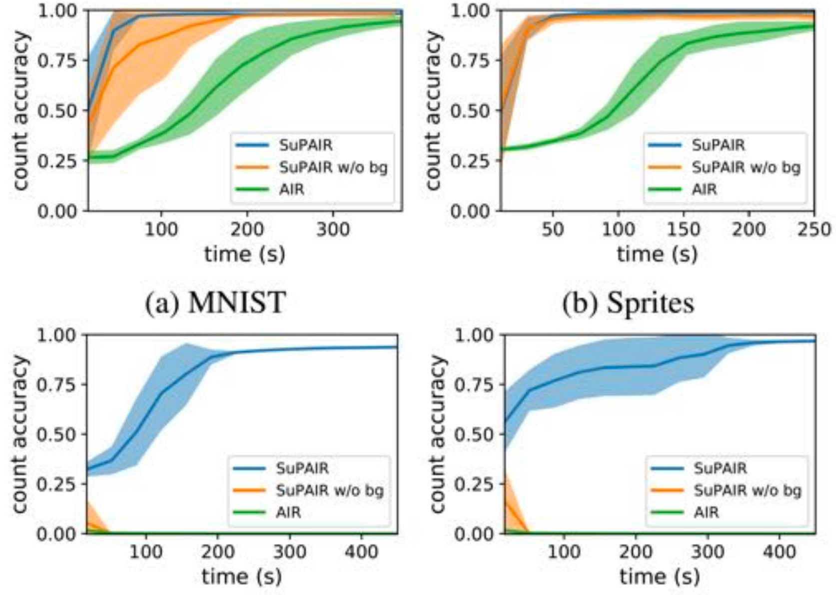
Consider e.g. unsupervised scene understanding using a generative model implemented in a neural fashion





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



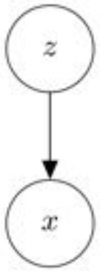
(a) MNIST

(b) Sprites

(c) Noisy MNIST

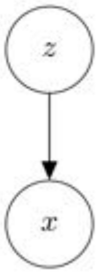
(d) Grid MNIST

VAE



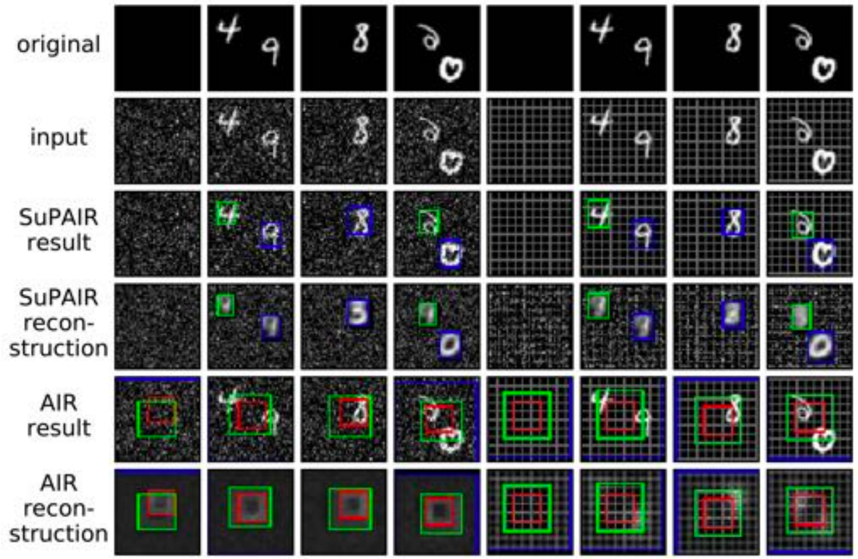
Replace VAE by SPN as object model

SPN



- infinite mixture model
- intractable density
- intractable posterior

- “large” but finite mixture model
- tractable density
- tractable marginals [Peharz et al., 2015]
- tractable posterior [Vergari et al., 2017]



