PSDDs for Tractable Learning in Structured and Unstructured Spaces

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UCLA

DeLBP

Aug 18, 2017

STAR AI RESEARCH LAB UCLA

References

Probabilistic Sentential Decision Diagrams
Doga Kisa, Guy Van den Broeck, Arthur Choi and Adnan Darwiche
KR, 2014

Learning with Massive Logical Constraints
Doga Kisa, Guy Van den Broeck, Arthur Choi and Adnan Darwiche
ICML LTPM workshop, 2014

Tractable Learning for Structured Probability Spaces
Arthur Choi, Guy Van den Broeck and Adnan Darwiche
IJCAI, 2015

Tractable Learning for Complex Probability Queries
Jessa Bekker, Jesse Davis, Arthur Choi, Adnan Darwiche, Guy Van den Broeck.
NIPS, 2015

Learning the Structure of PSDDs
Yitao Liang, Jessa Bekker and Guy Van den Broeck
UAI, 2017

Towards Compact Interpretable Models: Learning and Shrinking PSDDs
Yitao Liang and Guy Van den Broeck
IJCAI XAI workshop, 2017

(P)SDDs in Melbourne

- Sunday: Logical Foundations for Uncertainty and Machine Learning Workshop
  - Adnan Darwiche: *“On the Role of Logic in Probabilistic Inference and Machine Learning”*
  - YooJung Choi: *“Optimal Feature Selection for Decision Robustness in Bayesian Networks”*
- Sunday: Explainable AI Workshop
  - Yitao Liang: *“Towards Compact Interpretable Models: Learning and Shrinking PSDDs”*
- Tuesday: IJCAI
  - YooJung Choi (again)

Structured vs. unstructured probability spaces?

Running Example

Courses:

- Logic (L)
- Knowledge Representation (K)
- Probability (P)
- Artificial Intelligence (A)

Data

L	K	P	A	Students
0	0	1	0	6
0	0	1	1	54
0	1	1	1	10
1	0	0	0	5
1	0	1	0	1
1	0	1	1	0
1	1	0	0	17
1	1	1	0	4
1	1	1	1	3

Running Example

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- Logic (L)
- Knowledge Representation (K)
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Data

L	K	P	A	Students
0	0	1	0	6
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1	0	0	0	5
1	0	1	0	1
1	0	1	1	0
1	1	0	0	17
1	1	1	0	4
1	1	1	1	3

Constraints

- Must take at least one of Probability or Logic.
- Probability is a prerequisite for AI.
- The prerequisites for KR is either AI or Logic.

Probability Space

unstructured

L	K	P	A
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1
1	1	0	0
1	1	0	1
1	1	1	0
1	1	1	1

Structured Probability Space

unstructured

L	K	P	A
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1
1	1	0	0
1	1	0	1
1	1	1	0
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- Must take at least one of Probability or Logic.
- Probability is a prerequisite for AI.
- The prerequisites for KR is either AI or Logic.

7 out of 16 instantiations are impossible

structured

L	K	P	A
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1
1	1	0	0
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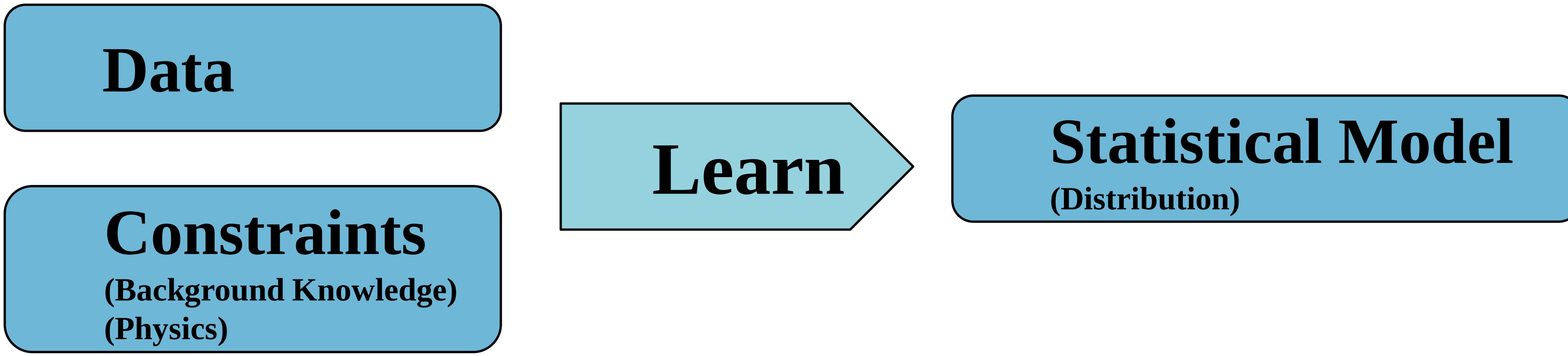
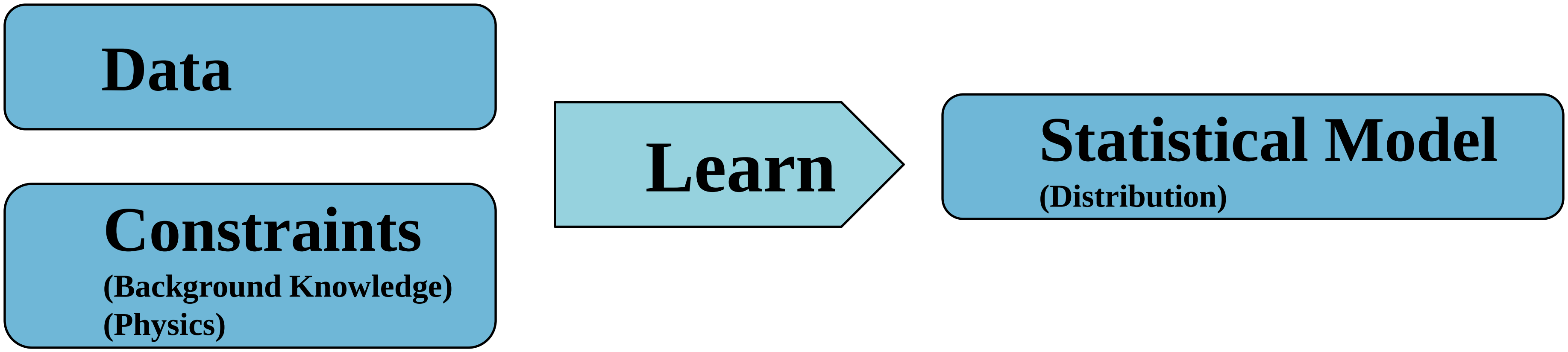
Learning with Constraints

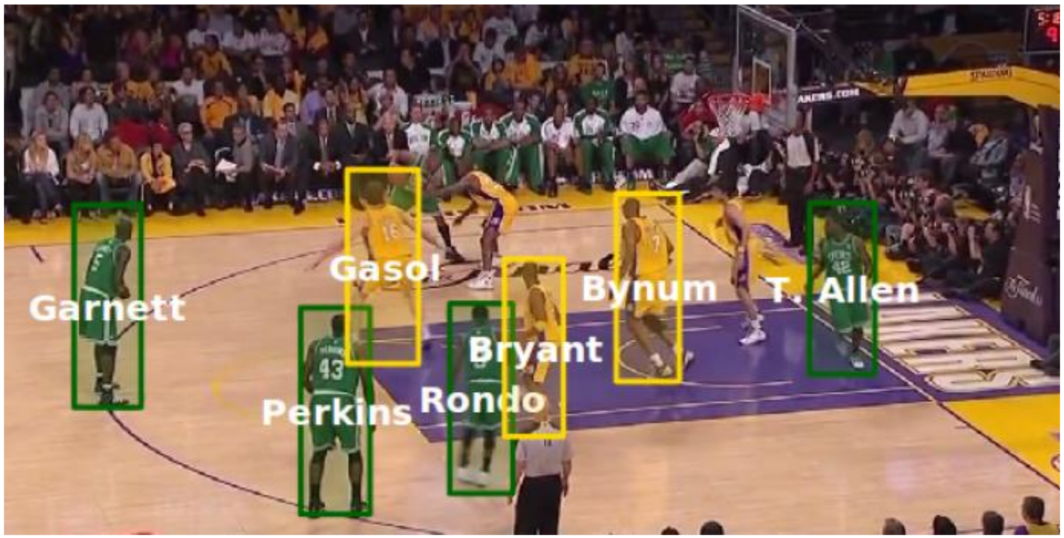


Learning with Constraints



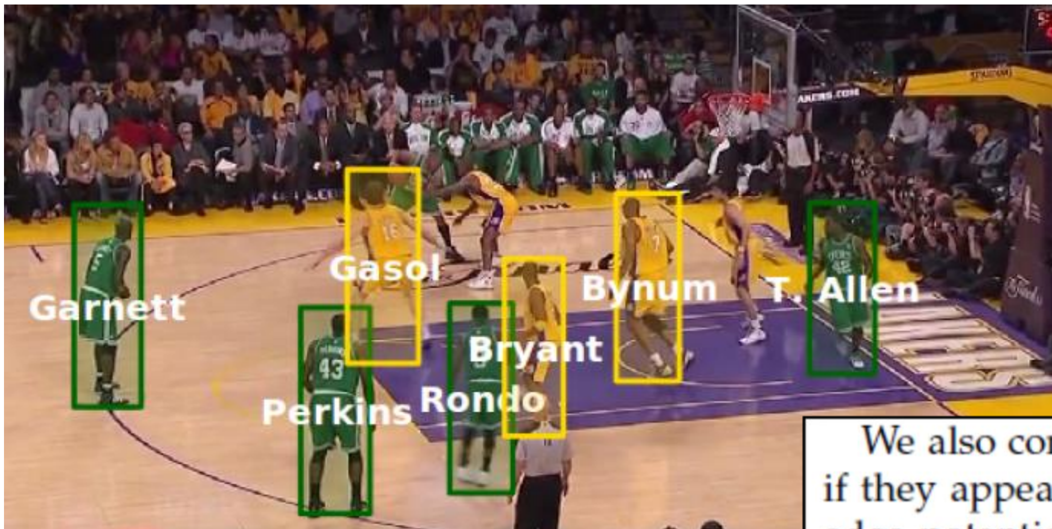
Learn a statistical model that assigns
zero probability
to instantiations that violate the constraints.

Example: Video



[Lu, W. L., Ting, J. A., Little, J. J., & Murphy, K. P. (2013). Learning to track and identify players from broadcast sports videos.]

Example: Video



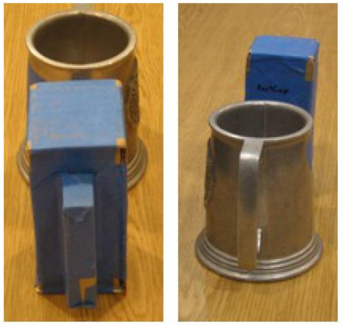
We also connect all pairs of identity nodes $y_{t,i}$ and $y_{t,j}$ if they appear in the same time t. We then introduce an edge potential that enforces mutual exclusion:

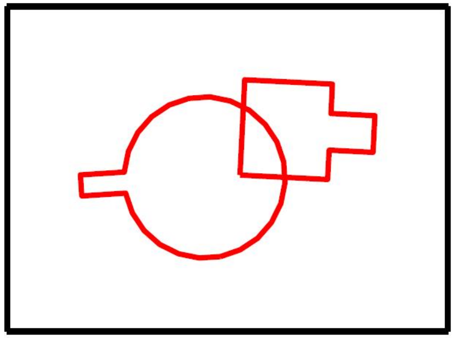
$$\psi_{\text{mutex}}(y_{t,i}, y_{t,j}) = \begin{cases} 1 & \text{if } y_{t,i} \neq y_{t,j} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

This potential specifies the constraint that a player can be appear only *once* in a frame. For example, if the i-th detection $y_{t,i}$ has been assign to Bryant, $y_{t,j}$ cannot have the same identity because Bryant is impossible to appear twice in a frame.

[Lu, W. L., Ting, J. A., Little, J. J., & Murphy, K. P. (2013). Learning to track and identify players from broadcast sports videos.]

Example: Robotics





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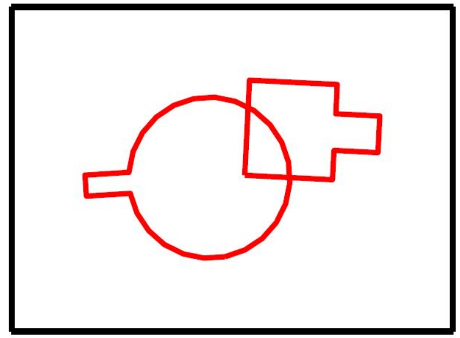

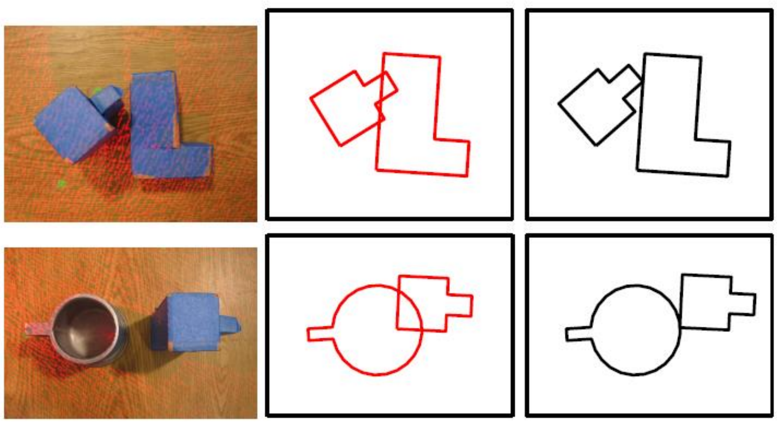

The method developed in this paper can be used in a broad variety of semantic mapping and object manipulation tasks, providing an efficient and effective way to incorporate collision constraints into a recursive state estimator, obtaining optimal or near-optimal solutions.

[Wong, L. L., Kaelbling, L. P., & Lozano-Perez, T., Collision-free state estimation. ICRA 2012]

Example: Language

- Non-local dependencies:

  At least one verb in each sentence

[Chang, M., Ratinov, L., & Roth, D. (2008). Constraints as prior knowledge],…, [Chang, M. W., Ratinov, L., & Roth, D. (2012). Structured learning with constrained conditional models.], [https://en.wikipedia.org/wiki/Constrained_conditional_model]

Example: Language

- Non-local dependencies:

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- Sentence compression

  If a modifier is kept, its subject is also kept

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- Information extraction

Citations	
Start	The citation must start with author or editor.
AppearsOnce	Each field must be a consecutive list of words, and can appear at most once in a citation.
Punctuation	State transitions must occur on punctuation marks.
BookJournal	The words *proc, journal, proceedings, ACM* are *JOURNAL* or *BOOKTITLE*.
...	...
TechReport	The words *tech, technical* are *TECH_REPORT*.
Title	Quotations can appear only in titles.
Location	The words *CA, Australia, NY* are *LOCATION*.

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- Information extraction
- Semantic role labeling
- … and many more!

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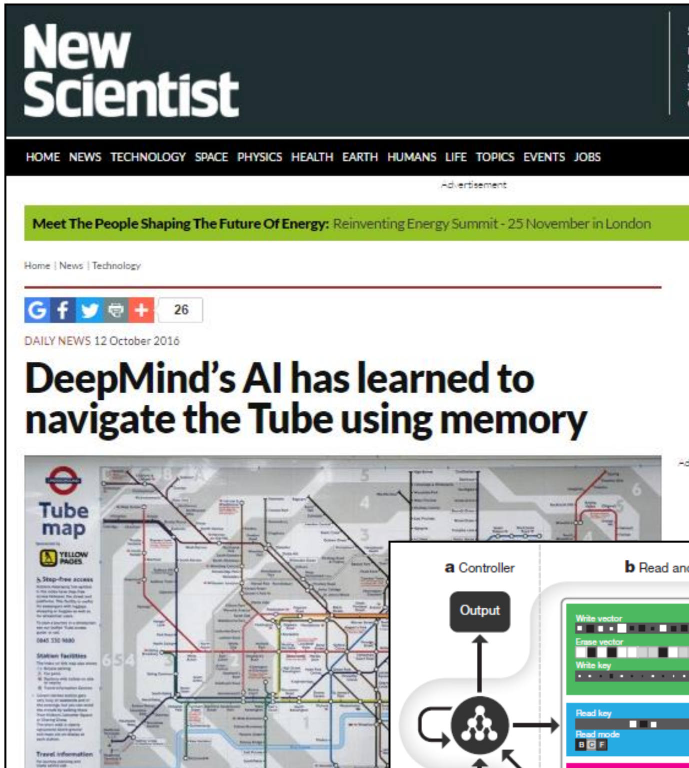
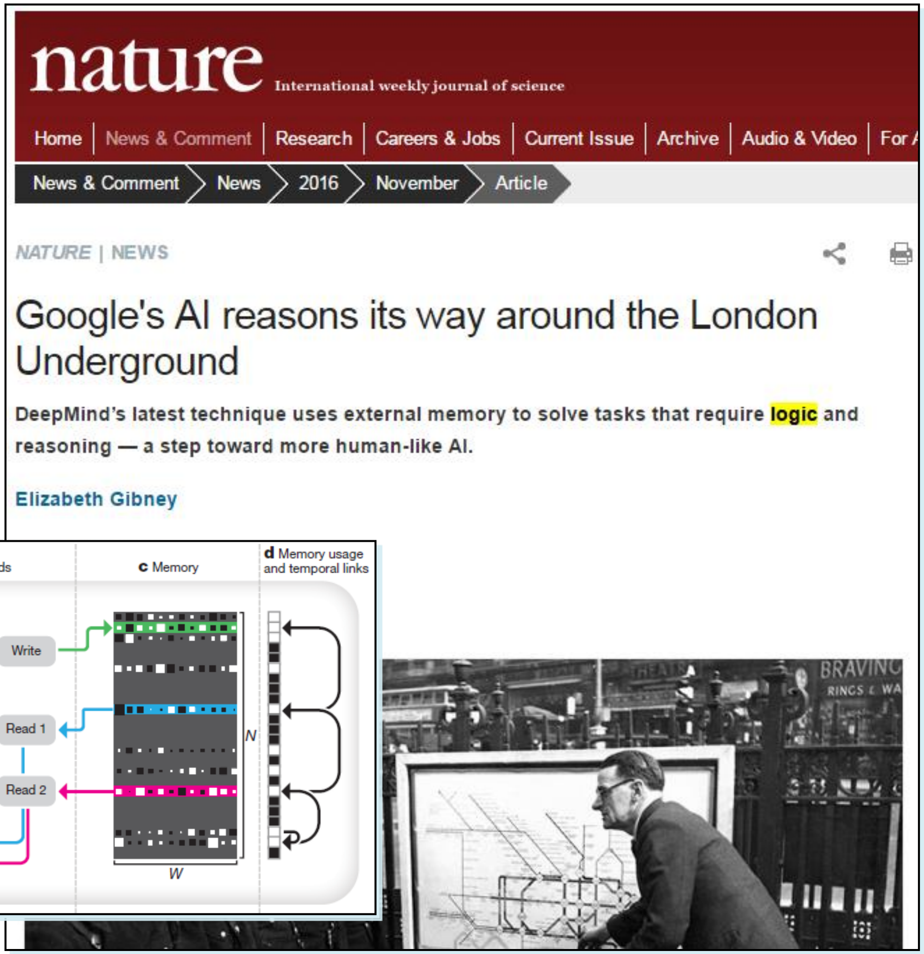
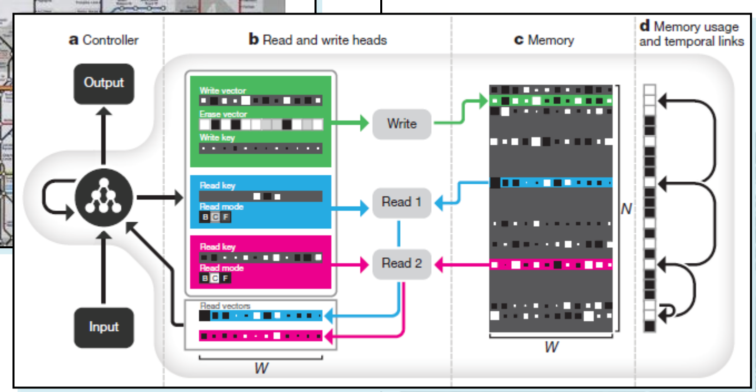
Example: Deep Learning







[Graves, A., Wayne, G., Reynolds, M., Harley, T., Danihelka, I., Grabska-Barwińska, A., et al.. (2016). Hybrid computing using a neural network with dynamic external memory. *Nature*, *538*(7626), 471-476.]

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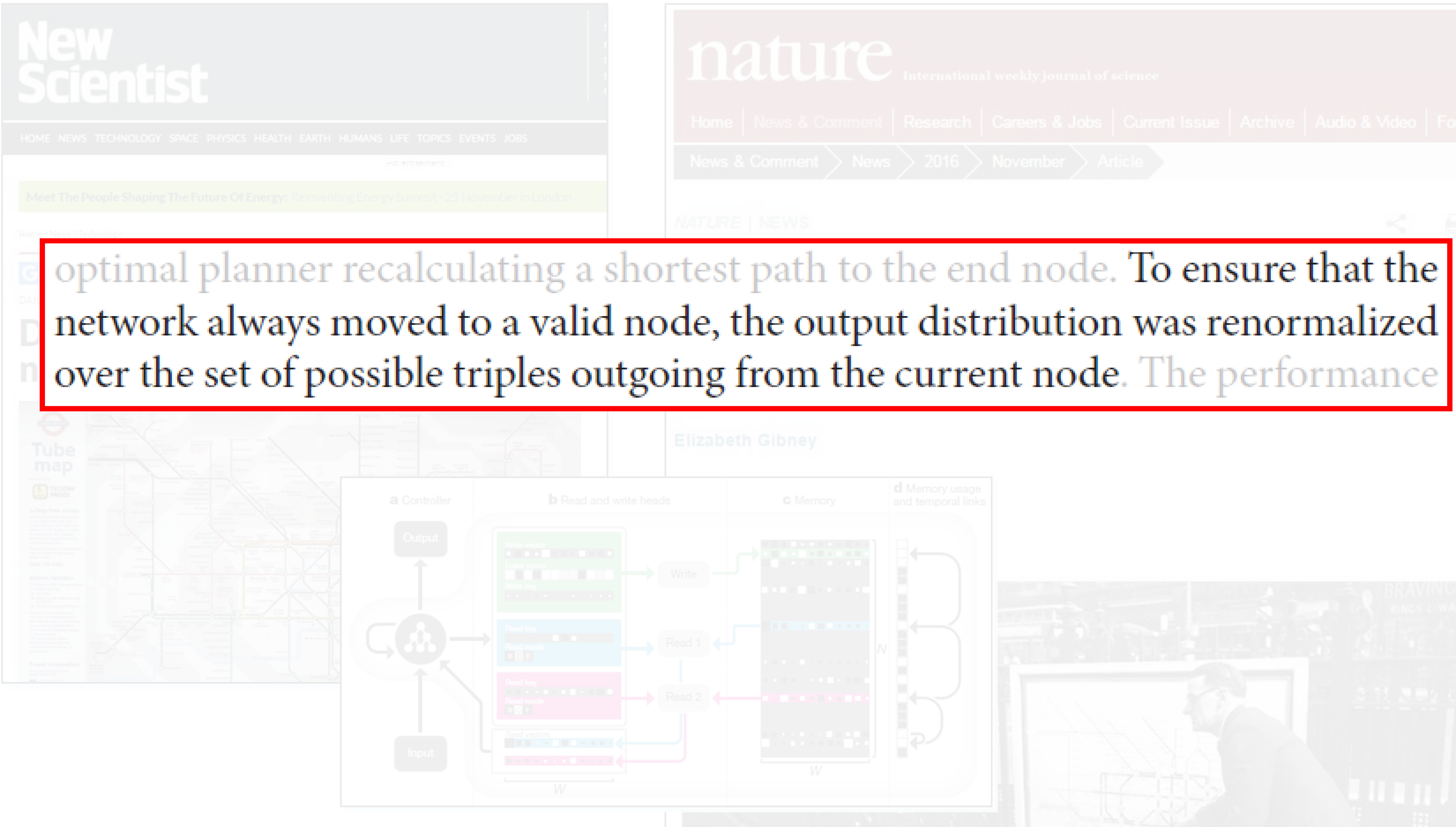

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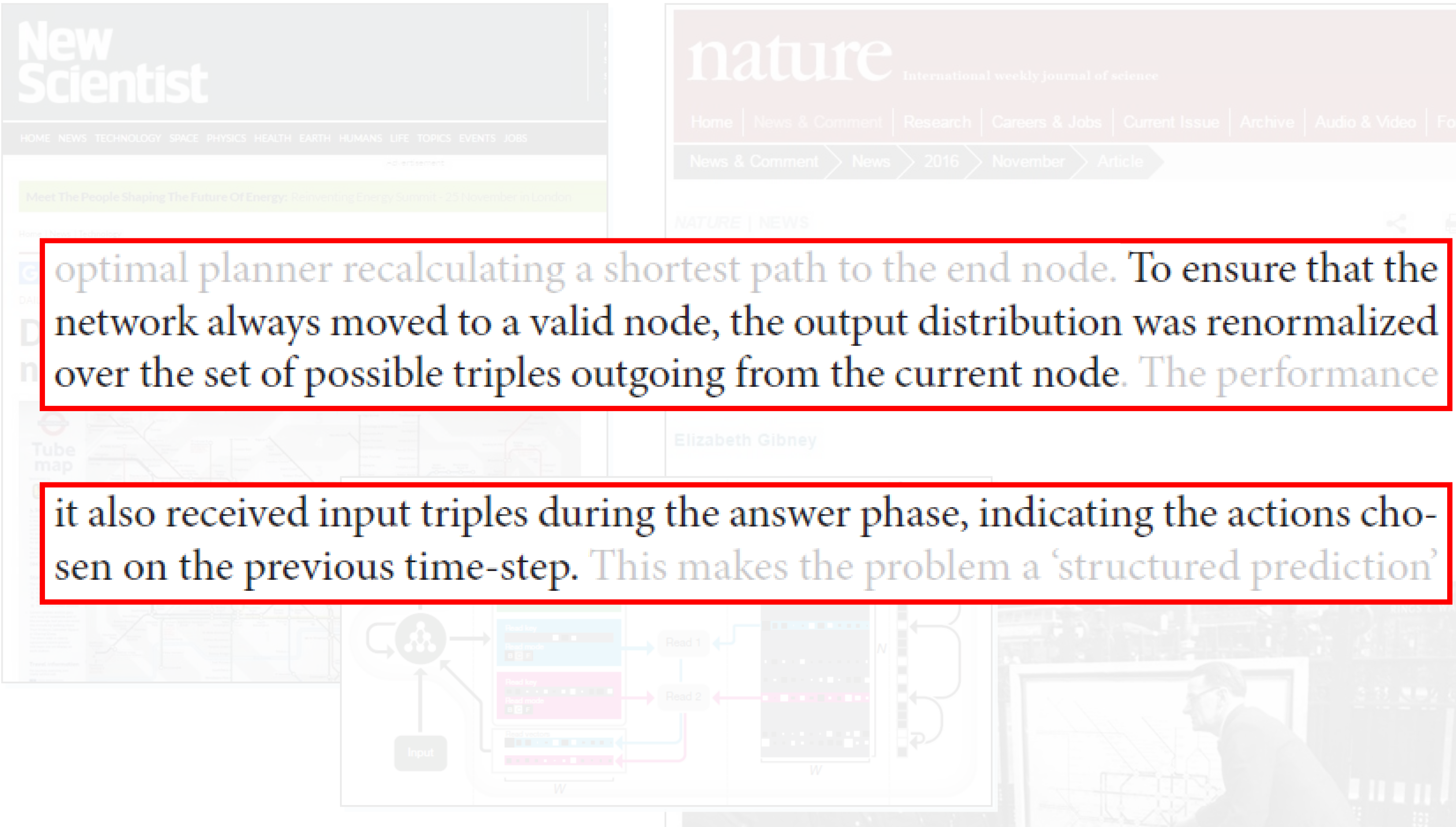

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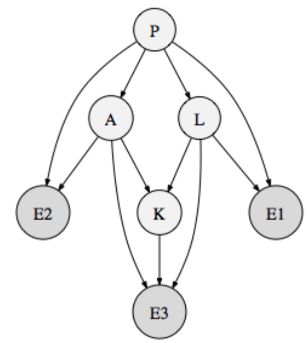
What are people doing now?

