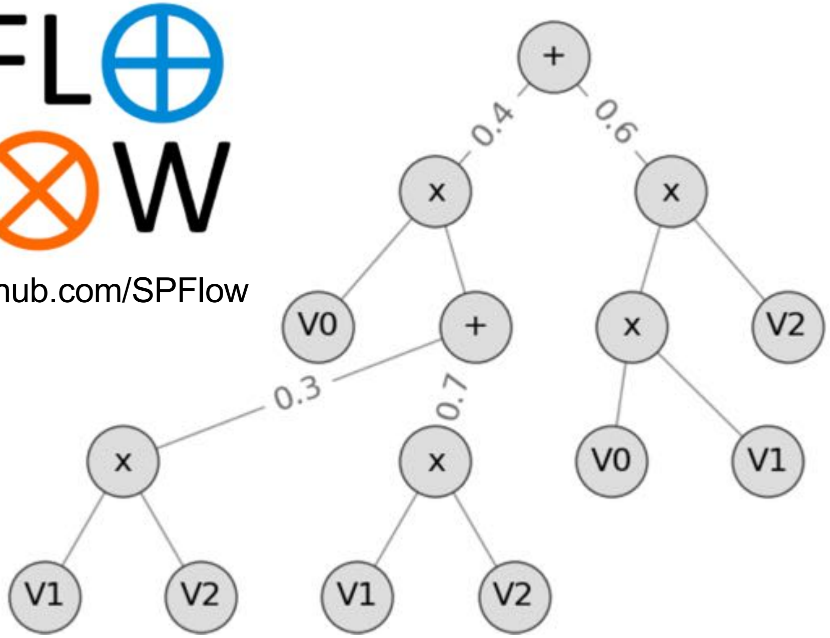
Deep machines that know when they do not know*

*Thanks for Pedro Domingos for making his slides publically available

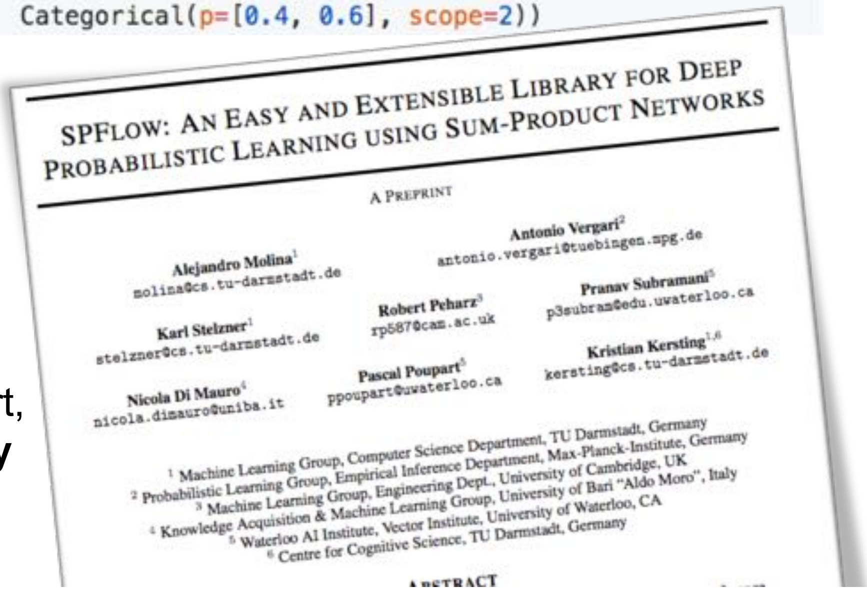
Kristian Kersting

github.com/SPFlow




```
from spn.structure.leaves.parametric.Parametric import Categorical

spn = 0.4 * (Categorical(p=[0.2, 0.8], scope=0) *
            (0.3 * (Categorical(p=[0.3, 0.7], scope=1) *
                    Categorical(p=[0.4, 0.6], scope=2))
           + 0.7 * (Categorical(p=[0.5, 0.5], scope=1) *
                    Categorical(p=[0.6, 0.4], scope=2))))
      + 0.6 * (Categorical(p=[0.2, 0.8], scope=0) *
               Categorical(p=[0.3, 0.7], scope=1) *
               Categorical(p=[0.4, 0.6], scope=2))
```



SPFLOW: AN EASY AND EXTENSIBLE LIBRARY FOR DEEP PROBABILISTIC LEARNING USING SUM-PRODUCT NETWORKS

A PREPRINT

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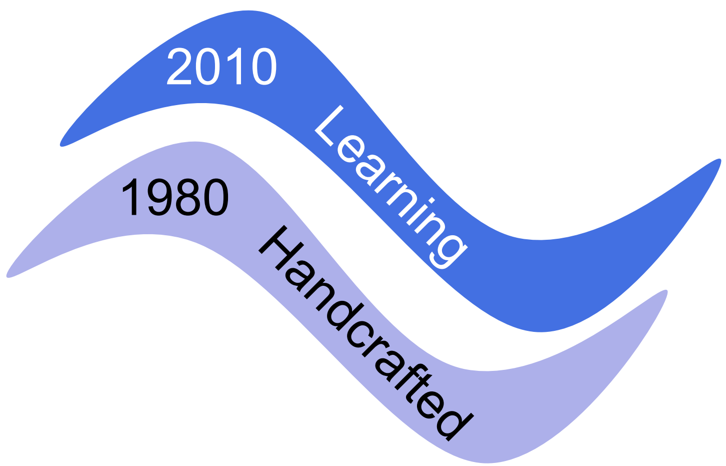
ABSTRACT

Alejandro Molina, Antonio Vergari, Karl Stelzner, Robert Peharz, Pranav Subramani, Nicola Di Mauro, Pascal Poupart, Kristian Kersting: **SPFlow: An Easy and Extensible Library for Deep Probabilistic Learning using Sum-Product Networks**. CoRR abs/1901.03704 (2019)

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



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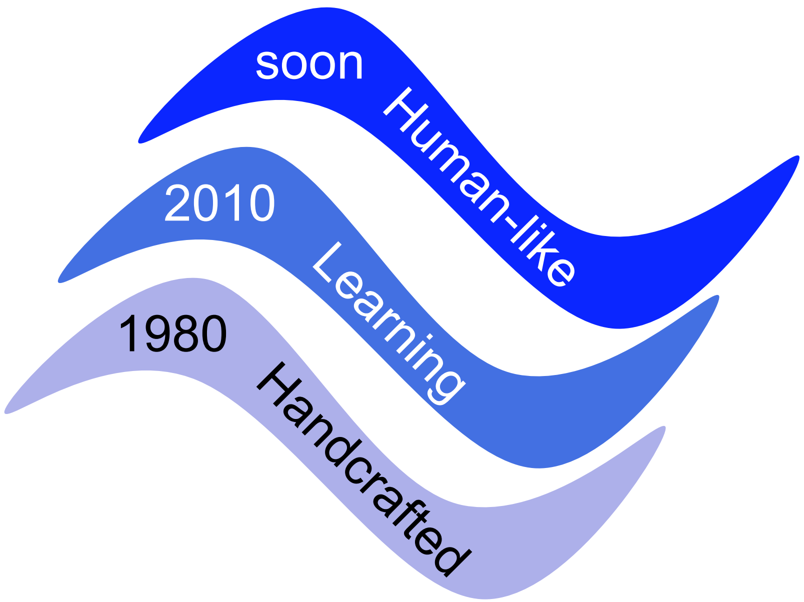
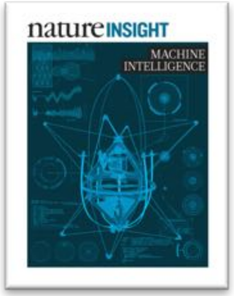


AI systems that can acquire human-like communication and reasoning capabilities, with the ability to recognise new situations and adapt to them.

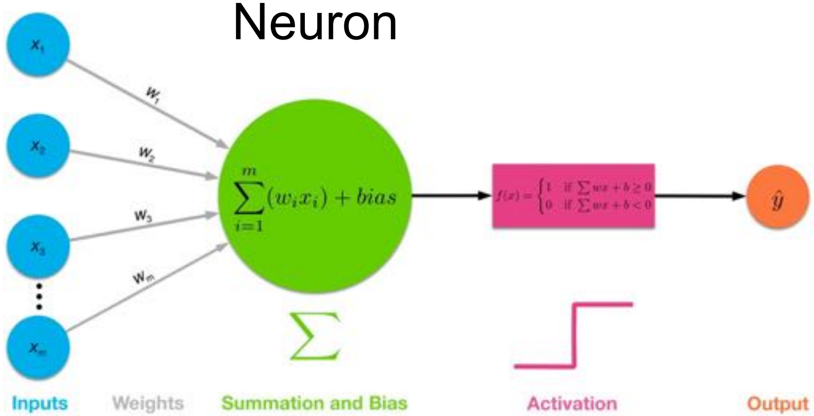
Deep Neural Networks

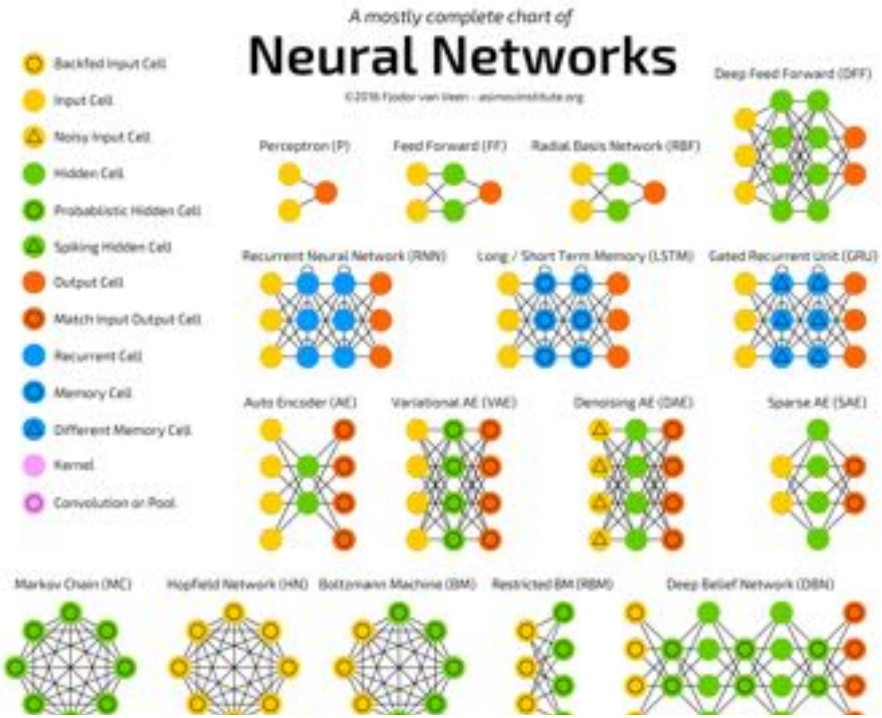


Potentially much more powerful than shallow architectures, represent computations

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

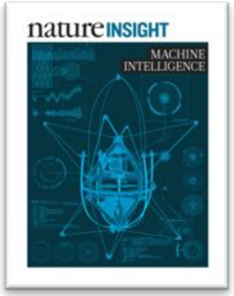
Neuron





Differentiable Programming

Deep Neural Networks



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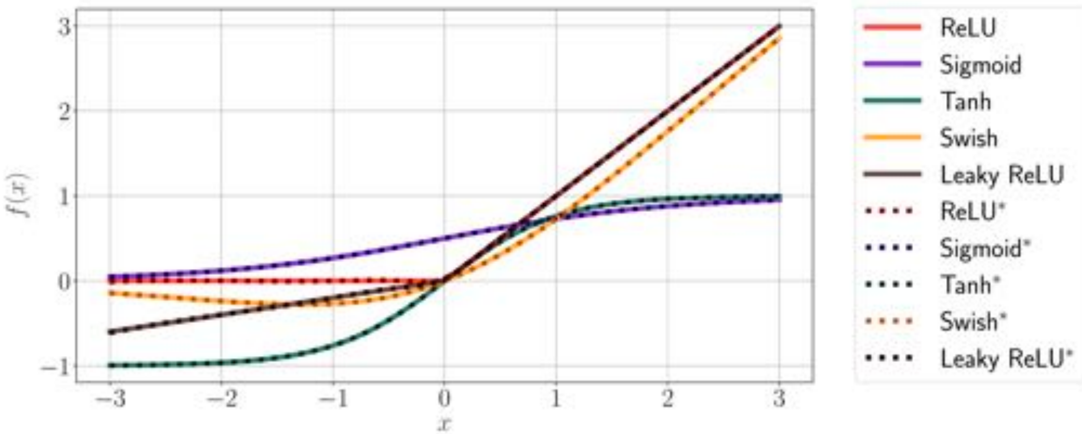
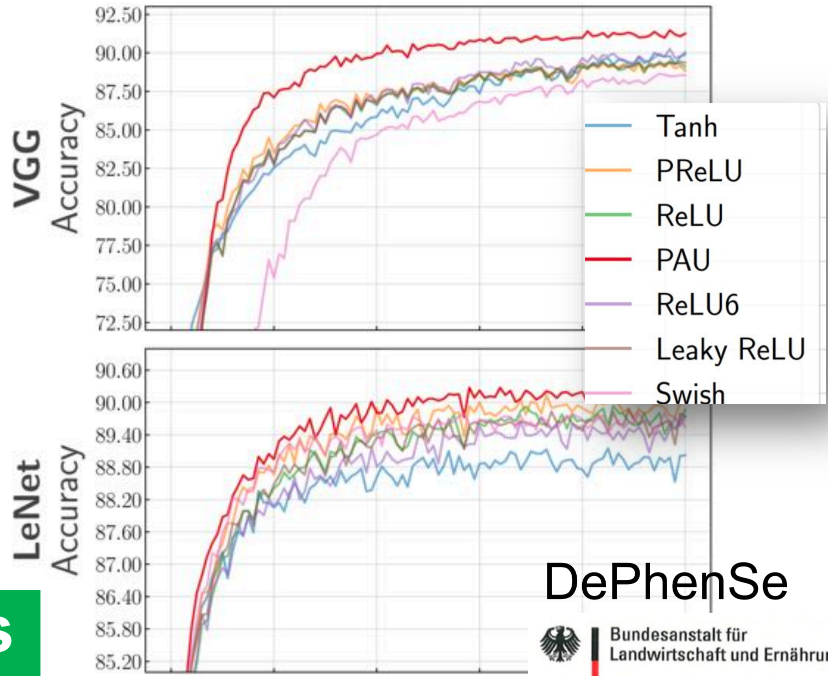