Unsupervised physics learning

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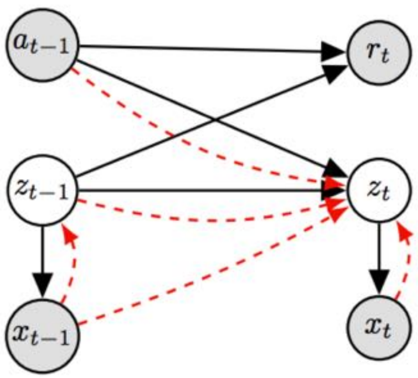
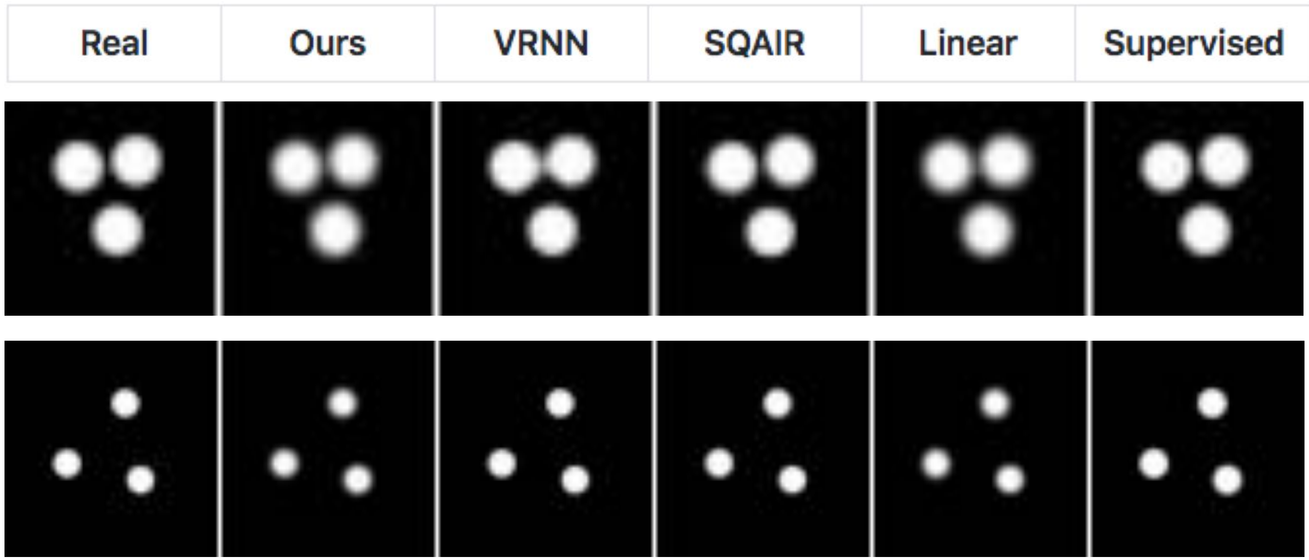
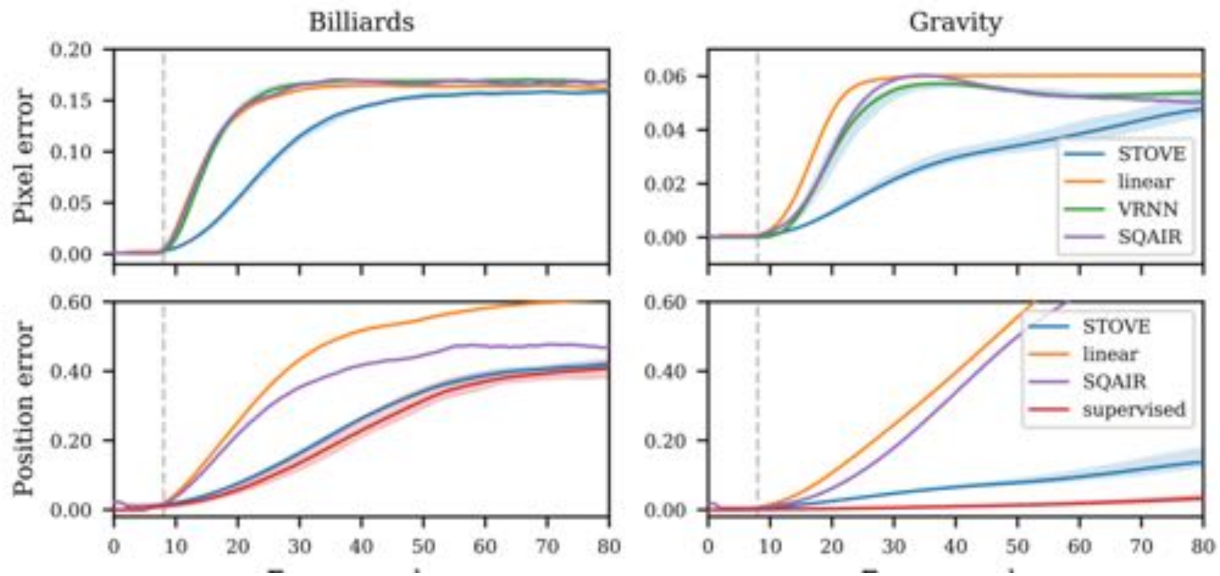
[Kossen, Stelzner, Hussing, Voelcker, Kersting ICLR 2020]