- Ignore constraints
- Handcraft into models
- Use specialized distributions
- Find non-structured encoding
- Try to learn constraints
- Hack your way around



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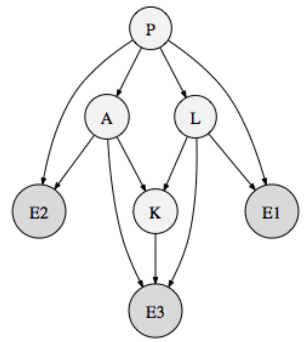

Accuracy ?
Specialized skill ?
Intractable inference ?
Intractable learning ?
Waste parameters ?
Risk predicting out of space ?

+

you are on your own ☹

Structured Probability Spaces

- Everywhere in ML!
  - Configuration problems, inventory, video, text, deep learning
  - Planning and diagnosis (physics)
  - Causal models: cooking scenarios (interpreting videos)
  - Combinatorial objects: parse trees, rankings, directed acyclic graphs, trees, simple paths, game traces, etc.

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No statistical ML boxes out there that take constraints as input! ☹

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<u>Goal</u>: Constraints as important as data! General purpose!

Specification Language: Logic

Structured Probability Space

unstructured

L	K	P	A
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1
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- Must take at least one of Probability or Logic.
- Probability is a prerequisite for AI.
- The prerequisites for KR is either AI or Logic.

7 out of 16 instantiations are impossible

structured

L	K	P	A
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1
1	1	0	0
1	1	0	1
1	1	1	0
1	1	1	1

Boolean Constraints

unstructured

L	K	P	A
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1
1	1	0	0
1	1	0	1
1	1	1	0
1	1	1	1

$$P \vee L$$
$$A \Rightarrow P$$
$$K \Rightarrow (P \vee L)$$

7 out of 16 instantiations are impossible

structured

L	K	P	A
0	0	0	0
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0	0	1	1
0	1	0	0
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0	1	1	1
1	0	0	0
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1	0	1	0
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Combinatorial Objects: Rankings

rank	sushi
1	fatty tuna
2	sea urchin
3	salmon roe
4	shrimp
5	tuna
6	squid
7	tuna roll
8	see eel
9	egg
10	cucumber roll

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10 items:
3,628,800
rankings

20 items:
2,432,902,008,176,640,000
rankings

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A_{ij} item i at position j (n items require n^2 Boolean variables)

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A_{ij} item *i* at position *j* (*n* items require n^2 Boolean variables)

An item may be assigned to more than one position

A position may contain more than one item

Encoding Rankings in Logic

A_{ij} : item i at position j

	pos 1	pos 2	pos 3	pos 4
item 1	A_{11}	A_{12}	A_{13}	A_{14}
item 2	A_{21}	A_{22}	A_{23}	A_{24}
item 3	A_{31}	A_{32}	A_{33}	A_{34}
item 4	A_{41}	A_{42}	A_{43}	A_{44}

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constraint: each item *i* assigned to a unique position (*n* constraints)

$$\bigvee_j A_{ij} \wedge \left(\bigwedge_{k \neq j} \neg A_{ik} \right)$$

Encoding Rankings in Logic

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total constraints	$2n$
unstructured space	2^{n^2}
structured space	$n!$

Structured Space for Paths

cf. Nature paper


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Google's AI reasons its way around the London Underground

DeepMind's latest technique uses external memory to solve tasks that require logic and reasoning — a step toward more human-like AI.

Elizabeth Gibney

13 October 2016

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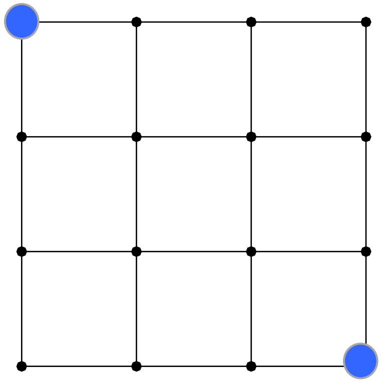

Structured Space for Paths

cf. Nature paper


nature
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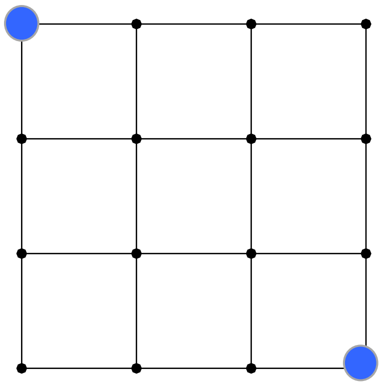

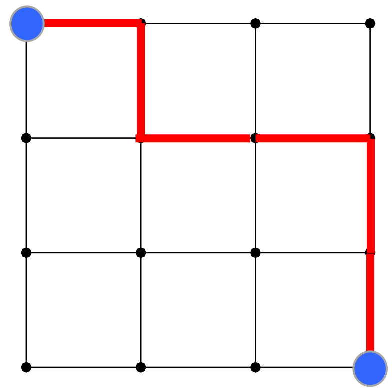

Good variable assignment (represents route)

184

Structured Space for Paths

cf. Nature paper


nature

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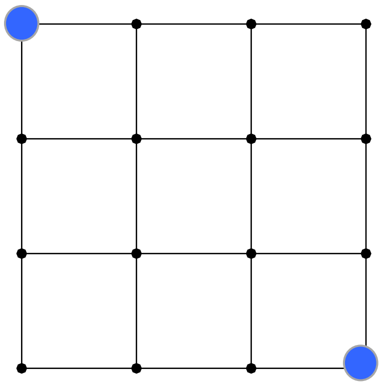
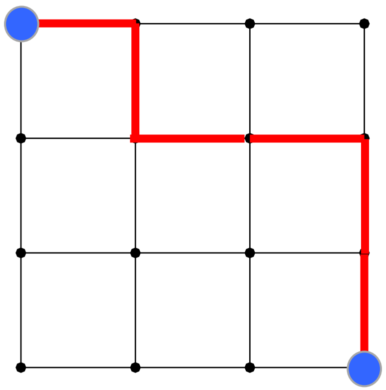
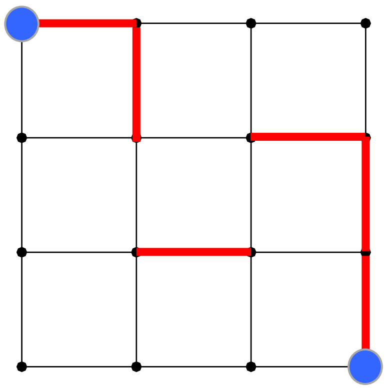






Good variable assignment (represents route)

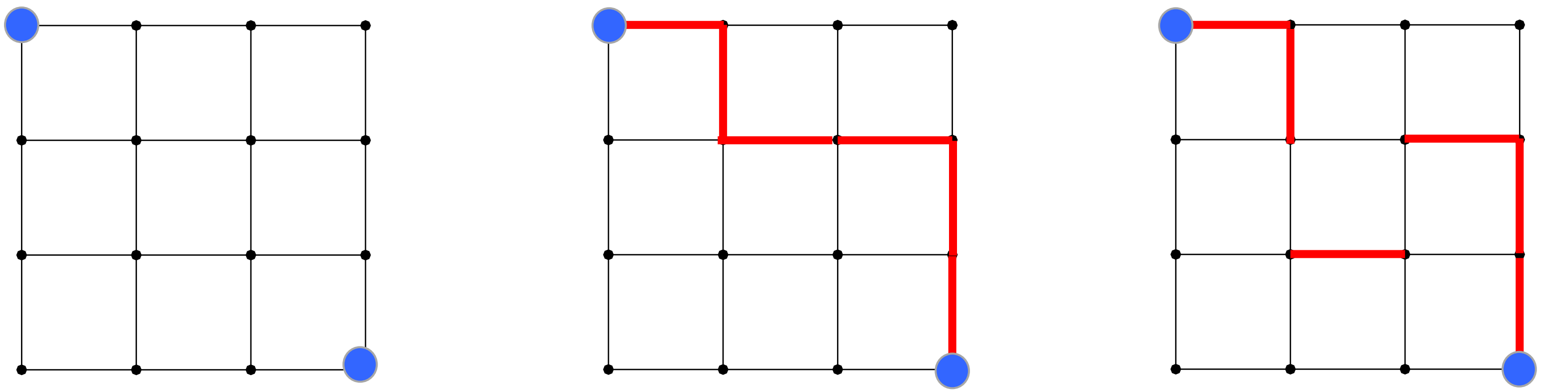
184

Bad variable assignment (does not represent route)

16,777,032

Structured Space for Paths

cf. Nature paper



Good variable assignment (represents route)

184

Bad variable assignment (does not represent route)

16,777,032

Space easily encoded in logical constraints ☺

See [Choi, Tavabi, Darwiche, AAAI 2016]

Structured Space for Paths

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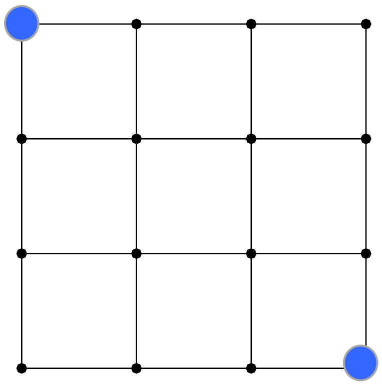

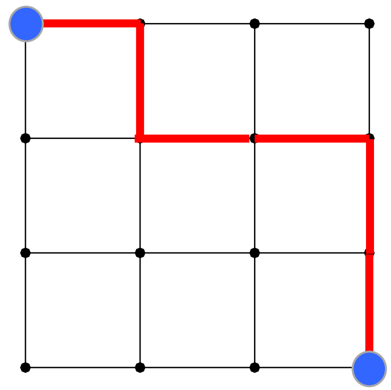

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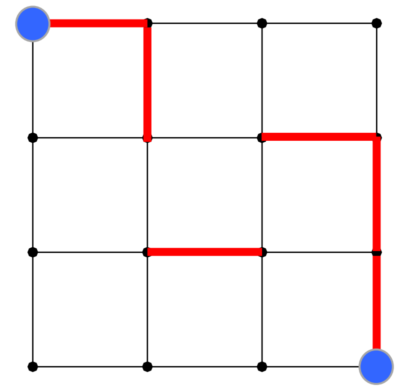

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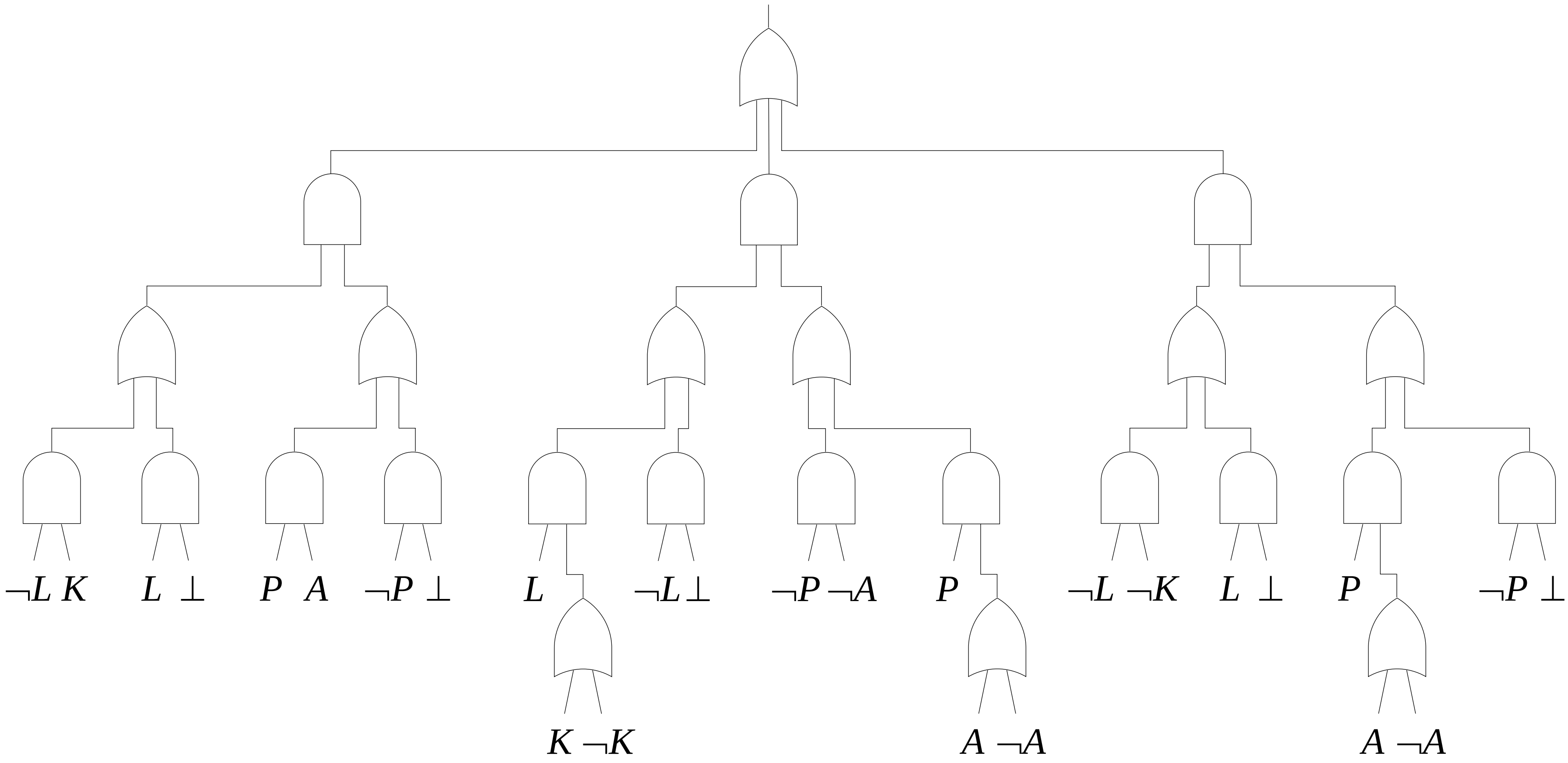
Unstructured probability space: 184+16,777,032 = 2^{24}

“Deep Architecture”

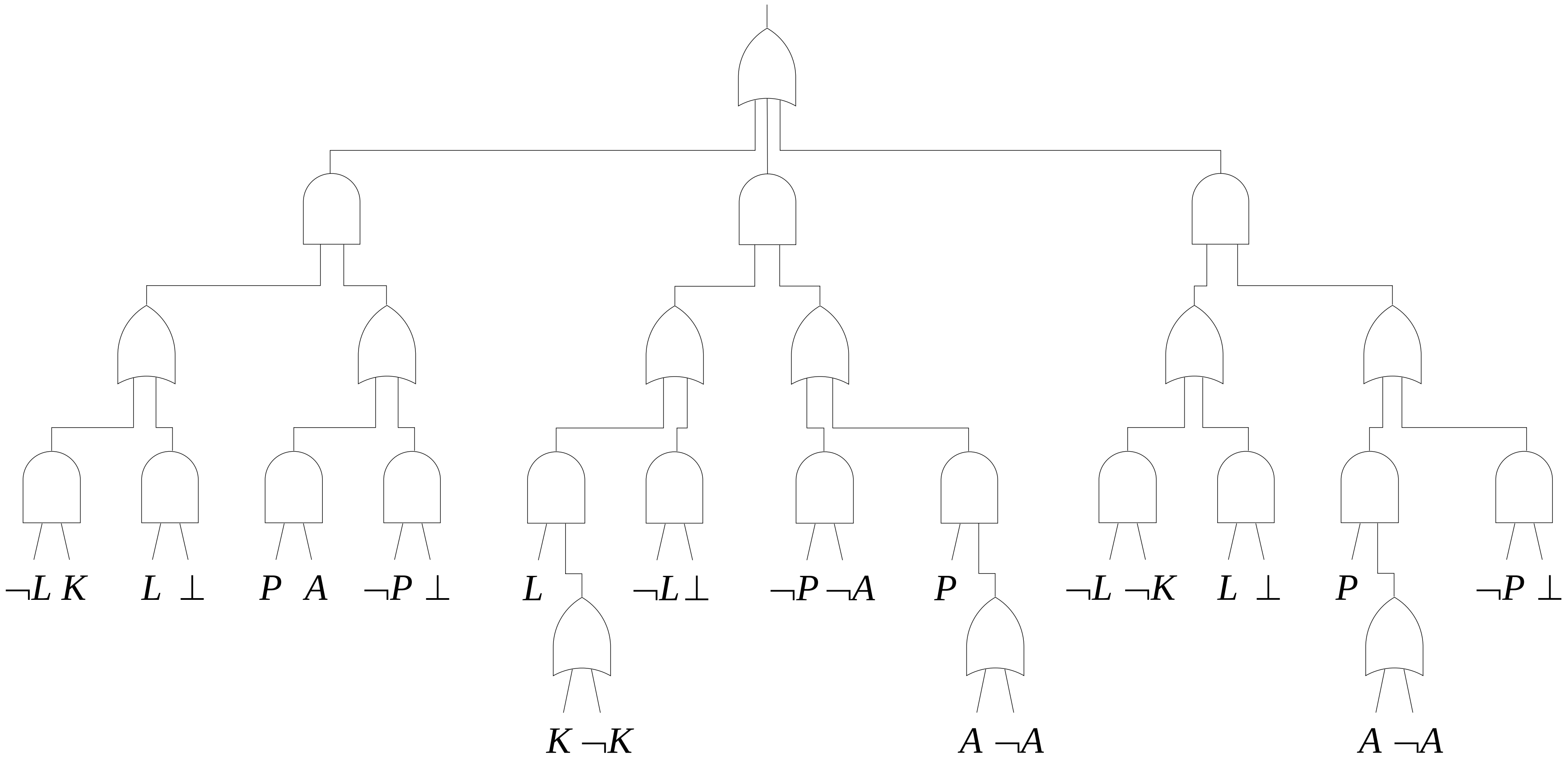
Logic + Probability

Logical Circuits

$P \vee L$
$A \Rightarrow P$
$K \Rightarrow (P \vee L)$



Property: Decomposability



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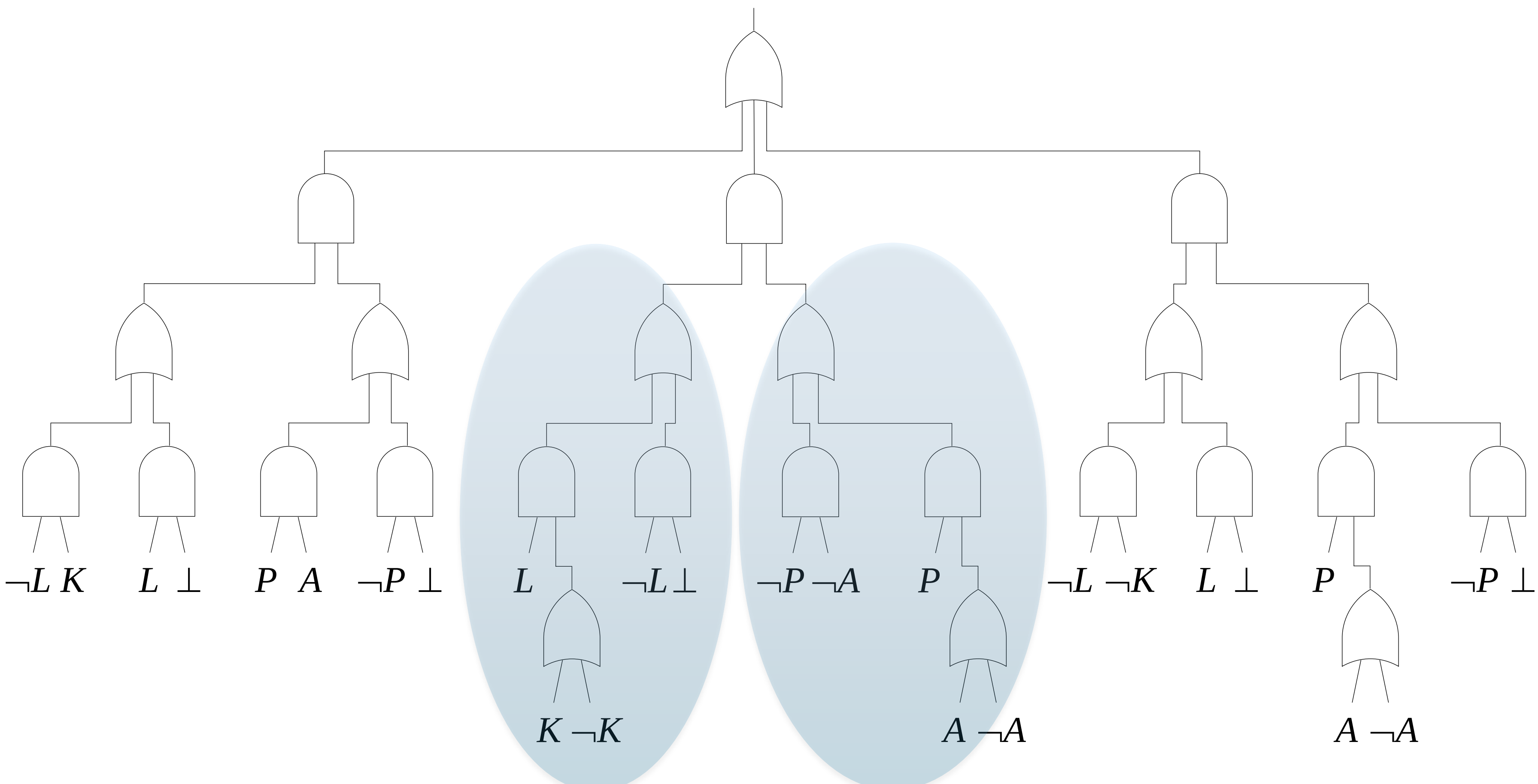
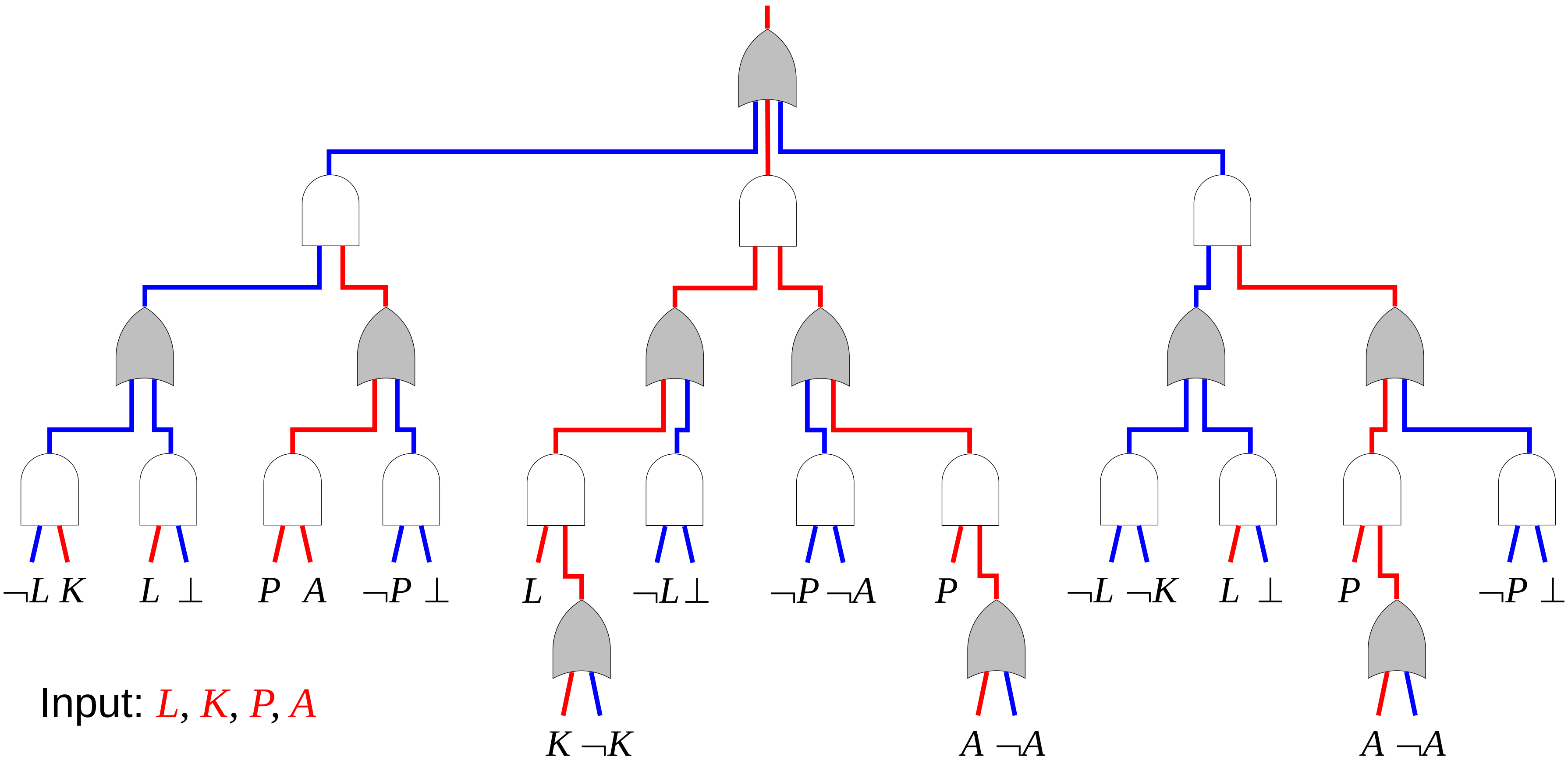
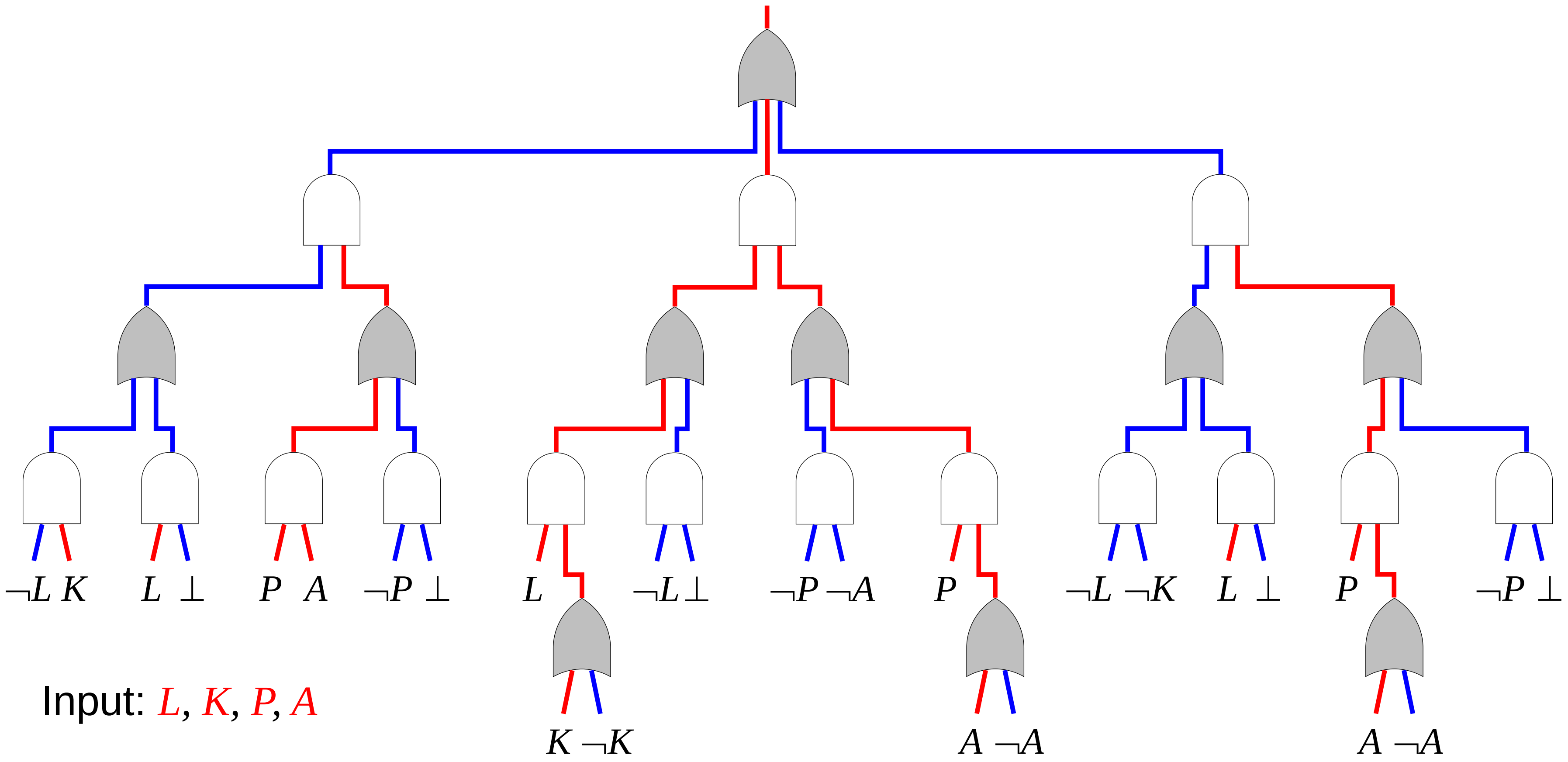