Fashion MNIST



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

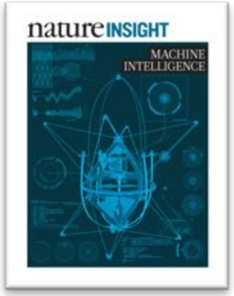
E2E-Learning Activation Functions

[Molina, Schramowski, Kersting arxiv:1901.03704 2019]

DePhenSe

Bundesanstalt für Landwirtschaft und Ernährung

Deep Neural Networks



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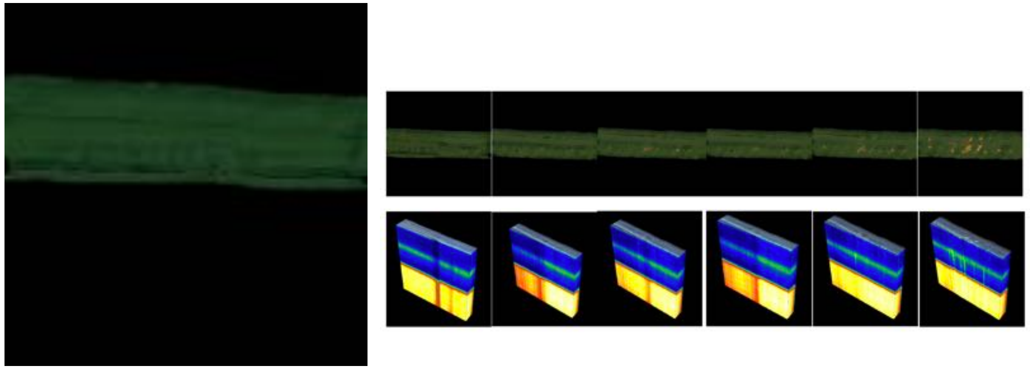

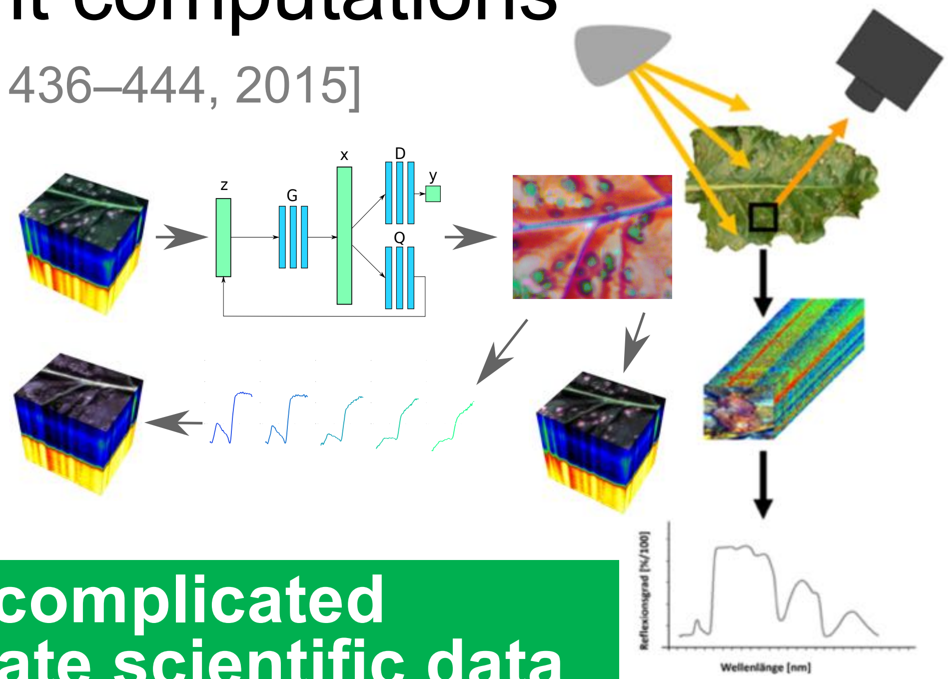

They "develop intuition" about complicated biological processes and generate scientific data

[Schramowski, Brugger, Mahlein, Kersting 2019]

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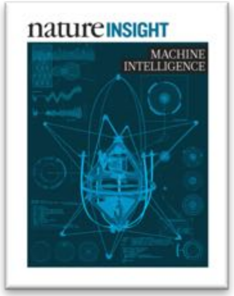
Deep Neural Networks



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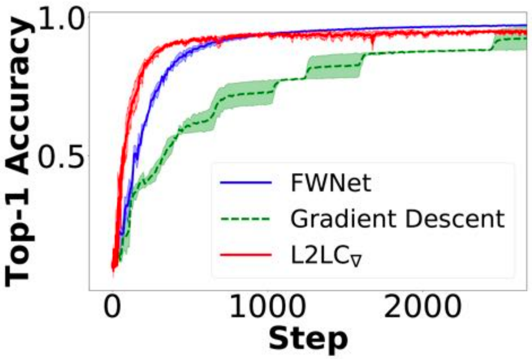

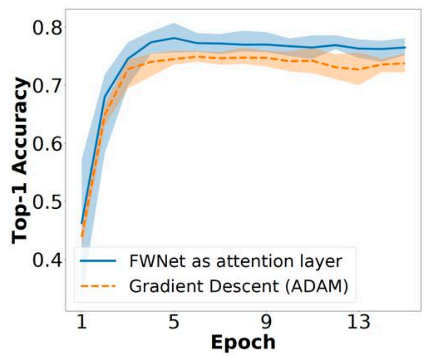

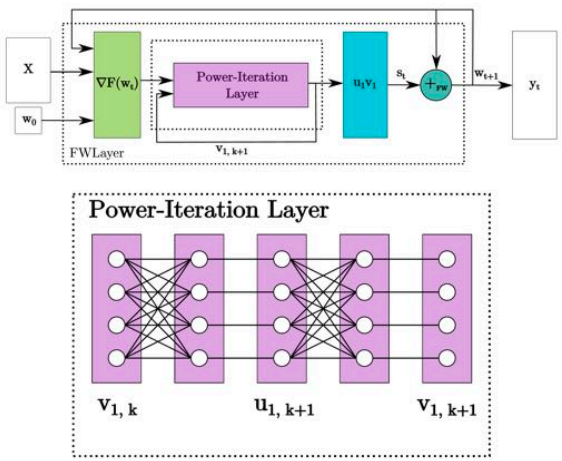

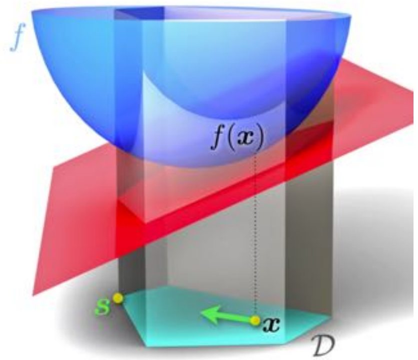

They “invent” constrained optimizers

DePhenSe

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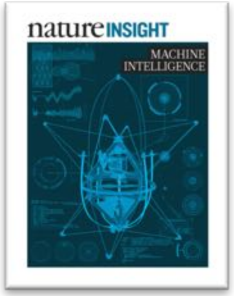
[Schramowski, Bauckhage, Kersting arXiv:1803.04300, 2018]



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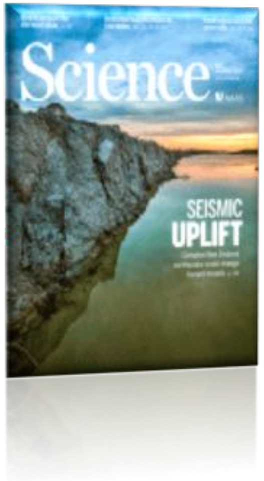

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REPORTS | PSYCHOLOGY

Semantics derived automatically from language corpora contain human-like biases

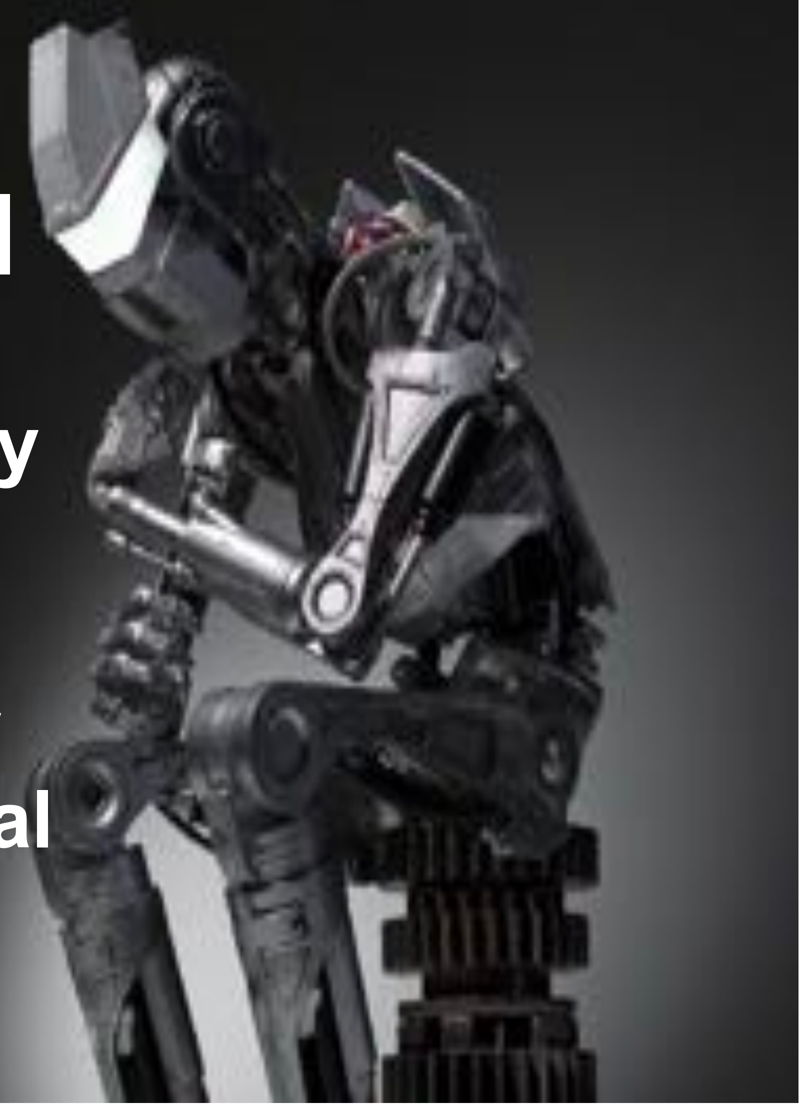
Aylin Caliskan[1,*], Joanna J. Bryson[1,2,*], Arvind Narayanan[1,*]

+ See all authors and affiliations

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

They “capture” stereotypes from human language

They can 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

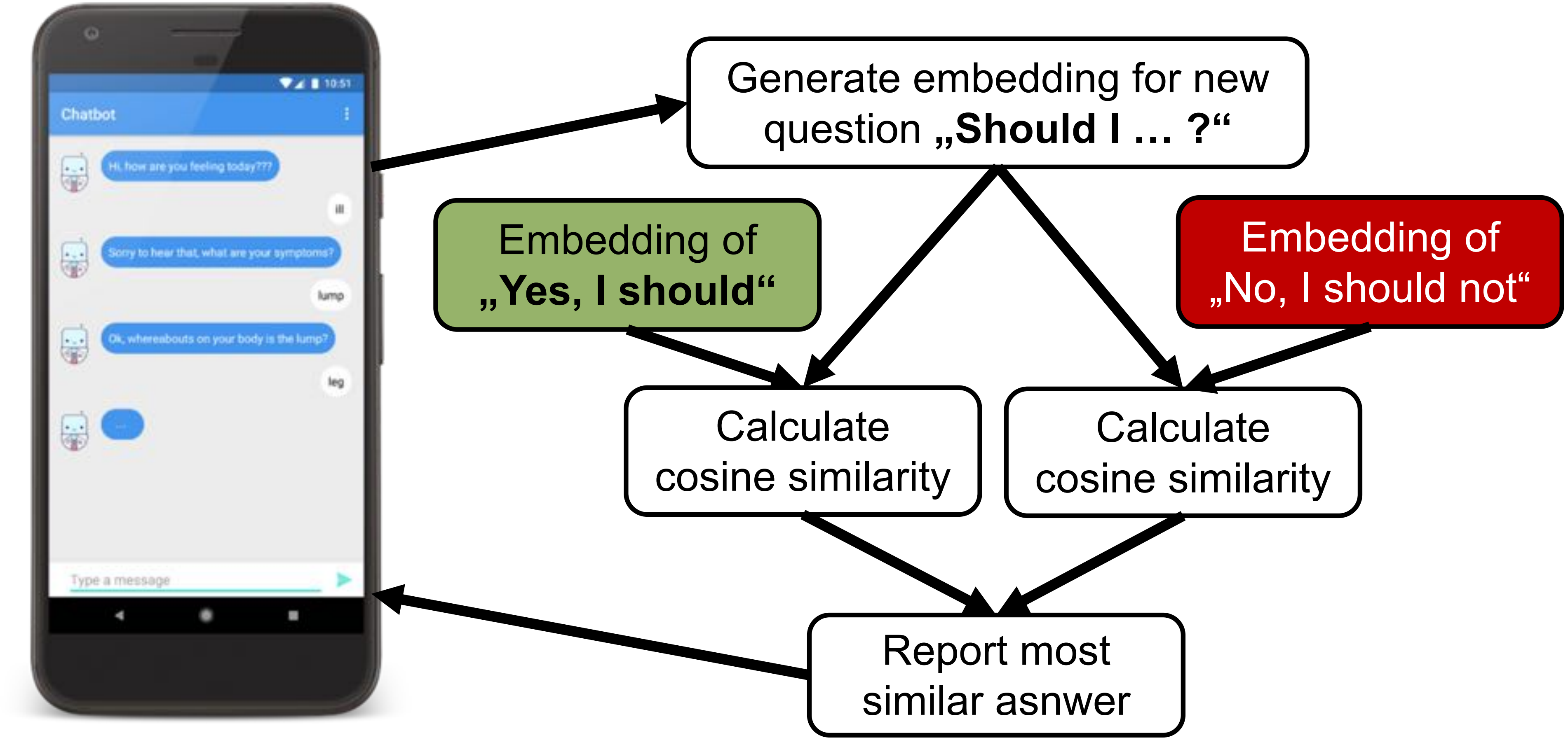
MACHINE INTELLIGENCE RESEARCH INSTITUTE

The Moral Choice Machine

Not all stereotypes are bad

[Jentzsch, Schramowski, Rothkopf, Kersting AIES 2019]