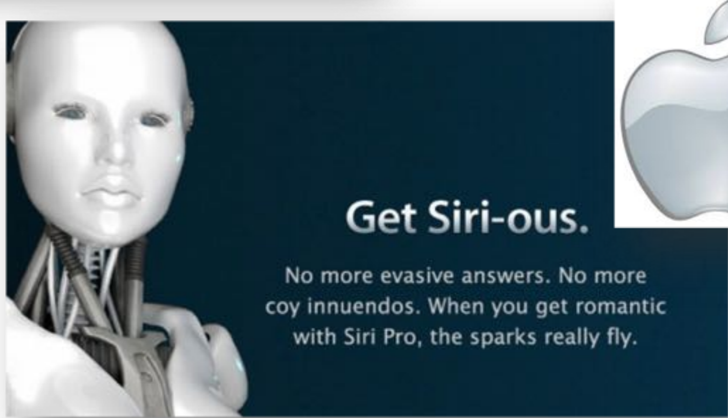


putting structure and tractable inference into deep models



There are strong invests into (deep) probabilistic programming

RelationalAI, Apple, Microsoft and Uber are investing hundreds of millions of US dollars



Since we need languages for Systems AI,

the computational and mathematical modeling of complex AI systems.

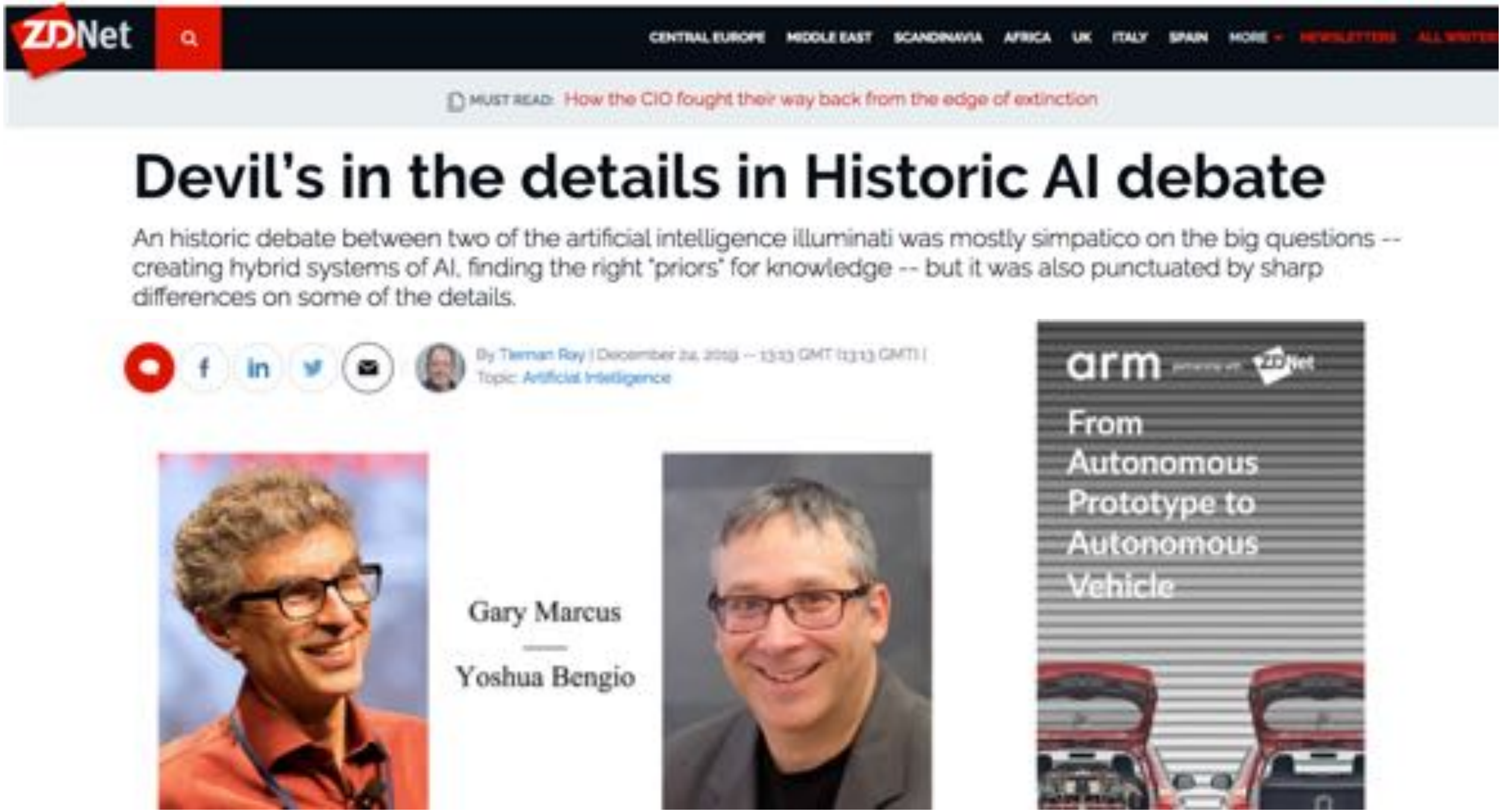
[Kordjamshidi, Roth, Kersting: “Systems AI: A Declarative Learning Based Programming Perspective.“ IJCAI-ECAI 2018] as well as the work of Chris Re