Property: Determinism



Input: L, K, P, A

Sentential Decision Diagram (SDD)



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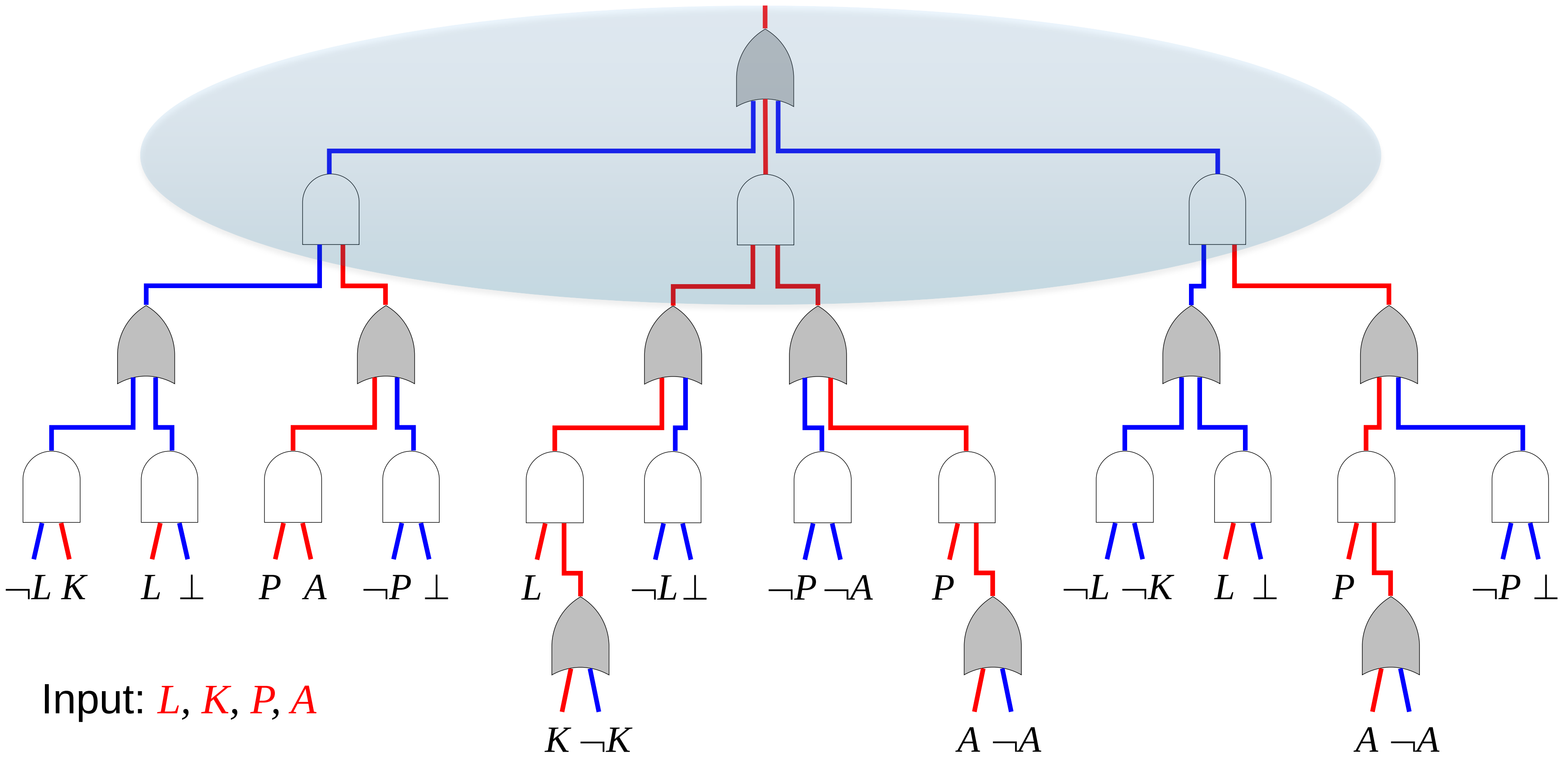

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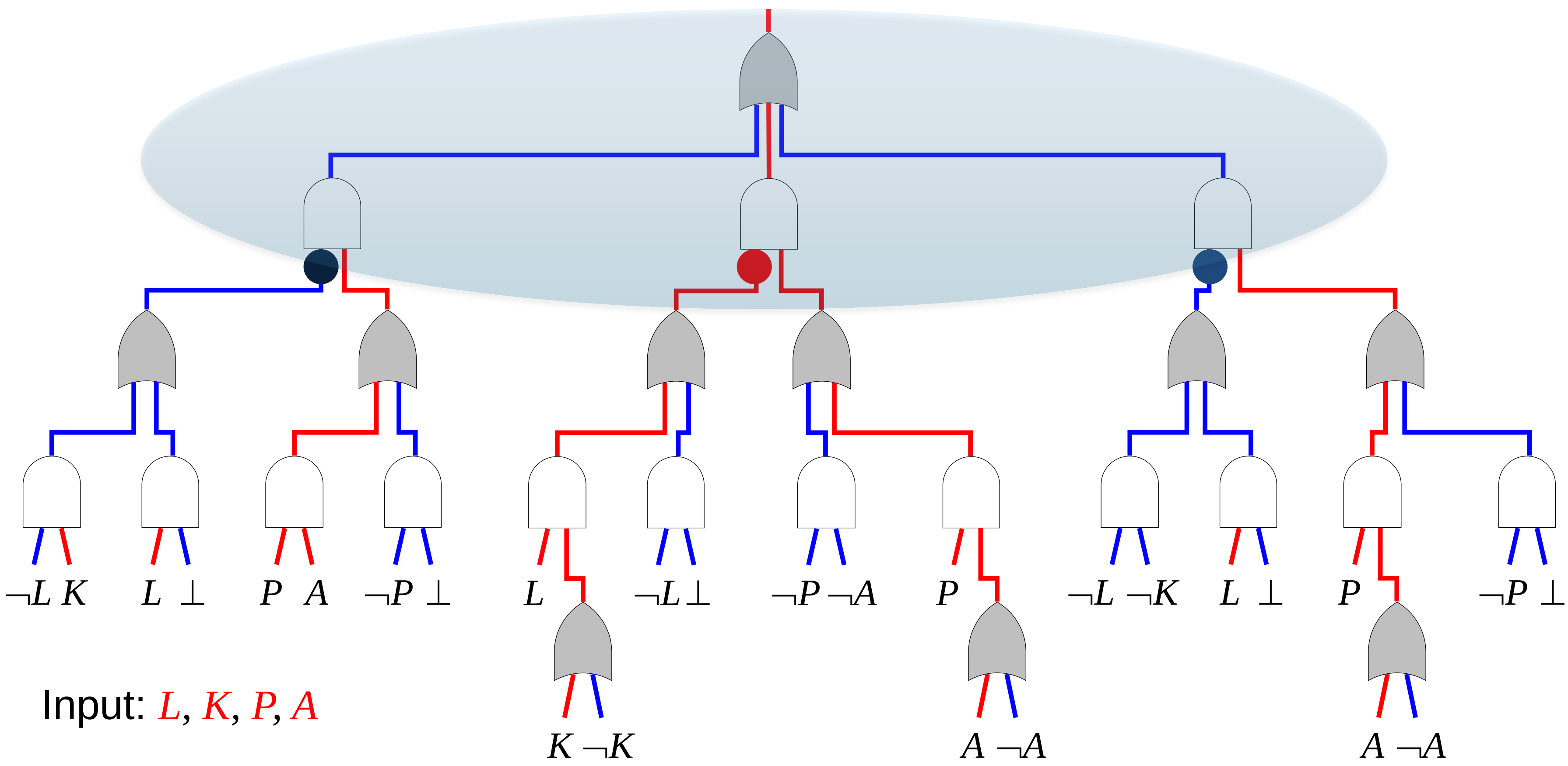

Input: L, K, P, A

Tractable for Logical Inference

- Is structured space empty? (SAT)
- Count size of structured space (#SAT)
- Check equivalence of spaces

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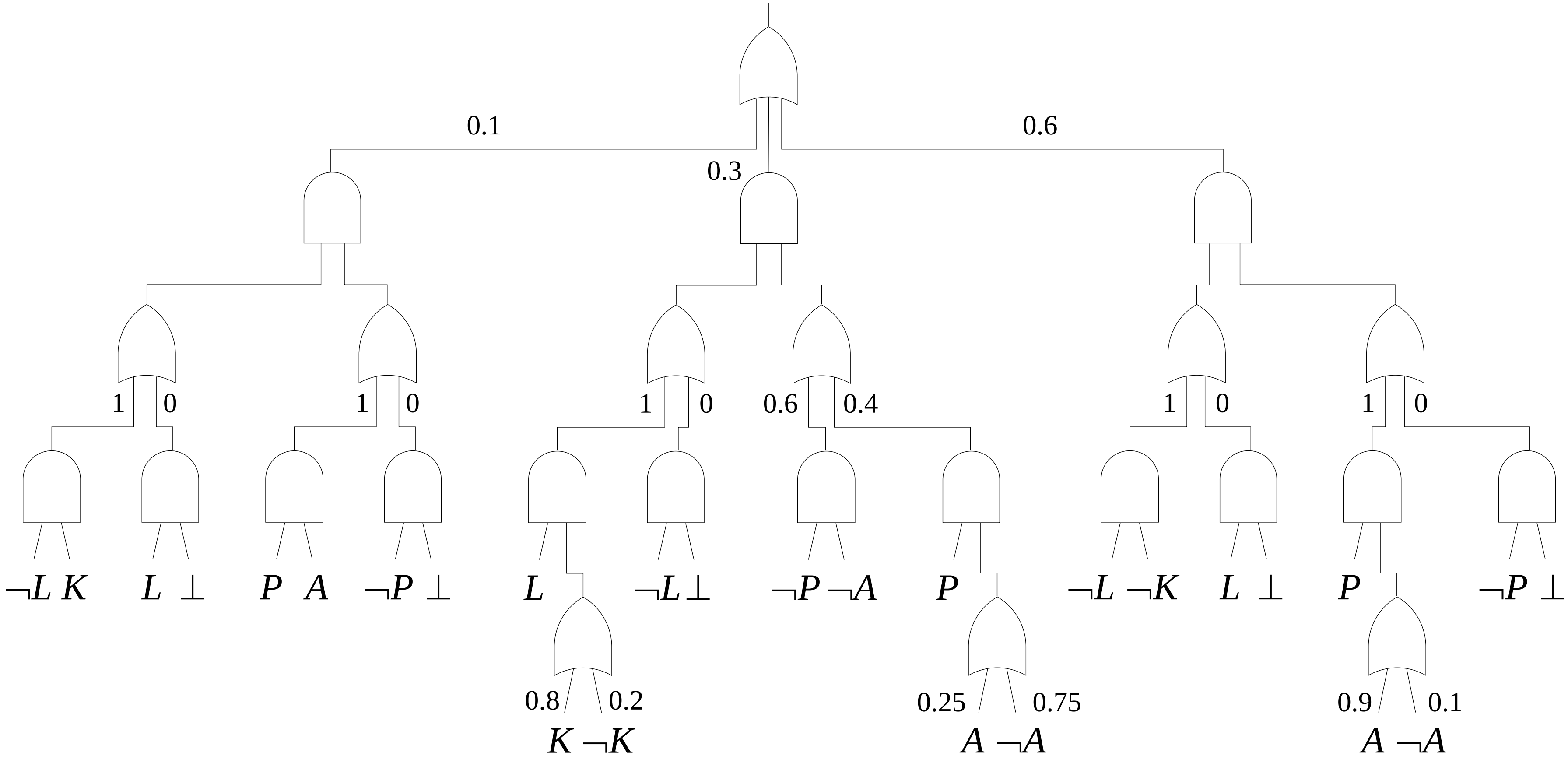
SCIENCE + TECHNOLOGY

Artificial intelligence framework developed by UCLA professor now powers Toyota websites

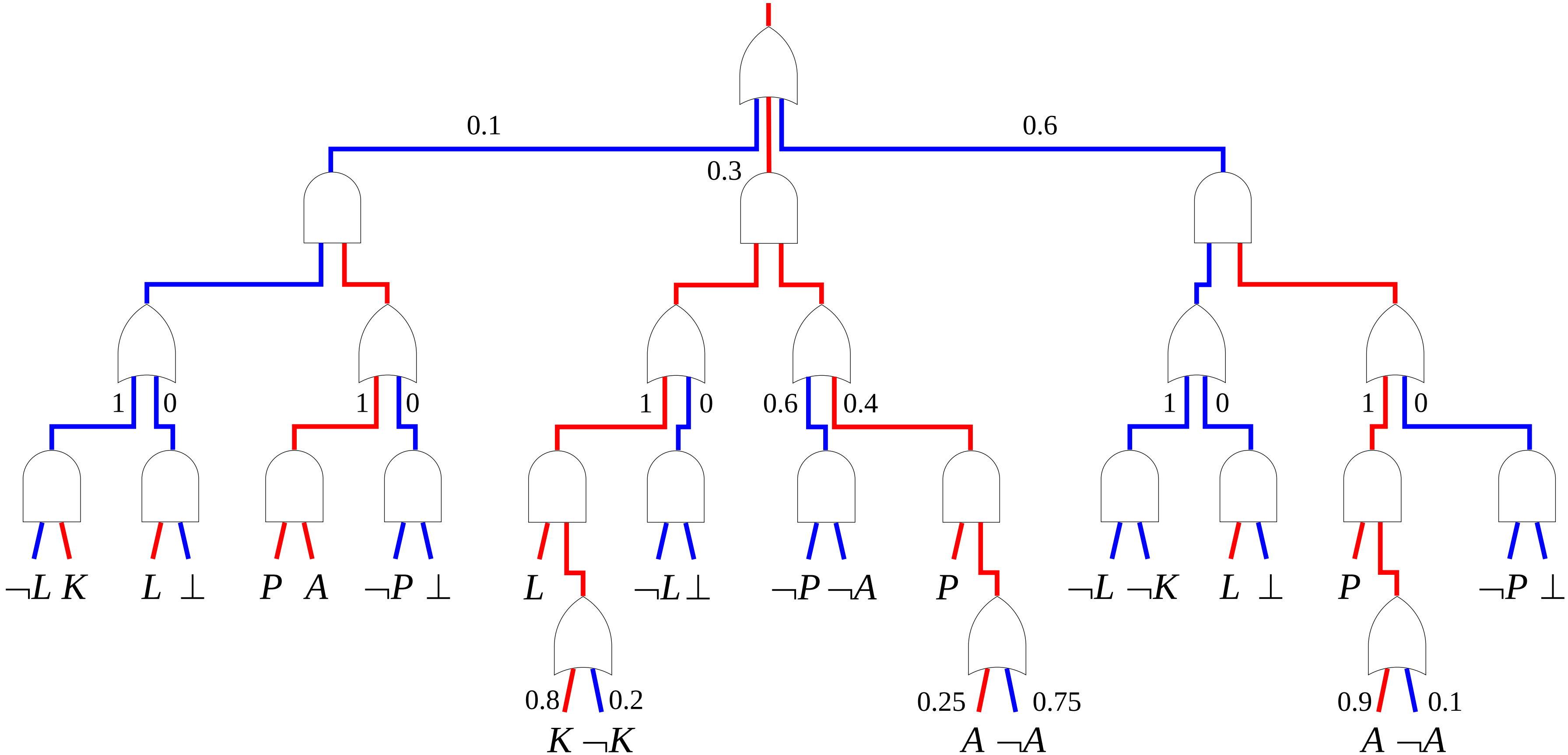
Adnan Darwiche's invention helps consumers customize their vehicles online

Matthew Chin | May 12, 2016

PSDD: Probabilistic SDD



PSDD: Probabilistic SDD



Input: *L*, *K*, *P*, *A*

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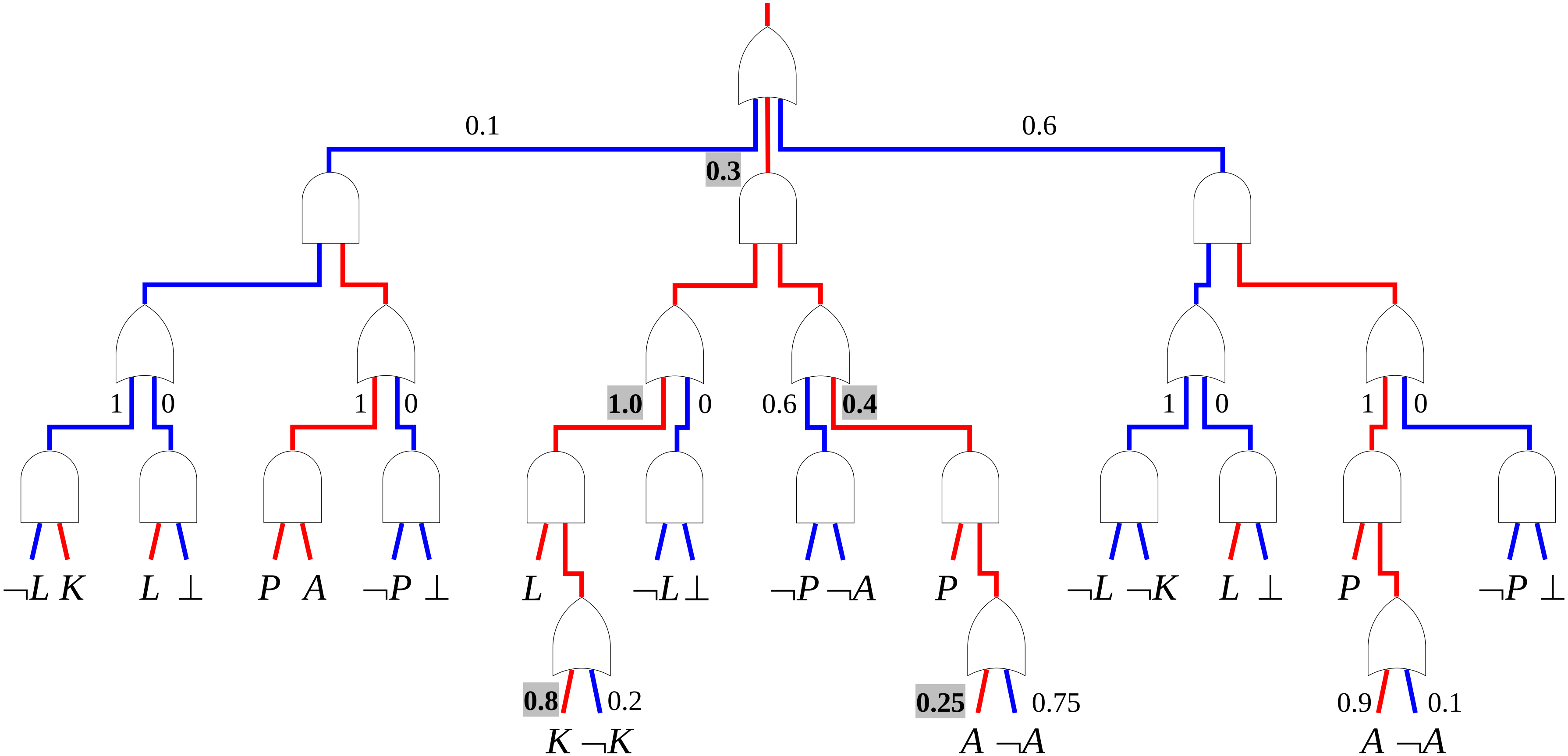