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



The Moral Choice Machine

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AAAI / ACM conference on
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TECHNISCHE UNIVERSITÄT DARMSTADT

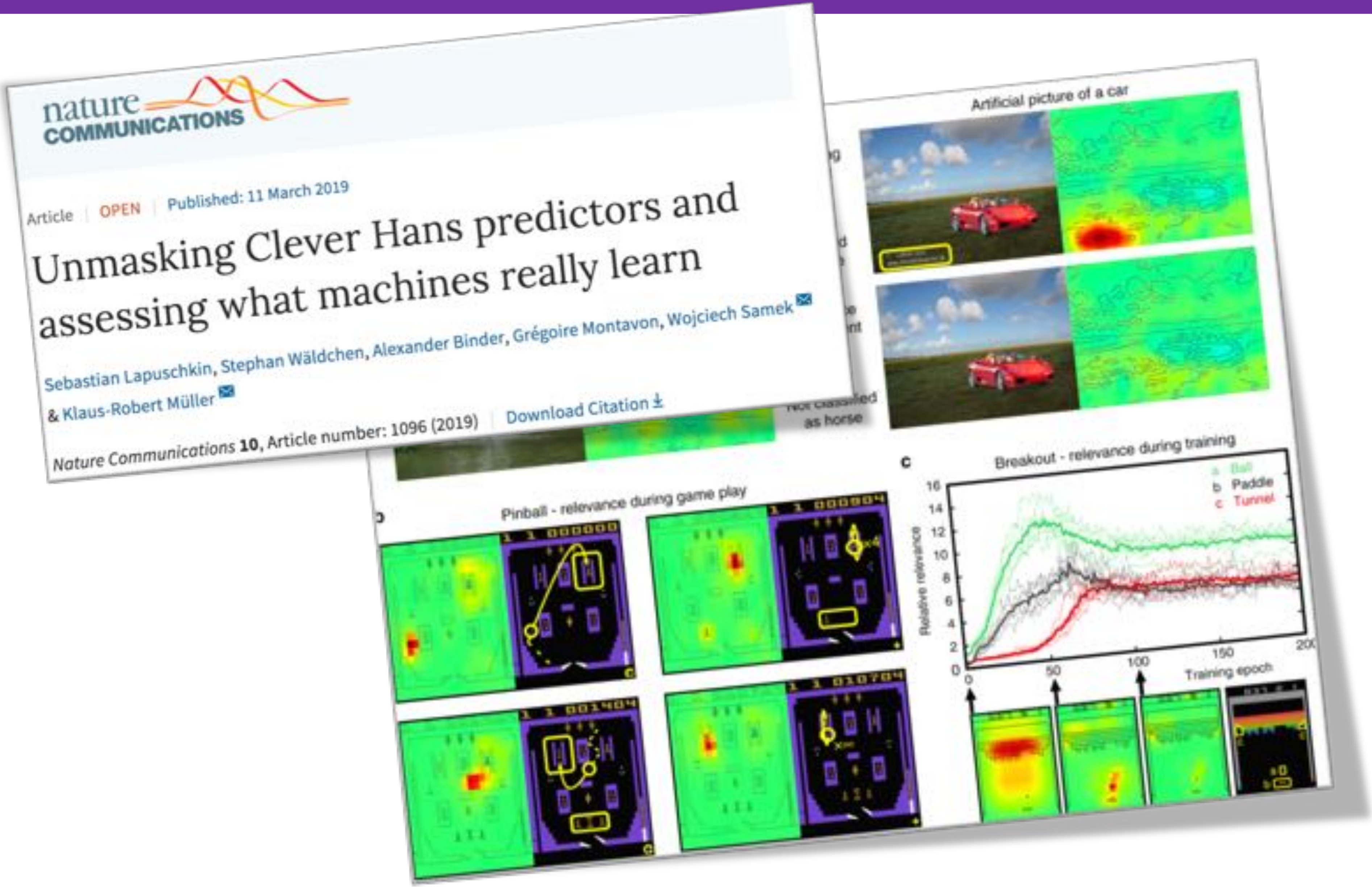
https://www.hr-fernsehen.de/sendungen-a-z/hauptsache-kultur/sendungen/hauptsache-kultur,sendung-56324.html

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

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

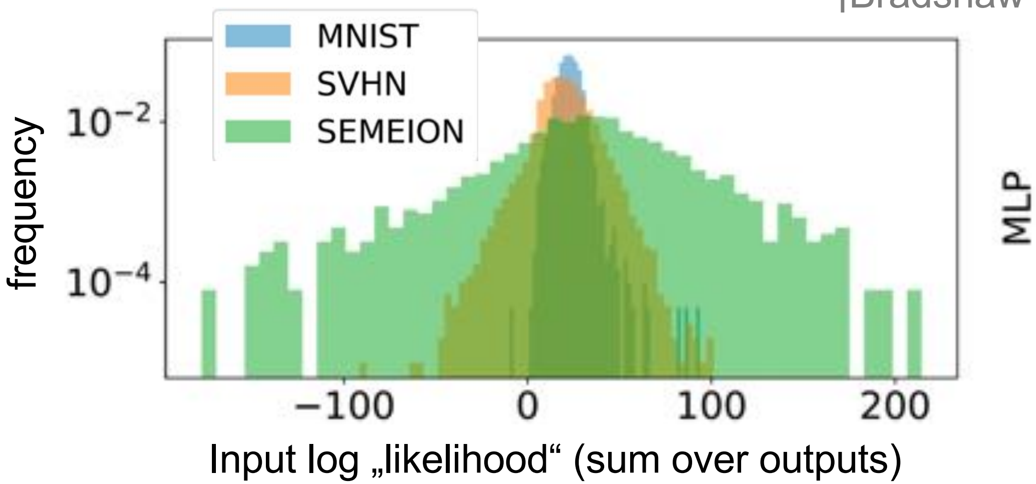
Train & Evaluate

SVHN

SEMEION

Transfer Testing

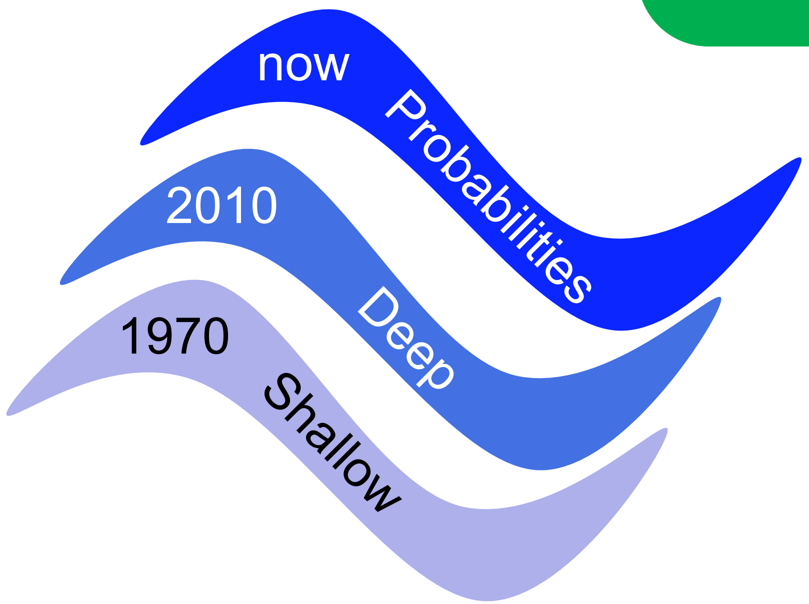
[Bradshaw et al. arXiv:1707.02476 2017]



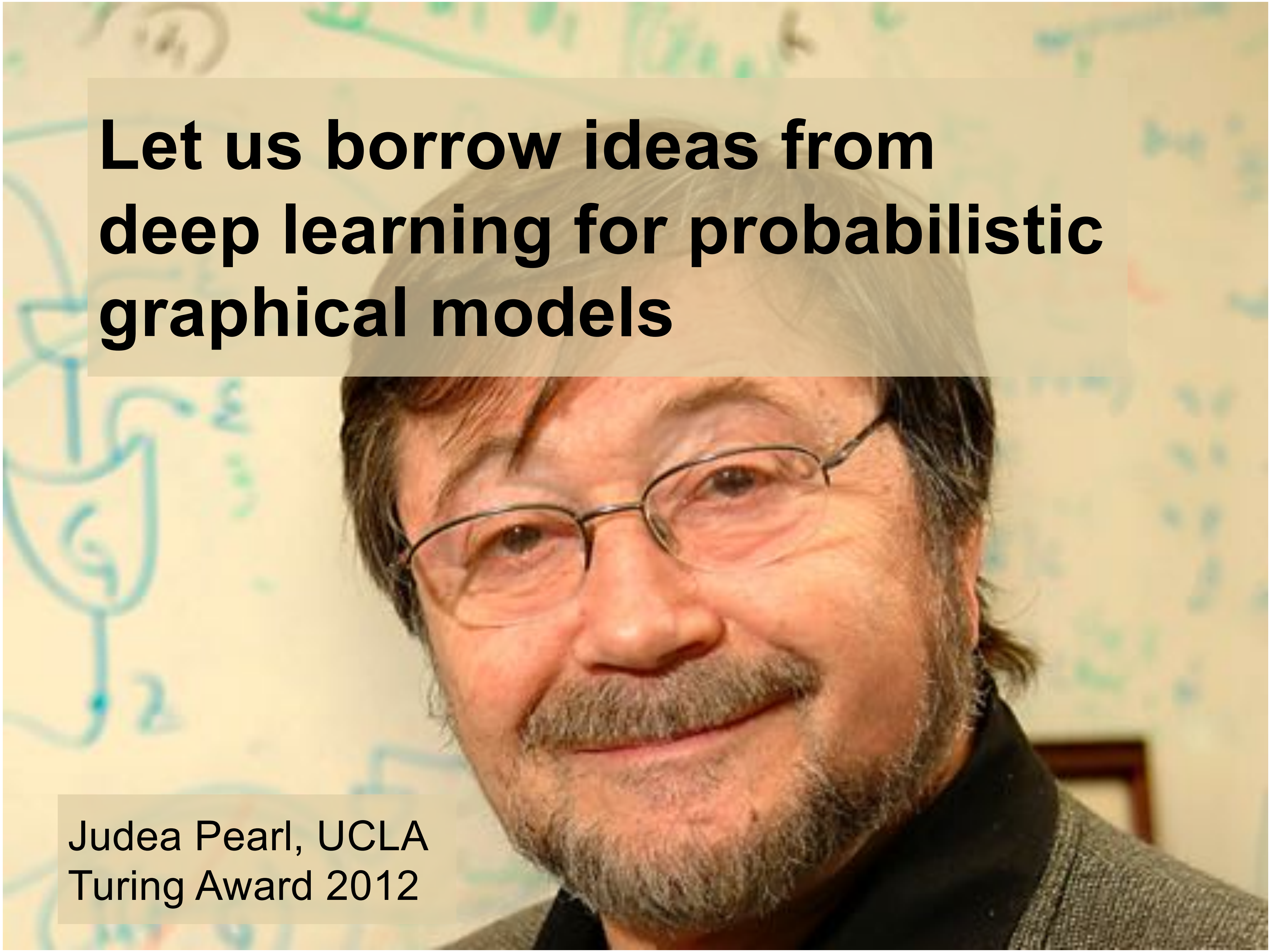
Many DNNs cannot distinguish the datasets