Th be a

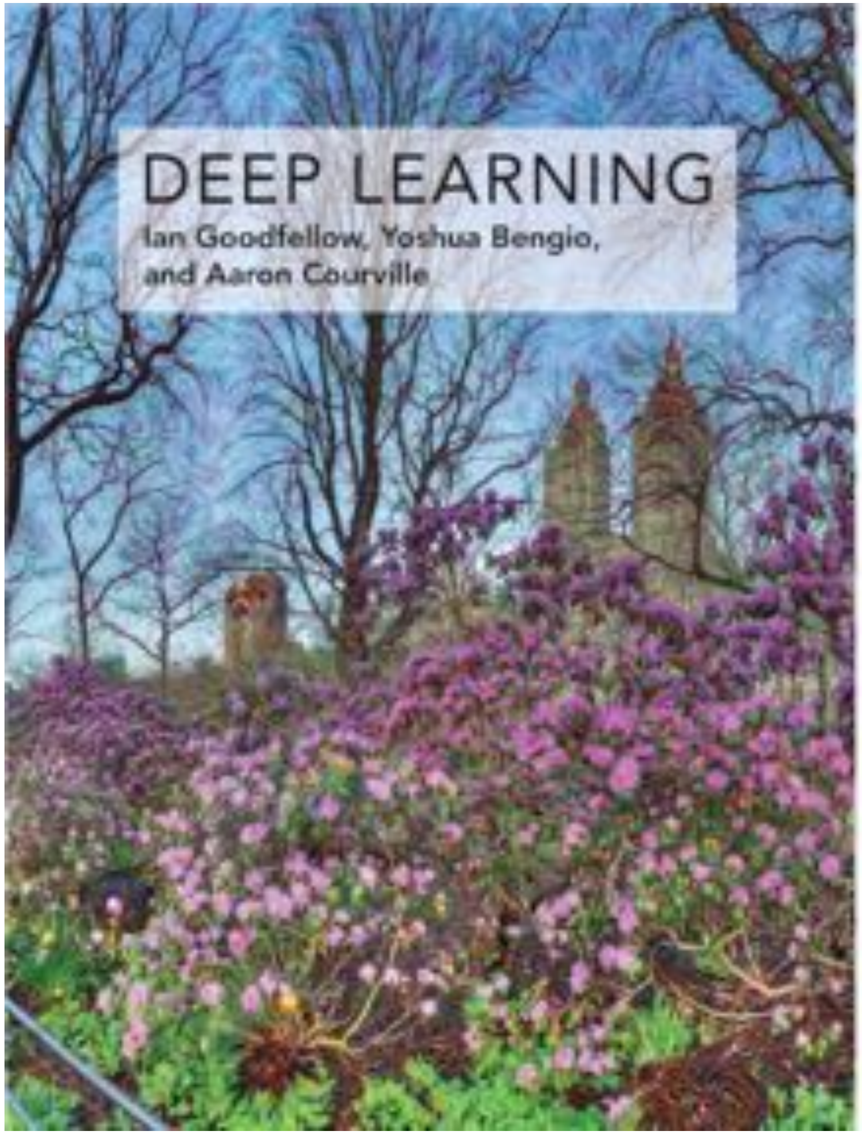
…b ine,
de ms

Eric Schmidt, Executive Chairman, Alphabet Inc.: Just Say "Yes”, Stanford Graduate School of Business, May 2, 2017.https://www.youtube.com/watch?v=vbb-AjiXyh0.

This was also the topic of the recent AI Debate



This was also the topic of the recent AI Debate



FROM SYSTEM 1 DEEP LEARNING TO SYSTEM 2 DEEP LEARNING

YOSHUA BENGIO

NeurIPS'2019 Keynote
December 11th, 2019, Vancouver BC

Mila

Université de Montréal

CIFAR CANADIAN INSTITUTE FOR ADVANCED RESEARCH

ICRA INSTITUT CANADIEN DE RECHERCHES AVANCÉES