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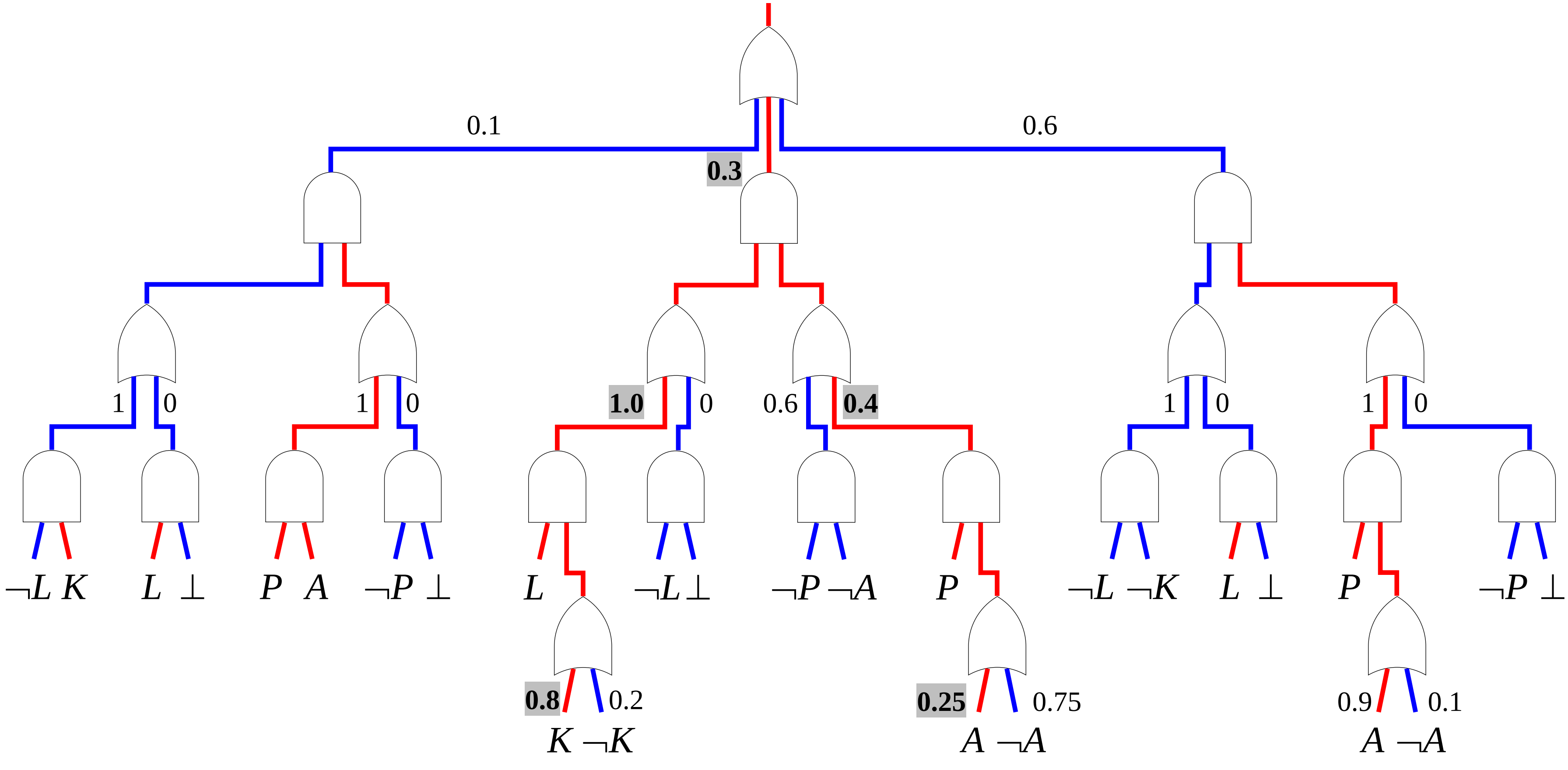
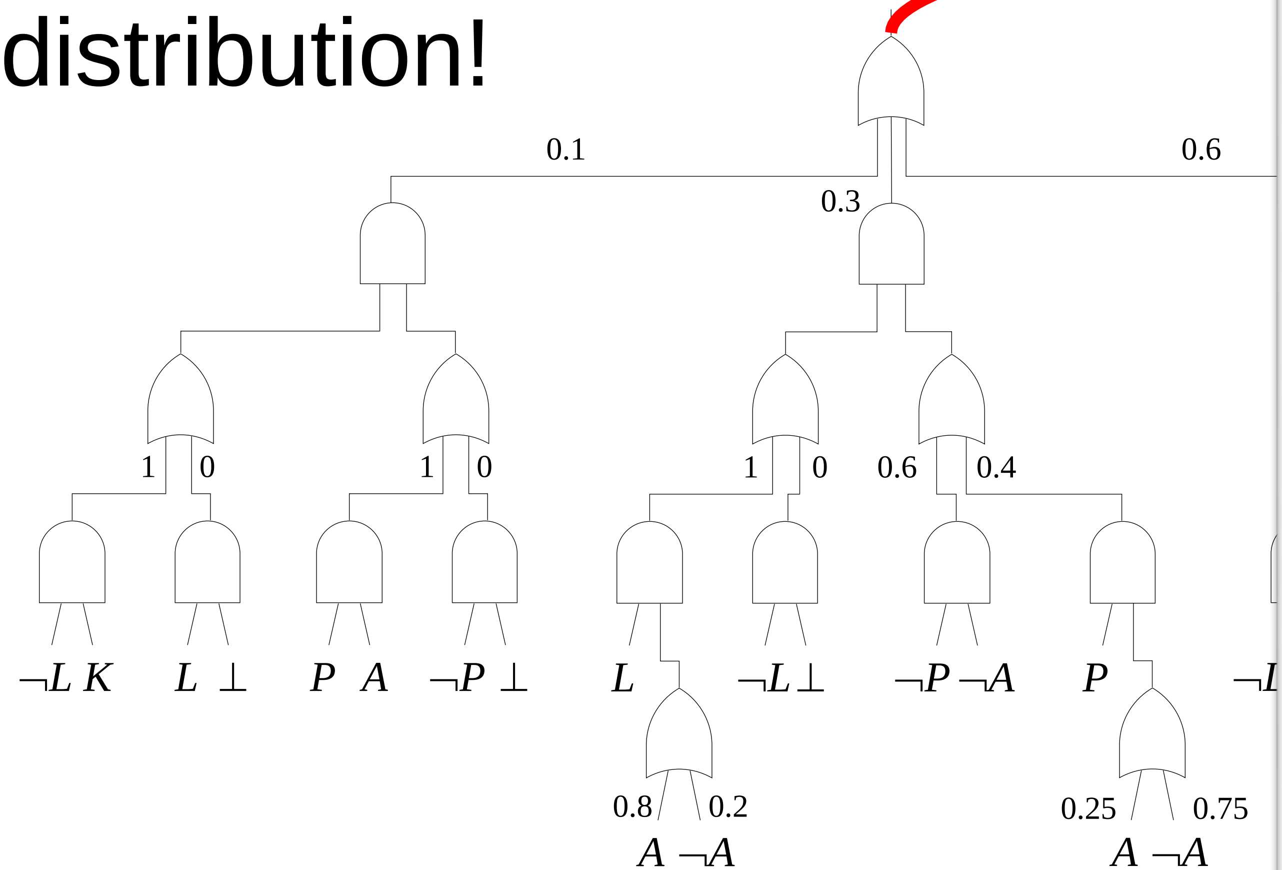


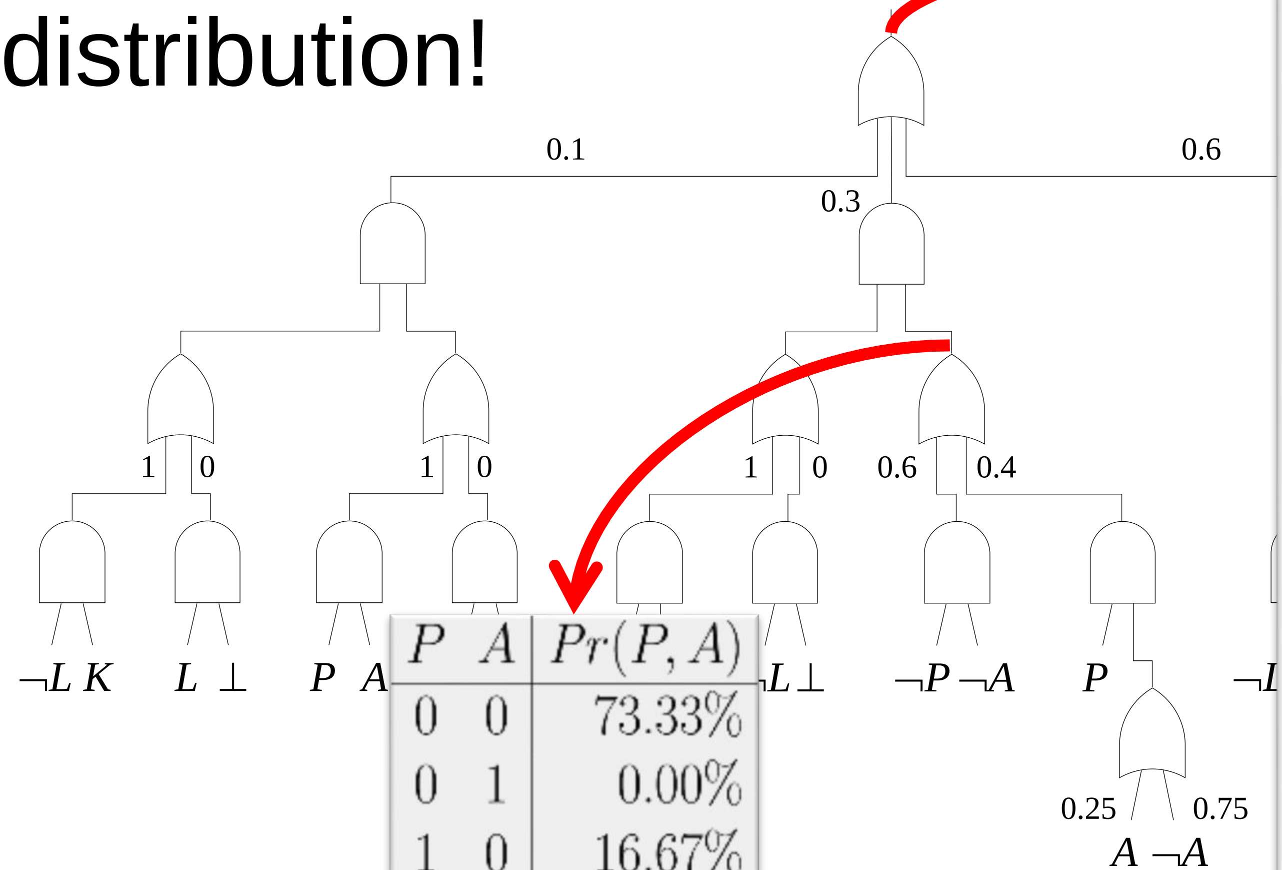
Input: L, K, P, A $\quad$ $\Pr(L,K,P,A) = 0.3 \times 1.0 \times 0.8 \times 0.4 \times 0.25 = 0.024$

PSDD nodes induce a normalized distribution!



L	K	P	A	$Pr(L,K,P,A)$
0	0	0	0	0.00%
0	0	0	1	0.00%
0	0	1	0	6.00%
0	0	1	1	54.00%
0	1	0	0	0.00%
0	1	0	1	0.00%
0	1	1	0	0.00%
0	1	1	1	10.00%
1	0	0	0	4.40%
1	0	0	1	0.00%
1	0	1	0	1.00%
1	0	1	1	0.60%
1	1	0	0	17.6%
1	1	0	1	0.00%
1	1	1	0	4.00%
1	1	1	1	2.40%

PSDD nodes induce a normalized distribution!



P	A	$Pr(P, A)$
0	0	73.33%
0	1	0.00%
1	0	16.67%
1	1	10.00%

L	K	P	A	$Pr(L, K, P, A)$
0	0	0	0	0.00%
0	0	0	1	0.00%
0	0	1	0	6.00%
0	0	1	1	54.00%
0	1	0	0	0.00%
0	1	0	1	0.00%
0	1	1	0	0.00%
0	1	1	1	10.00%
1	0	0	0	4.40%
1	0	0	1	0.00%
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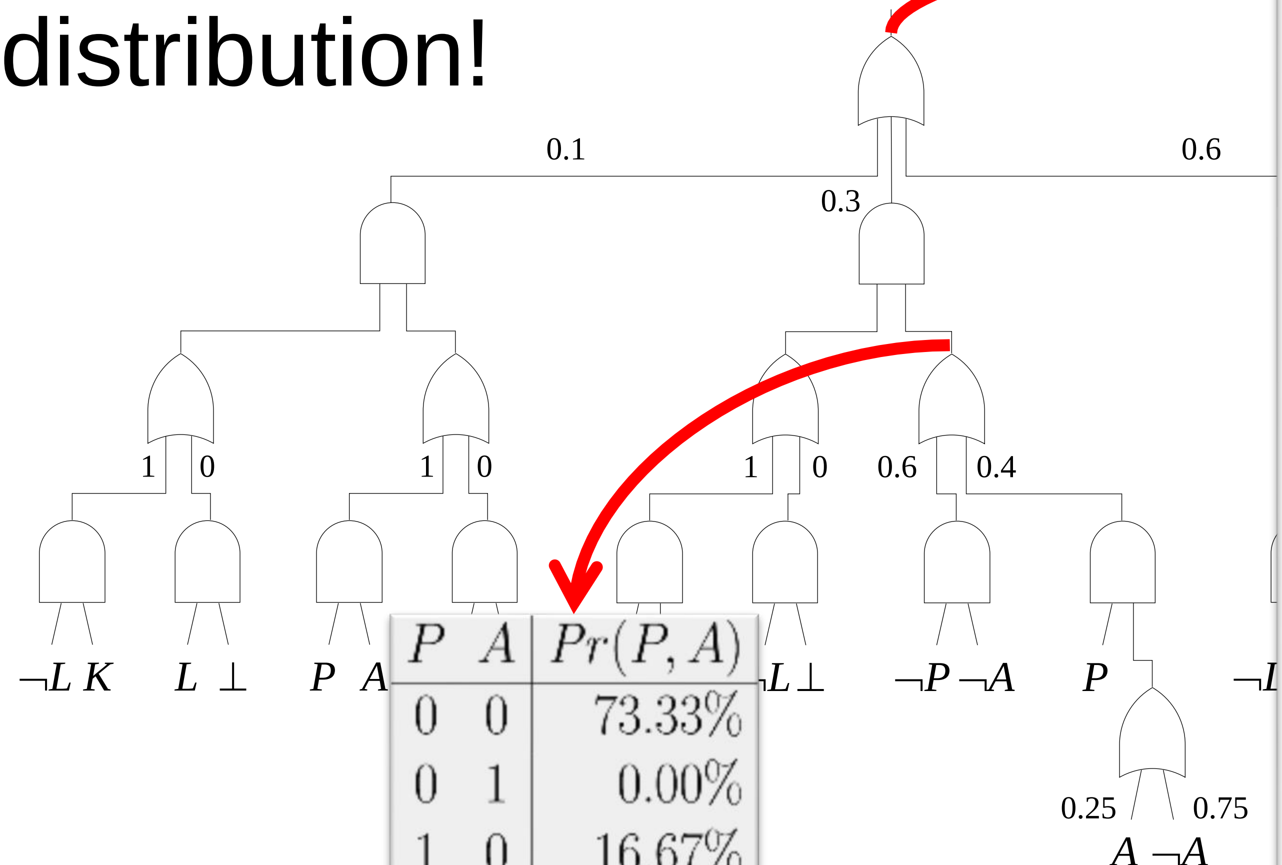

P	A	$Pr(P, A)$
0	0	73.33%
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L	K	P	A	$Pr(L, K, P, A)$
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0	0	0	1	0.00%
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1	1	0	1	0.00%
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Can read probabilistic independences off the circuit structure

Tractable for Probabilistic Inference

- **MAP inference**: Find most-likely assignment (otherwise NP-complete)
- Computing **conditional probabilities** Pr(x|y) (otherwise PP-complete)
- **Sample** from Pr(x|y)

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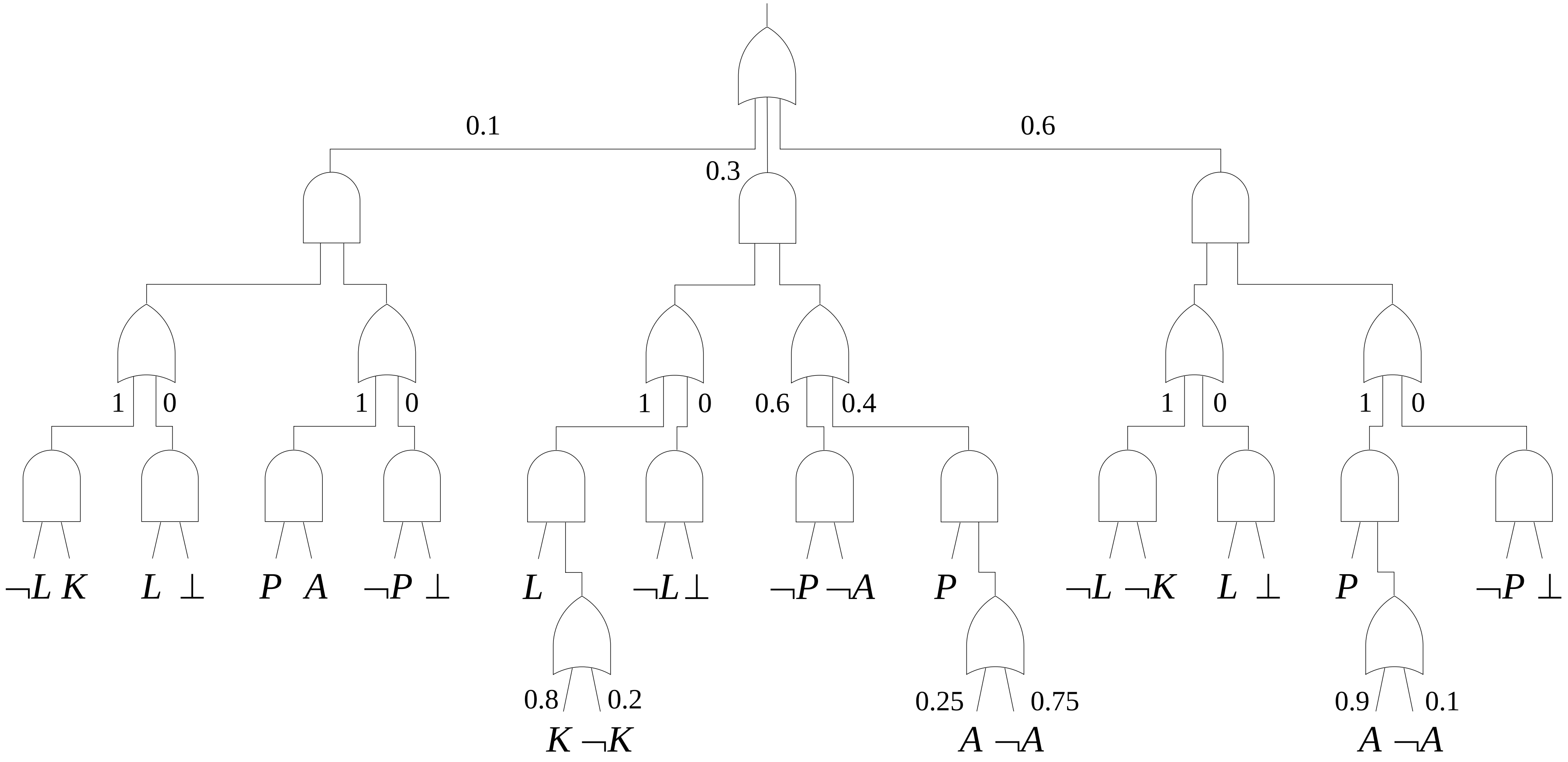
Learning PSDDs

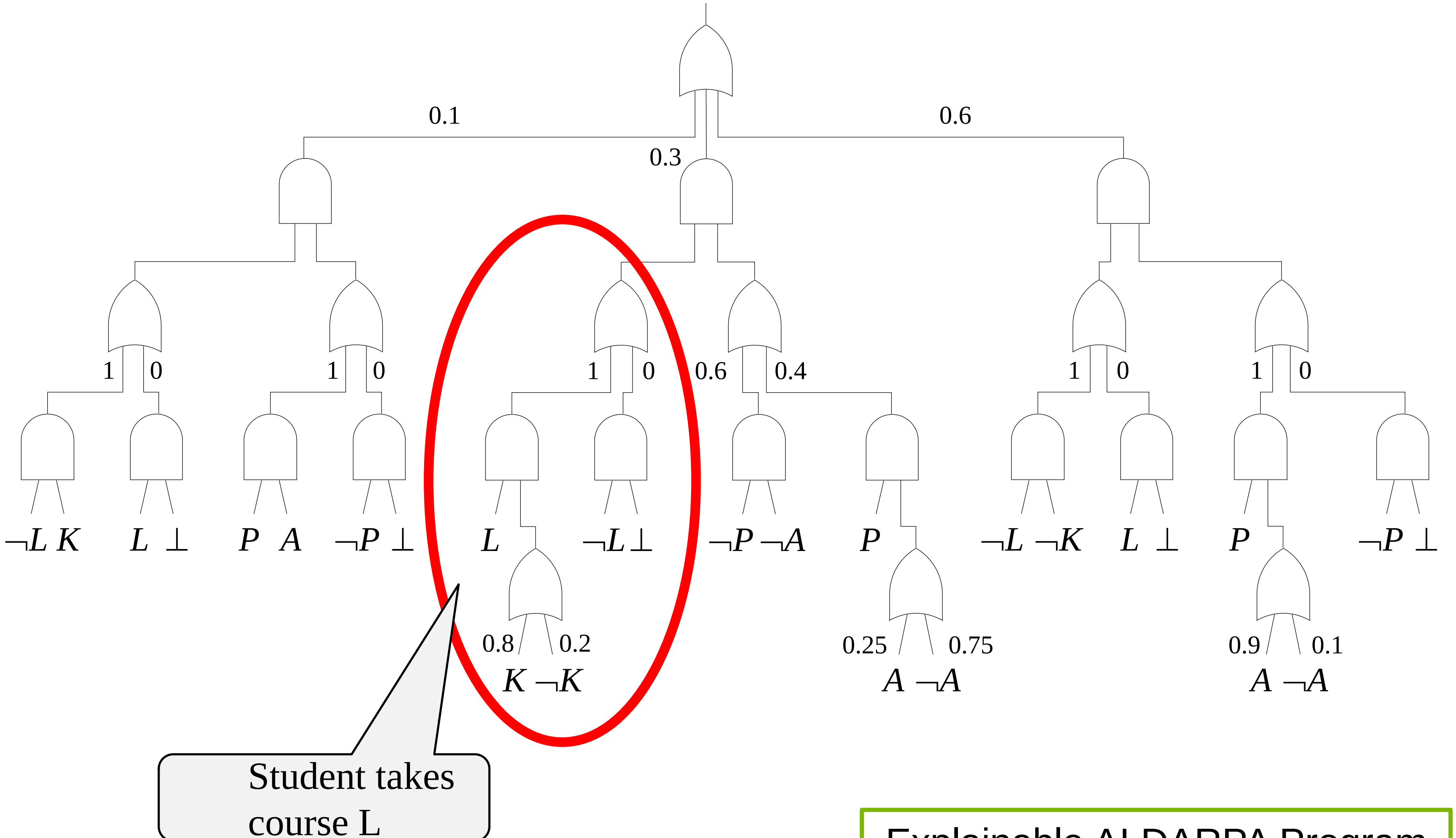
Logic + Probability + ML

Parameters are Interpretable



Explainable AI DARPA Program

Parameters are Interpretable



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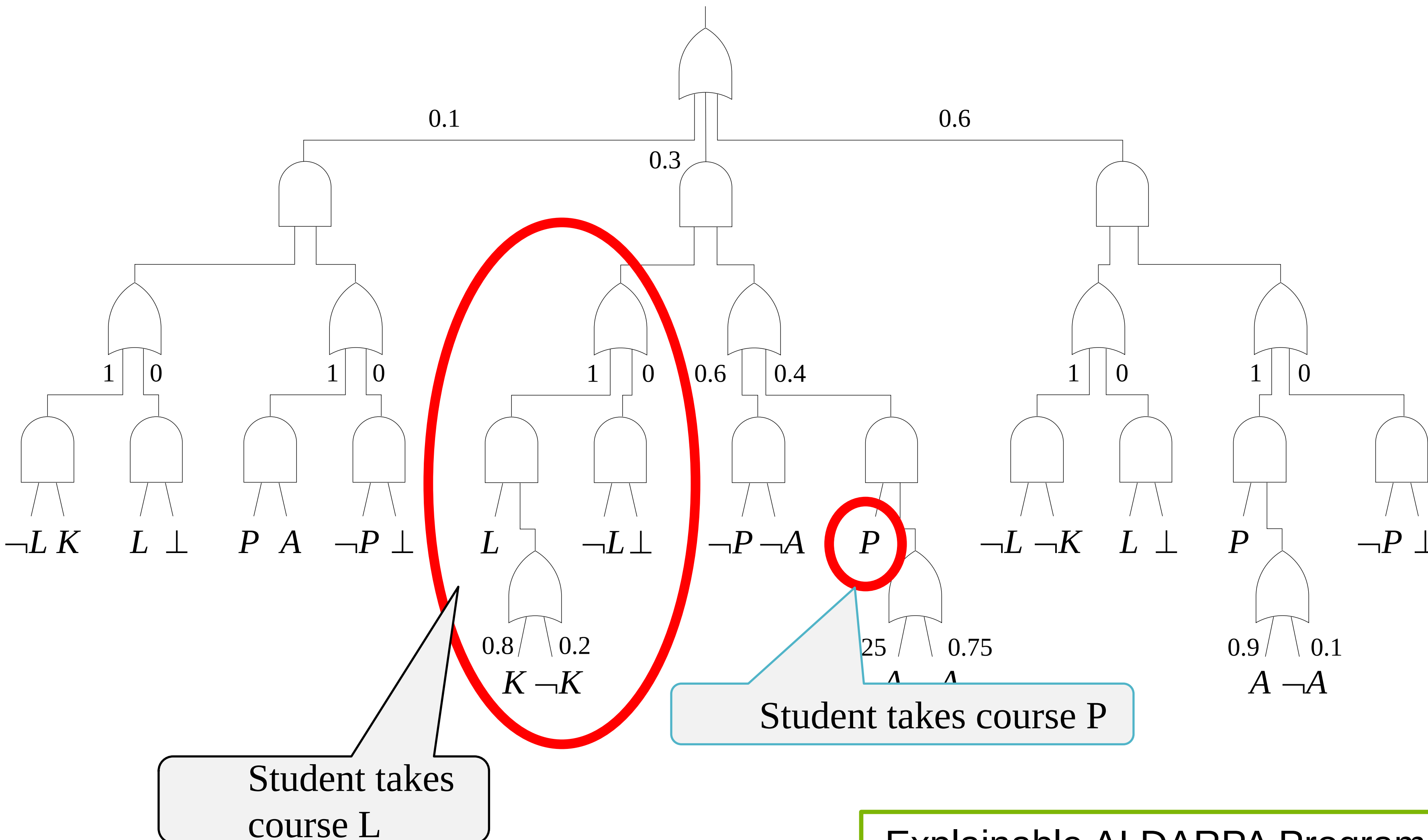

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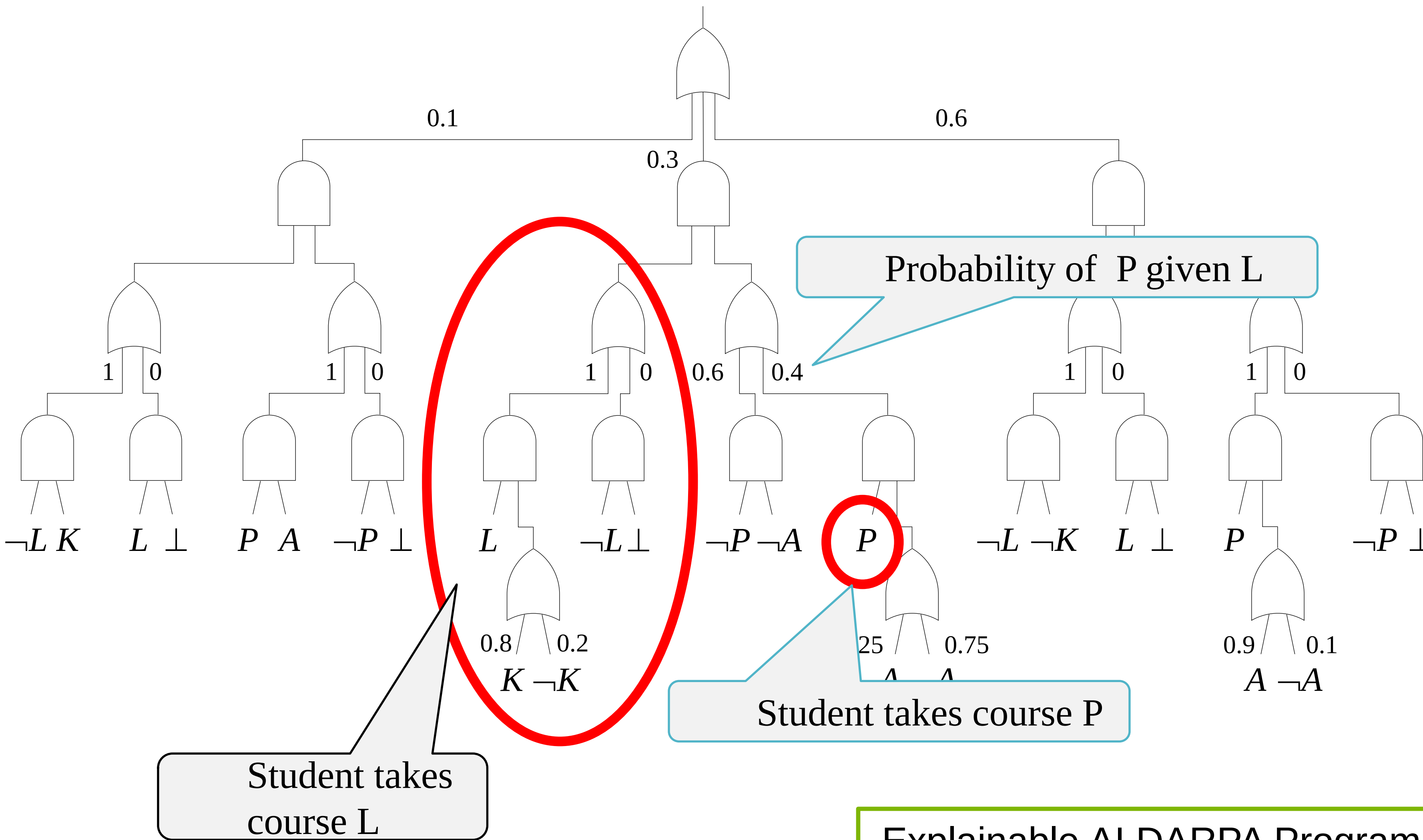

Explainable AI DARPA Program

Learning Algorithms

- Parameter learning:
  - Closed form max likelihood from complete data
  - One pass over data to estimate Pr(x|y)

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  Closed form max likelihood from complete data

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  Not a lot to say: very easy!

