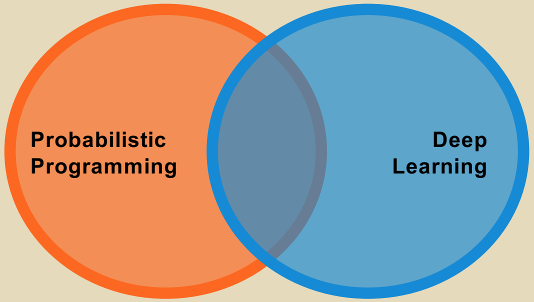
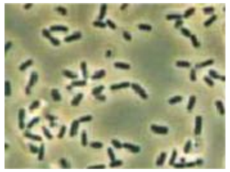
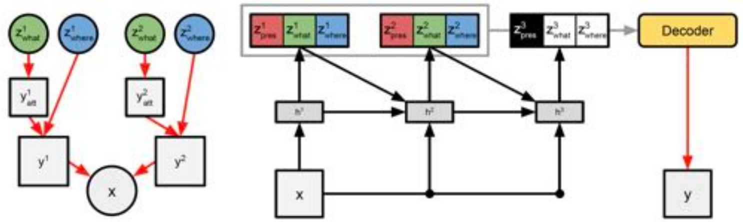
Deep Machines that know when they do not know



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



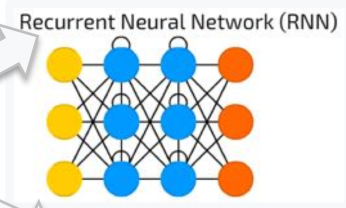


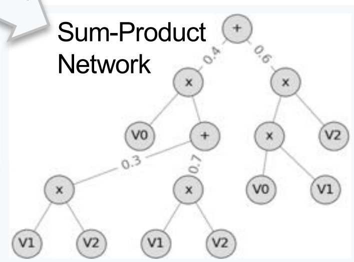
[Attend-Infer-Repeat (AIR) model, Hinton et al. NIPS 2016]

Probabilistic Programming: Easier modelling by programming generative models in a high-level, prob. language

Deep Probabilistic Prog.: Modelling and inference might be hard, so use a deep neural network for it

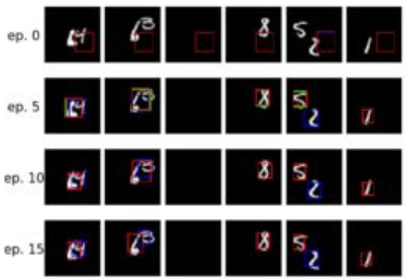
```
def prior_step(t):
    # Sample object pose. This is a 3-dimensional vector representing x,y position and size.
    z_where = pyro.sample('z_where_{}'.format(t),
                          dist.normal,
                          z_where_prior_mu, z_where_prior_sigma)

    # Sample object code. This is a 50-dimensional vector.
    z_what = pyro.sample('z_what_{}'.format(t),
                         dist.normal,
                         z_what_prior_mu, z_what_prior_sigma)

    y_att = decode(z_what)          # Map latent code to pixel space using the neural ne
```

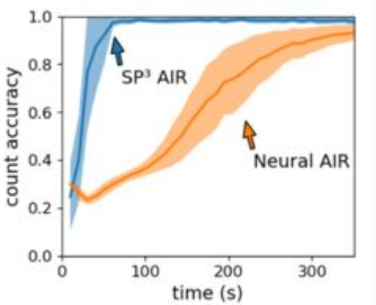




Sum-Product Probabilistic Programming: Making machine learning and data science easier [Stelzner, Molina, Peharz, Vergari, Trapp, Valera, Ghahramani, Kersting ProgProb 2018]

Use deep probabilistic models that feature tractable, deterministic inference






```
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
```

Kristian Kersting

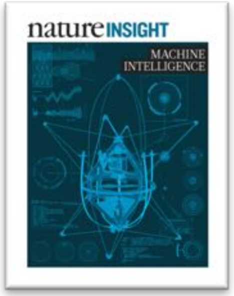
AI and ML have a strong impact

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

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

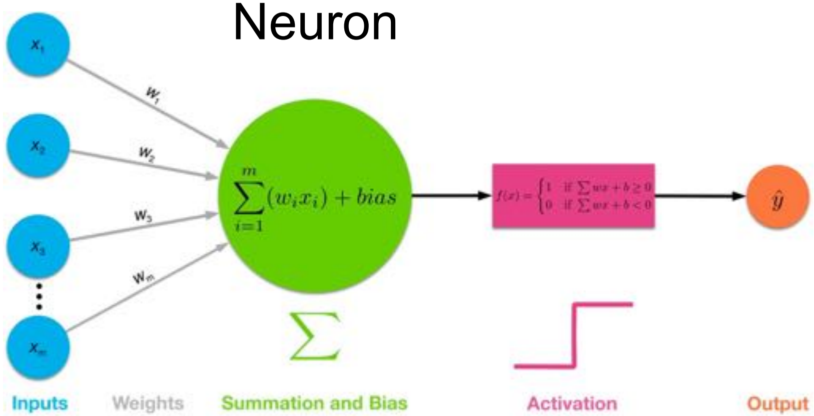
Provide the foundations, algorithms, and tools to develop systems that ease or even automate AI model discovery from data as much as possible

Deep Neural Networks

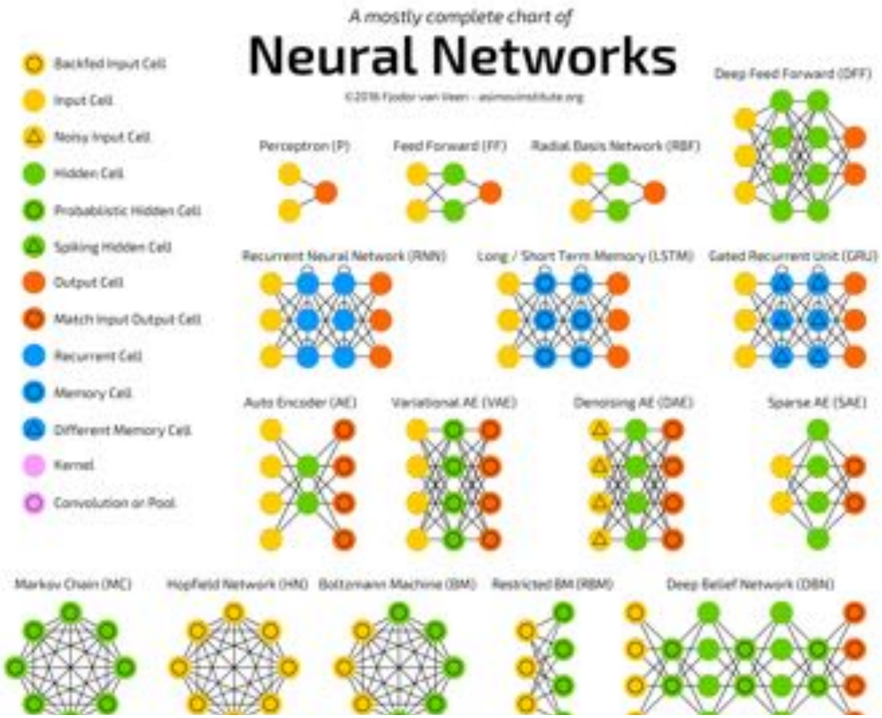


Potentially much more powerful than shallow architectures, represent computations

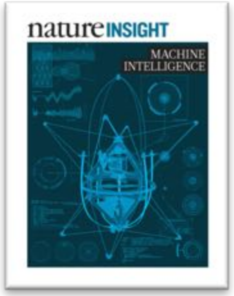
[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]



Differentiable Programming



Deep Neural Networks



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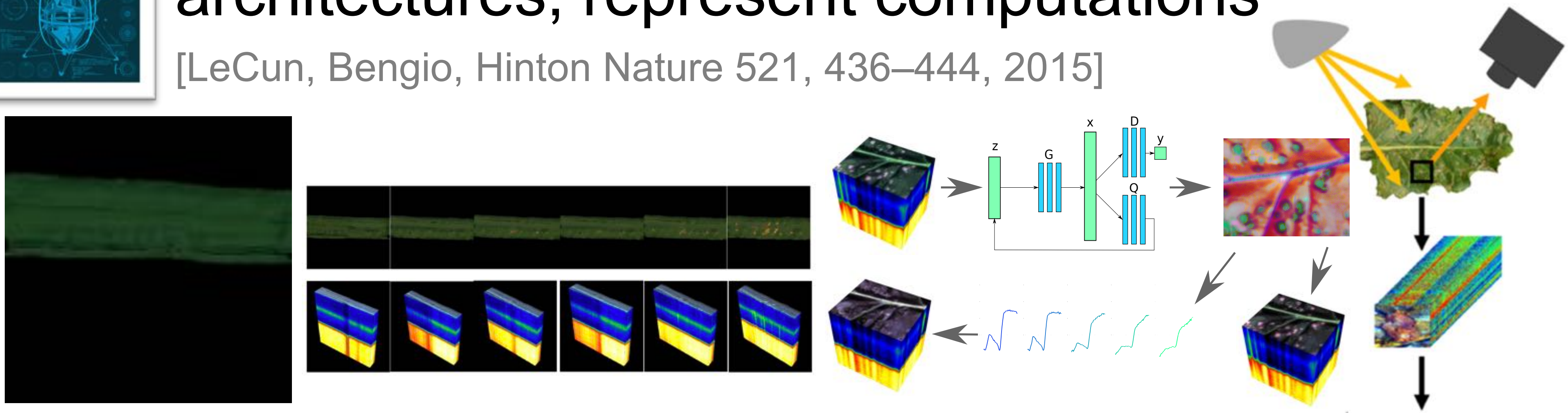
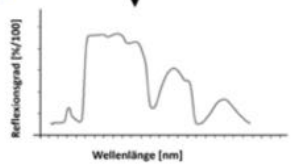




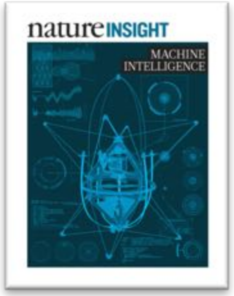
They “develop intuition” about complicated biological processes and generate scientific data

[Schramowski, Brugger, Mahlein, Kersting 2019]

DePhenSe

Bundesanstalt für Landwirtschaft und Ernährung

Deep Neural Networks



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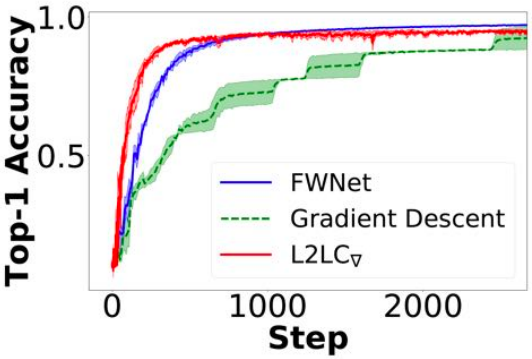
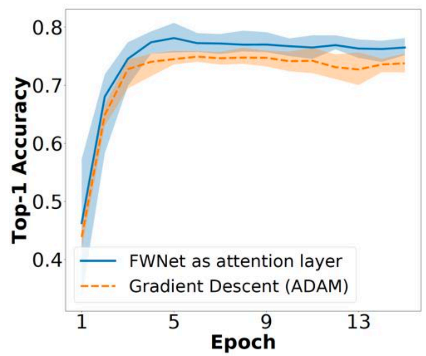
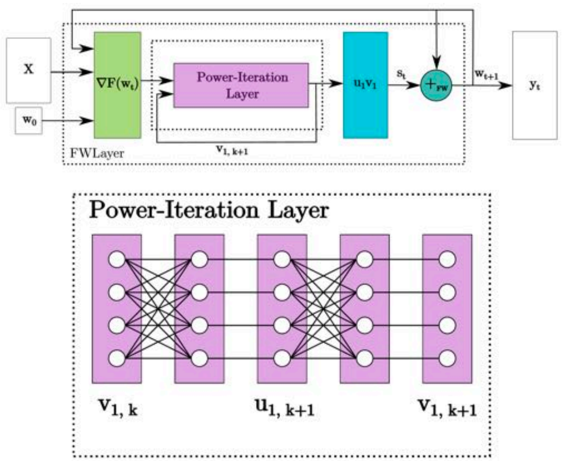
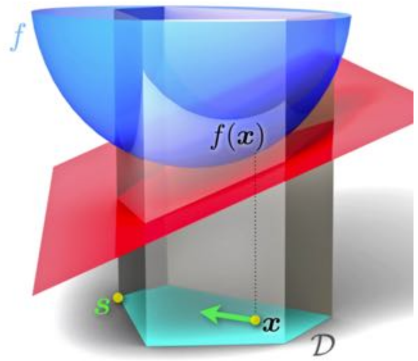