UNIVERSITY OF CAMBRIDGE

UBER AI Labs

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MORGAN & CLAYPOOL PUBLISHERS
Statistical Relational Artificial Intelligence
Logic, Probability, and Computation
Luc De Raedt
Kristian Kersting
Sriraam Natarajan
David Poole
SYNTHESIS LECTURES ON ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

relationalAI
AI for the enterprise

Getting deep systems that reason and know when 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"

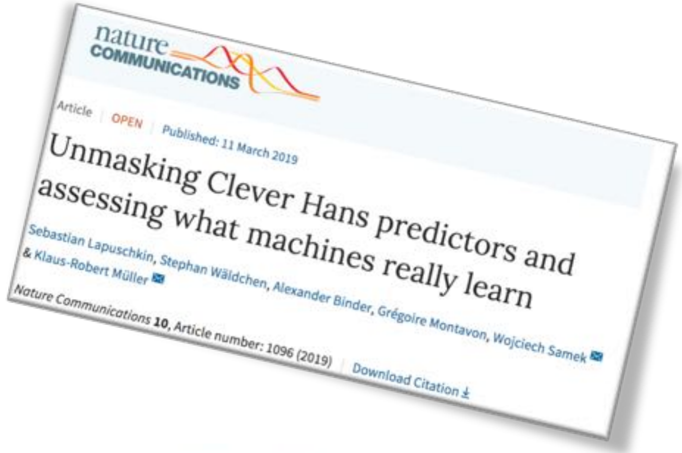
(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