Learning Algorithms

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  One pass over data to estimate Pr(x|y)

  $\boxed{\text{Not a lot to say: very easy!}}$

- Circuit learning (naïve):

  Compile constraints to SDD circuit

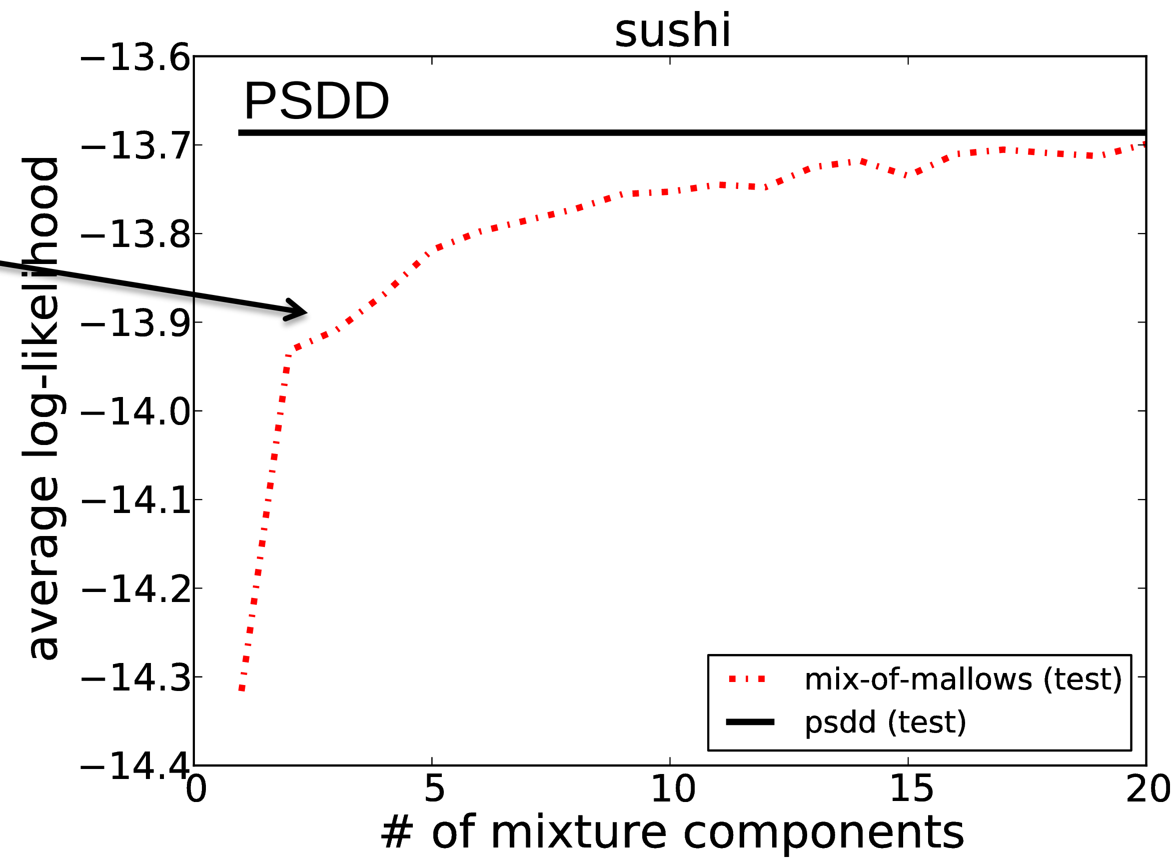
  – Use SAT solver technology

  Circuit does not depend on data

Learning Preference Distributions

Special-purpose distribution: Mixture-of-Mallows

- # of components from 1 to 20
- EM with 10 random seeds
- implementation of Lu & Boutilier



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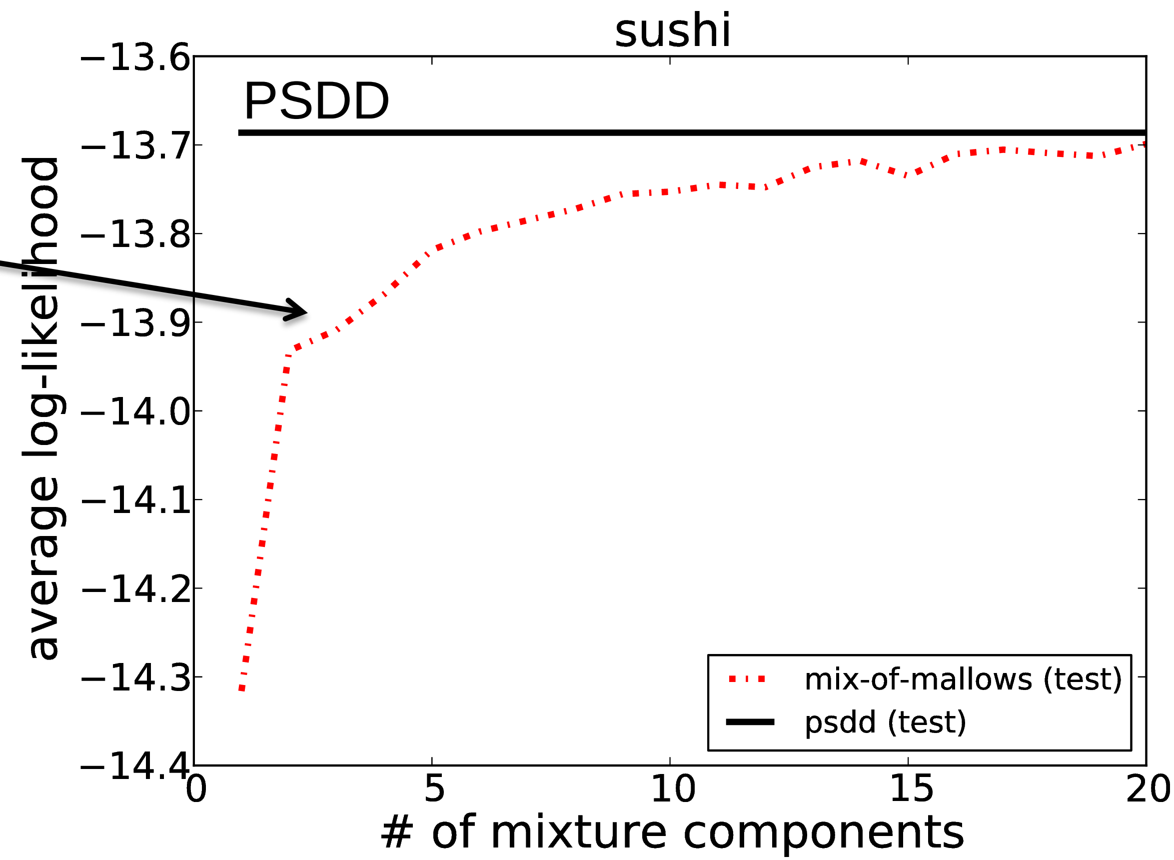


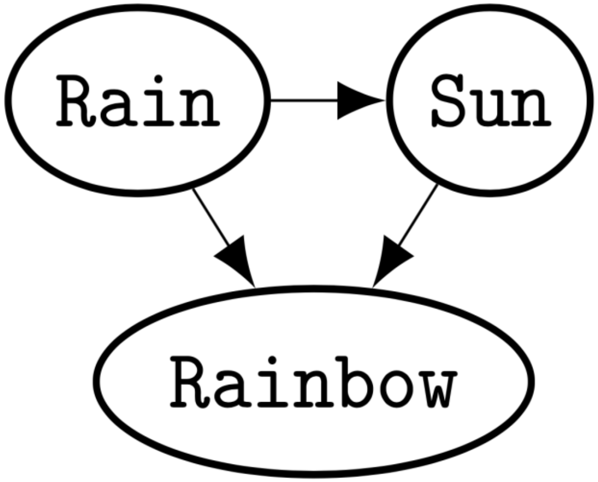
This is the naive approach, circuit does not depend on data!

Learn Circuit from Data

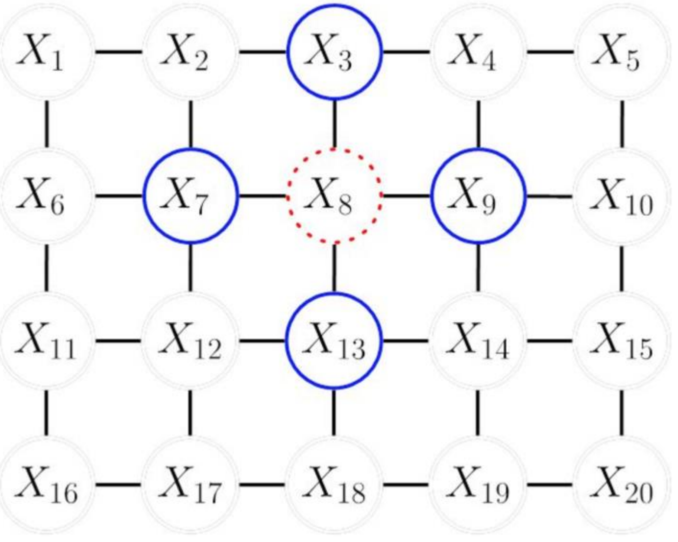
Even in unstructured spaces

Tractable Learning

Bayesian networks

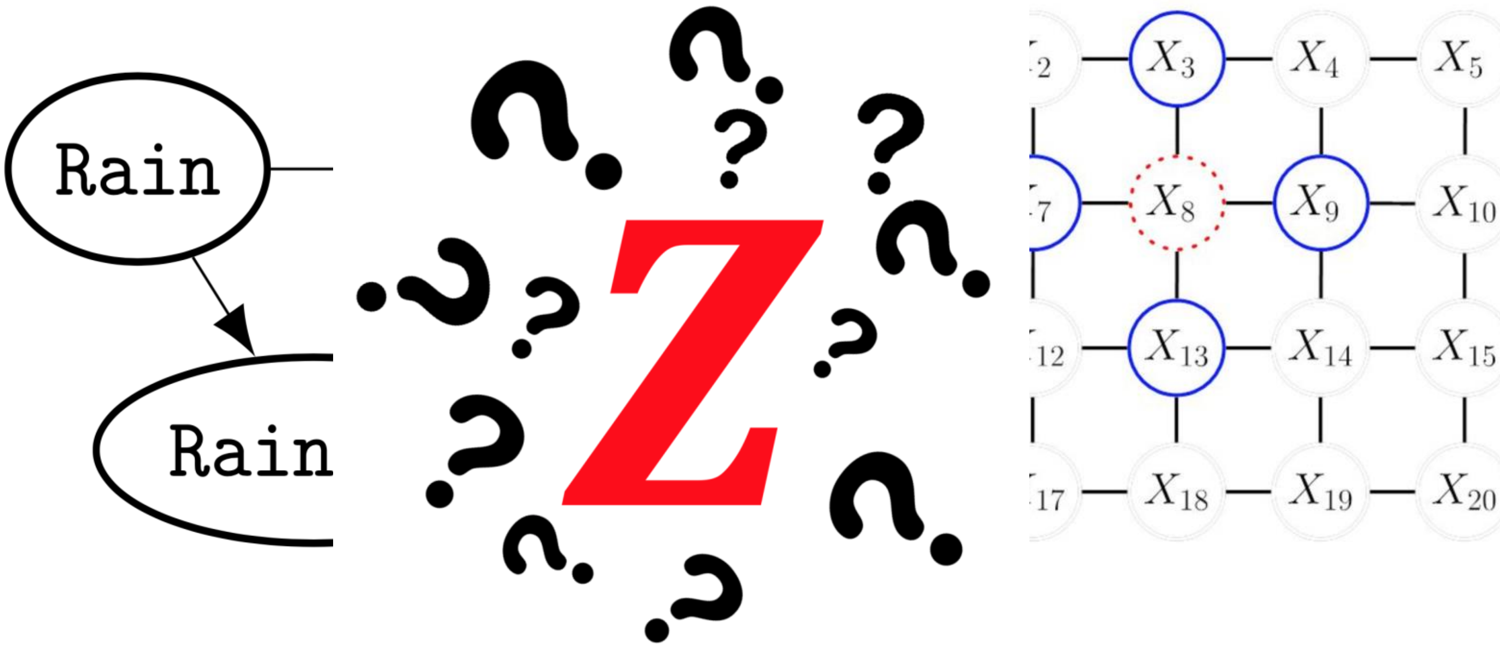


Markov networks



Tractable Learning

Bayesian networks Markov networks

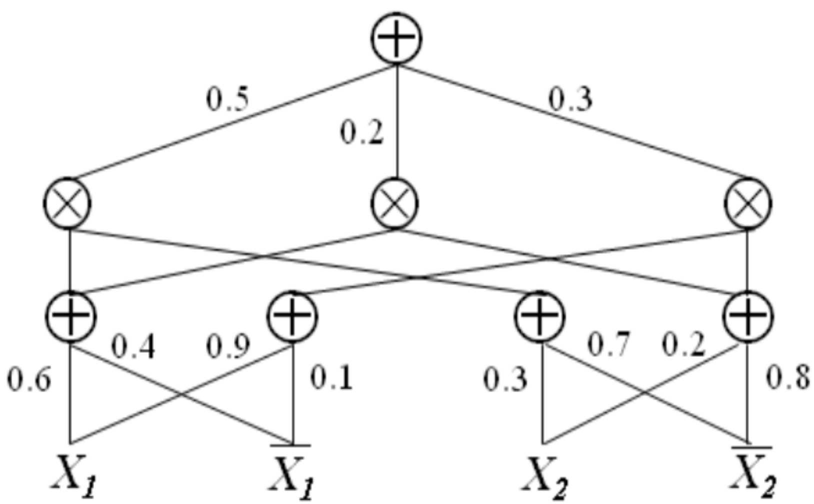


Do not support linear-time exact inference

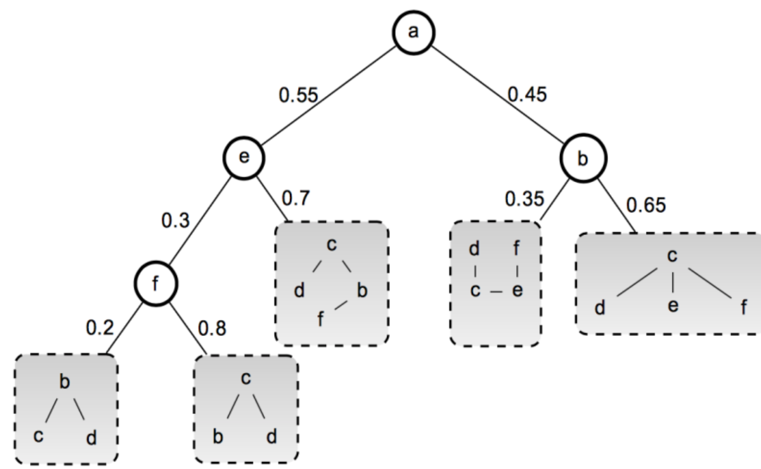
Tractable Learning

Historically: Polytrees, Chow-Liu trees, etc.

SPNs



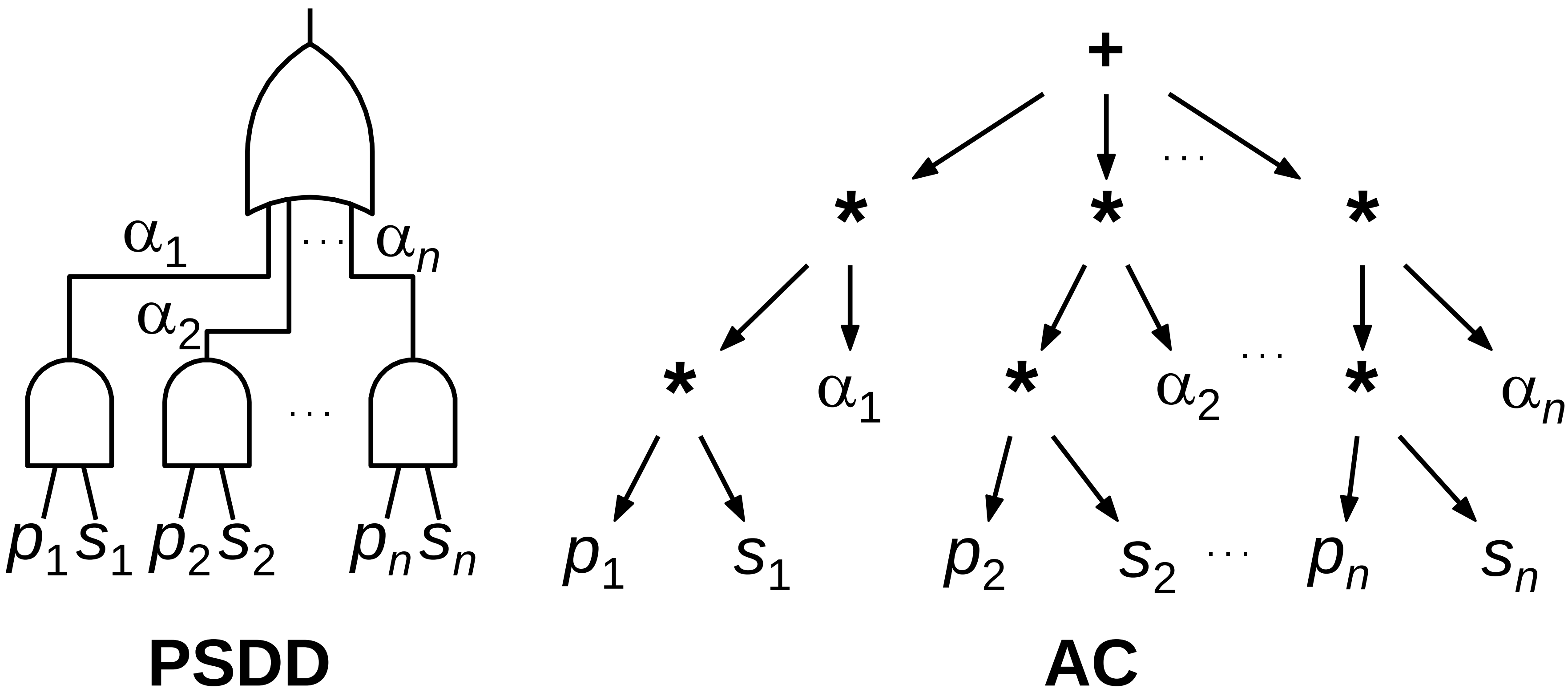
Cutset Networks



Both are Arithmetic Circuits (ACs)

[Darwiche, JACM 2003]

PSDDs are Arithmetic Circuits



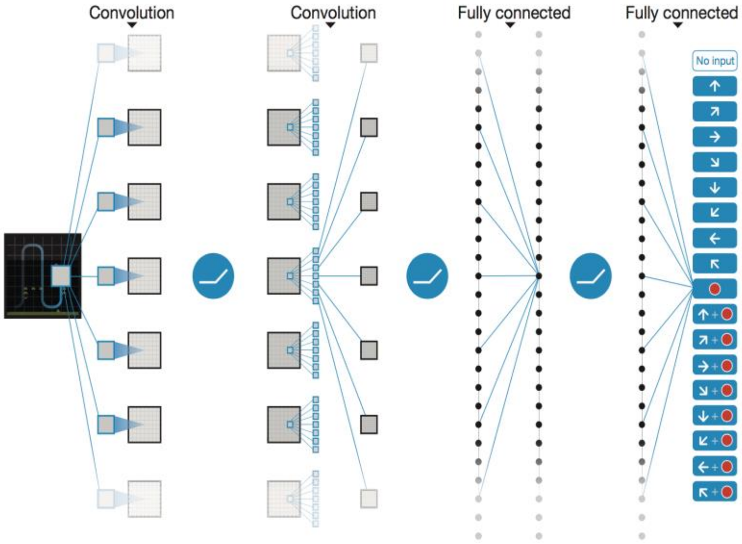
Tractable Learning

Strong Properties

Representational Freedom

Tractable Learning

DNN



Strong Properties

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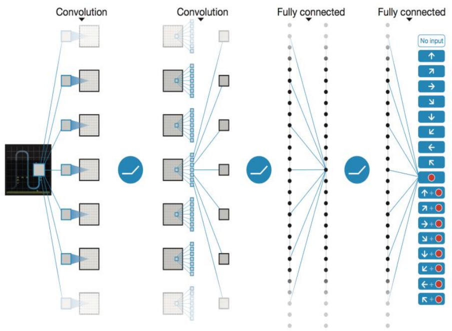

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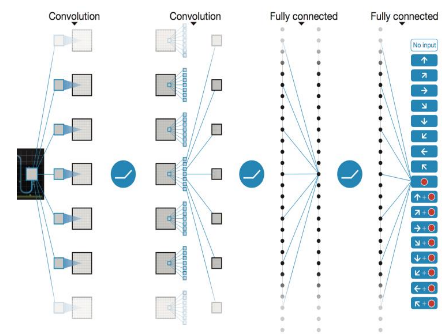
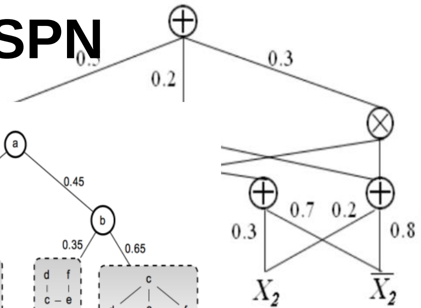


SPN



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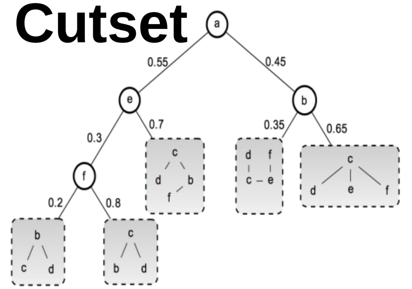