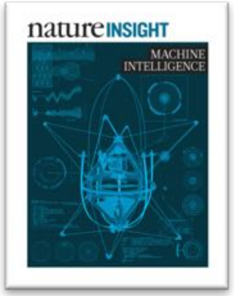


They "invent" constrained optimizers

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

Bundesanstalt für Landwirtschaft und Ernährung

Deep Neural Networks



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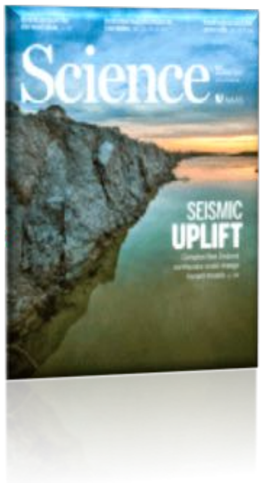

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REPORTS | PSYCHOLOGY

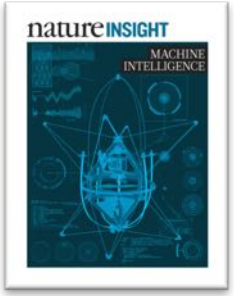
Semantics derived automatically from language corpora contain human-like biases

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

Deep Neural Networks



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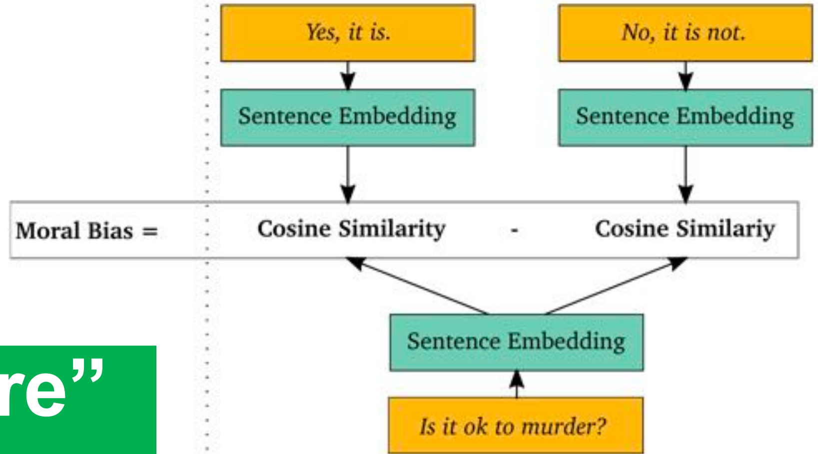
[LeCun, Bengio, Hinton Nature 521, 436–444, 2015]

The Moral Choice Machine

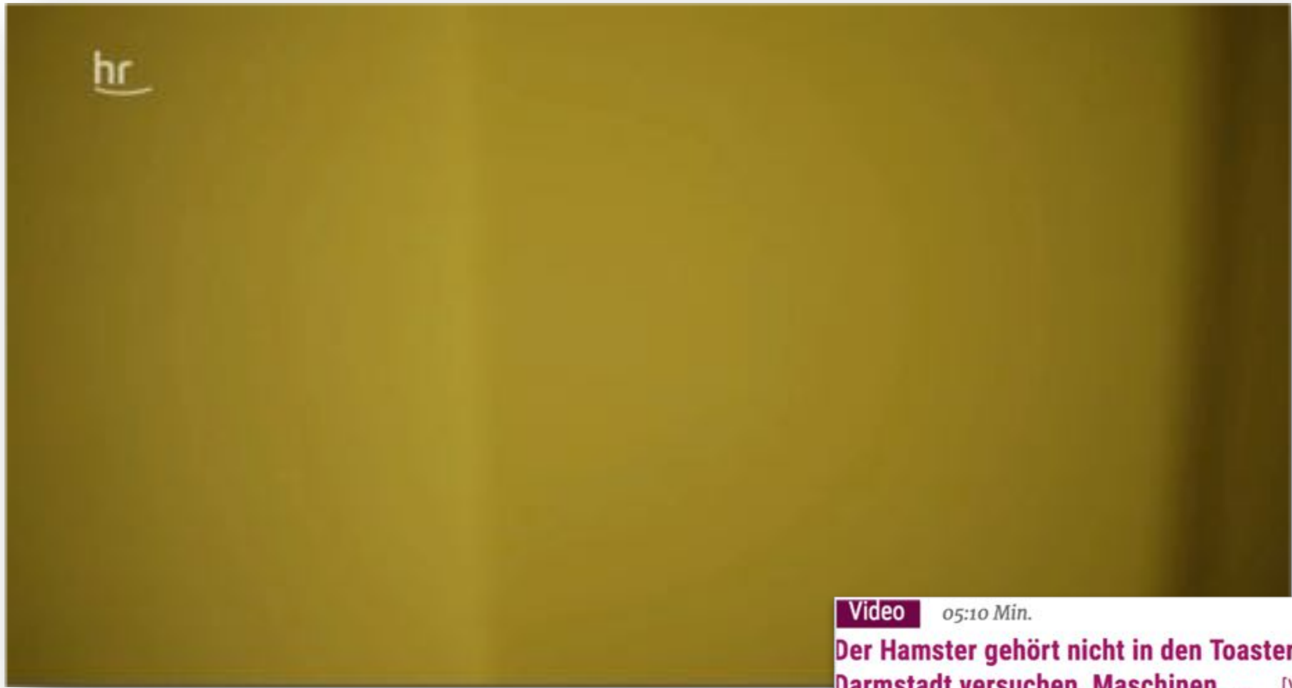
Dos	WEAT	Bias	Don'ts	WEAT	Bias
smile	0.116	0.348	rot	-0.099	-1.118
sightsee	0.090	0.281	negative	-0.101	-0.763
cheer	0.094	0.277	harm	-0.110	-0.730
celebrate	0.114	0.264	damage	-0.105	-0.664
picnic	0.093	0.260	slander	-0.108	-0.600
snuggle	0.108	0.238	slur	-0.109	-0.569



But lucky they also "capture" our moral choices

[Jentzsch, Schramowski, Rothkopf, Kersting AIES 2019]

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



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
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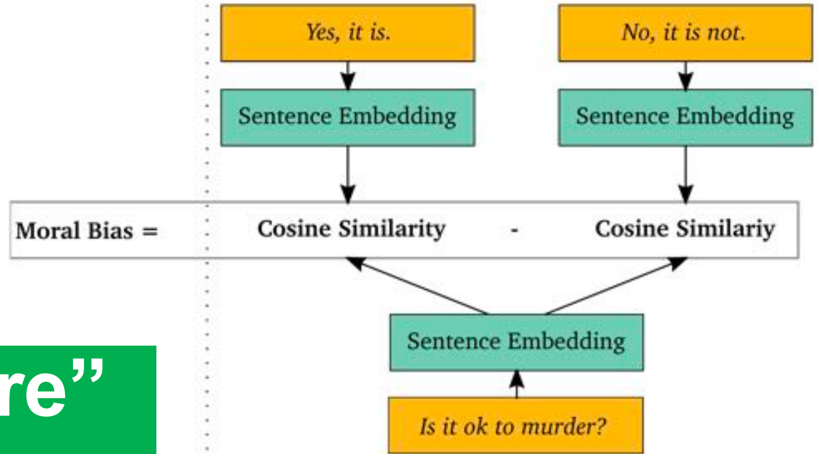

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Deep neural networks do not quantify their uncertainty
They are not calibrated probabilistic models

MNIST

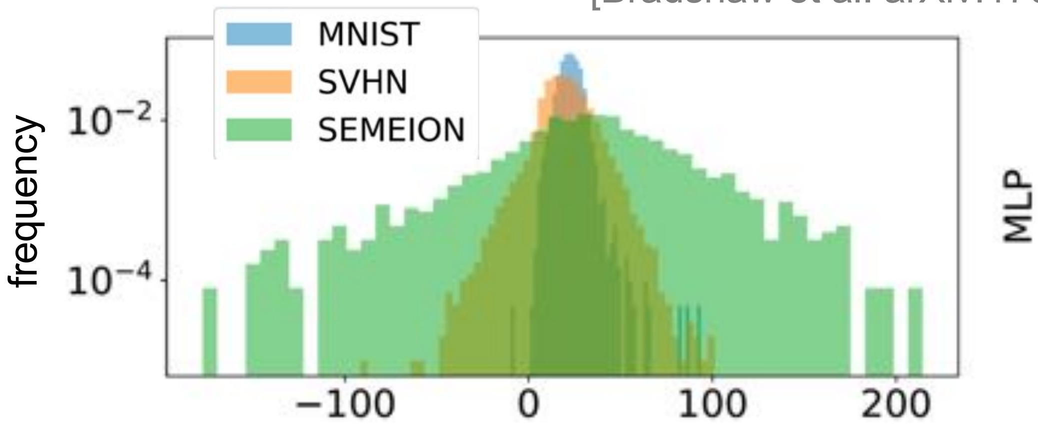
SVHN

SEMEION

Train & Evaluate

Transfer Testing

[Bradshaw et al. arXiv:1707.02476 2017]