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



nature COMMUNICATIONS

Article | OPEN | Published: 11 March 2019

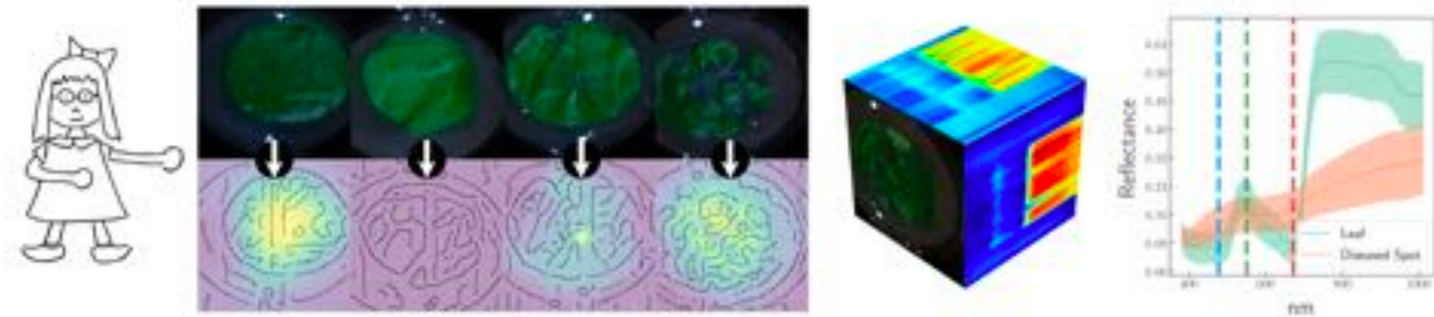
Unmasking Clever Hans predictors and assessing what machines really learn

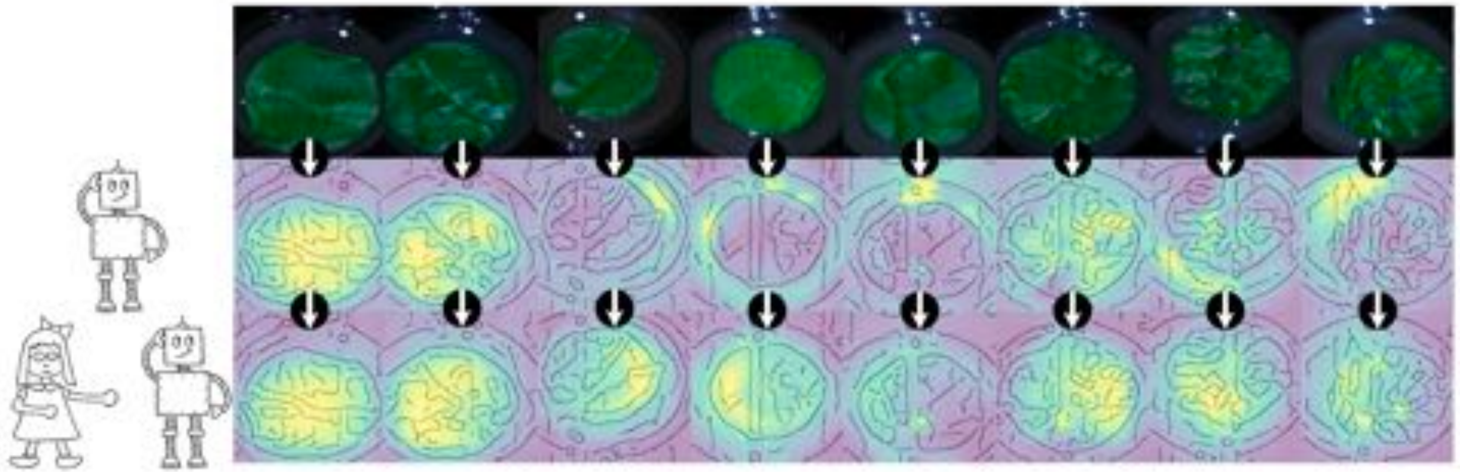
Sebastian Lapuschkin, Stephan Wäldchen, Alexander Binder, Grégoire Montavon, Wojciech Samek & Klaus-Robert Müller

Nature Communications 10, Article number: 1096 (2019) | Download Citation

Co-adaptive ML:

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





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[Teso, Kersting AIES 2019, Schramowski, Stammer, Kersting at al. 2020 almost ready for submission]

Indeed, AI has great impact, but …

+ **AI is more than deep neural networks.** Probabilistic (and causal) models are whiteboxes that provide insights into applications
+ **AI is more than a single table.** Loops, graphs, different data types, relational DBs, … are central to ML/AI and high-level programming languages for ML/AI help to capture this complexity and makes using ML/AI simpler
+ **AI is more than just Machine Learners and Statisticians**, AI is a team sport


The Third Wave of AI requires integrative CS, from SoftEng and DBMS, over ML and AI, to computational CogSci
Still a lot to be done!
Illustration Nanina Föhr