Strong Properties **Representational Freedom**

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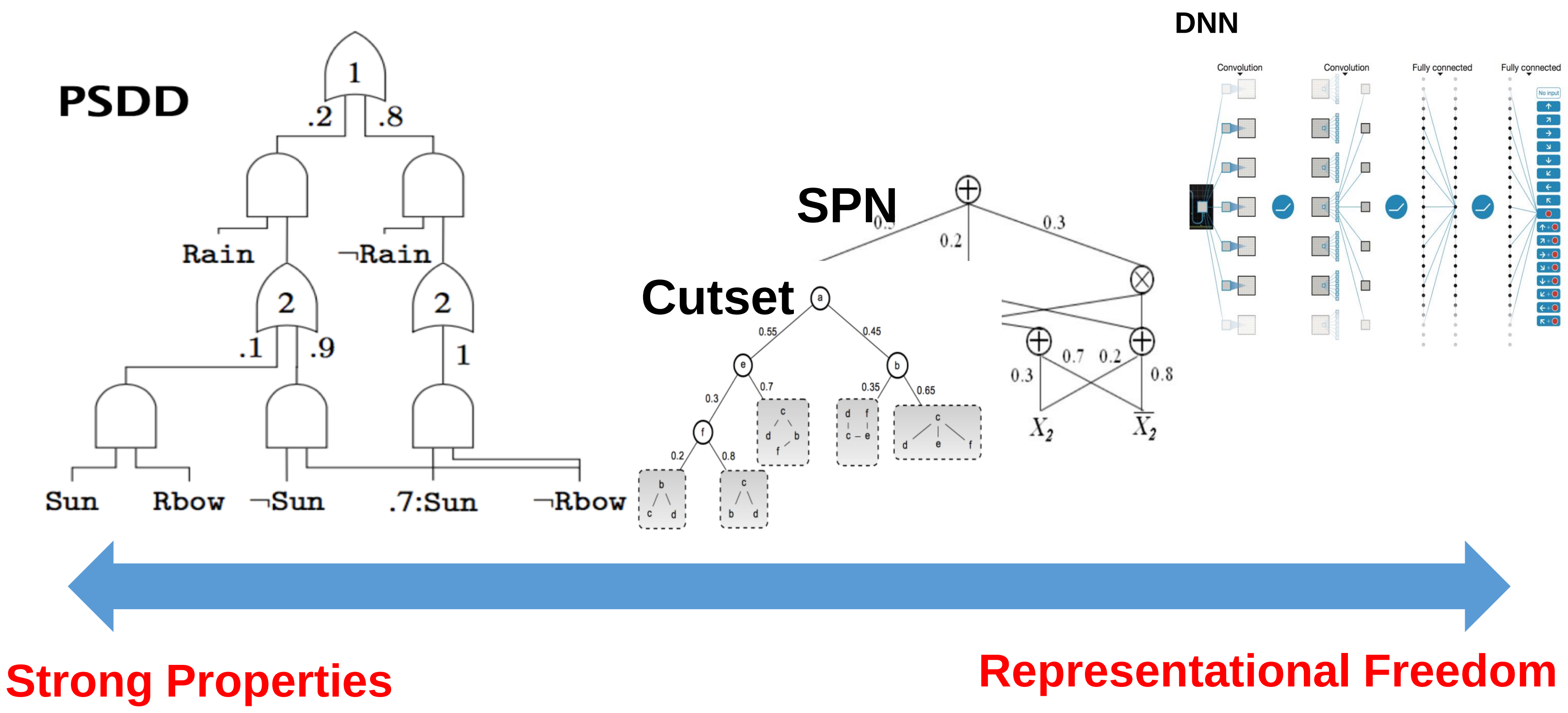
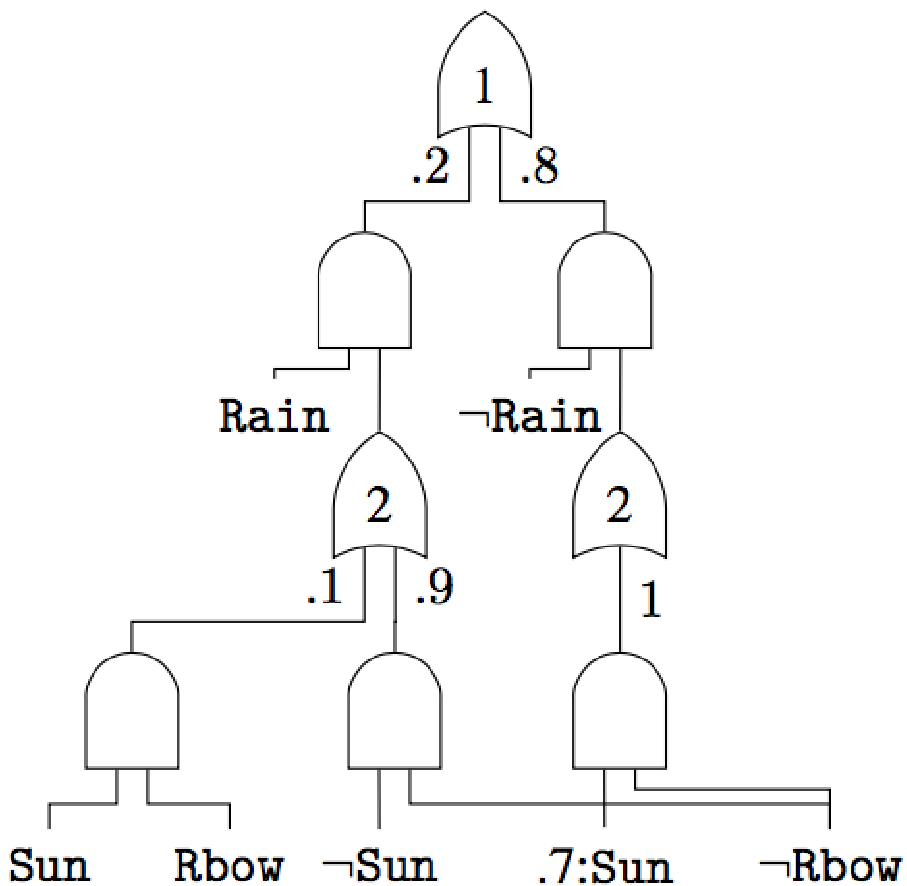


Perhaps the most powerful circuit proposed to date

PSDDs for the Logic-Phobic



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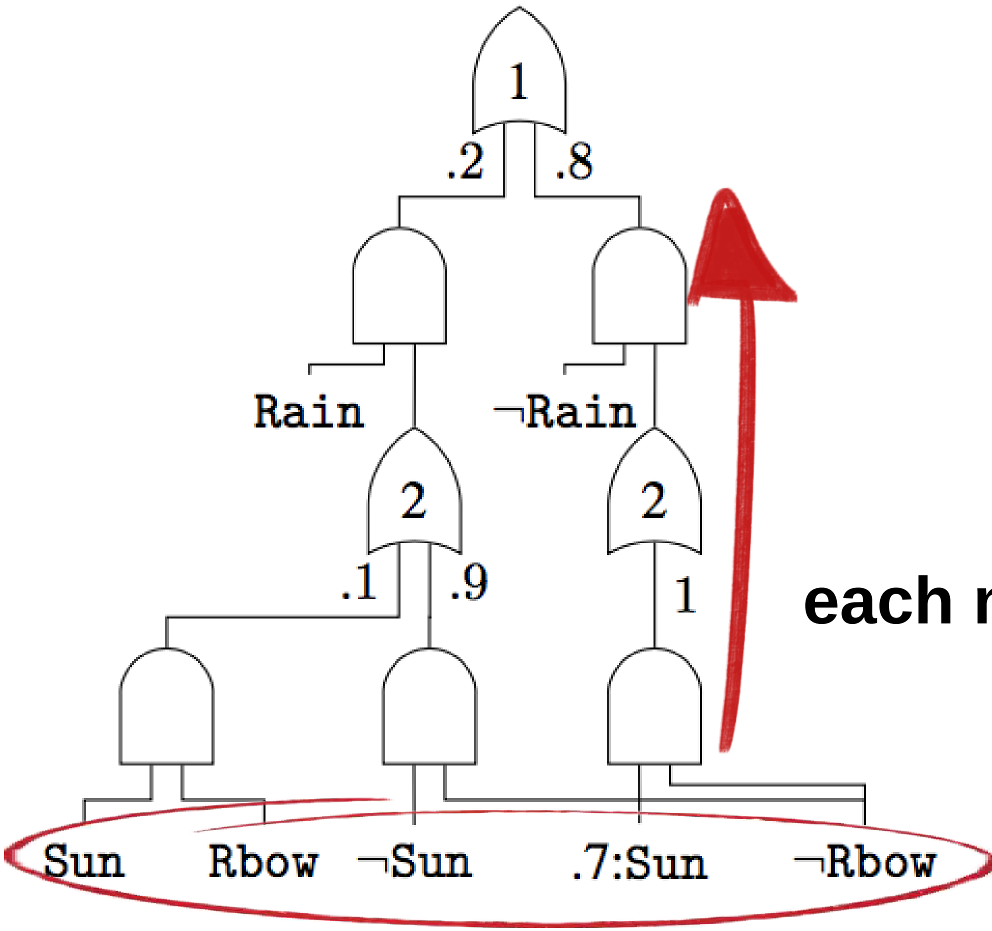
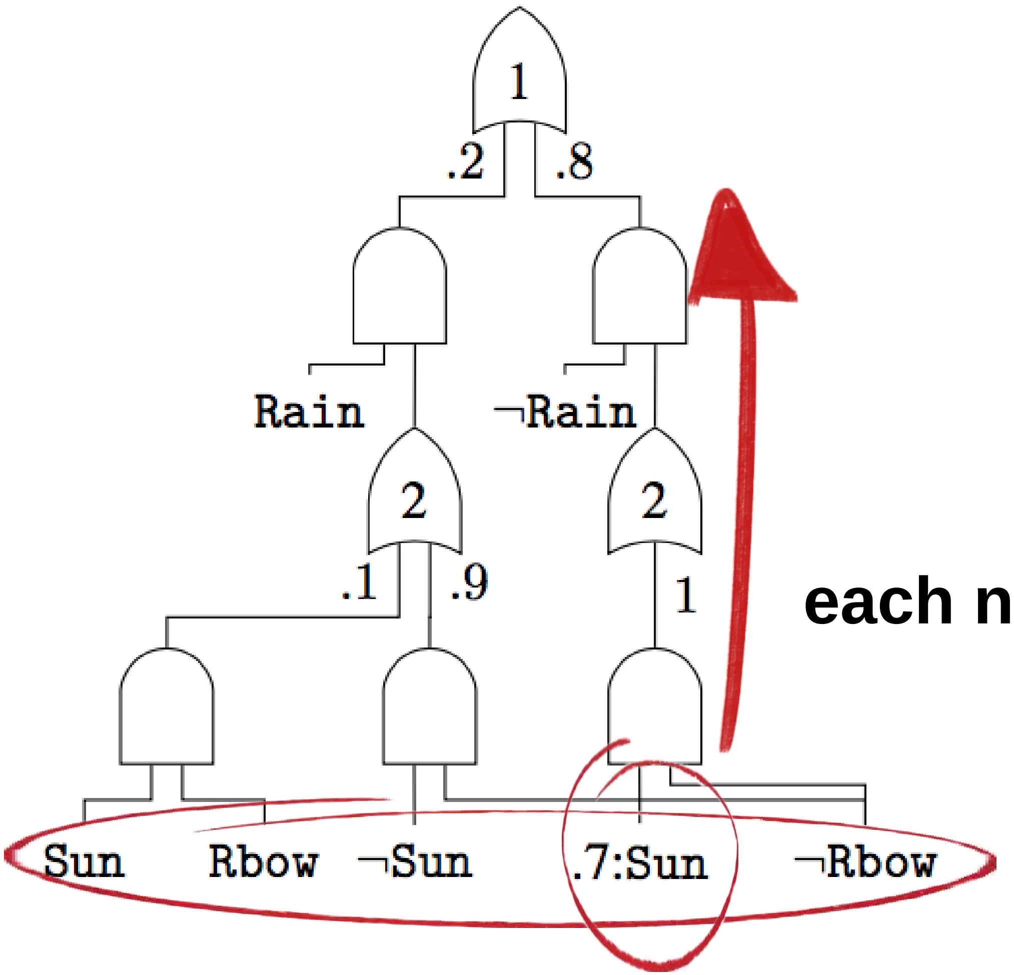


Bottom-up

each node is a distribution

PSDDs for the Logic-Phobic



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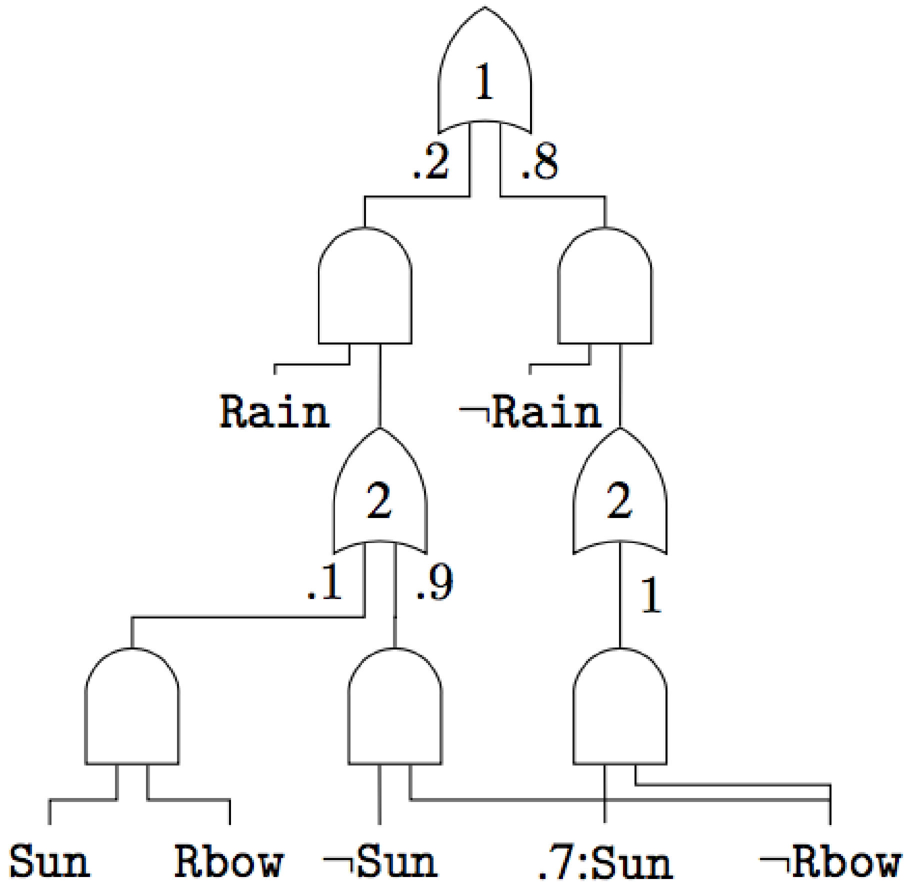

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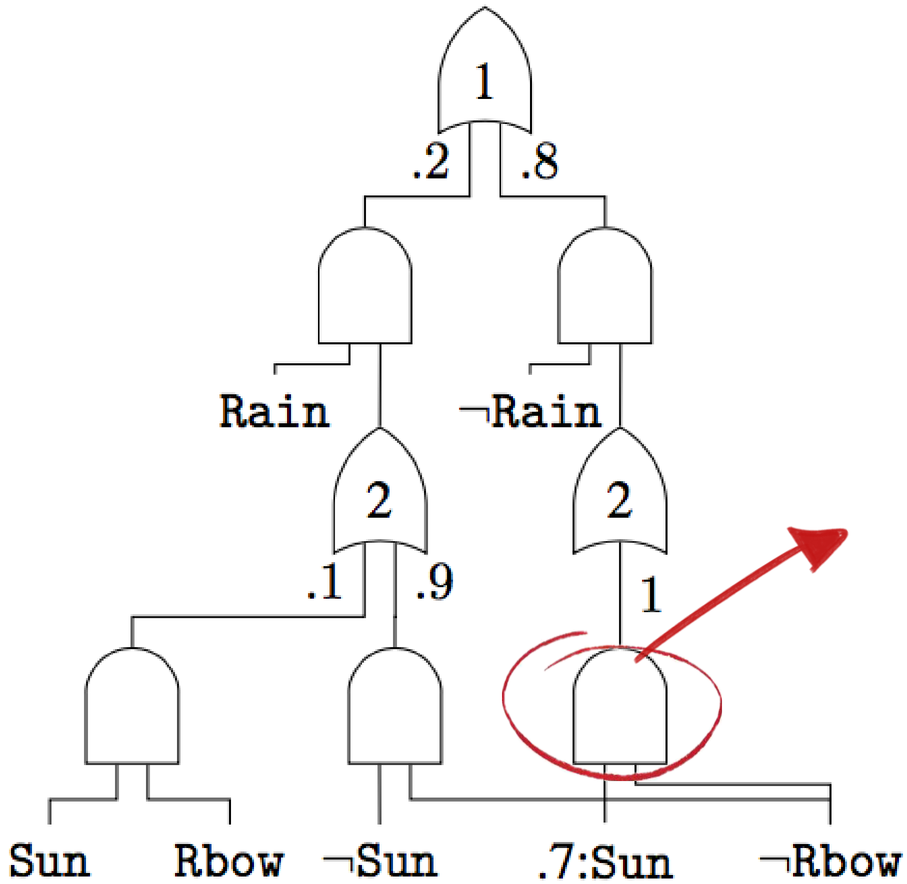
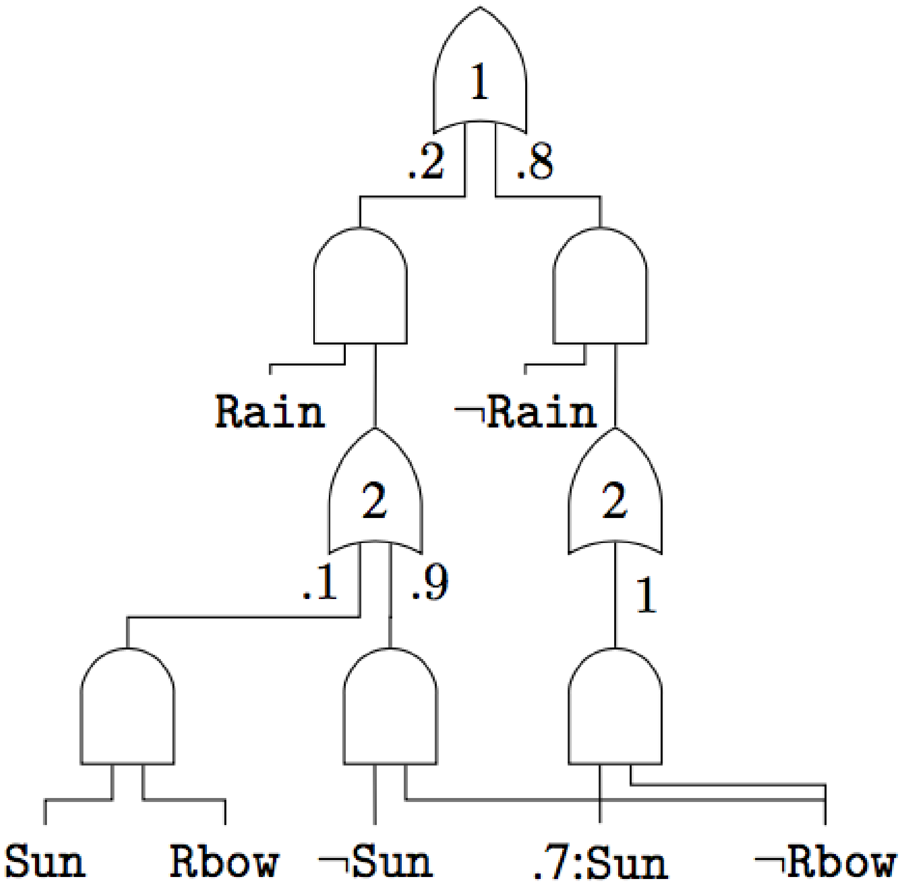
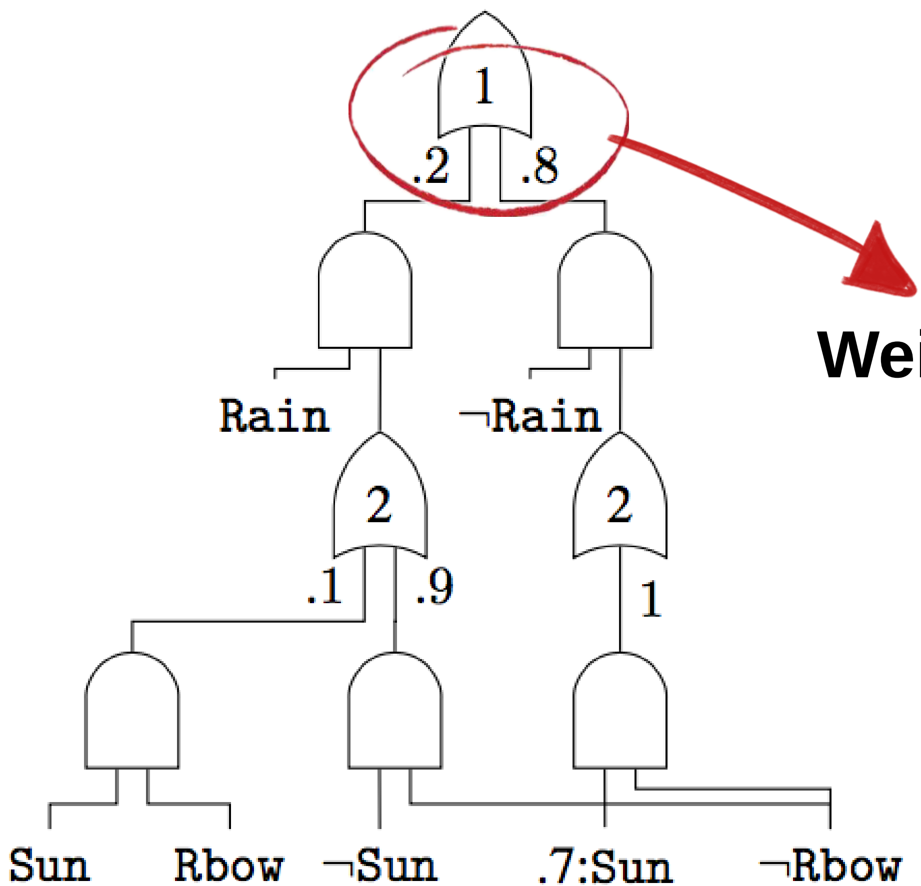


Multiply independent distributions

PSDDs for the Logic-Phobic

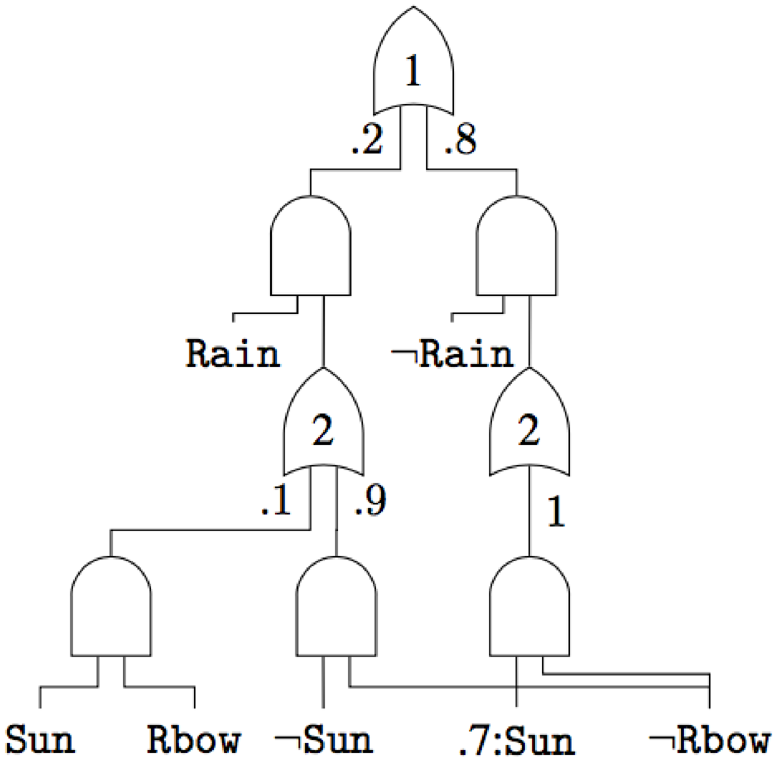


PSDDs for the Logic-Phobic



Weighted mixture of lower level distributions

PSDDs for the Logic-Phobic



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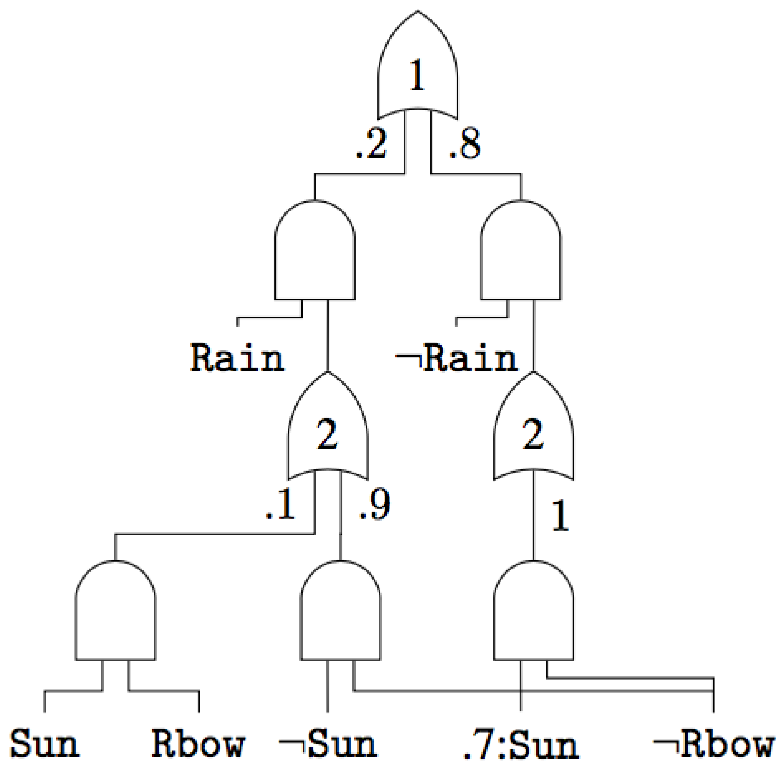
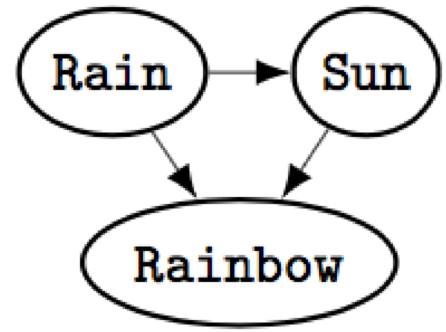




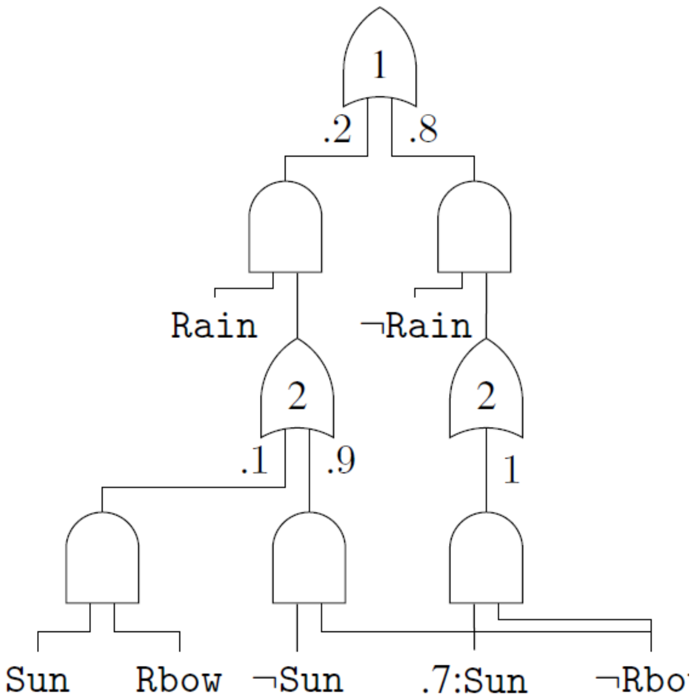
$$\Pr(\texttt{Rain}) = 0.2,$$

$$\Pr(\texttt{Sun} \mid \texttt{Rain}) = \begin{cases} 0.1 \text{ if } \ \ \texttt{Rain} \\ 0.7 \text{ if } \neg\texttt{Rain} \end{cases}$$