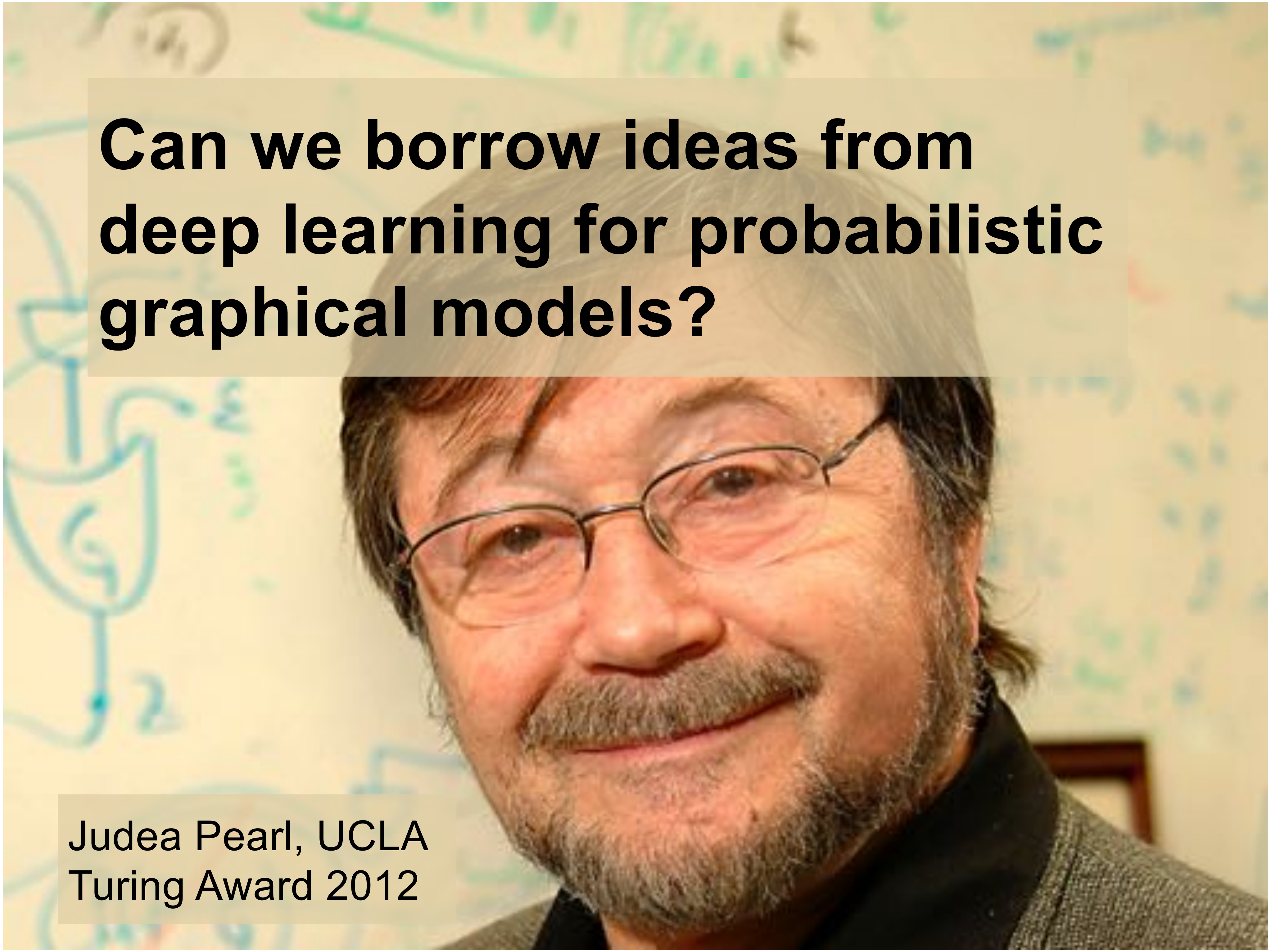


Input log „likelihood“ (sum over outputs)

[Peharz, Vergari, Molina, Stelzner, Trapp, Kersting, Ghahramani UDL@UAI 2018]

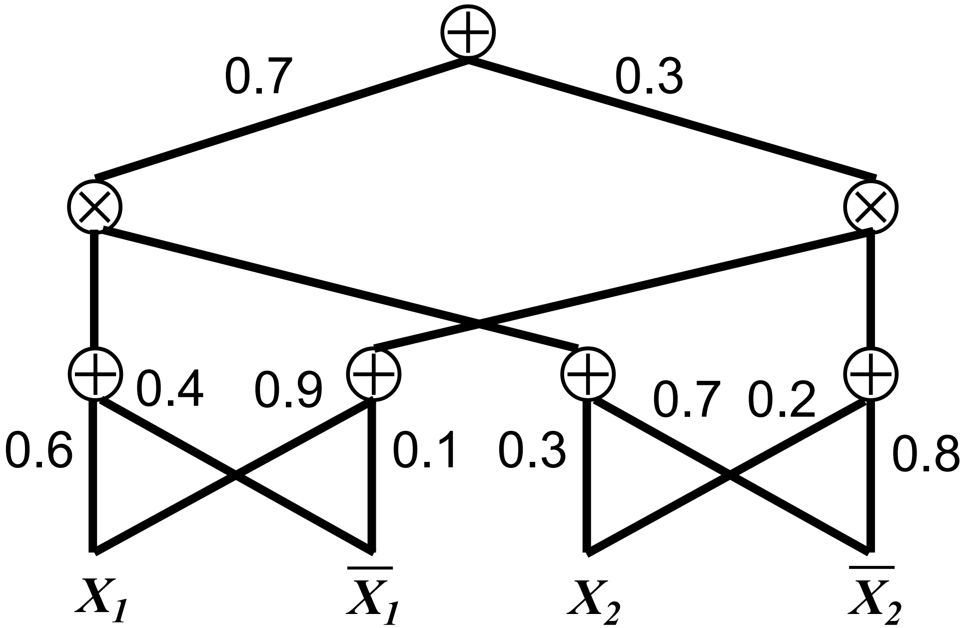
Getting deep systems that know when they don't know.

Can we borrow ideas from deep learning for probabilistic graphical models?



Judea Pearl, UCLA
Turing Award 2012

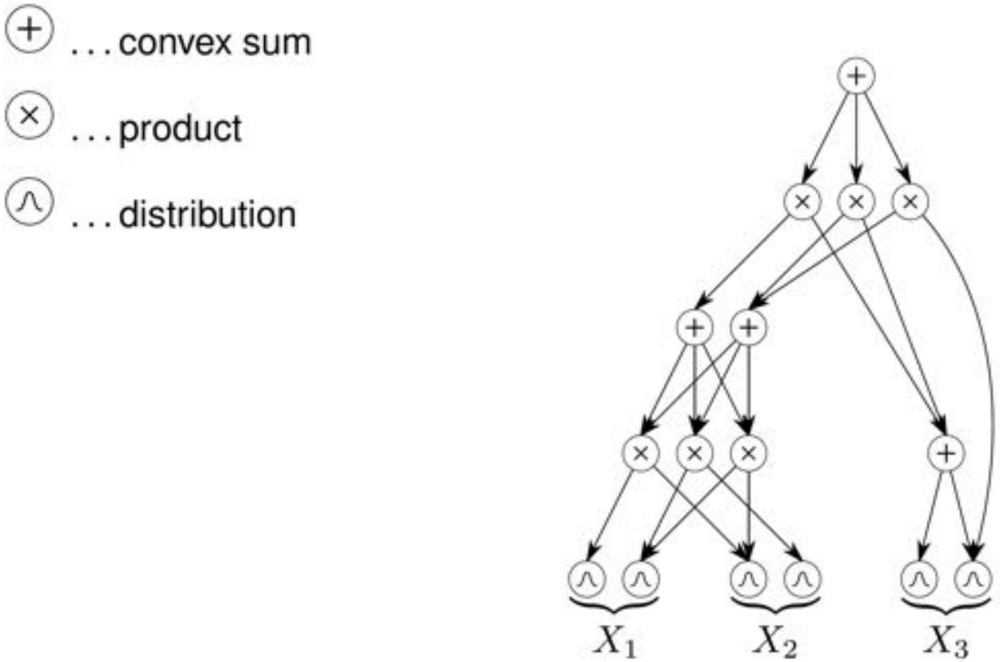
This results in Sum-Product Networks, a deep probabilistic learning framework



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

Inference is linear in size of network

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

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

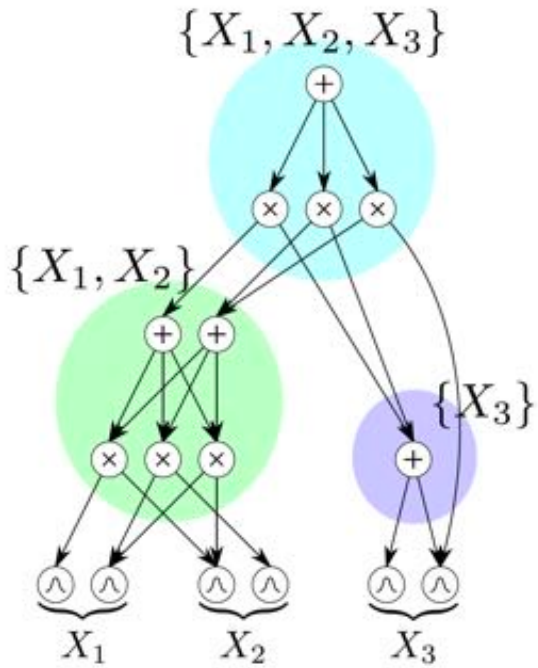
… convex sum

… product

… distribution

completeness
sum children: same scope

decomposability
product children:
non-overlapping scope



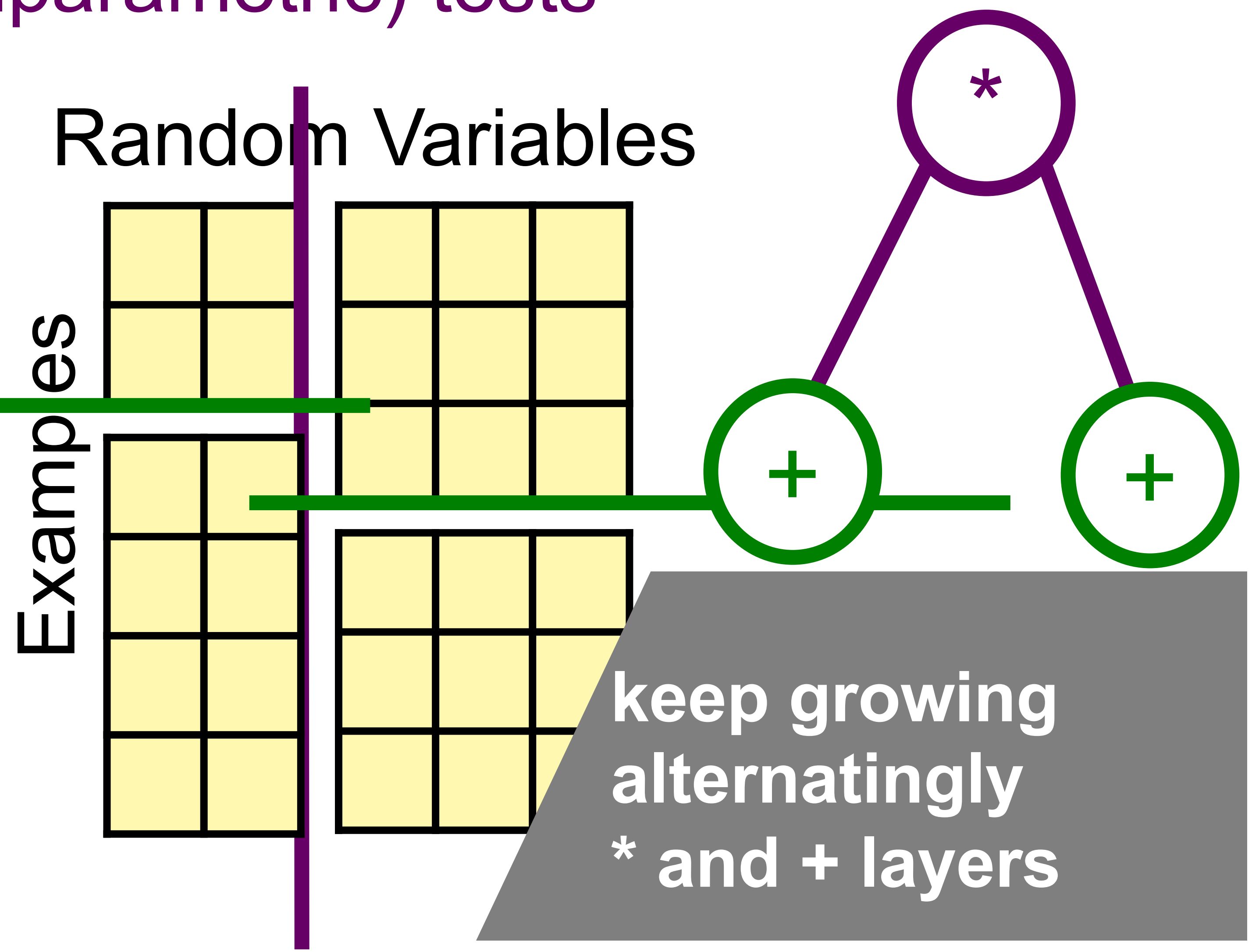
Computational graph (kind of TensorFlow graphs) that encodes how to compute probabilities