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

The third wave of deep learning



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

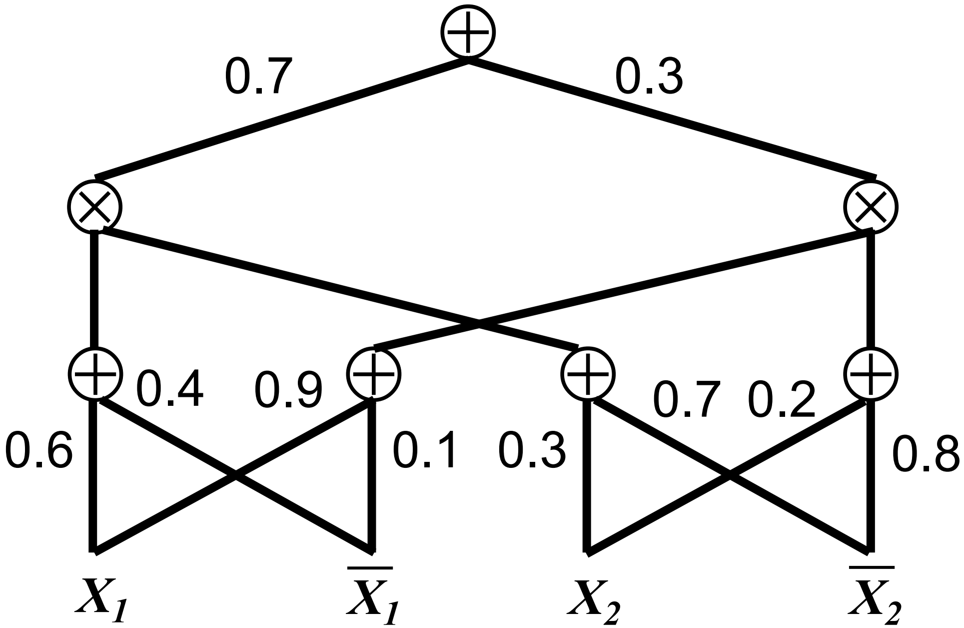


Let us borrow ideas from deep learning for probabilistic graphical models

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

Alternative Representation: Graphical Models as (Deep) Networks

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

$$\begin{aligned} P(X) = {} & 0.4 \cdot \mathrm{I}[X_1{=}1] \cdot \mathrm{I}[X_2{=}1] \\ & + 0.2 \cdot \mathrm{I}[X_1{=}1] \cdot \mathrm{I}[X_2{=}0] \\ & + 0.1 \cdot \mathrm{I}[X_1{=}0] \cdot \mathrm{I}[X_2{=}1] \\ & + 0.3 \cdot \mathrm{I}[X_1{=}0] \cdot \mathrm{I}[X_2{=}0] \end{aligned}$$

Alternative Representation: Graphical Models as (Deep) Networks

X_1	X_2	$P(X)$
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& + 0.2 \cdot \mathrm{I}[X_1{=}1] \cdot \mathrm{I}[X_2{=}0] \\
& + 0.1 \cdot \mathrm{I}[X_1{=}0] \cdot \mathrm{I}[X_2{=}1] \\
& + 0.3 \cdot \mathrm{I}[X_1{=}0] \cdot \mathrm{I}[X_2{=}0]
\end{aligned}
$$

Shorthand using Indicators

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

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

Summing Out Variables

Let us say, we want 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

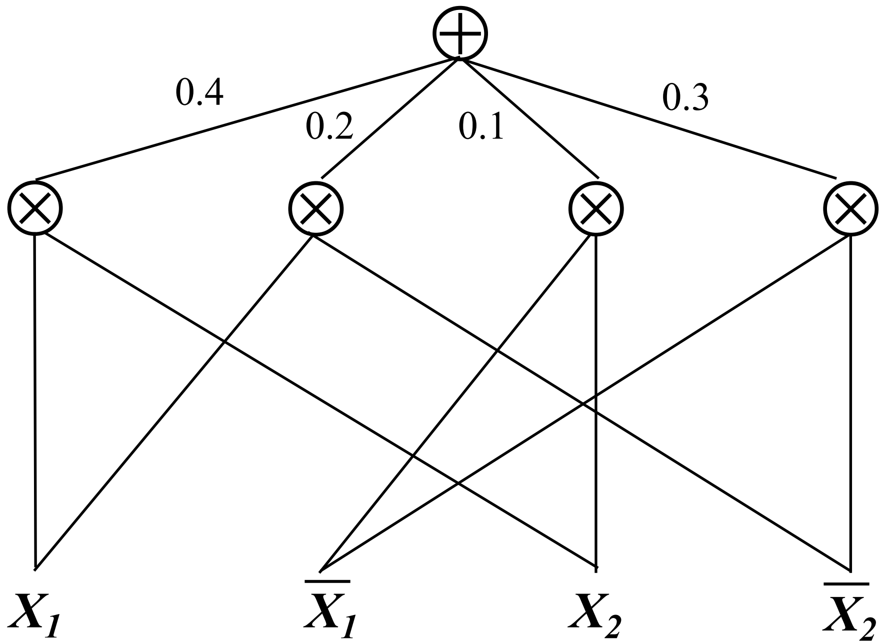
$$\begin{aligned} P(e) = &\ \mathbf{0.4 \cdot X_1 \cdot X_2} \\ &+ \mathbf{0.2 \cdot X_1 \cdot \overline{X}_2} \\ &+ 0.1 \cdot \overline{X}_1 \cdot X_2 \\ &+ 0.3 \cdot \overline{X}_1 \cdot \overline{X}_2 \end{aligned}$$

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

Easy: Set both indicators of X2 to 1

This can be represented 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

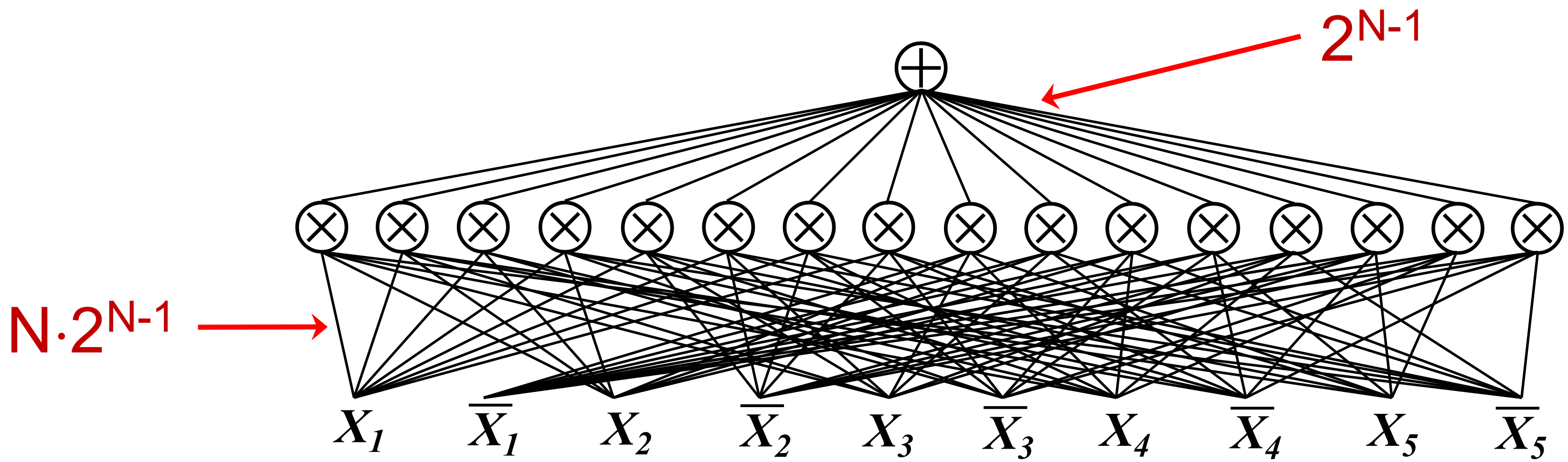


network polynomial

However, the network polynomial of a distribution might be exponentially large

Example: Parity

Uniform distribution over states with even number of 1's

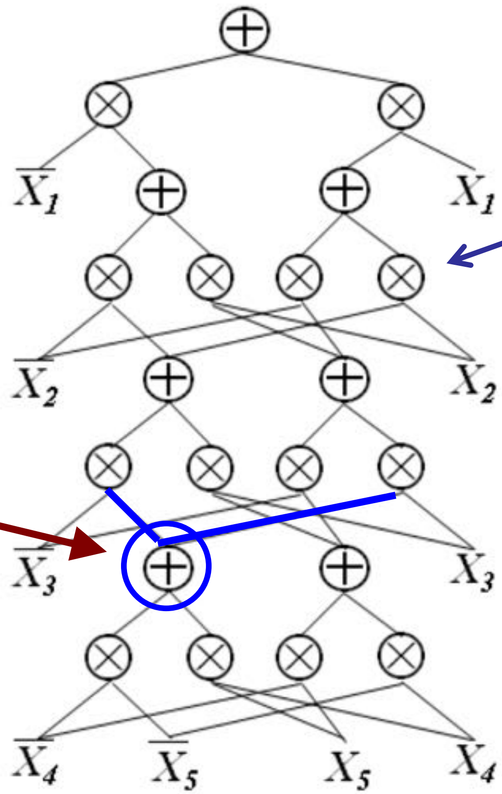


Make the computational graphs deep

Example: Parity

Uniform distribution over states with even number of 1's

Reuse partial computation

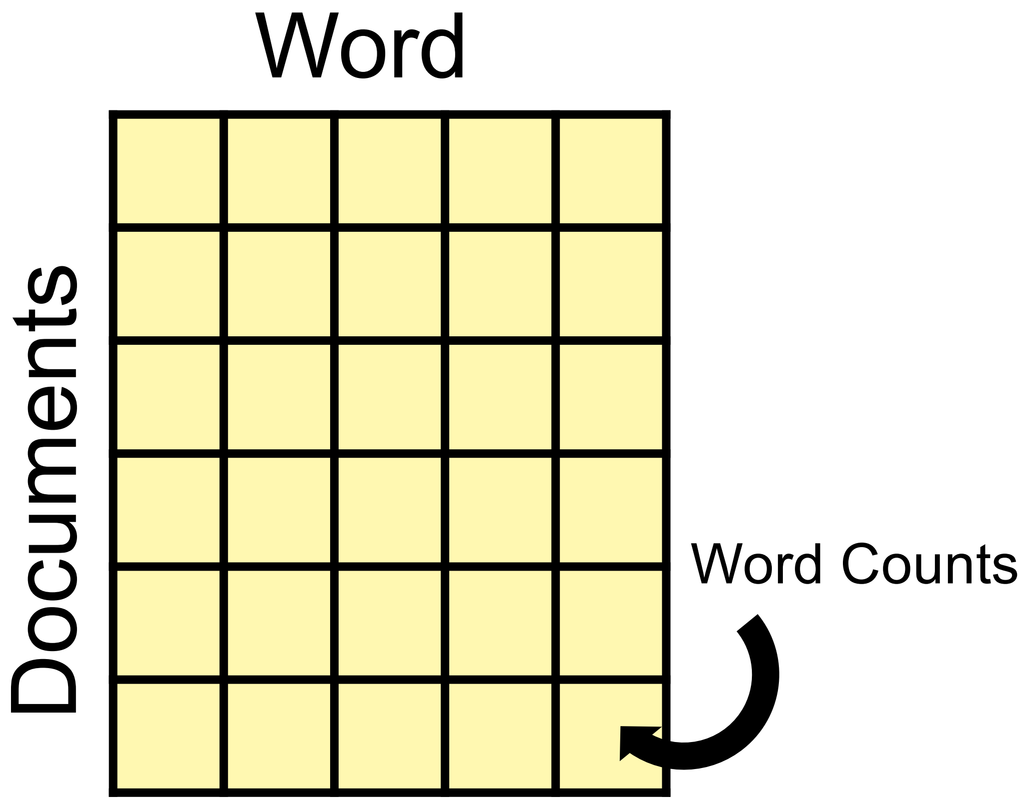


Induce many hidden layers

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

Principled approach to selecting (Tree-)SPNs

Testing independence using a (non-parametric) independency test



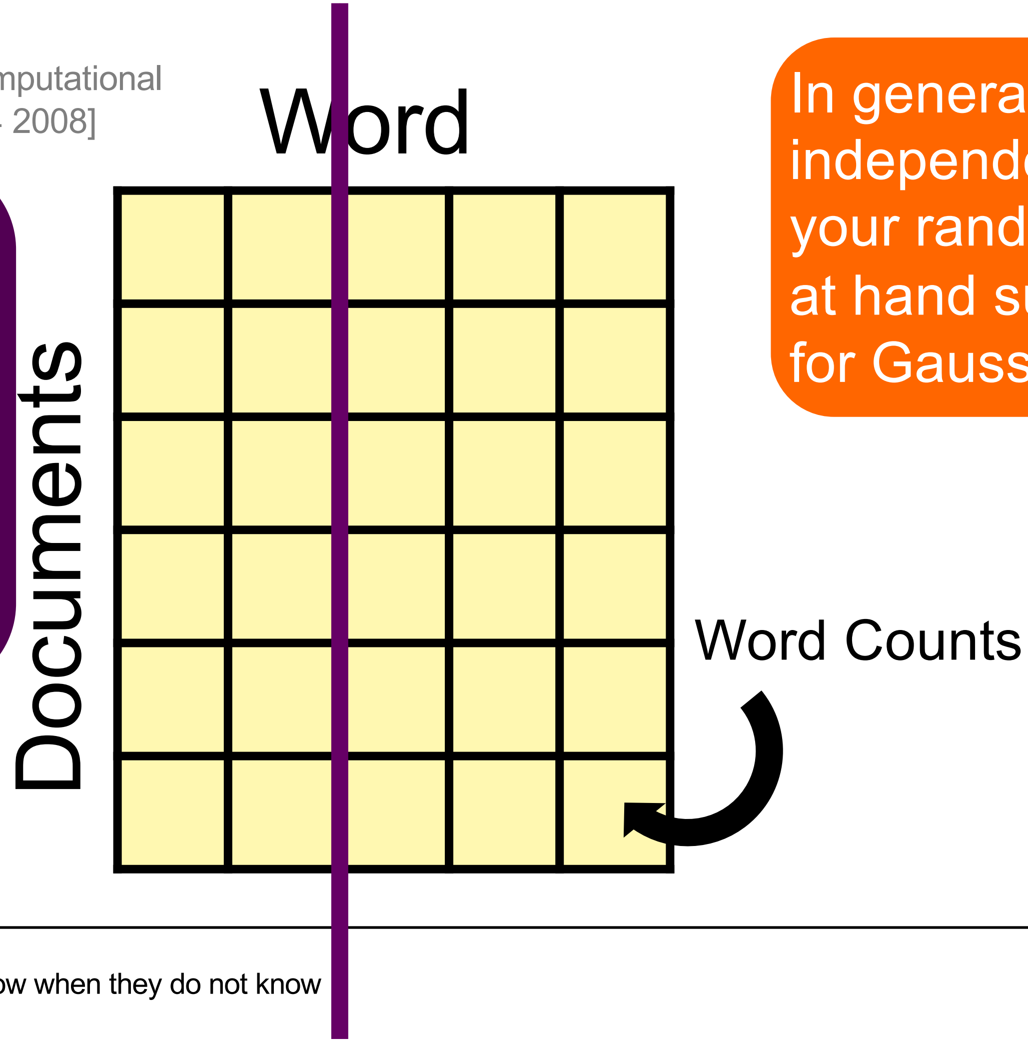
[Poon, Domingos UAI'11; Molina, Natarajan, Kersting AAAI´17]