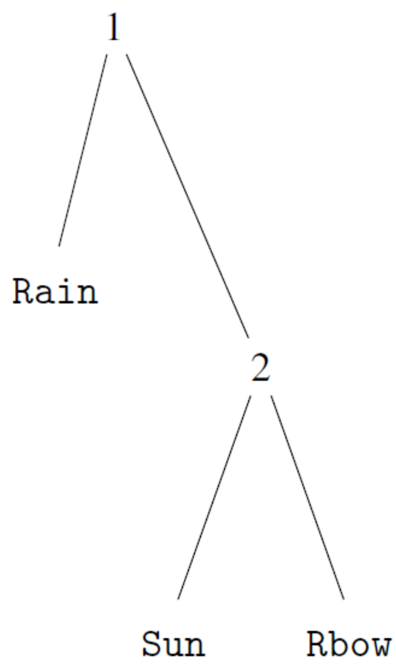
$$\Pr(\texttt{Rbow} \mid \texttt{R}, \texttt{S}) = \begin{cases} 1 \text{ if } \texttt{Rain} \wedge \texttt{Sun} \\ 0 \text{ otherwise} \end{cases}$$

Variable Trees (vtrees)

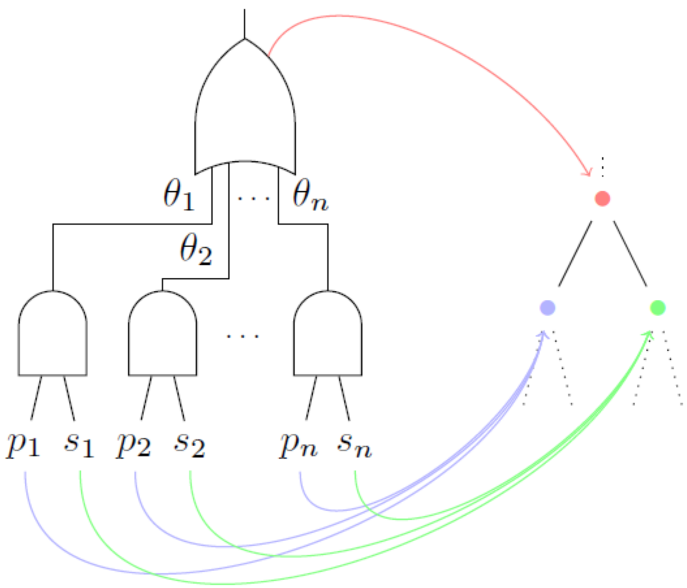
PSDD



Vtree



Correspondence



Learning Variable Trees

- How much do vars depend on each other?

$$\mathrm{MI}(\mathbf{X},\mathbf{Y}) = \sum_{X\in\mathbf{X}} \sum_{Y\in\mathbf{Y}} \Pr(X,Y) \log \frac{\Pr(X,Y)}{\Pr(X)\Pr(Y)}$$

- Learn vtree by hierarchical clustering

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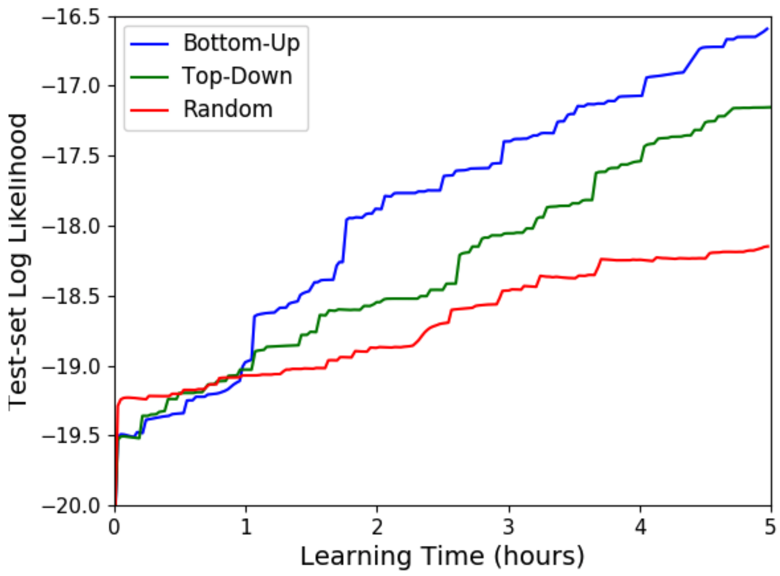
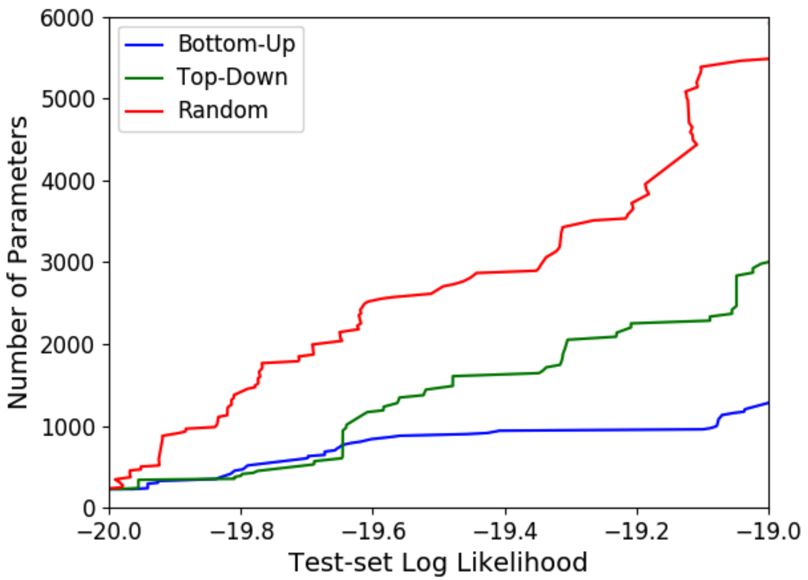
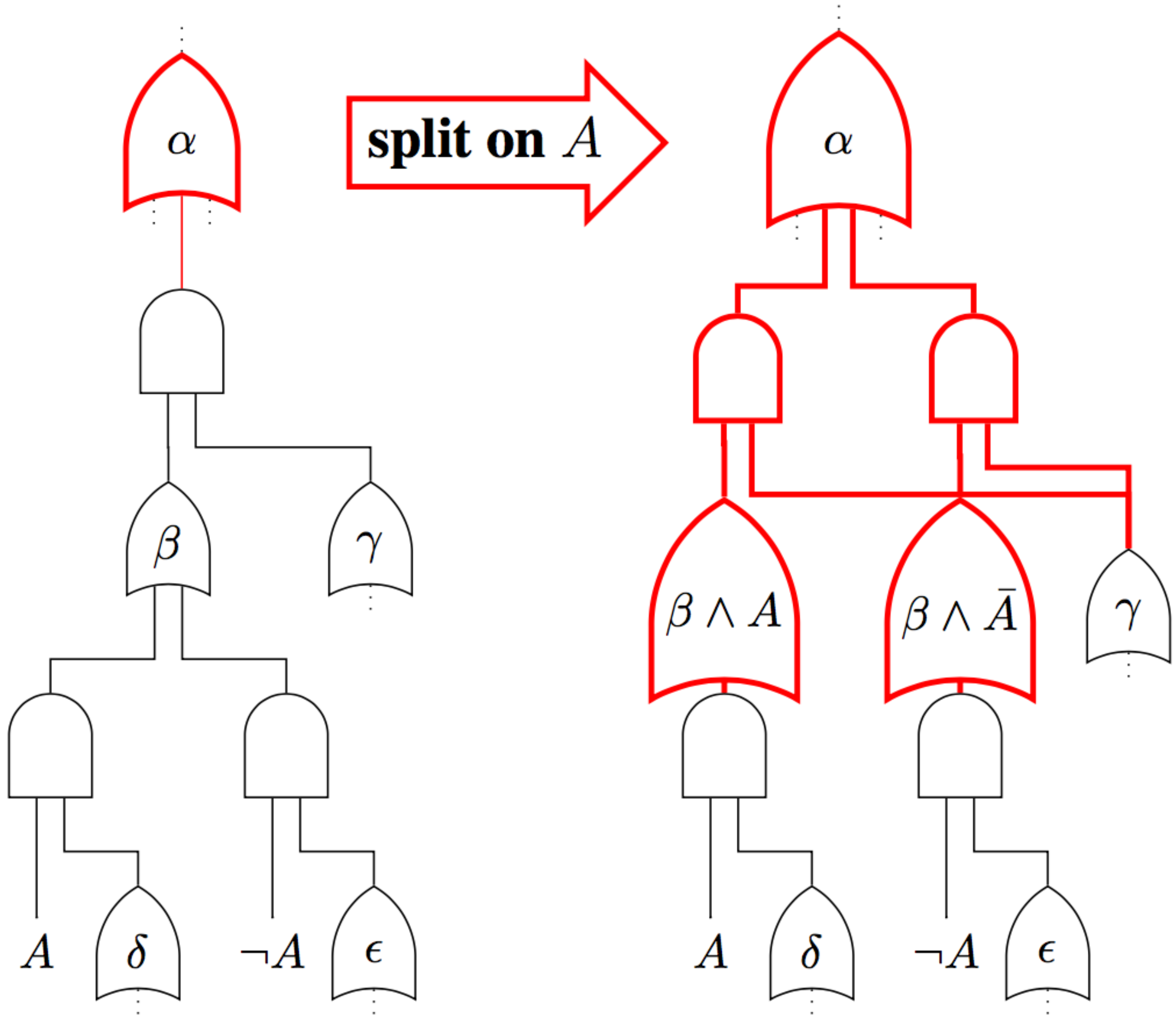
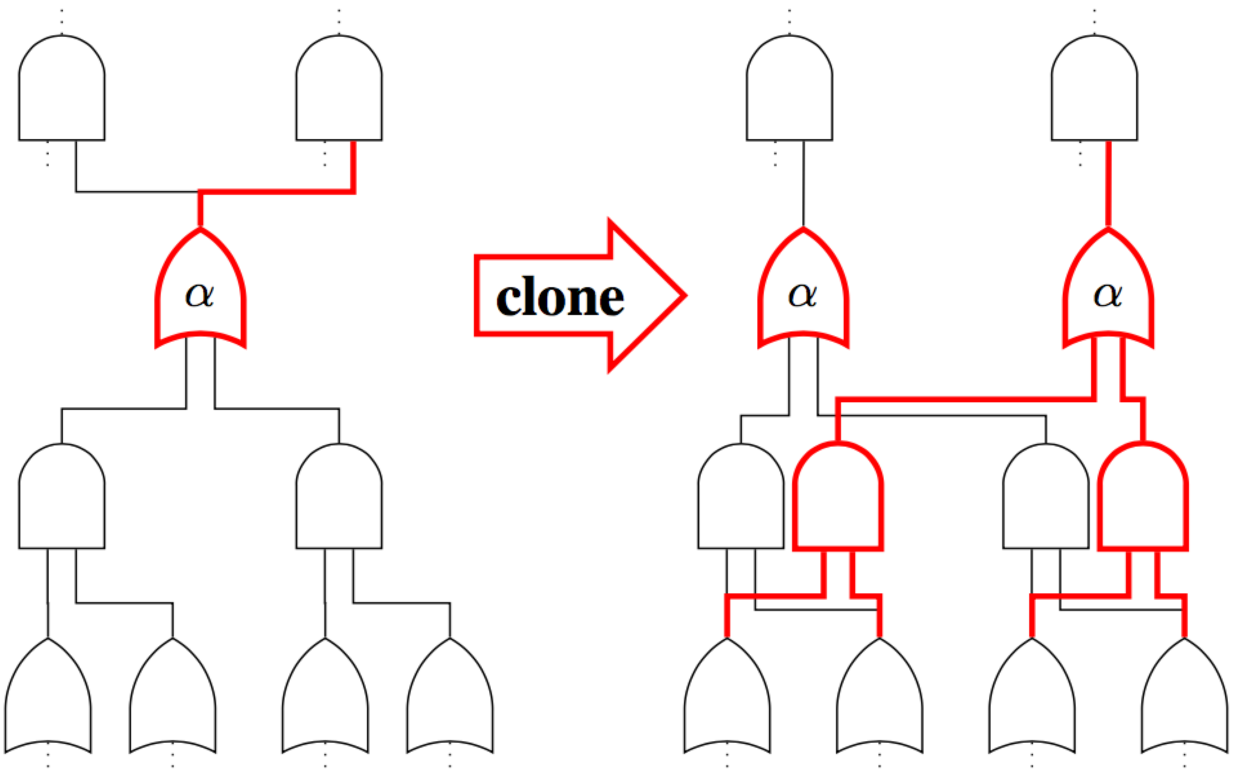




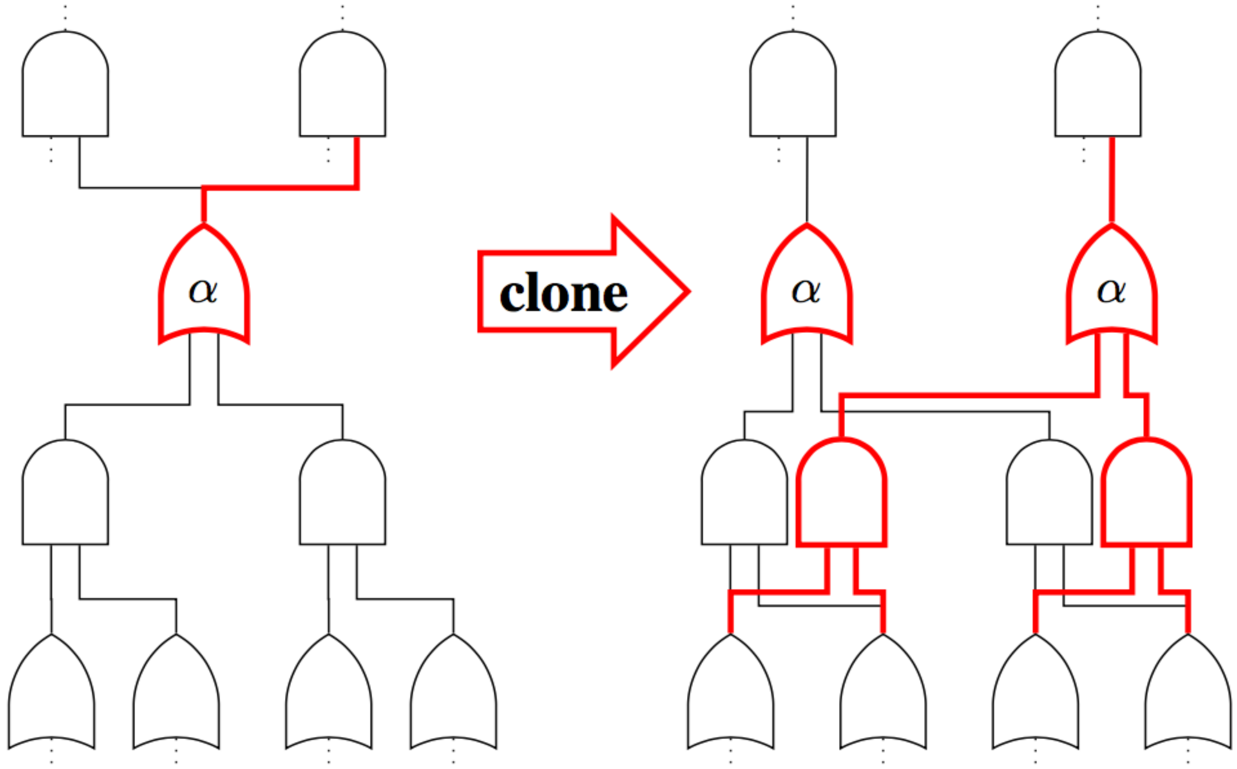
Learning Primitives



Learning Primitives

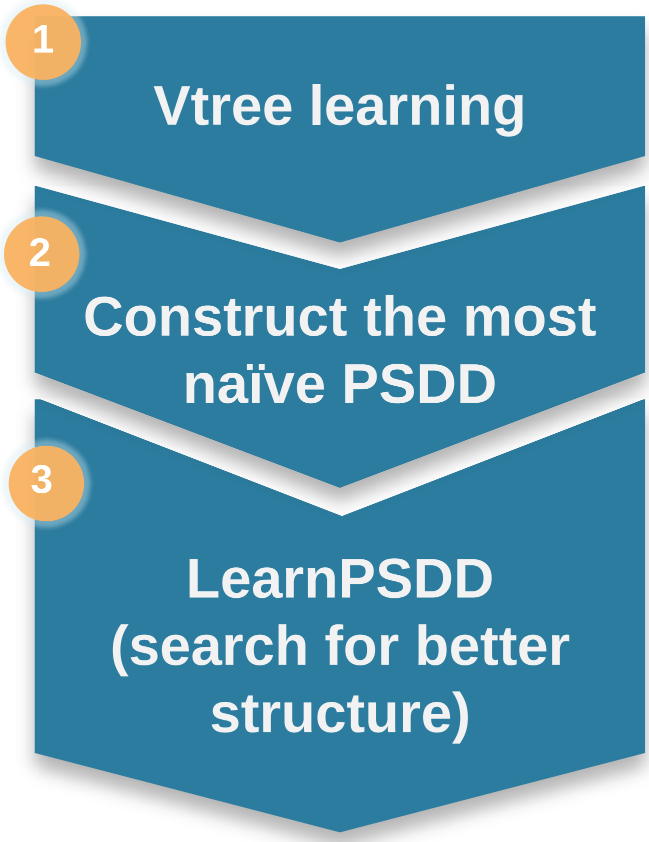


Learning Primitives

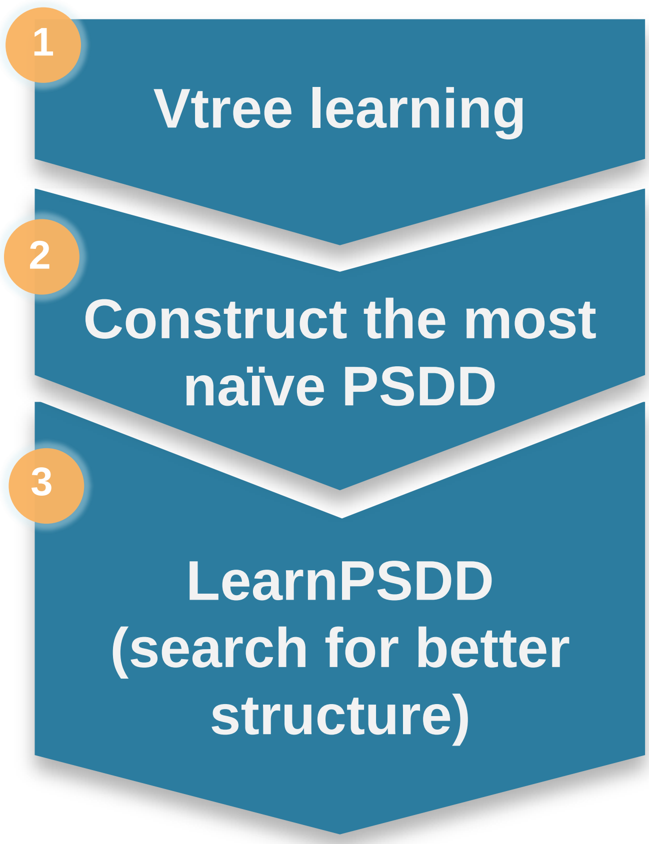


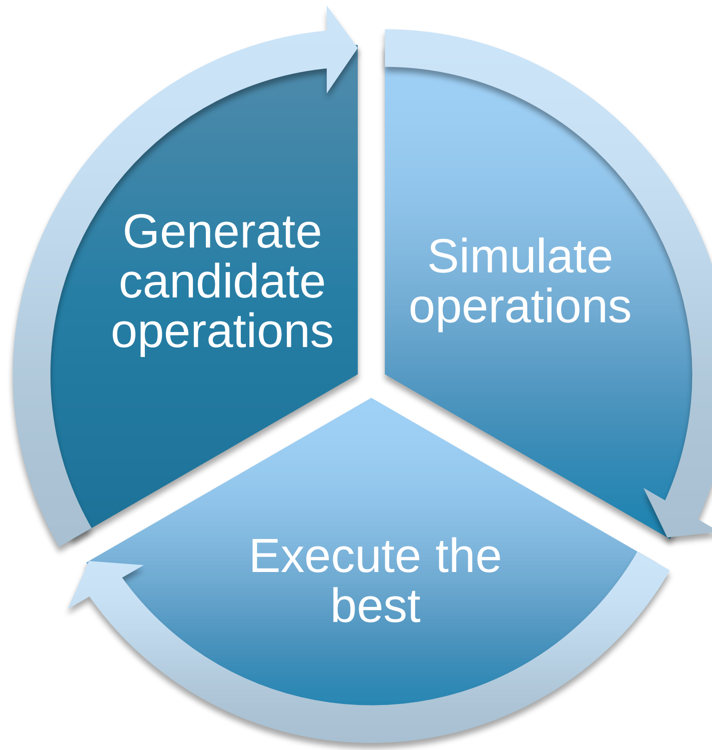
Primitives maintain PSDD properties and structured space!

LearnPSDD


1
Vtree learning
2
Construct the most naïve PSDD
3
LearnPSDD (search for better structure)

LearnPSDD





$$\text{score} = \frac{\ln \mathcal{L}(r' \mid \mathcal{D}) - \ln \mathcal{L}(r \mid \mathcal{D})}{\text{size}(r') - \text{size}(r)}$$

Experiments on 20 datasets

Datasets	|Var|	|Train|	|Valid|	|Test|	LearnPSDD		EM-LearnPSDD		SearchSPN	Merged L-SPN		Merged O-SPN	
					LL	Size	LL	Size	LL	LL	Size	LL	Size
NLTCS	16	16181	2157	3236	$-6.03^{\dagger *}$	3170	$\mathbf{-6.03}^{*}$	2147	-6.07	-6.04	3988	-6.05	1152
MSNBC	17	291326	38843	58265	$-6.05^{\dagger}$	8977	$\mathbf{-6.04}^{*}$	3891	-6.06	-6.46	2440	-6.08	9478
KDD	64	1800992	19907	34955	$-2.16^{\dagger}$	14974	$\mathbf{-2.12}^{*}$	9182	$\mathbf{-2.16}$	-2.14	6670	-2.19	16608
Plants	69	17412	2321	3482	-14.93	13129	-13.79^{*}	13951	$-13.12^{\dagger}$	$\mathbf{-12.69}$	47802	-13.49	36960
Audio	100	15000	2000	3000	-42.53	13765	-41.98^{*}	9721	$-40.13^{\dagger}$	$\mathbf{-40.02}$	10804	-42.06	6142
Jester	100	9000	1000	4116	-57.67	11322	-53.47^{*}	7014	$-53.08^{\dagger}$	$\mathbf{-52.97}$	10002	-55.36	4996
Netflix	100	15000	2000	3000	-58.92	10997	-58.41^{*}	6250	$-56.91^{\dagger}$	$\mathbf{-56.64}$	11604	-58.64	6142
Accidents	111	12758	1700	2551	-34.13	10489	-33.64^{*}	6752	$-30.02^{\dagger}$	$\mathbf{-30.01}$	13322	-30.83	6846
Retail	135	22041	2938	4408	-11.13	4091	$\mathbf{-10.81}^{*}$	7251	$-10.97^{\dagger}$	-10.87	2162	-10.95	3158
Pumsb-Star	163	12262	1635	2452	-34.11	10489	-33.67^{*}	7965	$-28.69^{\dagger}$	$\mathbf{-24.11}$	17604	-24.34	18338
DNA	180	1600	400	1186	-89.11^{*}	6068	-92.67	14864	$-81.76^{\dagger}$	$\mathbf{-85.51}$	4320	-87.49	1430
Kosarek	190	33375	4450	6675	$-10.99^{\dagger}$	11034	-10.81^{*}	10179	-11.00	$\mathbf{-10.62}$	5318	-10.98	6712
MSWeb	294	29441	32750	5000	$-10.18^{\dagger}$	11389	-9.97^{*}	14512	-10.25	$\mathbf{-9.90}$	16484	-10.06	12770
Book	500	8700	1159	1739	-35.90	15197	-34.97^{*}	11292	$-34.91^{\dagger}$	$\mathbf{-34.76}$	11998	-37.44	11916
EachMovie	500	4524	1002	591	-56.43^{*}	12483	-58.01	16074	$-53.28^{\dagger}$	$\mathbf{-52.07}$	15998	-58.05	19846
WebKB	839	2803	558	838	-163.42	10033	-161.09^{*}	18431	$-157.88^{\dagger}$	$\mathbf{-153.55}$	20134	-161.17	10046
Reuters-52	889	6532	1028	1530	-94.94	10585	-89.61^{*}	9546	$-86.38^{\dagger}$	$\mathbf{-83.90}$	46232	-87.49	28334
20NewsGrp.	910	11293	3764	3764	-161.41	12222	-161.09^{*}	18431	$-153.63^{\dagger}$	$\mathbf{-154.67}$	43684	-161.46	29016
BBC	1058	1670	225	330	-260.83	10585	$\mathbf{-253.19}^{*}$	20327	$-252.13^{\dagger}$	-253.45	21160	-260.59	8454
AD	1556	2461	327	491	-30.49^{*}	9666	-31.78	9521	$-16.97^{\dagger}$	-16.77	49790	$\mathbf{-15.39}$	31070