Inference is linear in size of network

And there is a way to select models

Testing independence of random variables using e.g. (nonparametric) tests

Conditoning, e.g., via clustering



[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]

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

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

TECHNISCHE UNIVERSITÄT DARMSTADT

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

UNIVERSITY OF WATERLOO

CAML

MADESI

Max Planck Institute for Intelligent Systems

UNIVERSITY OF CAMBRIDGE

VECTOR INSTITUTE

DFG

Federal Ministry of Education and Research

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)])
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spn = Sum(weights=[0.4, 0.6], children=[p2, p4])

assign_ids(spn)
rebuild_scopes_bottom_up(spn)

return spn
```
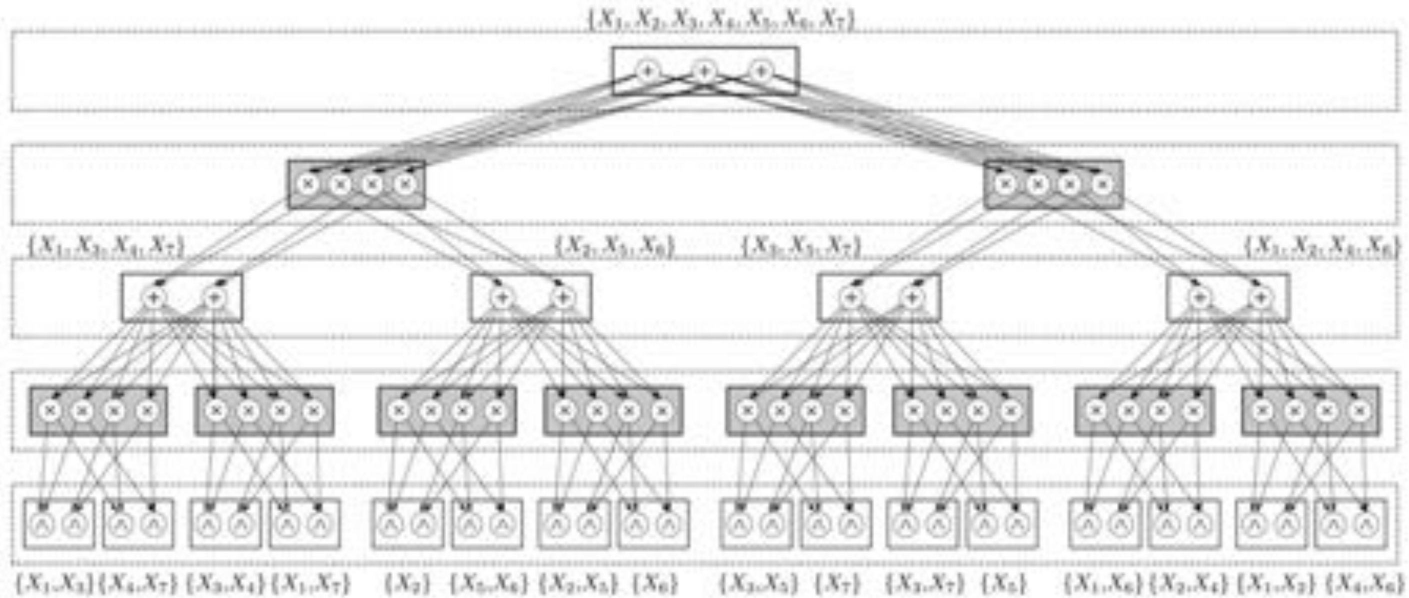

Domain Specific Language, Inference, EM, and Model Selection as well as Compilation of SPNs into TF and PyTorch and also into flat, library-free code even suitable for running on devices: C/C++,GPU, FPGA

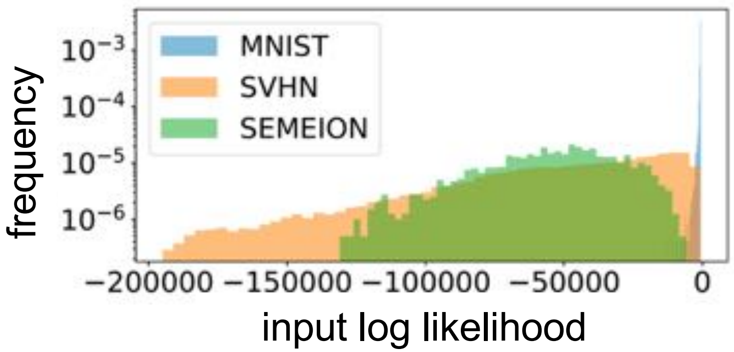
SPFlow, an open-source Python library providing a simple interface to inference, learning and manipulation routines for deep and tractable probabilistic models called Sum-Product Networks (SPNs). The library allows one to quickly create SPNs both from data and through a domain specific language (DSL).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

Random sum-product networks

[Peharz, Vergari, Molina, Stelzner, Trapp, Kersting, Ghahramani UDL@UAI 2018]



		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)



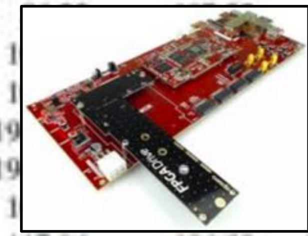
outliers
prototypes

outliers
prototypes

[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.

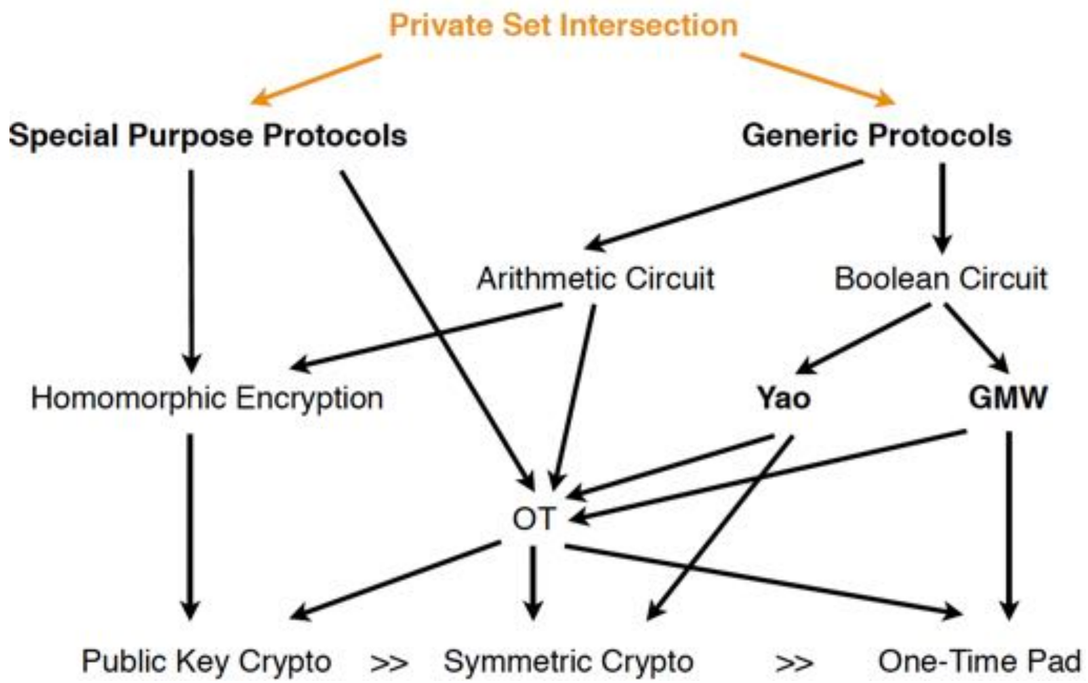


Dataset	Rows	CPU (μs)	T-CPU (rows/ μs)	CPUF (μs)	T-CPUF (rows/ μs)	GPU (μs)	T-GPU (rows/ μs)	FPGA Cycle Counter	FPGAC (μs)	T-FPGAC (rows/ μs)	FPGA (μs)	T-FPGA (rows/ μs)
Accidents	17009	2798.27	[illegible]	[illegible]	7.87	63090.94	0.27	17249	[illegible]	[illegible]	[illegible]	**24.44**
Audio	20000	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 data science 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]

Learning the Structure of Autoregressive Deep Models such as PixelCNNs [van den Oord et al. NIPS 2016]

CSPNs
PixelCNNs

Learn Conditional SPN by testing conditional independence and using conditional clustering, using e.g. [Zhang et al. UAI 2011; Lee, Honovar UAI 2017; He et al. ICDM 2017; Zhang et al. AAAI 2018; Runge AISTATS 2018]

Conditional SPNs

[Shao, Molina, Vergari, Peharz, Kersting 2019]

CAML
DFG