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)



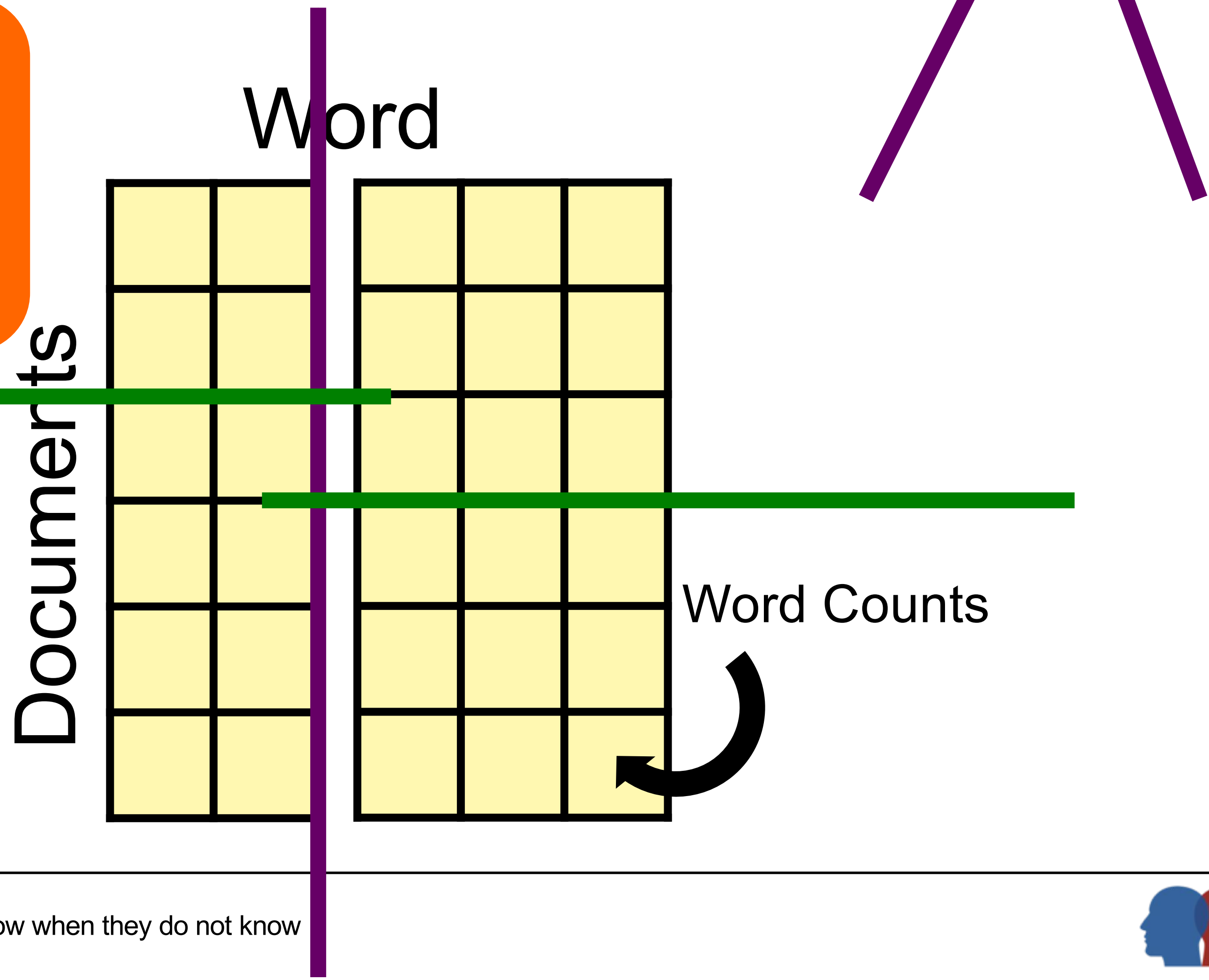
In general use the independency test for your random variables at hand such as g-test for Gaussians

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 Poisson Dependency Networks or random splits



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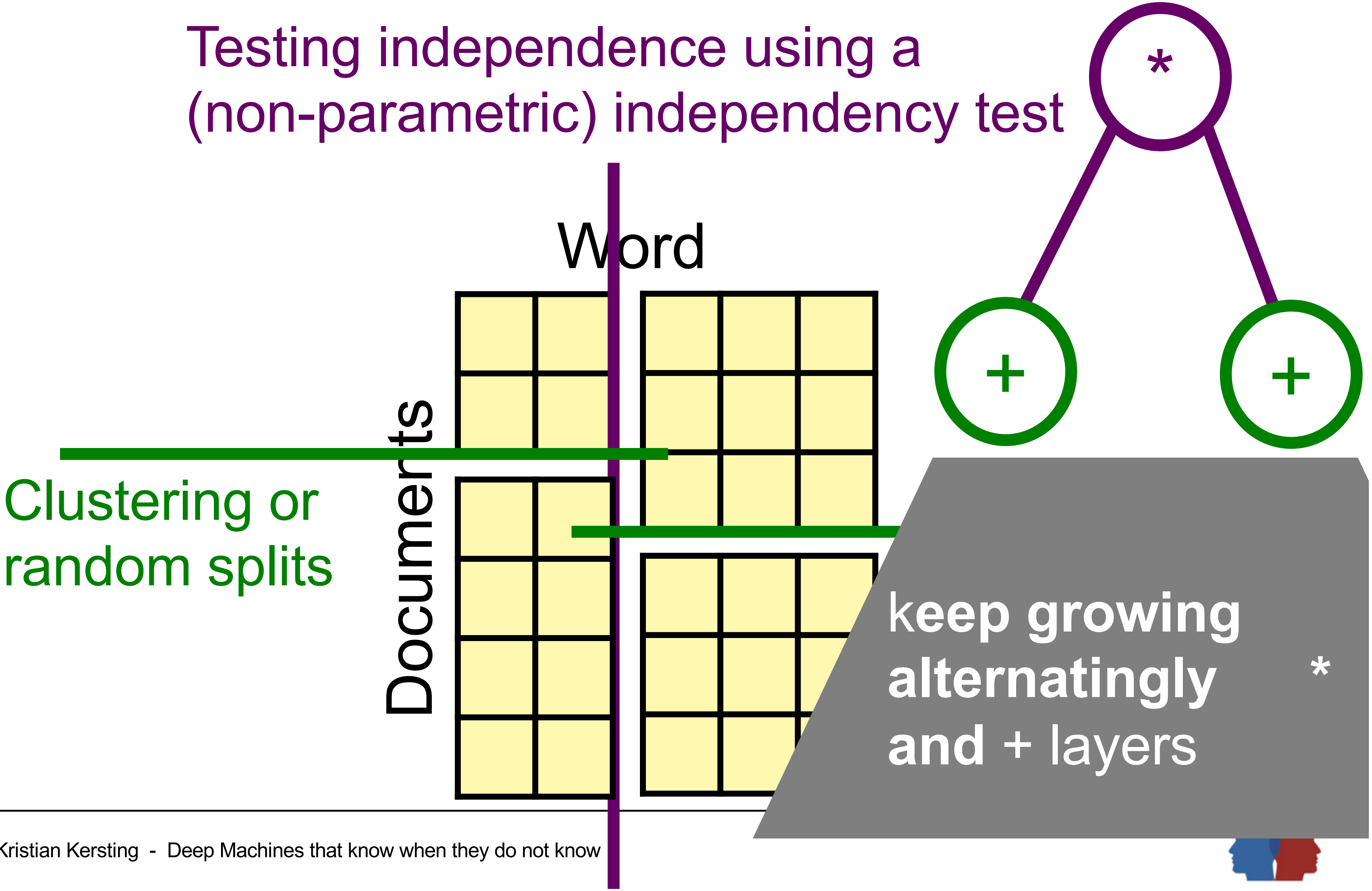

Random sum-product networks

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

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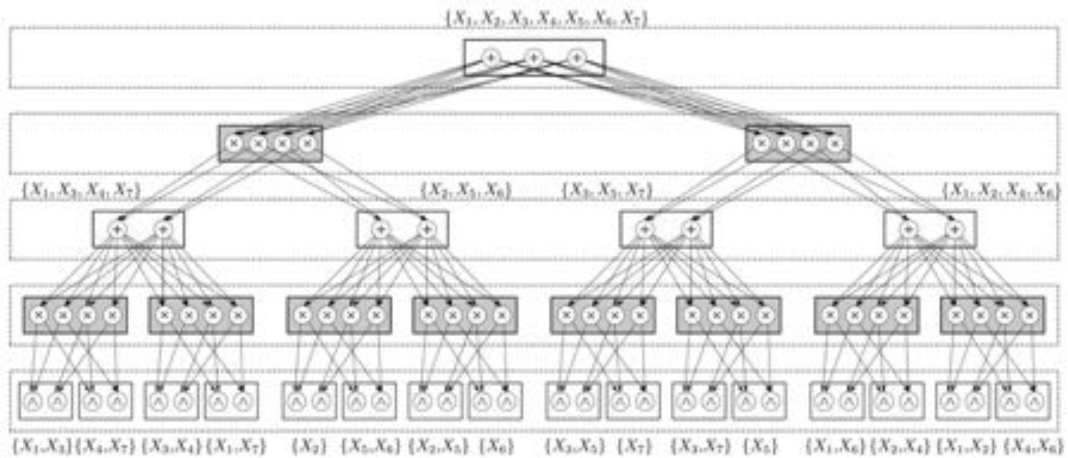
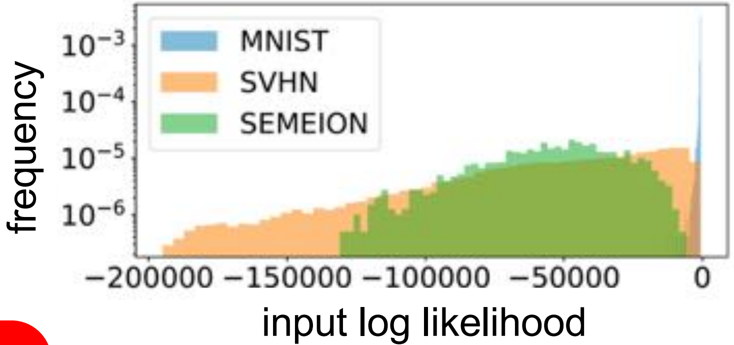
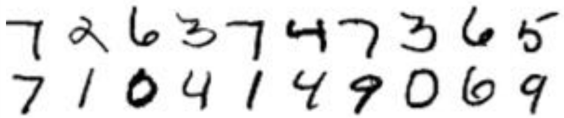


Similar to Random Forests, build a random SPN structure over univariate distributions. This can be done in an informed way or completely at random

		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

Random sum-product networks

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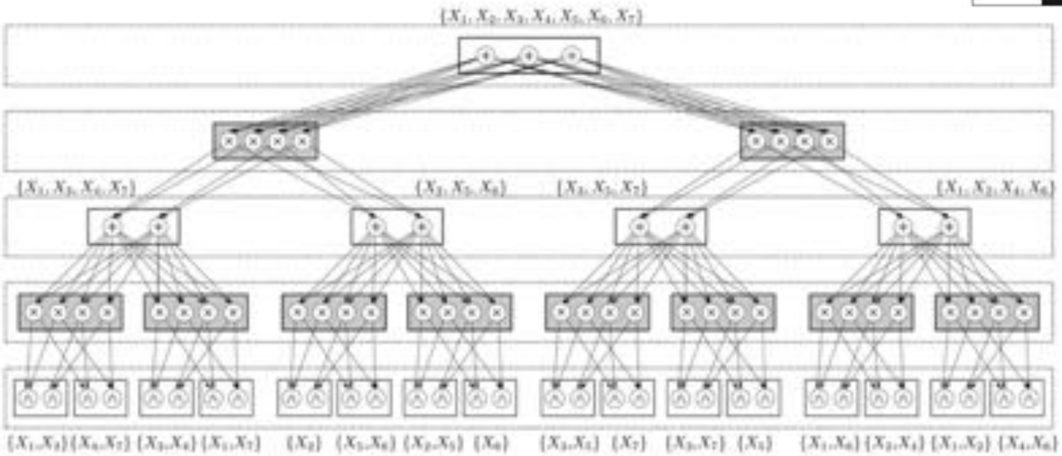
TECHNISCHE UNIVERSITÄT DARMSTADT
UNI GRAZ
UBER AI Labs

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



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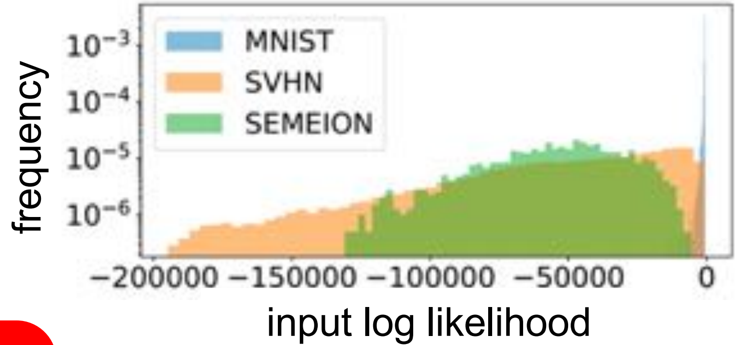

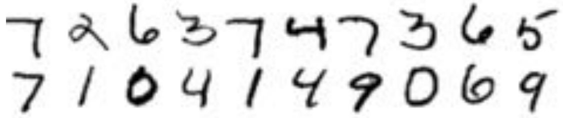
outliers
prototypes


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

[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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UNIVERSITY OF WATERLOO
CAML
MADESI
Max Planck Institute for Intelligent Systems
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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

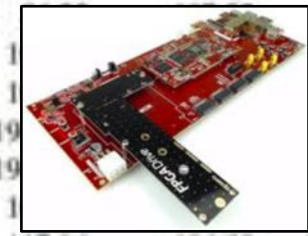
SPFlow, an open-source Python library providing a simple interface to inference, learning and manipulation routines for deep and tractable probabilistic models called Sum-Product Networks (SPNs). The library allows one to quickly create SPNs both from data and through a domain specific language (DSL). It efficiently implements several probabilistic inference

[Sommer, Oppermann, Molina, Binnig, Kersting, Koch ICDD 2018]

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?