Learn Conditional SPN by testing conditional independence and using conditional clustering, using e.g.
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Conditional SPNs

[Shao, Molina, Vergari, Peharz, Kersting 2019]

CAML

DFG

	50% Evidence		80% Evidence	
Dataset	DACL	CSPN	DACL	CSPN
Nltcs	-2.770	-2.787	-1.255	-1.254
Msnbc	**-2.918**	-3.165	**-1.557**	-1.654
KDD	**-0.998**	-1.048	-0.386	-0.396
Plants	-4.655	-4.720	-1.812	-1.804
Audio	-18.958	-18.759	-7.337	-7.223
Jester	-24.830	-24.544	-9.998	**-9.768**
Netflix	-26.245	**-25.914**	-10.482	-10.352
Accidents	**-9.718**	-11.587	**-3.493**	-4.045
Retail	**-4.825**	-5.600	-1.687	-1.653
Pumsb.	**-6.363**	-7.383	-2.594	-2.618
DNA	-34.737	**-30.289**	-12.116	**-7.994**
W/T/L	2/4/5		2/7/2	

Learn Conditional SPN by testing conditional independence and using conditional clustering, using e.g. [Zhang et al. UAI 2011; Lee, Honovar UAI 2017; He et al. ICDM 2017; Zhang et al. AAAI 2018; Runge AISTATS 2018]

Conditional SPNs

[Shao, Molina, Vergari, Peharz, Kersting 2019]

Functional weights realized as neural network

Learn Conditional SPN by testing conditional independence and using conditional clustering, using e.g.

[Zhang et al. UAI 2011; Lee, Honovar UAI 2017; He et al. ICDM 2017; Zhang et al. AAAI 2018; Runge AISTATS 2018]

Conditional SPNs

[Shao, Molina, Vergari, Peharz, Kersting 2019]

CAML

DFG

Generally, we can explore more of deep learning for probability distributions: **Residual SPN**
Short cuts among (sub)mixtures)

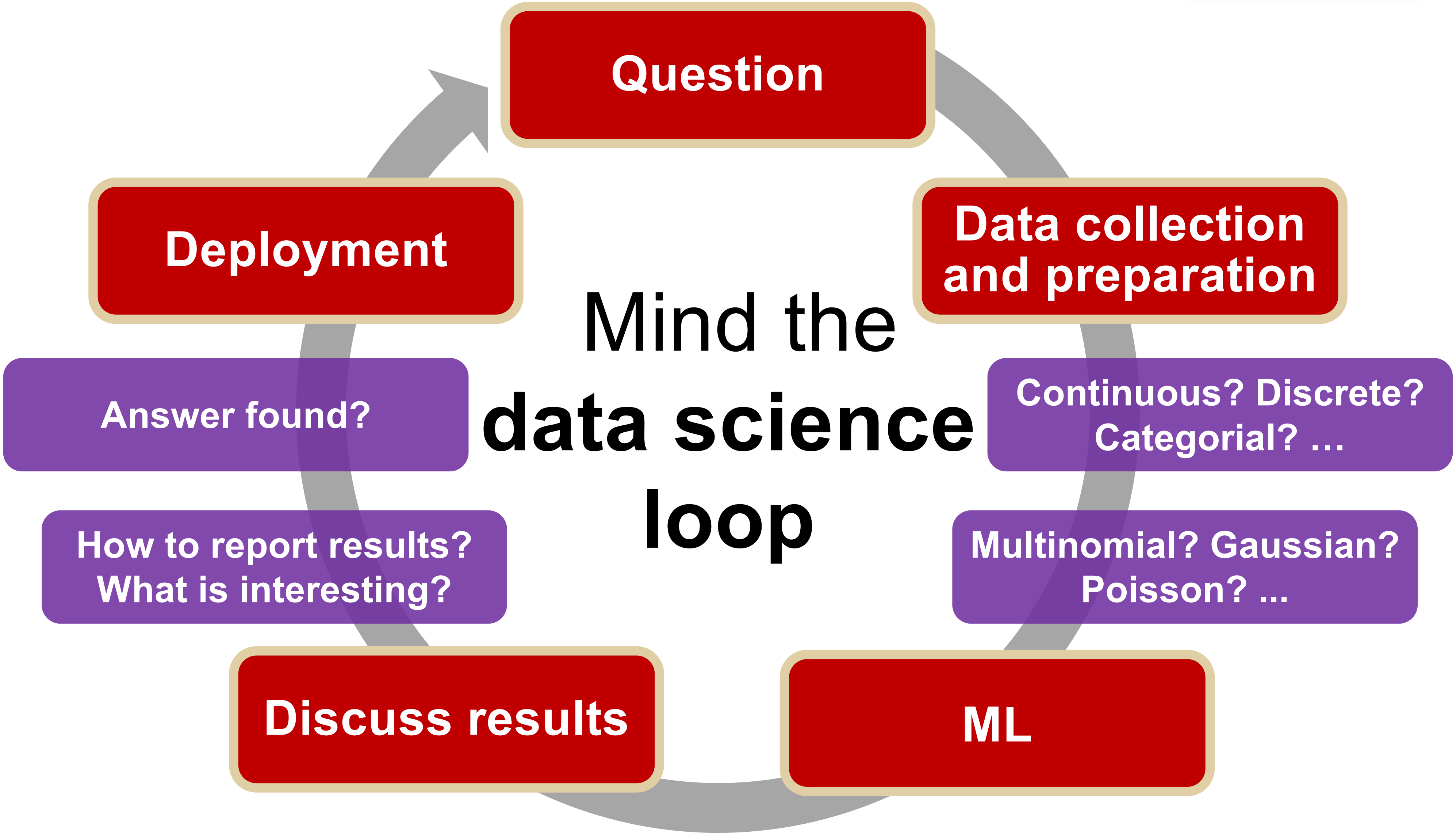
[Ventola, Molina, Stelzner, Kersting 2019]

Log Likelihood

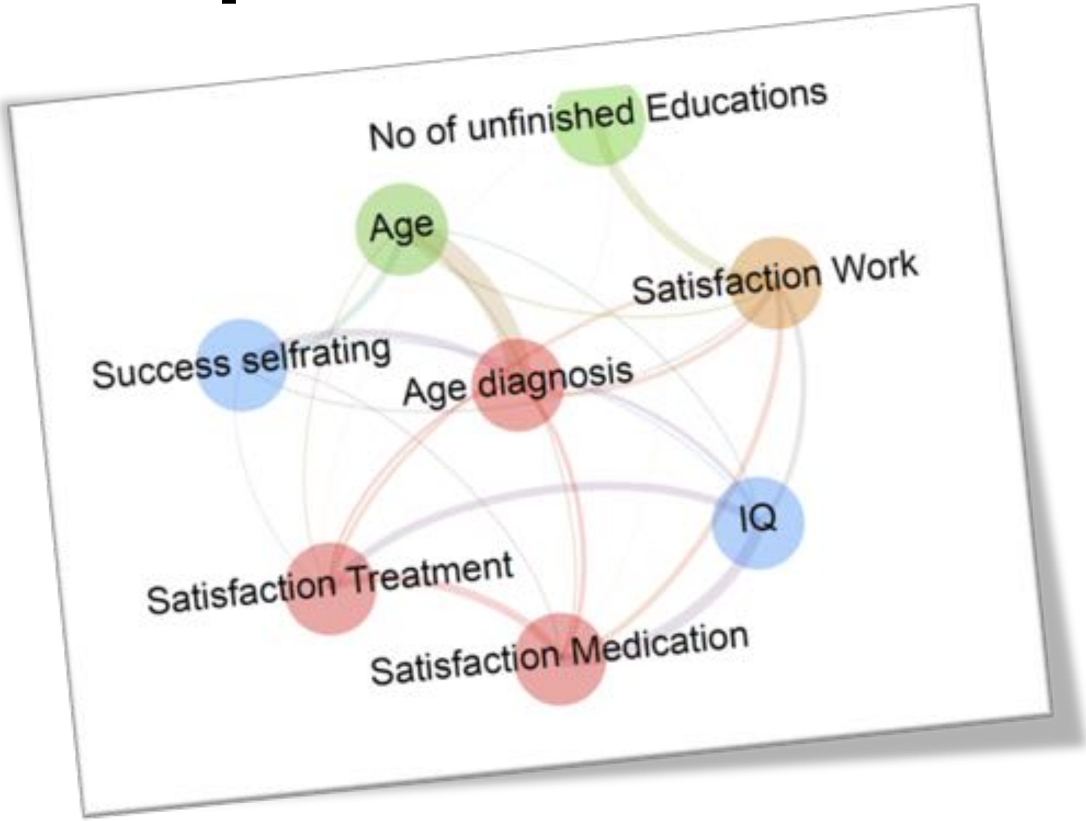
	Best weak SPN+opt	Simple Mixture+opt	LearnSPN+opt	ResSPN+opt	BigMix ResSPN+opt
NLTCS	-6.153	-6.064	-6.355	-6.030	-6.020
KDDCup2k	-2.194	-2.173	-2.384	-2.150	-2.153
Audio5	-42.639	-42.069	-44.363	-41.526	-40.848
Audio10	-42.639	-41.919	-44.363	-40.345	-40.259
Jester	55.335	-53.393	-54.934	-54.455	-53.214
Netflix	-60.330	-59.668	-62.024	-58.734	-58.085

Running Times

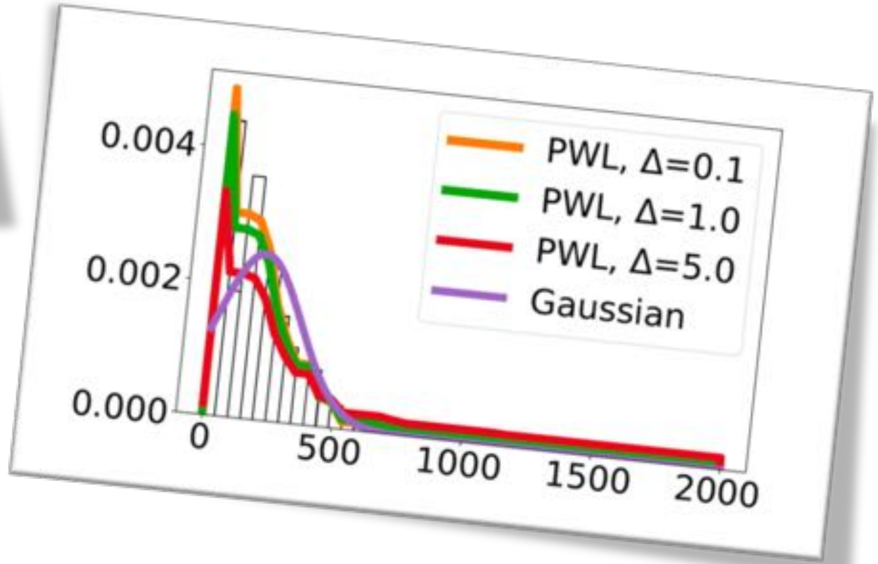
	Best weak SPN+opt	Simple Mixture+opt	LearnSPN+opt	ResSPN+opt	BigMix ResSPN+opt
NLTCS	31	117	20	2606	2909
KDDCup2k	264	3686	2788	2461	7236
Audio5	56	165	255	172	340
Audio10	31	187	255	10841	10641
Jester	74	128	183	92	186
Netflix	25	86	166	105	196


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

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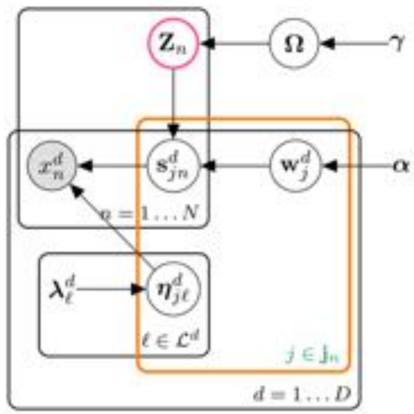
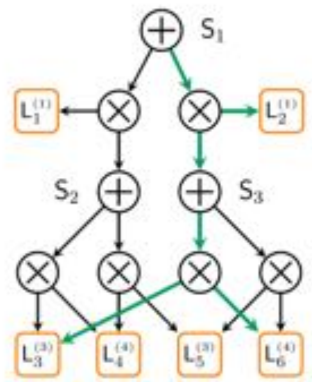
missing value

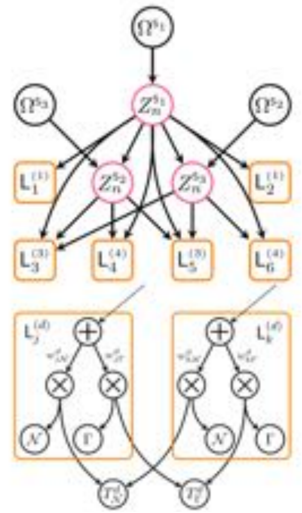
We can even automatically discovers the statistical types and parametric forms of the variables



Bayesian Type Discovery

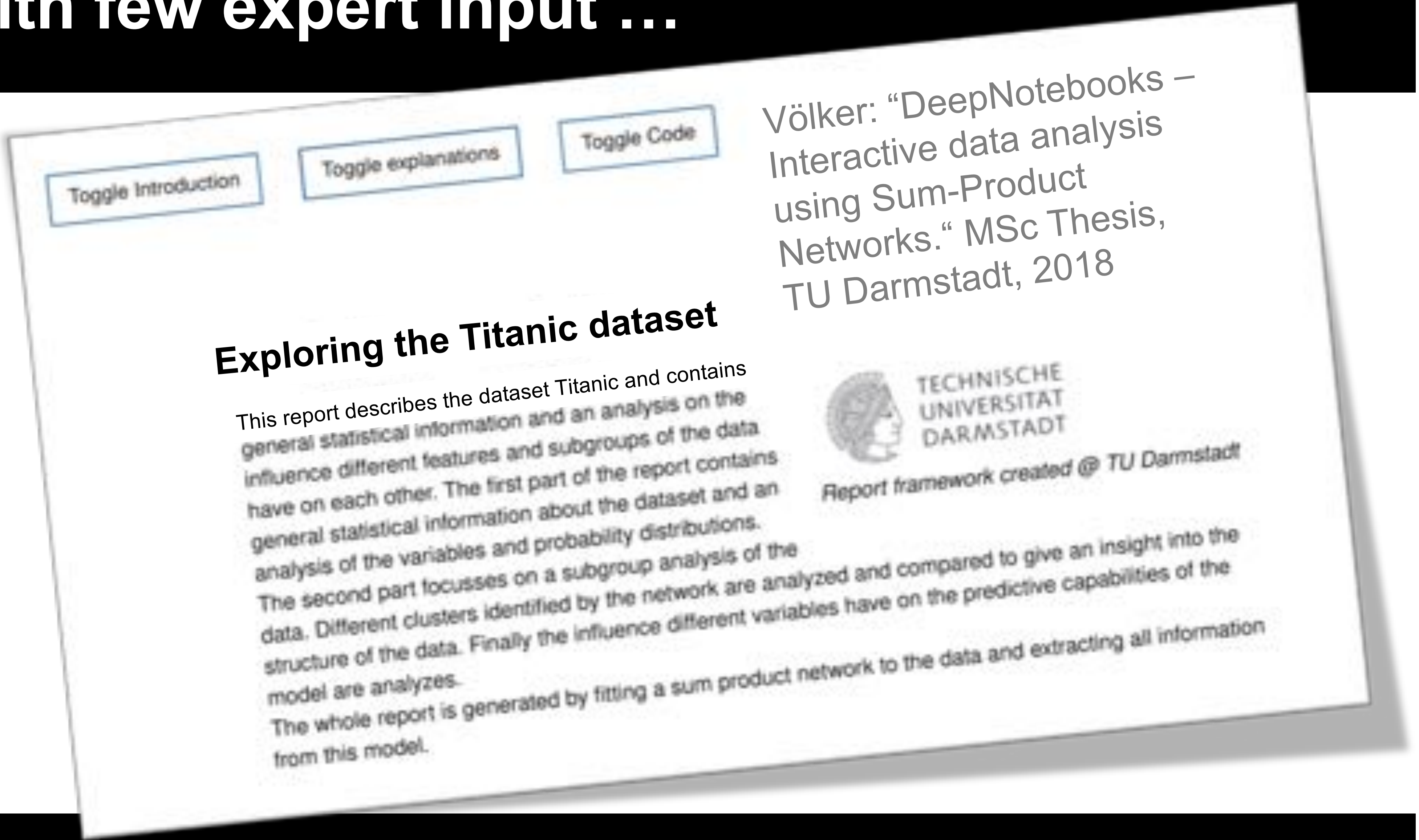


Mixed Sum-Product Network



Automatic Statistician

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

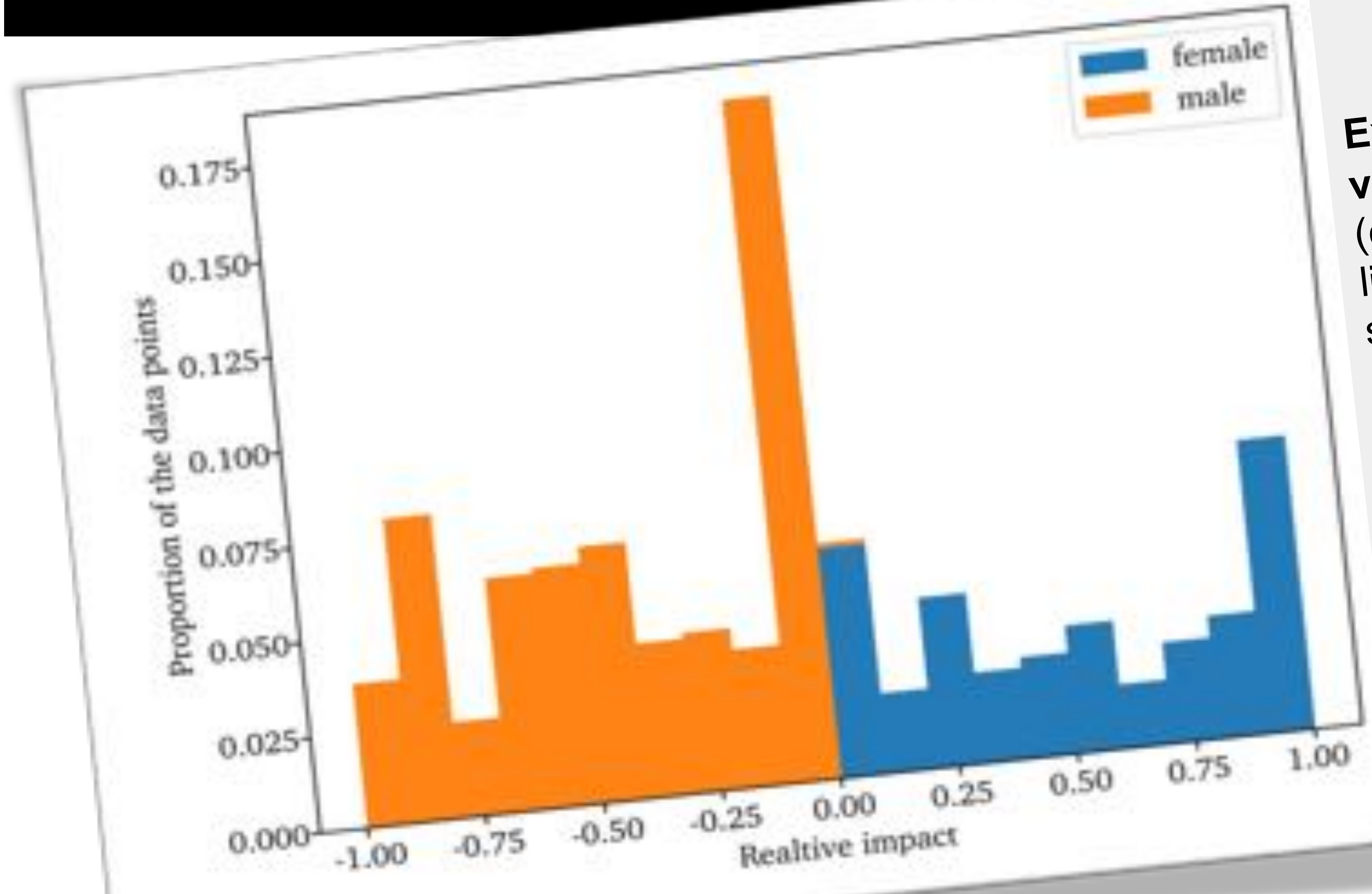


Völker: "DeepNotebooks – Interactive data analysis using Sum-Product Networks." MSc Thesis, TU Darmstadt, 2018

…and can compile data reports automatically

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

The machine understands the data with no 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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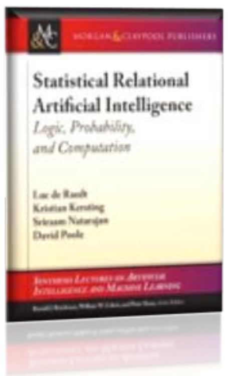
May 18, 2018

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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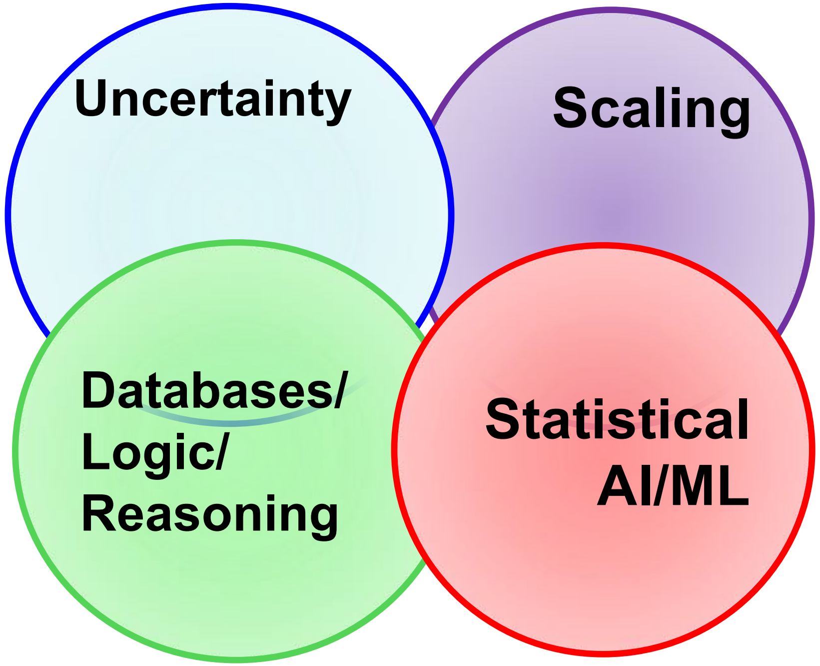
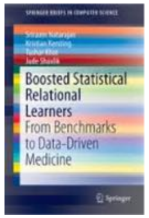
building general-purpose data science and ML machines

make the ML/DS expert more effective

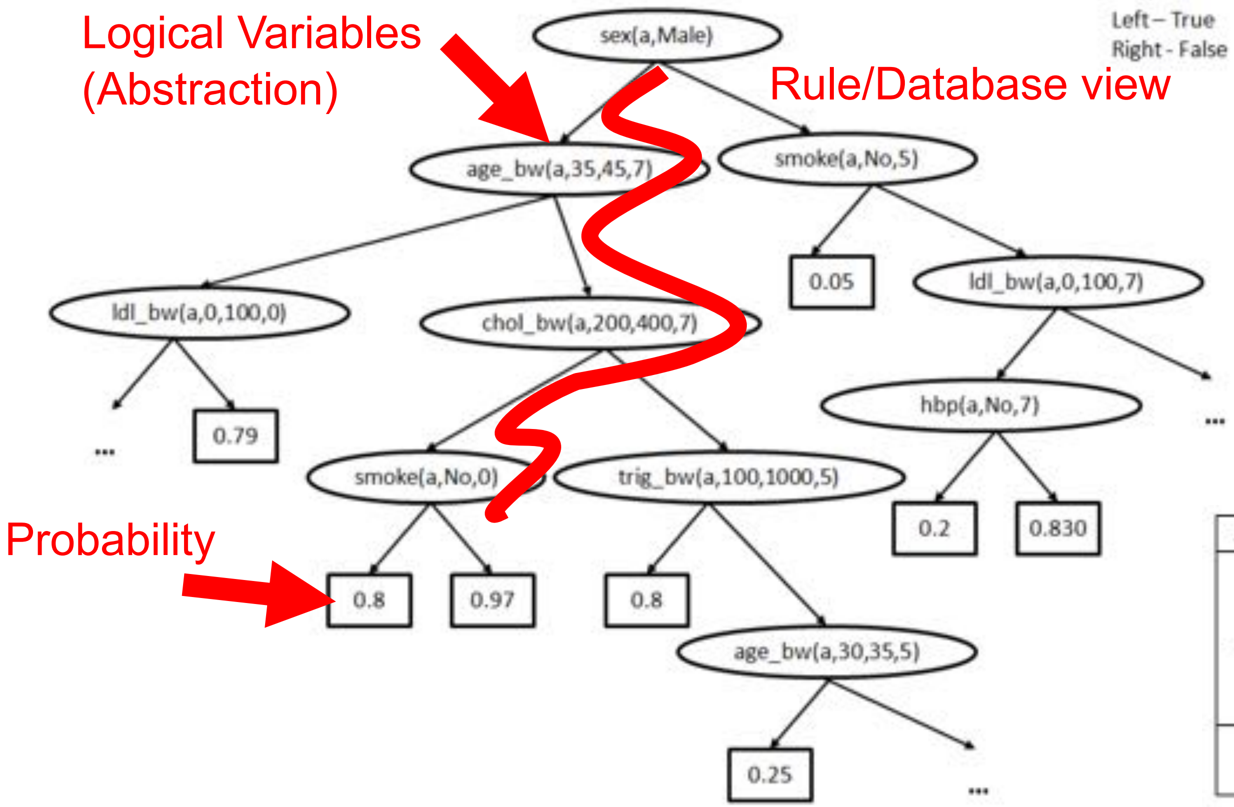
increases the number of people who can successfully build ML/DS applications





Understanding Electronic Health Records

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



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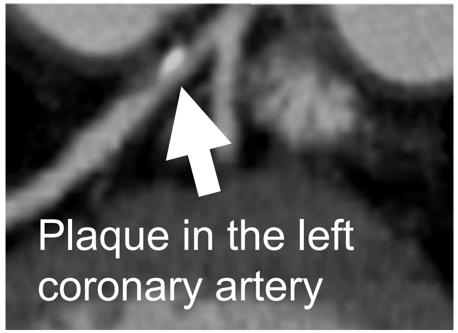


[Circulation; 92(8), 2157-62, 1995; JACC; 43, 842-7, 2004]

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

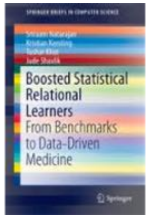
25%

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

state-of-the-art

[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

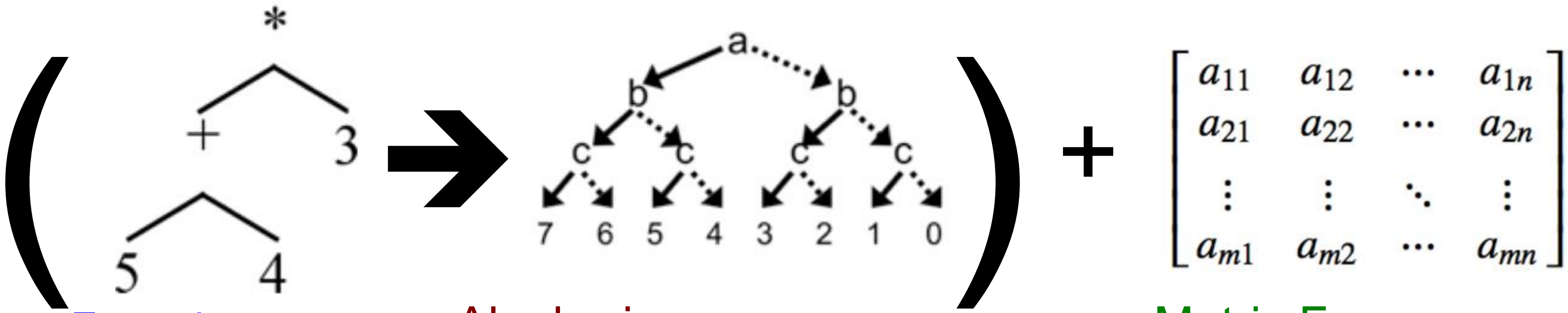
BoostSRL Wiki

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

New field: Probabilistic Programming



Formulae parse trees

Algebraic Decision Diagrams

Matrix Free Optimization

Problem Statistics				Symbolic IPM		Ground IPM
name	#vars	#constr	$nnz(A)$	|ADD|	time[s]	time[s]
factory	131.072	688.128	4.000.000	1819	6899	**516**
factory0	524.288	2.752.510	15.510.000	1895	**6544**	7920
factory1	2.097.150	11.000.000	59.549.700	2406	**34749**	159730
factory2	4.194.300	22.020.100	119.099.000	2504	**36248**	$\geq$ 48hrs.

>4.8x faster

Applies to QPs but here illustrated on MDPs for a factory agent which must paint two objects and connect them. The objects must be smoothed, shaped and polished and possibly drilled before painting, each of which actions require a number of tools which are possibly available. Various painting and connection methods are represented, each having an effect on the quality of the job, and each requiring tools. Rewards (required quality) range from 0 to 10 and a discounting factor of 0. 9 was used used

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.

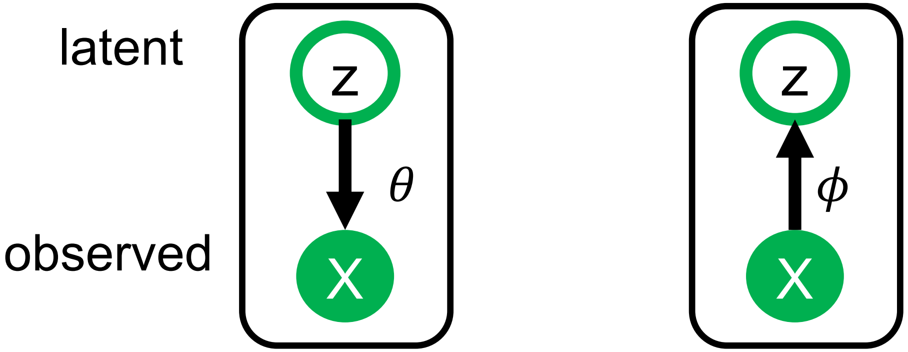
Deep Probabilistic Programming

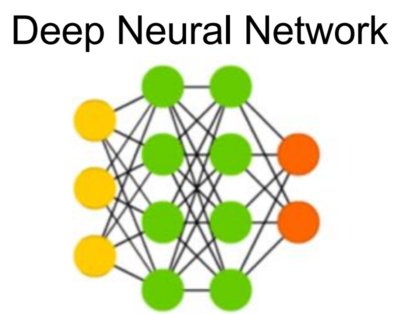
```python
import pyro.distributions as dist