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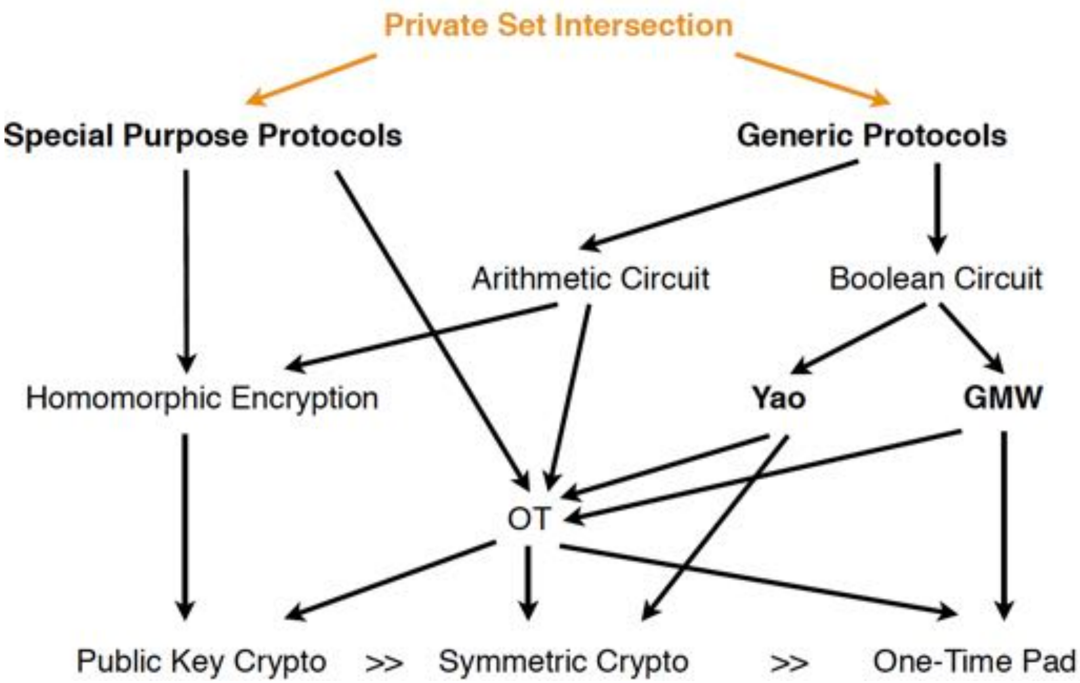
Federal Ministry of Education and Research



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

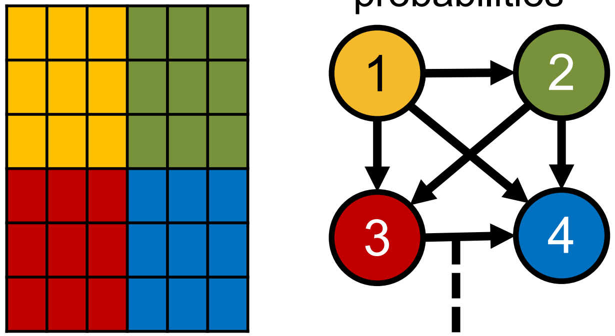
Homomorphic sum-product network

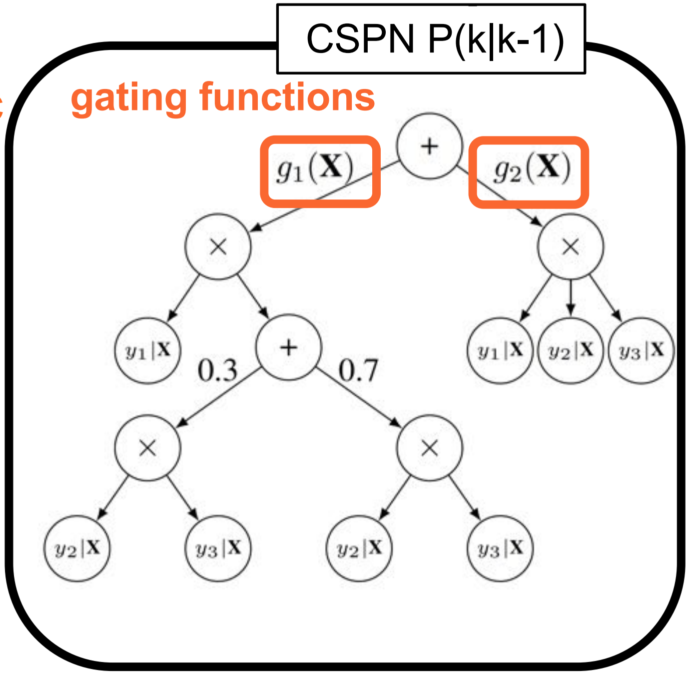
[Molina, Weinert, Treiber, Schneider, Kersting to be submitted 2019]

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

chain rule of probabilities





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]