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]

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

Sum-Product 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])
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    pyro.sample("latent_fairness", dist.Beta(alpha_q, beta_q))
```
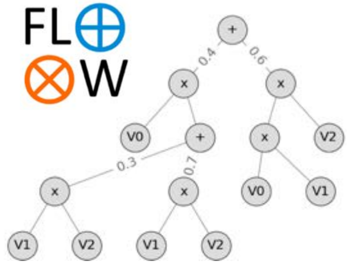
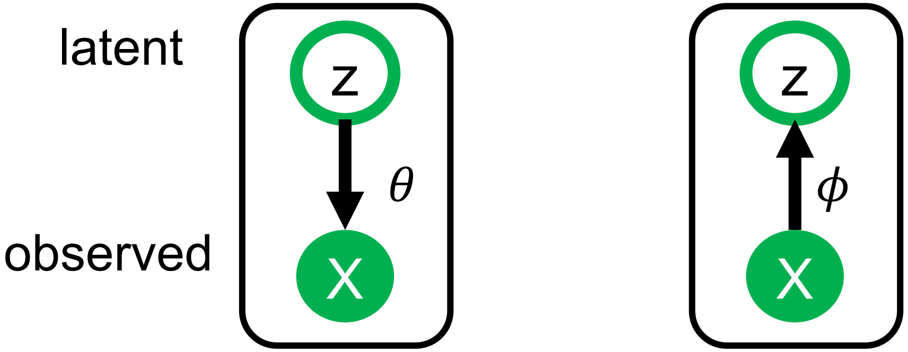

Sum-Product Network



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

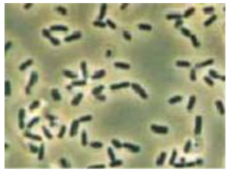


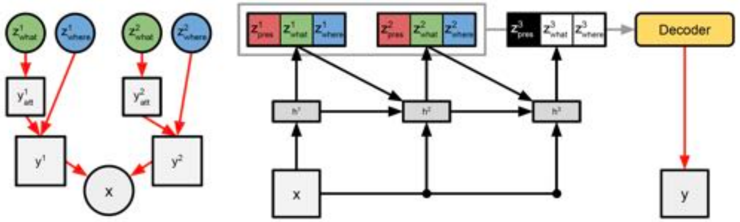
Deep Neural Network

(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

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



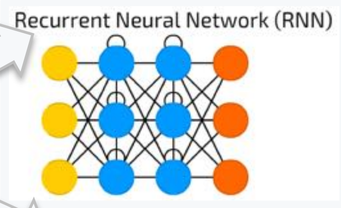


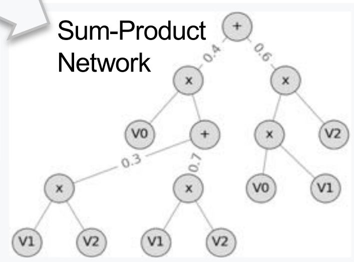
[Attend-Infer-Repeat (AIR) model, Hinton et al. NIPS 2016]

Probabilistic Programming:
Easier modelling by programming generative models in a high-level, prob. language

Deep Probabilistic Prog.:
Modelling and inference might be hard, so use a deep neural network for it

```
def prior_step(t):
    # Sample object pose. This is a 3-dimensional vector representing x,y position and size.
    z_where = pyro.sample('z_where_{}'.format(t),
                          dist.normal,
                          z_where_prior_mu, z_where_prior_sigma)

    # Sample object code. This is a 50-dimensional vector.
    z_what = pyro.sample('z_what_{}'.format(t),
                         dist.normal,
                         z_what_prior_mu, z_what_prior_sigma)

    y_att = decode(z_what)            # Map latent code to pixel space using the neural ne
```

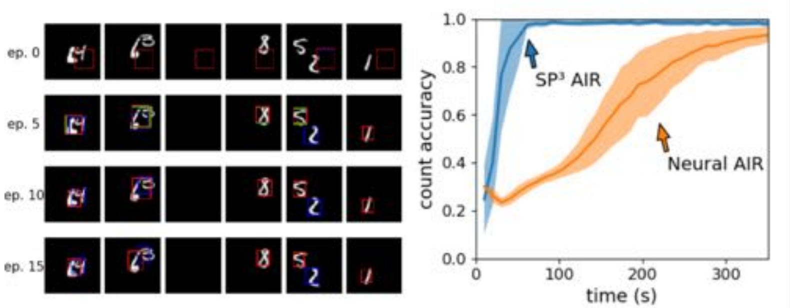




Sum-Product Probabilistic Programming:
Making machine learning and data science easier [Stelzner, Molina, Peharz, Vergari, Trapp, Valera, Ghahramani, Kersting ProgProb 2018]

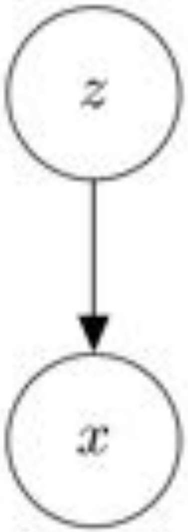
Use deep probabilistic models that feature tractable, deterministic inference

```
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
```



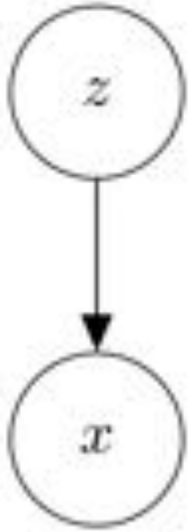
Actually, the main idea is to replace the VAEs within AIR by SPNs

VAE



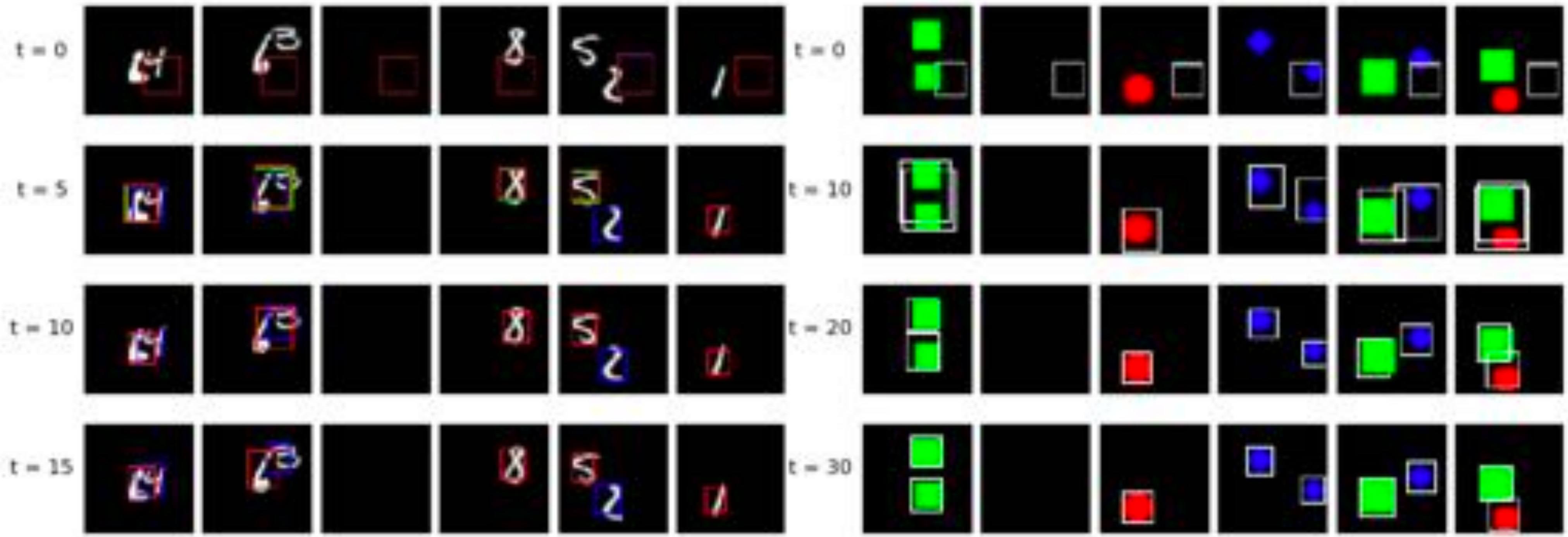
- infinite mixture model
- intractable density
- intractable posterior

SPN



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

Sum-Product Attent-Infer Repeat



[Stelzner, Peharz, Kersting 2019]

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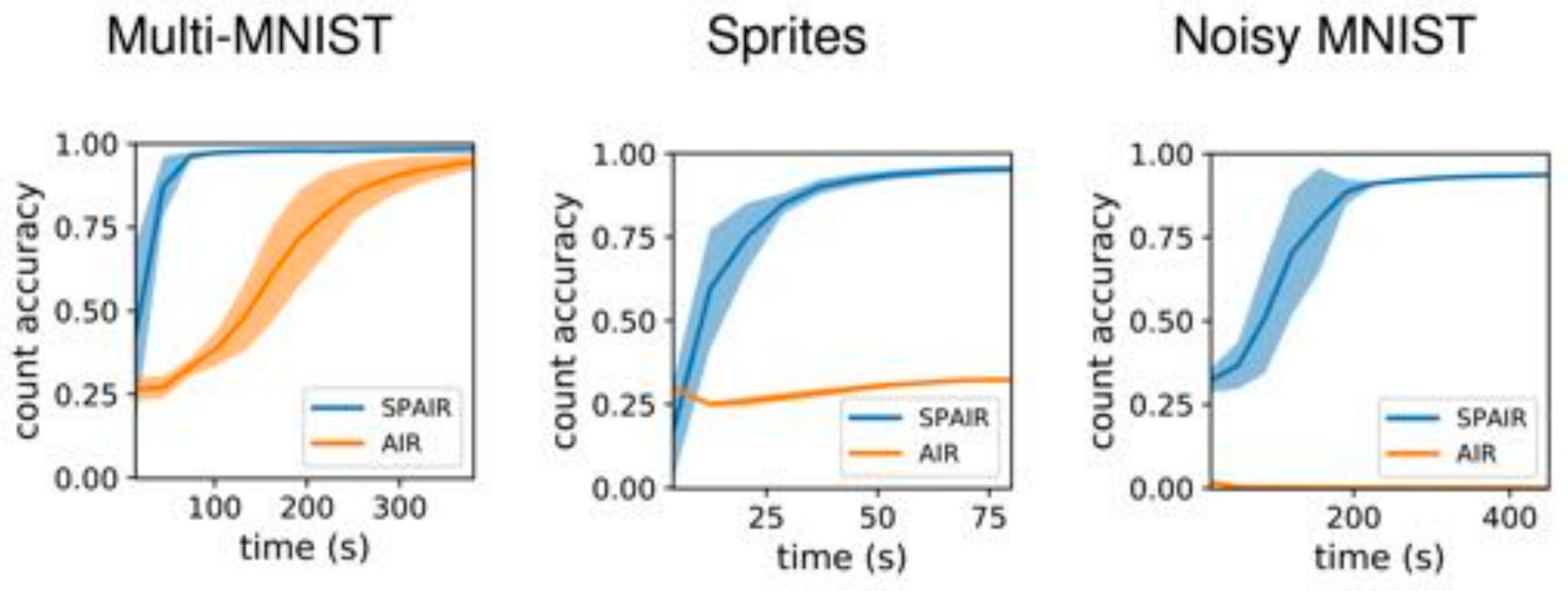
Sum-Product Attent-Infer Repeat



[Stelzner, Peharz, Kersting 2019]

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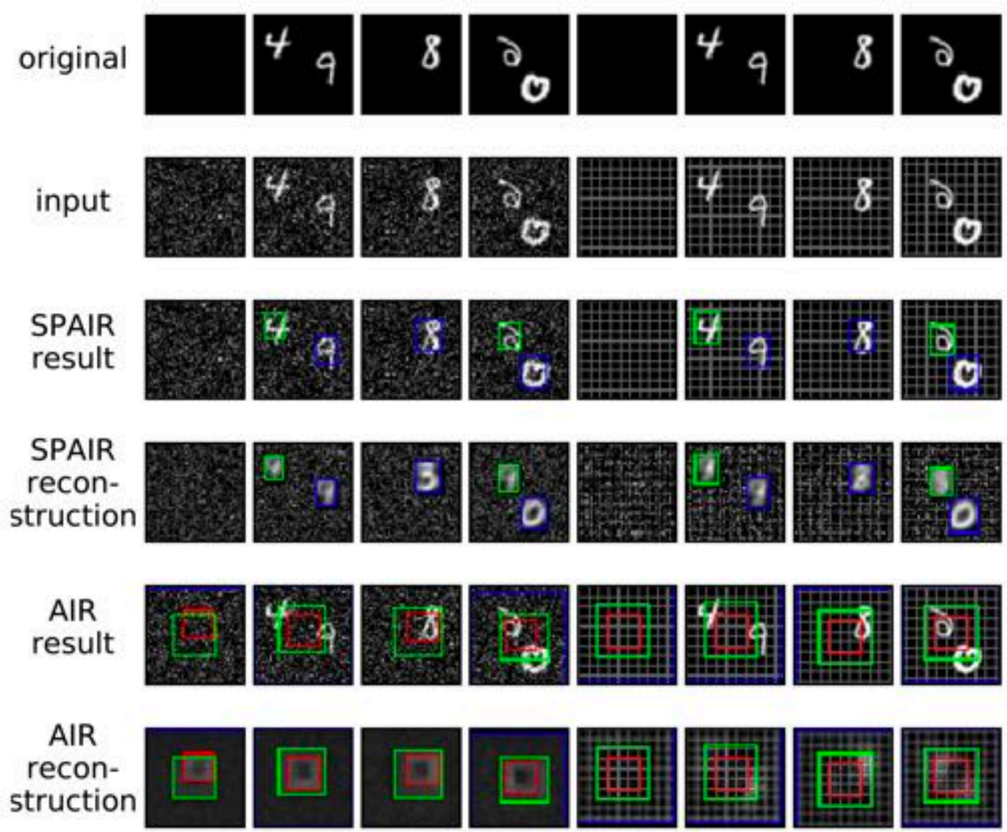
Sum-Product Attent-Infer Repeat



[Stelzner, Peharz, Kersting 2019]

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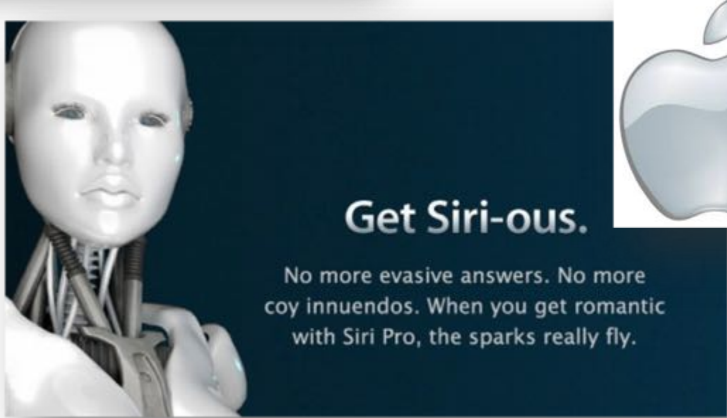
There are strong invests into (deep) probabilistic programming

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.

[Laue et al. NeurIPS 2018; Kordjamshidi, Roth, Kersting: “Systems AI: A Declarative Learning Based Programming Perspective.“ IJCAI-ECAI 2018]

Th … y

…bu … e,
d

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.

Overall, AI/ML/DS indeed refine "formal" science, 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 data science and high-level programming languages for DS help to capture this complexity
- **AI is more than just Machine Learners and Statisticians**

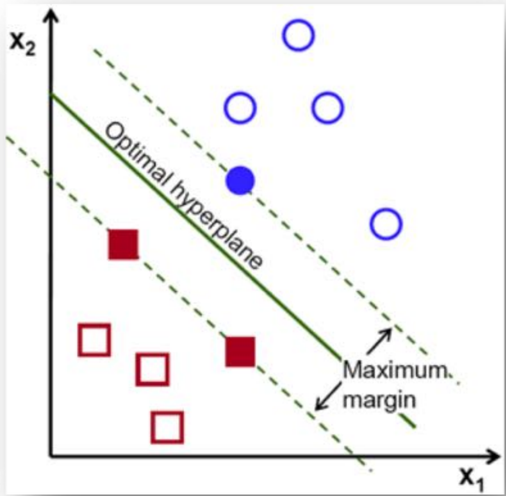
Learning-based programming offers a framework for building systems that help to go beyond, democratize, and even automize traditional AI/ML/DS

Not every Data Science machine is generative

$$\min_{\mathbf{w},b,\boldsymbol{\xi}} \ \mathcal{P}(\mathbf{w},b,\boldsymbol{\xi}) = \frac{1}{2}\mathbf{w}^2 + C\sum_{i=1}^{n}\xi_i$$

$$\text{subject to} \ \begin{cases} \forall i \quad y_i(\mathbf{w}^\top\Phi(\mathbf{x}_i)+b) \geq 1-\xi_i \\ \forall i \quad \xi_i \geq 0 \end{cases}$$

Not everyone likes to turn math into code



Support Vector Machines
Cortes, Vapnik MLJ 20(3):273-297, 1995

High-level Languages for Mathematical Programs

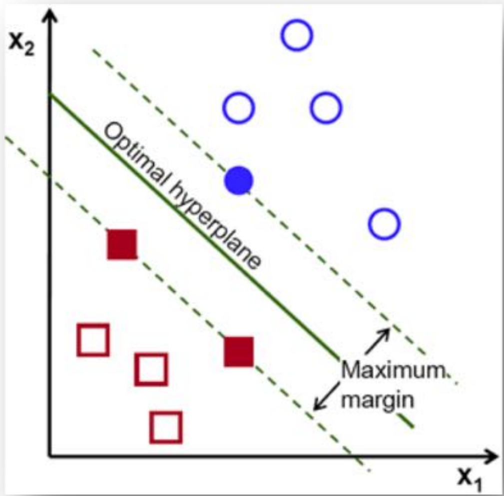
Write down SVM in „paper form.“ The machine compiles it into solver form.

```
#QUADRATIC OBJECTIVE
minimize: sum{J in feature(I,J)} weight(J)**2 + c1 * slack + c2 * coslack;

#labeled examples should be on the correct side
subject to forall {I in labeled(I)}: labeled(I)*predict(I) >= 1 - slack(I);

#slacks are positive
subject to forall {I in labeled(I)}: slack(I) >= 0;
```

Embedded within Python s.t. loops and rules can be used

reloop

RELOOP: A Toolkit for Relational Convex Optimization



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