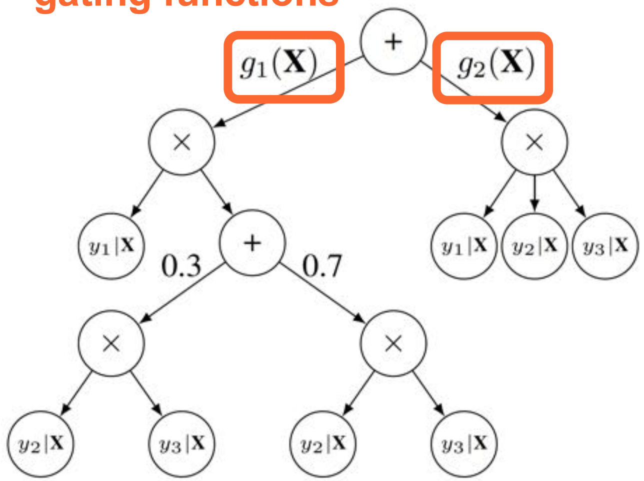
CAML DFG

[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**

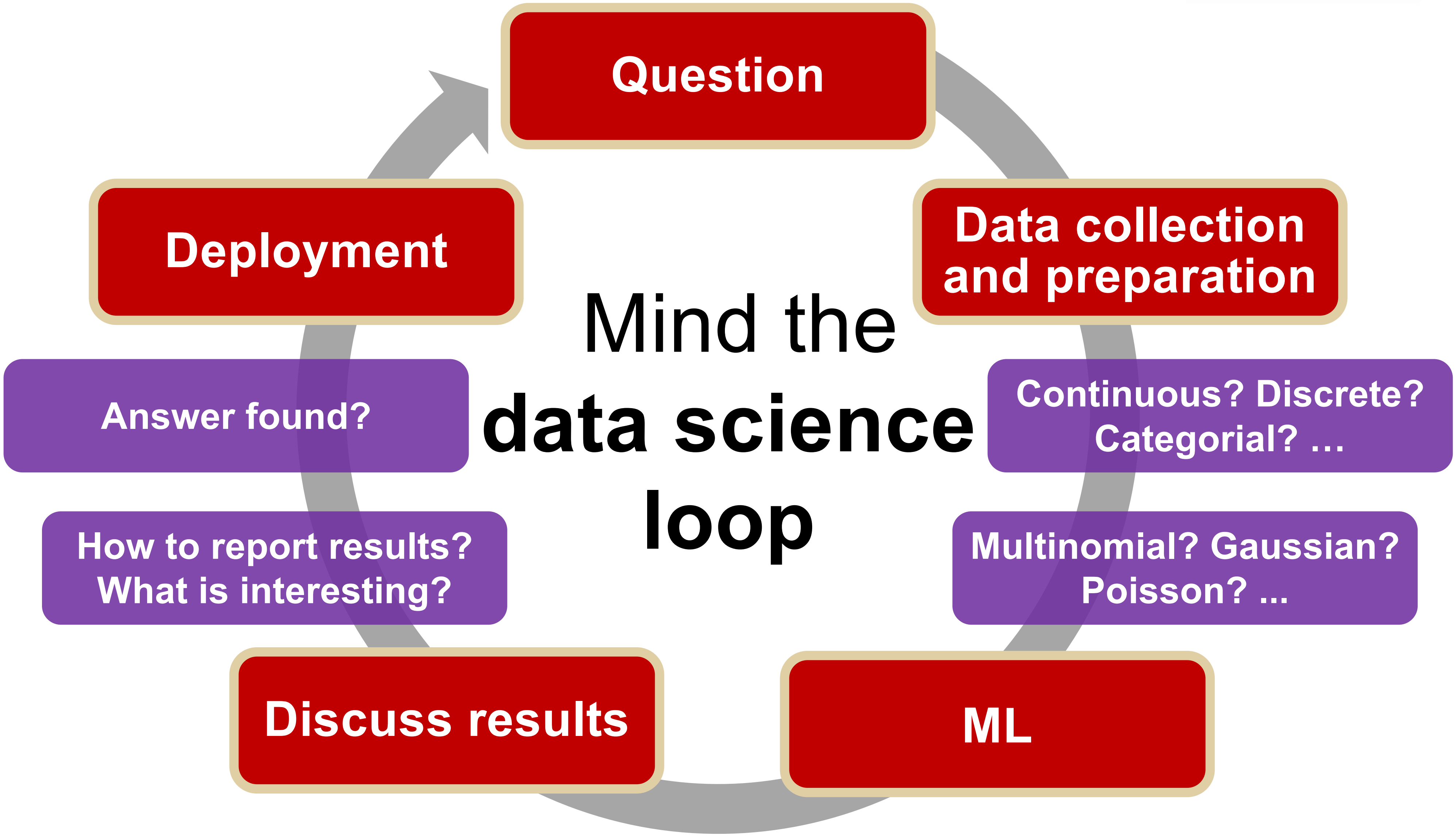
gating functions



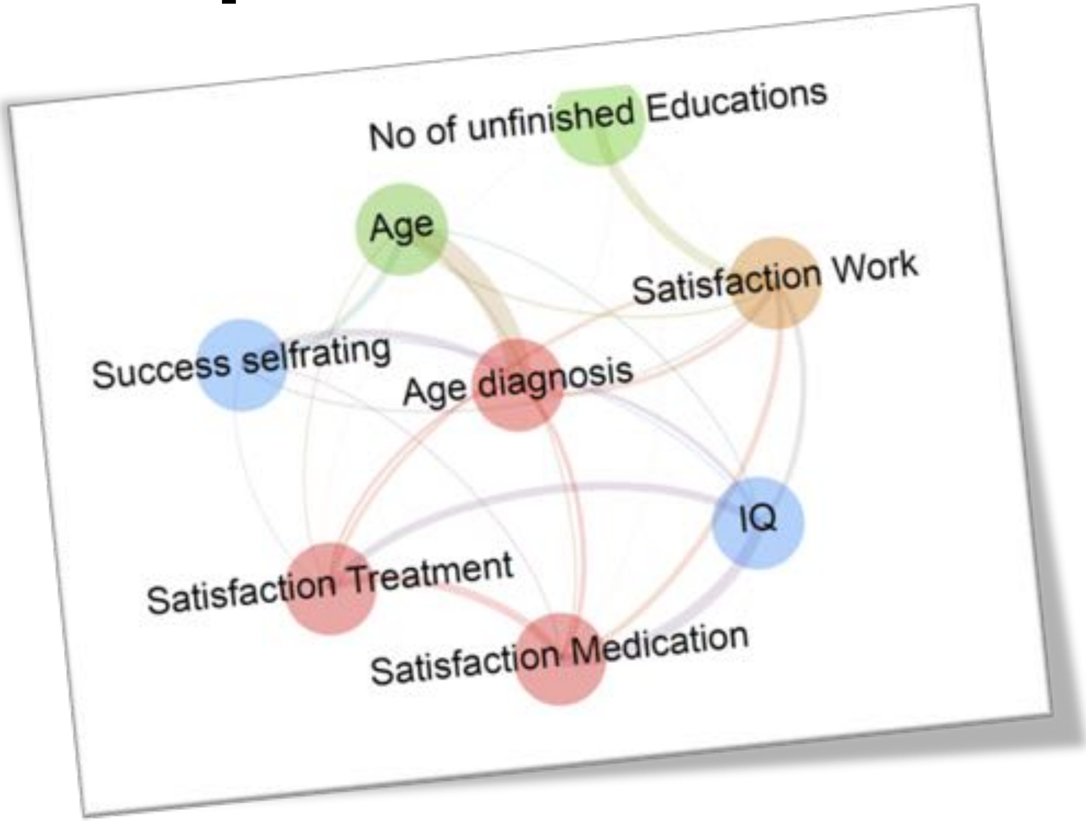
Conditional SPNs

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

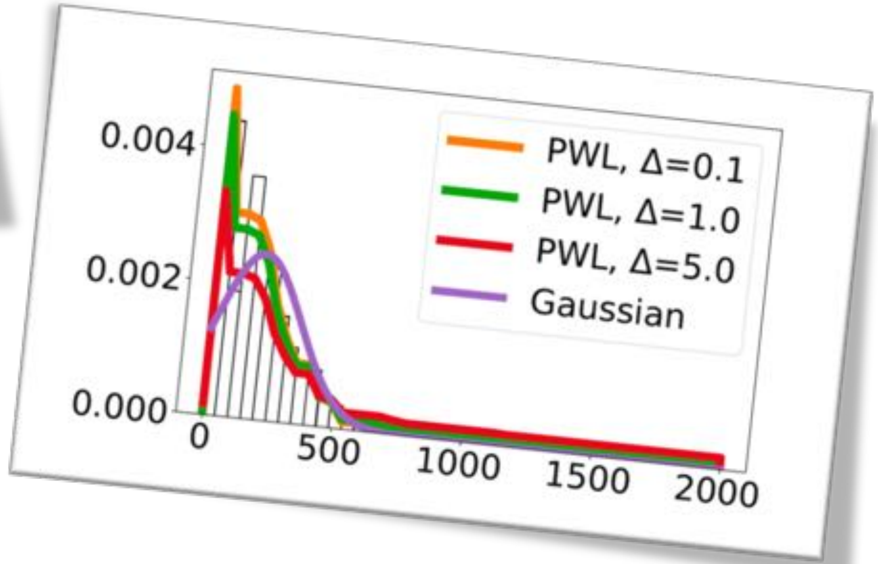
CAML DFG


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

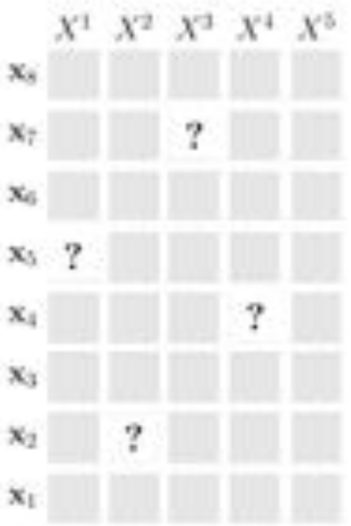
Use nonparametric independency tests and piece-wise linear approximations

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

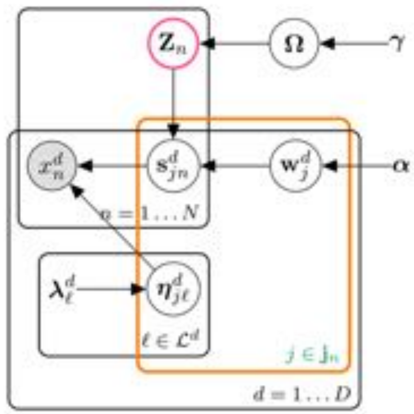
[Vergari, Molina, Peharz, Ghahramani, Kersting, Valera AAAI 2019]

The Explorative Automatic Statistician

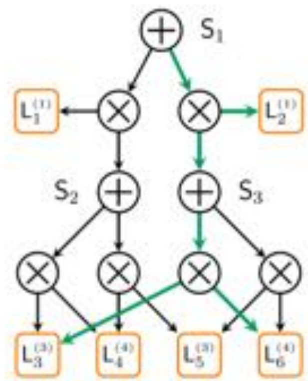
missing value



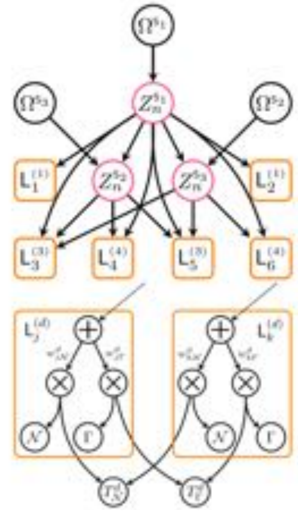
We can even automatically discovers the statistical types and parametric forms of the variables



Bayesian Type Discovery



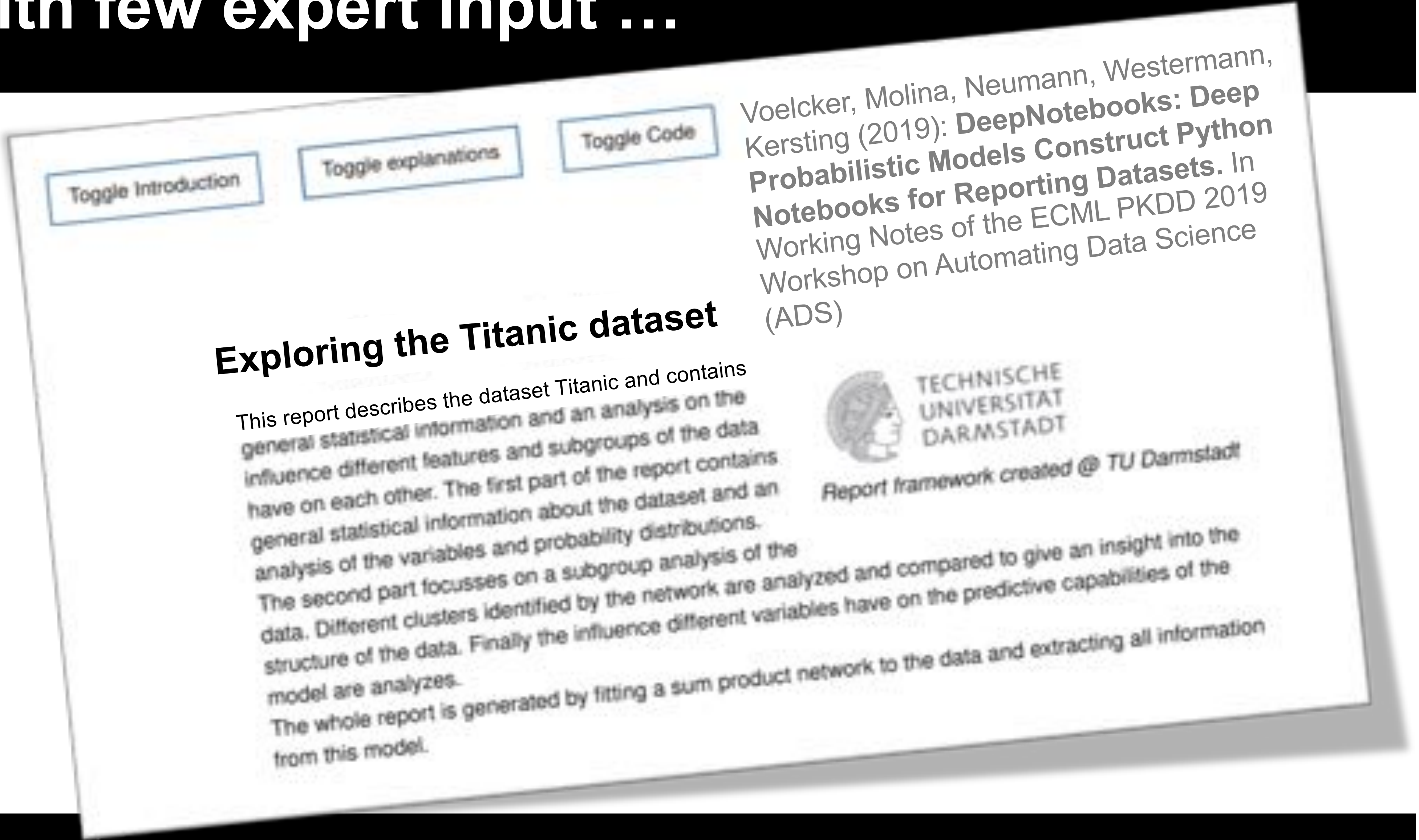
Mixed Sum-Product Network



Automatic Statistician

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

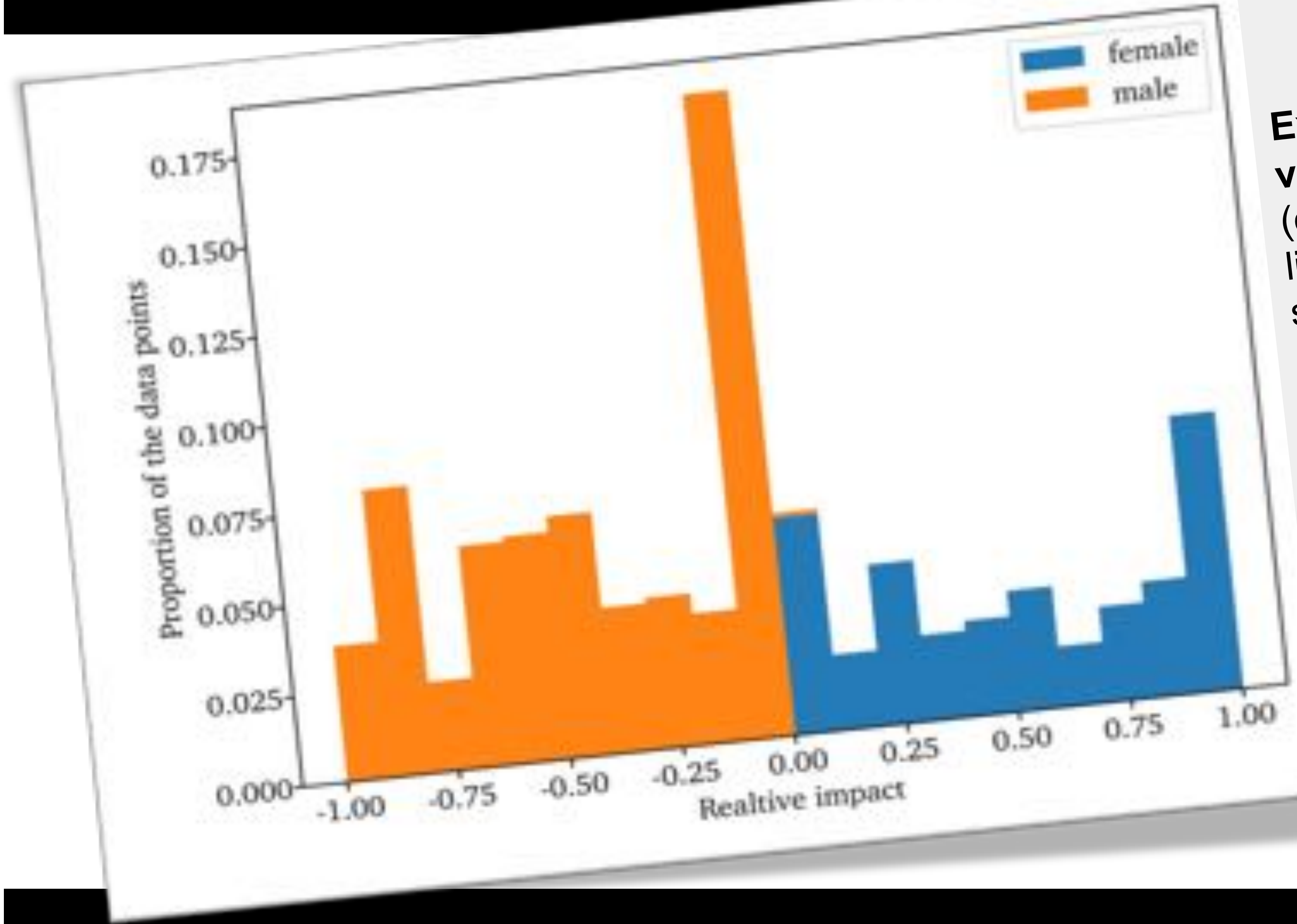
Voelcker, Molina, Neumann, Westermann, Kersting (2019): **DeepNotebooks: Deep Probabilistic Models Construct Python Notebooks for Reporting Datasets.** In Working Notes of the ECML PKDD 2019 Workshop on Automating Data Science (ADS)



…and can compile data reports automatically

*[Baehrens, Schroeter, Harmeling, Kawanabe, Hansen, Müller JMLR 11:1803-1831, 2010]

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



Explanation vector* (computable in linear time in the sizre of the SPN) **showing the impact of "gender" on the chances of survival for the Titanic dataset**

…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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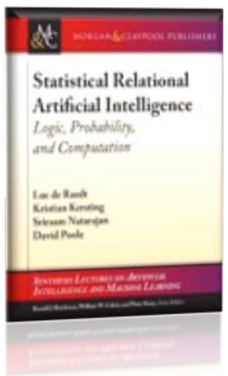
May 18, 2018

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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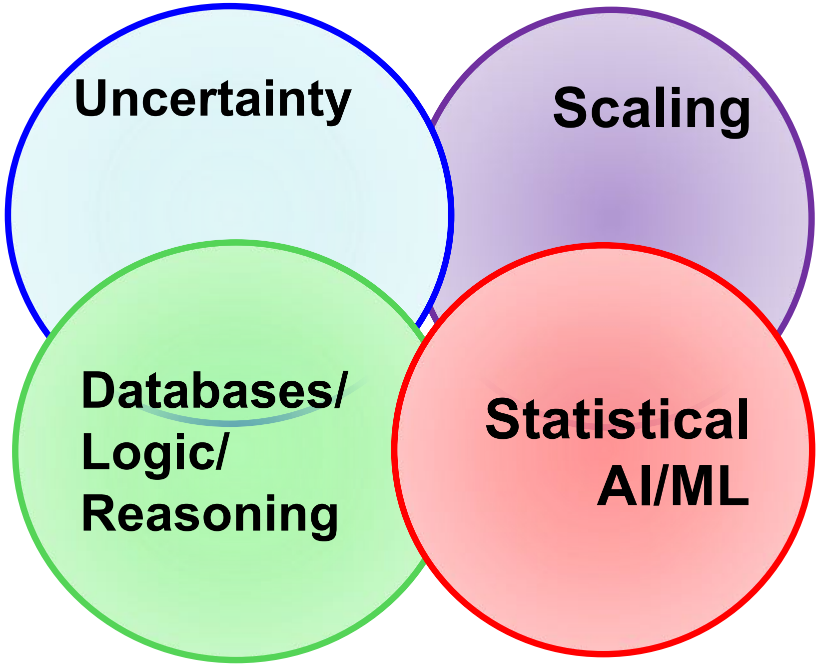
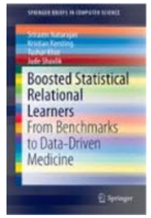
building general-purpose data science and ML machines

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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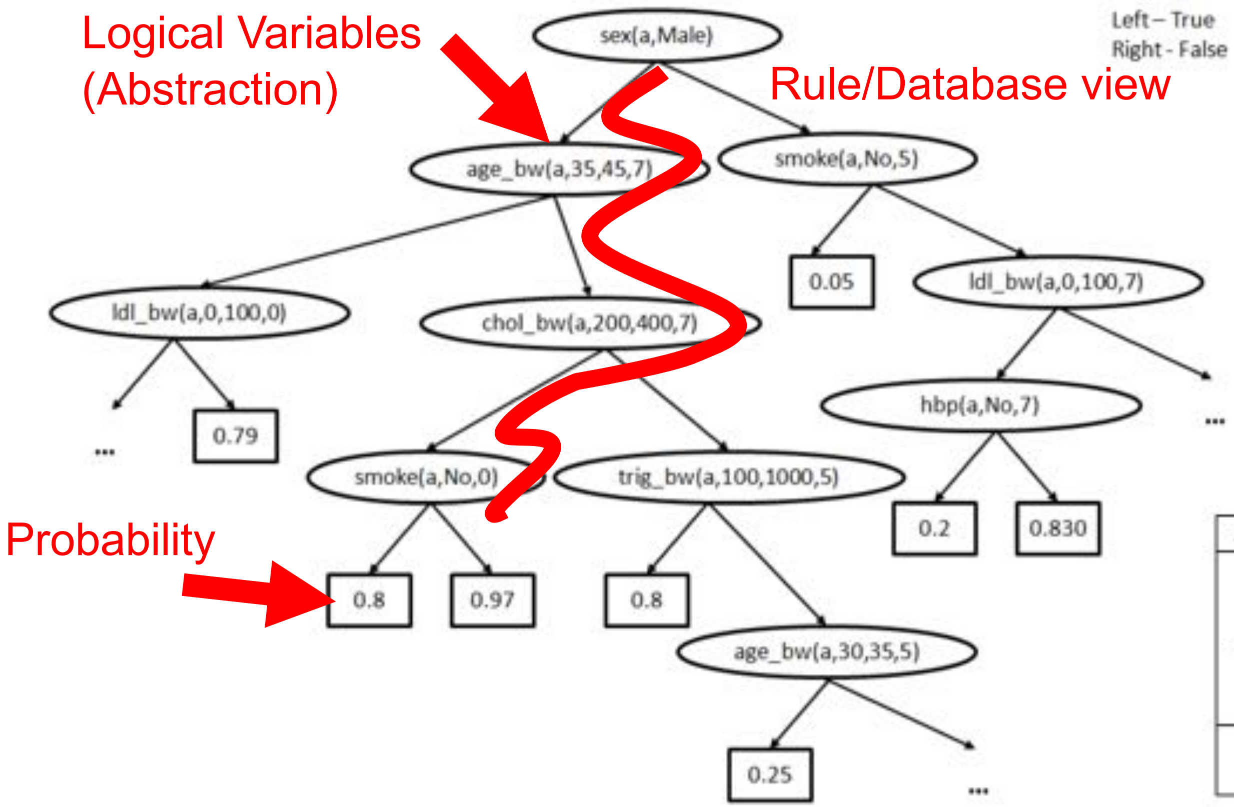
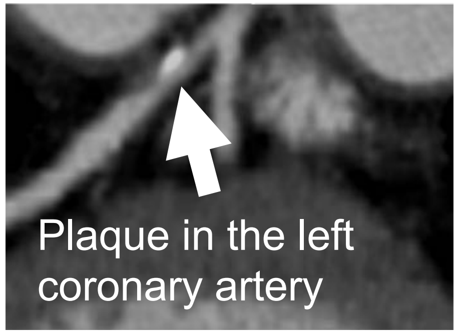




[Circulation; 92(8), 2157-62, 1995; JACC; 43, 842-7, 2004]

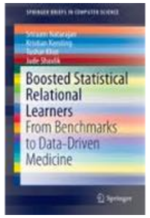
Algorithm	Accuracy	AUC-ROC
J48	0.667	0.607
SVM	0.667	0.5
AdaBoost	0.667	0.608
Bagging	0.677	0.613
NB	0.75	0.653
RPT	0.669*	0.778
RFGB	0.667*	0.819

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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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.

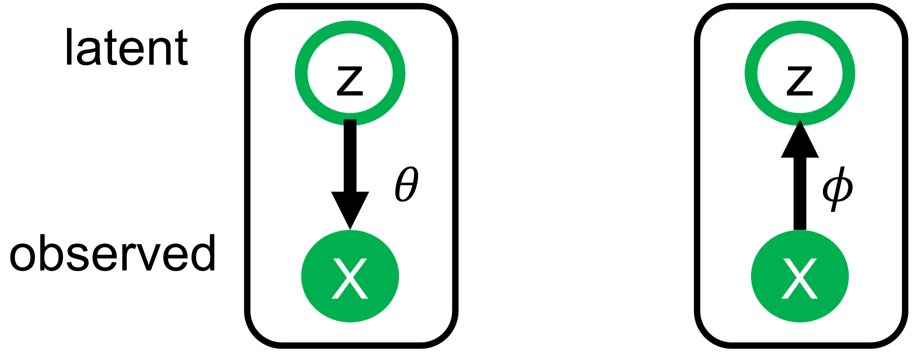
Deep Probabilistic Programming

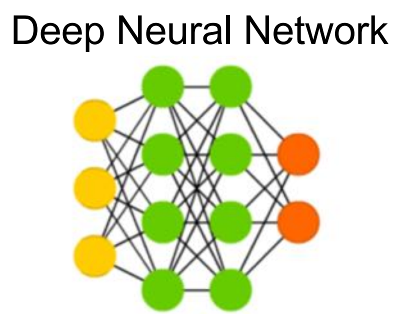
```python
import pyro.distributions as dist

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])
```

```python
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

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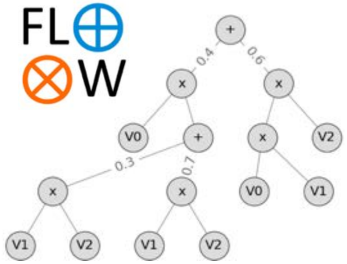
```

Sum-Product Network



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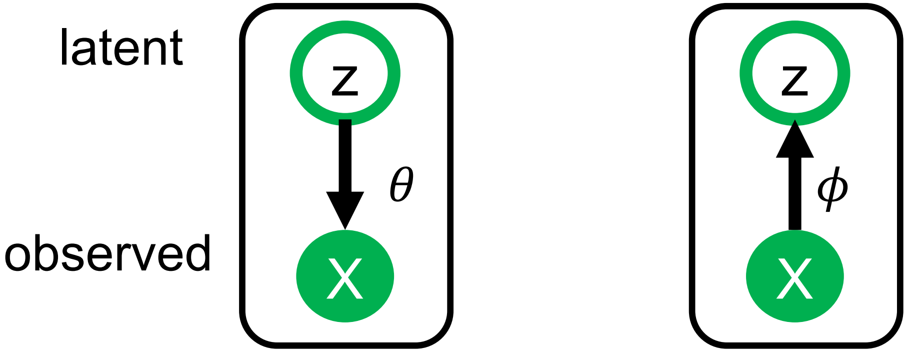

Deep Neural Network

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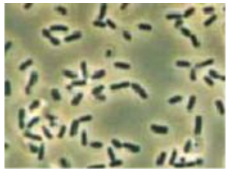
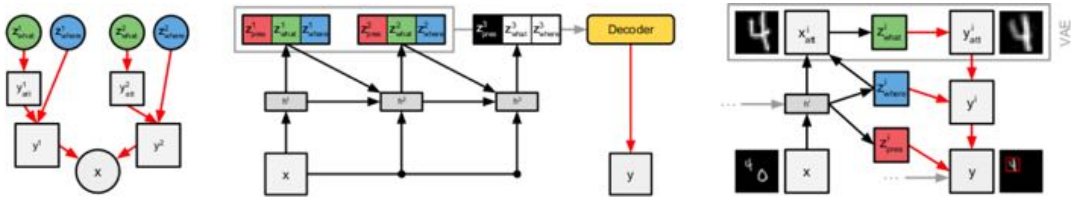
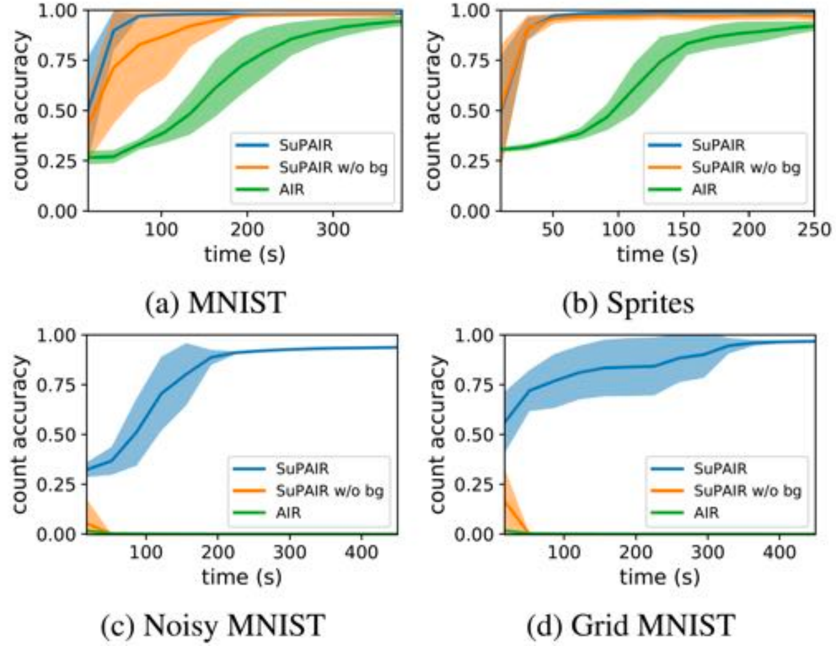
Consider e.g. unsupervised scene understanding using a generative model implemented in a neural fashion

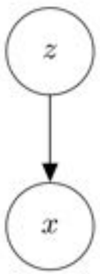




[Attend-Infer-Repeat (AIR) model, Hinton et al. NIPS 2016]

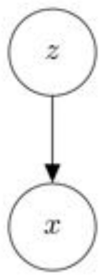


VAE



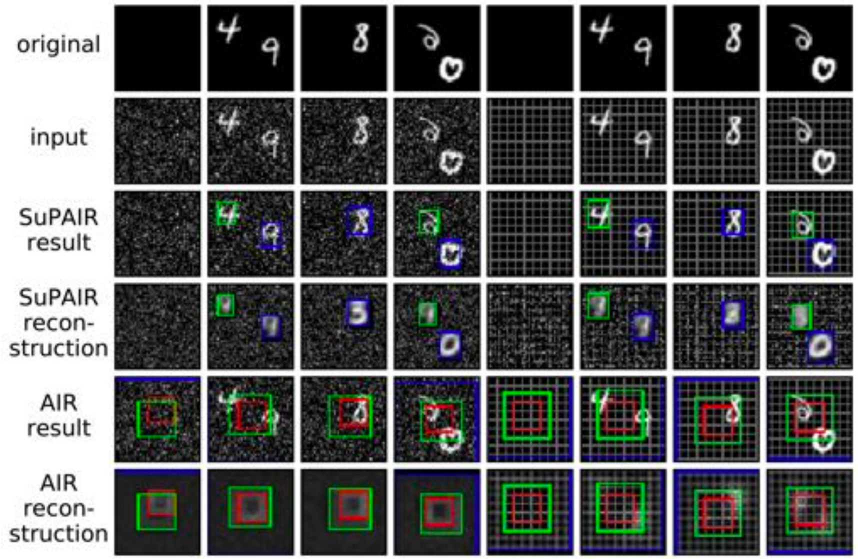
Replace VAE by SPN as object model

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]



There are strong invests into (deep) probabilistic programming

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

UBER AI Labs

Microsoft Research

relationalAI
AI for the enterprise

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]

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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.

UNIVERSITY OF CAMBRIDGE

UBER AI Labs

Max Planck Institute for Intelligent Systems

UNI GRAZ

FLOW

TECHNISCHE UNIVERSITÄT DARMSTADT

Microsoft Research

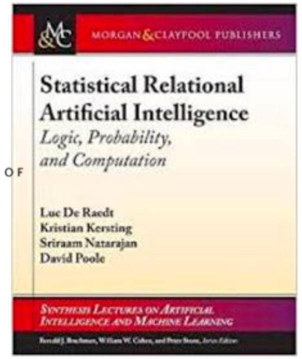
UBER AI Labs

KATHOLIEKE UNIVERSITEIT LEUVEN

THE UNIVERSITY OF TEXAS AT DALLAS

TECHNISCHE UNIVERSITÄT DARMSTADT

UBC THE UNIVERSITY OF BRITISH COLUMBIA



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

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

Centre for Cognitive Science

Josh Tenenbaum, MIT

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

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

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

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= The third wave of AI requires integrative CS, from SoftEng and DBMS, over ML and AI, to computational CogSci

A lot left to be done