Experiments on 20 datasets

Compare with O-SPN: smaller size in 14, better LL in 11, win on both in 6

Compare with L-SPN: smaller size in 14, better LL in 6, win on both in 2

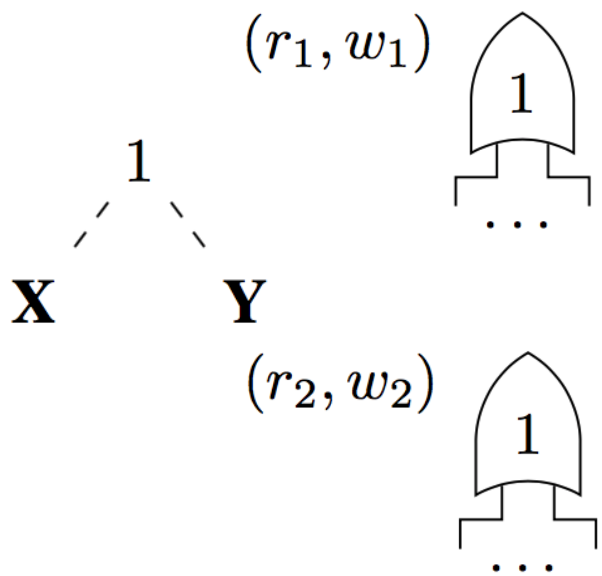
Experiments on 20 datasets

Compare with O-SPN: smaller size in 14, better LL in 11, win on both in 6

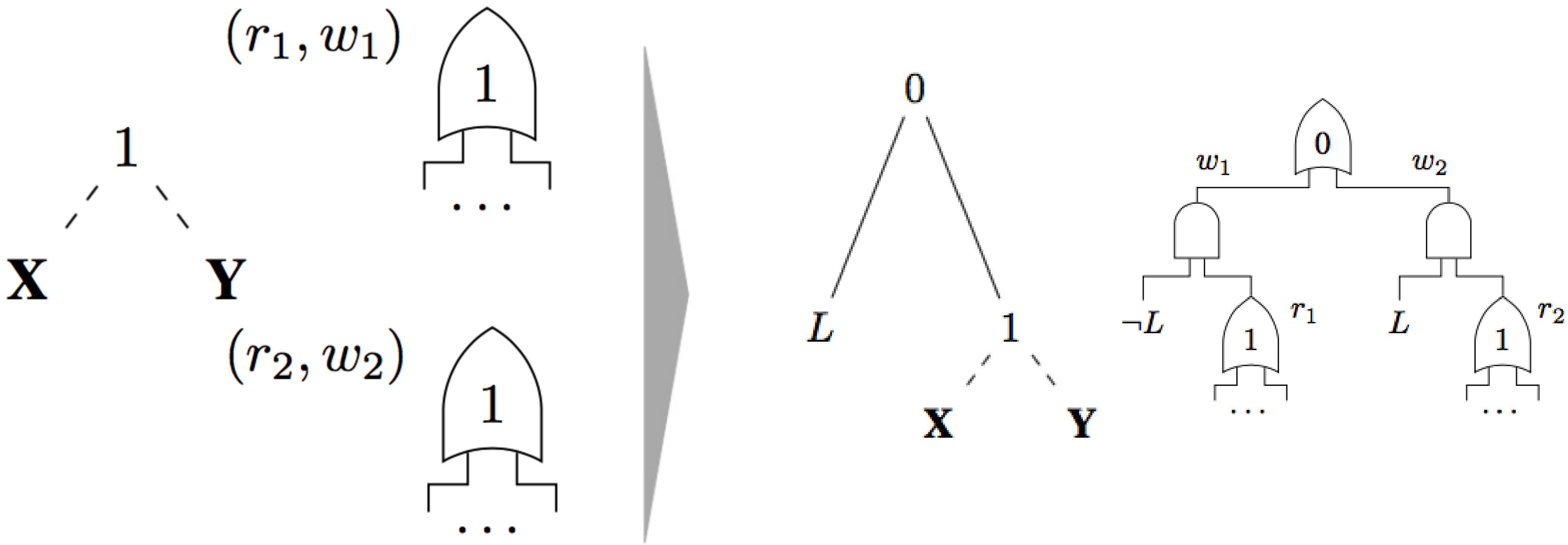
Compare with L-SPN: smaller size in 14, better LL in 6, win on both in 2

Comparable in performance & Smaller in size

Ensembles of PSDDs

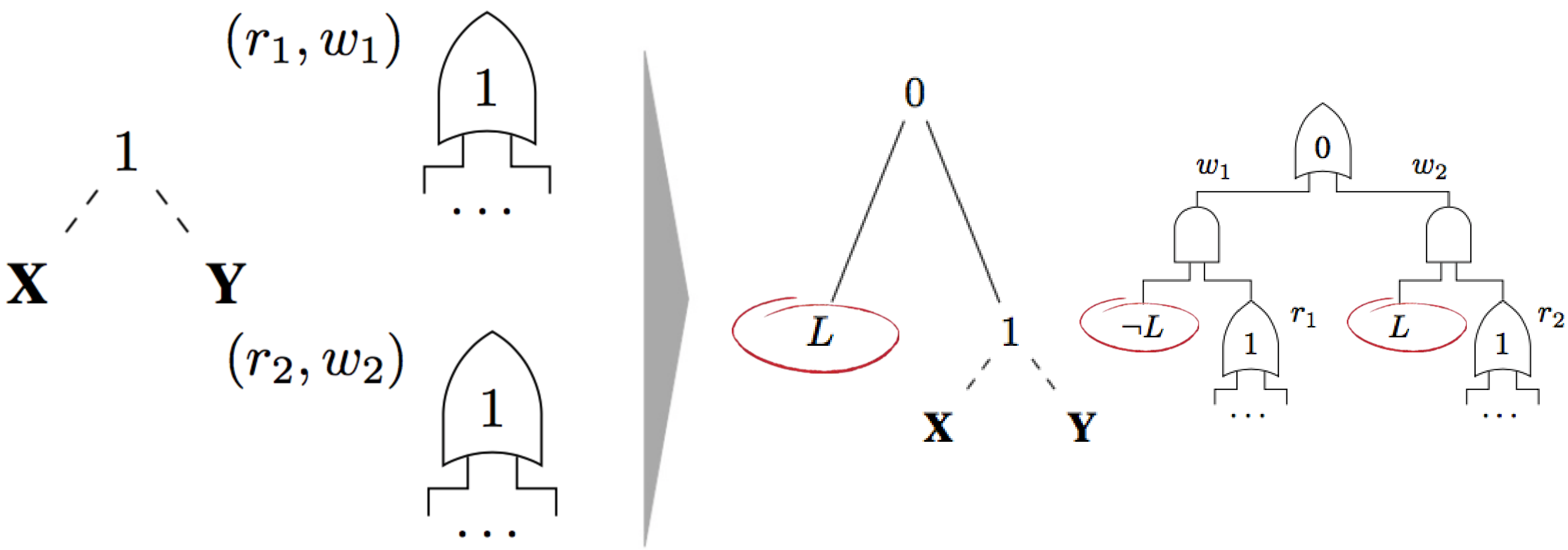


Ensembles of PSDDs



EM/Bagging

Ensembles of PSDDs



EM/Bagging

State-of-the-Art Performance

Datasets	|Var|	LearnPSDD Ensemble	Best-to-Date
NLTCS	16	$-5.99^{\dagger}$	-6.00
MSNBC	17	$-6.04^{\dagger}$	$-6.04^{\dagger}$
KDD	64	$-2.11^{\dagger}$	-2.12
Plants	69	-13.02	$-11.99^{\dagger}$
Audio	100	-39.94	$-39.49^{\dagger}$
Jester	100	-51.29	$-41.11^{\dagger}$
Netflix	100	$-55.71^{\dagger}$	-55.84
Accidents	111	-30.16	$-24.87^{\dagger}$
Retail	135	$-10.72^{\dagger}$	-10.78
Pumsb-Star	163	-26.12	$-22.40^{\dagger}$
DNA	180	-88.01	$-80.03^{\dagger}$
Kosarek	190	$-10.52^{\dagger}$	-10.54
MSWeb	294	-9.89	$-9.22^{\dagger}$
Book	500	-34.97	$-30.18^{\dagger}$
EachMovie	500	-58.01	$-51.14^{\dagger}$
WebKB	839	-161.09	$-150.10^{\dagger}$
Reuters-52	889	-89.61	$-80.66^{\dagger}$
20NewsGrp.	910	-155.97	$-150.88^{\dagger}$
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State-of-the-Art Performance

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NLTCS	16	$-5.99^{\dagger}$	-6.00
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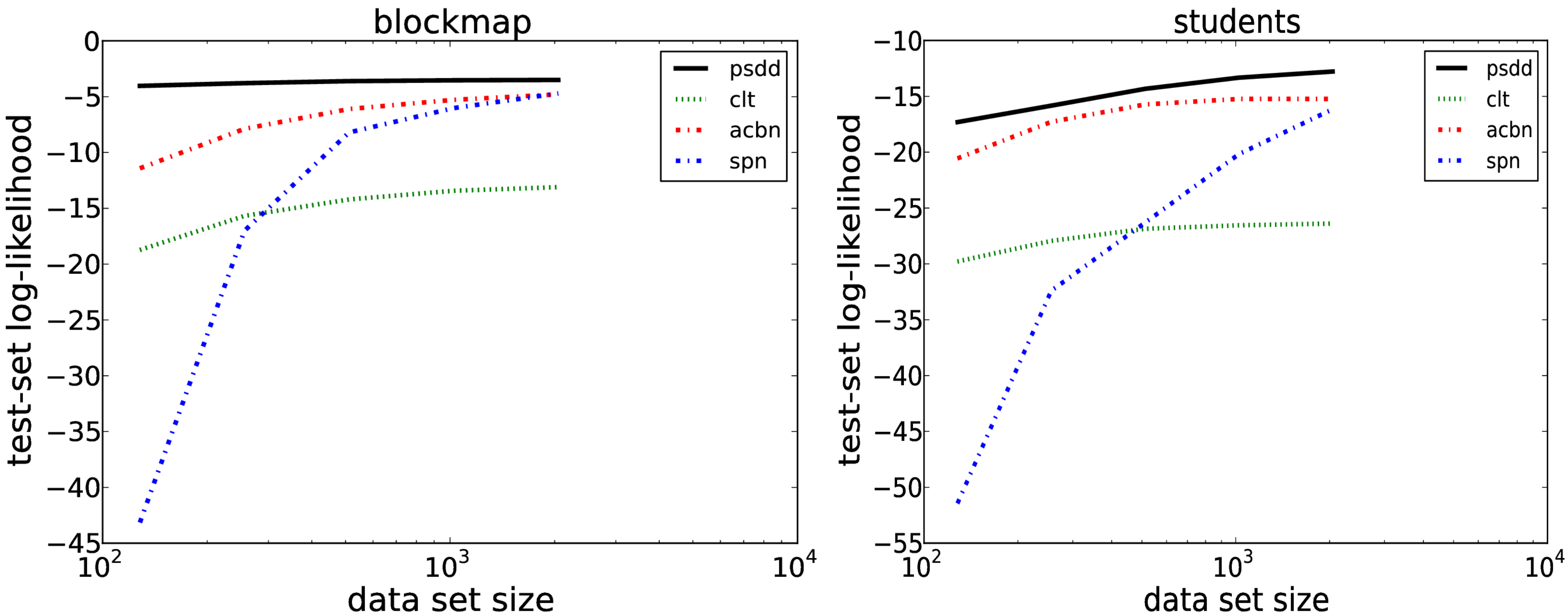
AD	1556	-31.78	$-14.36^{\dagger}$

State of the art in 6 datasets

What happens if you **ignore** constraints?



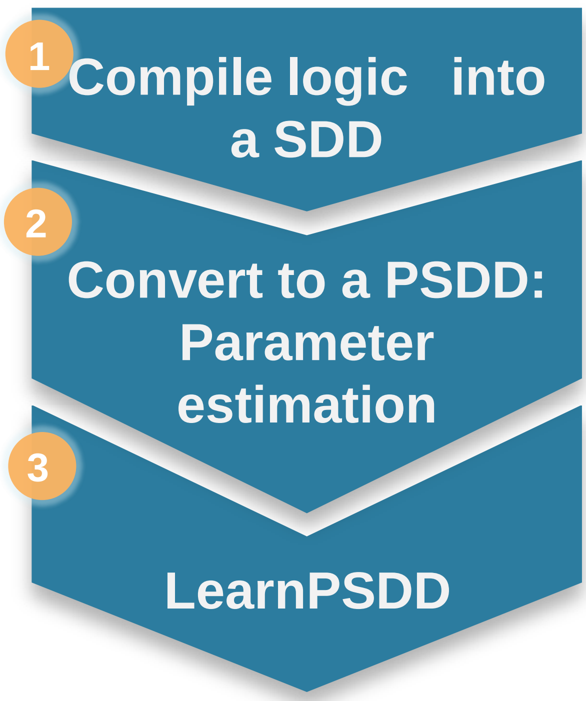
What happens if you **ignore** constraints?

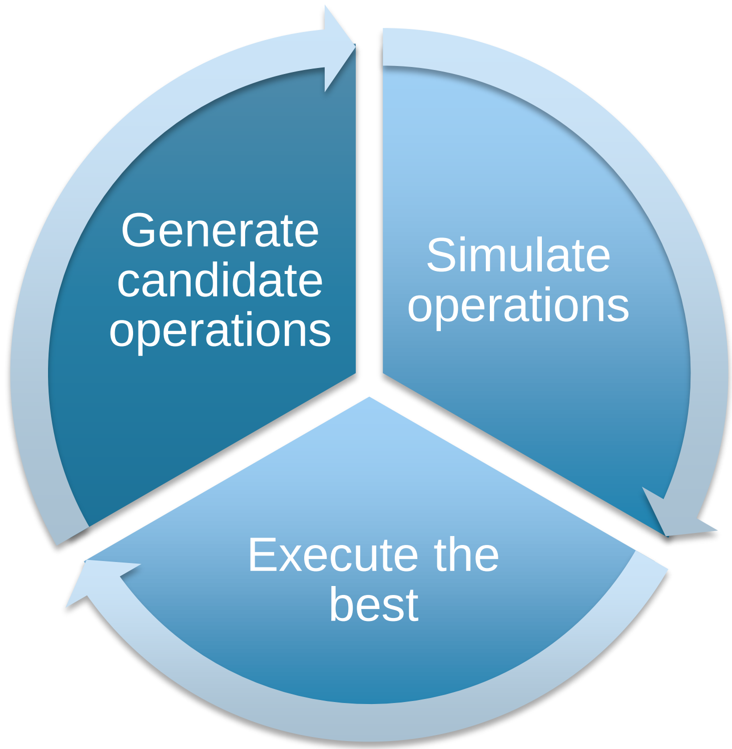
Roadmap

1. Compile logic into a SDD
2. Convert to a PSDD: Parameter estimation
3. LearnPSDD

What happens if you **ignore** constraints?

Roadmap





What happens if you **ignore** constraints?

Discrete multi-valued data

$\boldsymbol{A}$: $\boldsymbol{a_1}, \boldsymbol{a_2}, \boldsymbol{a_3}$

$$\left\{\begin{array}{c} \boldsymbol{a_1} \wedge \neg \boldsymbol{a_2} \wedge \neg \boldsymbol{a_3} \\ \vee \\ \neg \boldsymbol{a_1} \wedge \boldsymbol{a_2} \wedge \neg \boldsymbol{a_3} \\ \vee \\ \neg \boldsymbol{a_1} \wedge \neg \boldsymbol{a_2} \wedge \boldsymbol{a_3} \end{array}\right.$$

What happens if you **ignore** constraints?

Discrete multi-valued data

$\boldsymbol{A}$: $\boldsymbol{a_1, a_2, a_3}$

$$\begin{cases} a_1 \wedge \neg a_2 \wedge \neg a_3 \\ \vee \\ \neg a_1 \wedge a_2 \wedge \neg a_3 \\ \vee \\ \neg a_1 \wedge \neg a_2 \wedge a_3 \end{cases}$$

Datasets	**No Constraint**	**PSDD**	**LEARNPSDD**
Adult	-18.41	-14.14	-12.86
CovType	-14.39	-8.81	-7.32

What happens if you **ignore** constraints?

Discrete multi-valued data

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$$\left\{\begin{array}{c} a_1 \wedge \neg a_2 \wedge \neg a_3 \\ \vee \\ \neg a_1 \wedge a_2 \wedge \neg a_3 \\ \vee \\ \neg a_1 \wedge \neg a_2 \wedge a_3 \end{array}\right.$$

Datasets	No Constraint	PSDD	LEARNPSDD
Adult	-18.41	-14.14	-12.86
CovType	-14.39	-8.81	-7.32

Never omit domain constraints

Complex queries

and

Learning from constraints

Incomplete Data

a classical
complete dataset

id	X	Y	Z
1	x_1	y_2	z_1
2	x_2	y_1	z_2
3	x_2	y_1	z_2
4	x_1	y_1	z_1
5	x_1	y_2	z_2

closed-form
(maximum-likelihood
estimates are unique)

Incomplete Data

a classical
complete dataset

id	X	Y	Z
1	x_1	y_2	z_1
2	x_2	y_1	z_2
3	x_2	y_1	z_2
4	x_1	y_1	z_1
5	x_1	y_2	z_2

closed-form
(maximum-likelihood
estimates are unique)

a classical
incomplete dataset

id	X	Y	Z
1	x_1	y_2	?
2	x_2	y_1	?
3	?	?	z_2
4	?	y_1	z_1
5	x_1	y_2	z_2

EM algorithm
(on PSDDs)

Incomplete Data

a classical complete dataset

id	X	Y	Z
1	x_1	y_2	z_1
2	x_2	y_1	z_2
3	x_2	y_1	z_2
4	x_1	y_1	z_1
5	x_1	y_2	z_2

closed-form (maximum-likelihood estimates are unique)

a classical incomplete dataset

id	X	Y	Z
1	x_1	y_2	?
2	x_2	y_1	?
3	?	?	z_2
4	?	y_1	z_1
5	x_1	y_2	z_2

EM algorithm (on PSDDs)

a new type of incomplete dataset

id	X	Y	Z
1	$X \equiv Z$		
2	x_2 and (y_2 or z_2)		
3	$x_2 \Rightarrow y_1$		
4	$X \oplus Y \oplus Z \equiv 1$		
5	x_1 and y_2 and z_2		

Missed in the ML literature

Structured Datasets

a classical **complete** dataset
(e.g., total rankings)

id	1^{st} sushi	2^{nd} sushi	3^{rd} sushi	…
1	fatty tuna	sea urchin	salmon roe	…
2	fatty tuna	tuna	shrimp	…
3	tuna	tuna roll	sea eel	…
4	fatty tuna	salmon roe	tuna	…
5	egg	squid	shrimp	…

a classical **incomplete** dataset
(e.g., top-*k* rankings)

id	1^{st} sushi	2^{nd} sushi	3^{rd} sushi	…
1	fatty tuna	sea urchin	?	…
2	fatty tuna	?	?	…
3	tuna	tuna roll	?	…
4	fatty tuna	salmon roe	?	…
5	egg	?	?	…

Structured Datasets

a classical **complete** dataset
(e.g., total rankings)

id	1^{st} sushi	2^{nd} sushi	3^{rd} sushi	…
1	fatty tuna	sea urchin	salmon roe	…
2	fatty tuna	tuna	shrimp	…
3	tuna	tuna roll	sea eel	…
4	fatty tuna	salmon roe	tuna	…
5	egg	squid	shrimp	…

a new type of **incomplete** dataset
(e.g., **partial** rankings)

id	1^{st} sushi	2^{nd} sushi	3^{rd} sushi	…
1	(fatty tuna > sea urchin) and (tuna > sea eel)			…
2	(fatty tuna is 1^{st}) and (salmon roe > egg)			…
3	tuna > squid			…
4	egg is last			…
5	egg > squid > shrimp			…

(represents constraints on possible *total rankings*)

Learning from Incomplete Data

- Movielens Dataset:
  - 3,900 movies, 6,040 users, 1m ratings
  - take ratings from 64 most rated movies
  - ratings 1-5 converted to pairwise prefs.
- PSDD for **partial** rankings
  - 4 tiers
  - 18,711 parameters

movies by expected tier

rank	movie
1	The Godfather
2	The Usual Suspects
3	Casablanca
4	The Shawshank Redemption
5	Schindler's List
6	One Flew Over the Cuckoo's Nest
7	The Godfather: Part II
8	Monty Python and the Holy Grail
9	Raiders of the Lost Ark
10	Star Wars IV: A New Hope

PSDD Sizes

items	tier size	Size		
n	k	SDD	Structured Space	Unstructured Space
8	2	443	840	$1.84 \cdot 10^{19}$
27	3	4,114	$1.18 \cdot 10^{9}$	$2.82 \cdot 10^{219}$
64	4	23,497	$3.56 \cdot 10^{18}$	$1.04 \cdot 10^{1233}$
125	5	94,616	$3.45 \cdot 10^{31}$	$3.92 \cdot 10^{4703}$
216	6	297,295	$1.57 \cdot 10^{48}$	$7.16 \cdot 10^{14044}$
343	7	781,918	$4.57 \cdot 10^{68}$	$7.55 \cdot 10^{35415}$

Structured Queries

rank	movie
1	Star Wars V: The Empire Strikes Back
2	Star Wars IV: A New Hope
3	The Godfather
4	The Shawshank Redemption
5	The Usual Suspects

Structured Queries

- no other Star Wars movie in top-5
- at least one comedy in top-5

rank	movie
1	Star Wars V: The Empire Strikes Back
2	Star Wars IV: A New Hope
3	The Godfather
4	The Shawshank Redemption
5	The Usual Suspects

Structured Queries

rank	movie
1	Star Wars V: The Empire Strikes Back
2	Star Wars IV: A New Hope
3	The Godfather
4	The Shawshank Redemption
5	The Usual Suspects

- no other Star Wars movie in top-5
- at least one comedy in top-5

rank	movie
1	Star Wars V: The Empire Strikes Back
2	American Beauty
3	The Godfather
4	The Usual Suspects
5	The Shawshank Redemption

Structured Queries

rank	movie
1	Star Wars V: The Empire Strikes Back
2	Star Wars IV: A New Hope
3	The Godfather
4	The Shawshank Redemption
5	The Usual Suspects

- no other Star Wars movie in top-5
- at least one comedy in top-5

rank	movie
1	Star Wars V: The Empire Strikes Back
2	American Beauty
3	The Godfather
4	The Usual Suspects
5	The Shawshank Redemption

diversified recommendations via
logical constraints

Conclusions

- Structured spaces are everywhere ☺
- PSDDs build on logical circuits
  1. Tractability
  2. Semantics
  3. Natural encoding of structured spaces
- Learning is effective
  1. From constraints encoding structured space

     State of the art learning preference distributions
  2. From standard unstructured datasets using search

     State of the art on standard tractable learning datasets
- Novel settings for inference and learning

  Structured spaces / learning from constraints / complex queries

References

Probabilistic Sentential Decision Diagrams
Doga Kisa, Guy Van den Broeck, Arthur Choi and Adnan Darwiche
KR, 2014

Learning with Massive Logical Constraints
Doga Kisa, Guy Van den Broeck, Arthur Choi and Adnan Darwiche
ICML LTPM workshop, 2014

Tractable Learning for Structured Probability Spaces
Arthur Choi, Guy Van den Broeck and Adnan Darwiche
IJCAI, 2015

Tractable Learning for Complex Probability Queries
Jessa Bekker, Jesse Davis, Arthur Choi, Adnan Darwiche, Guy Van den Broeck.
NIPS, 2015

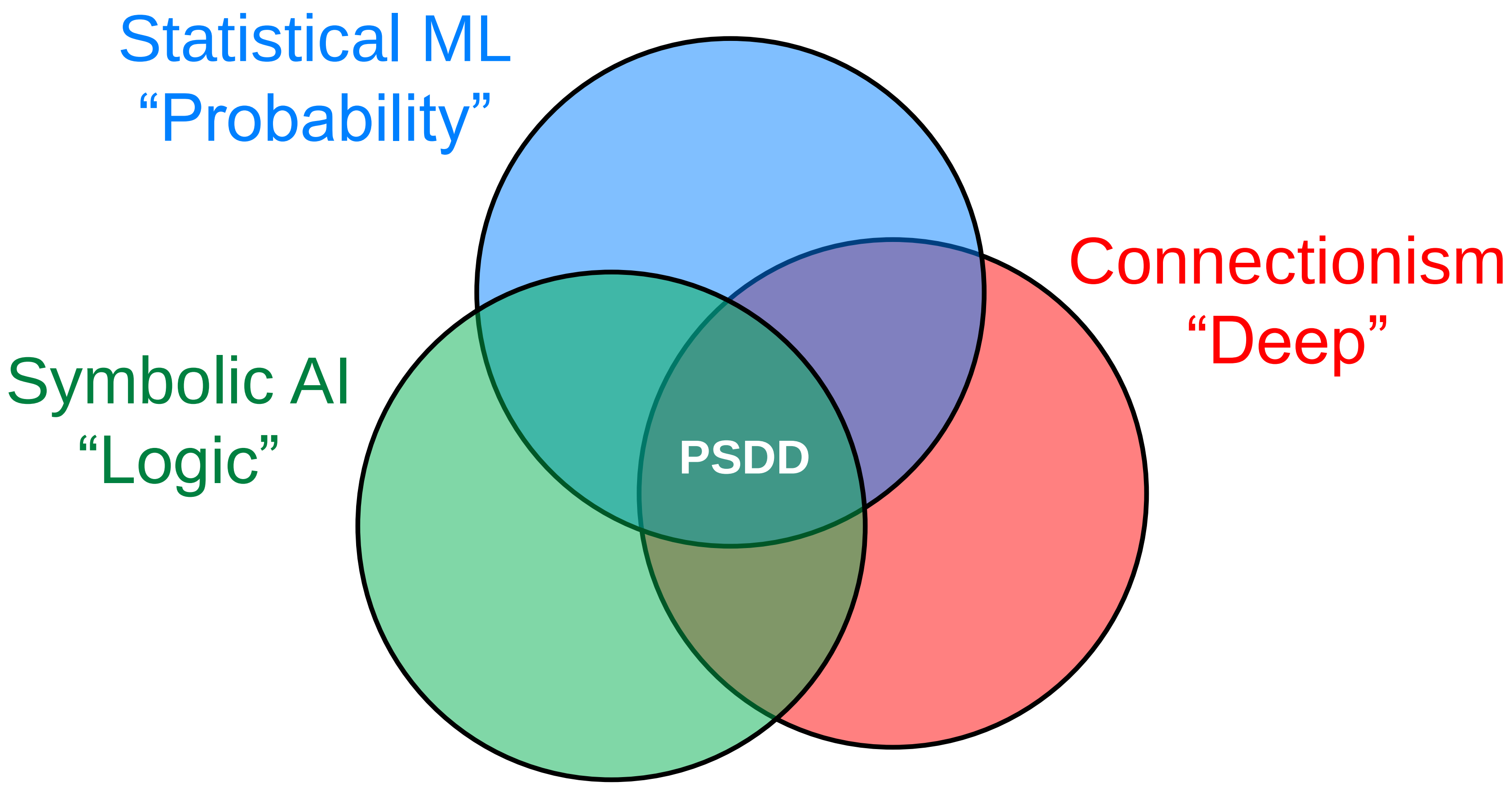
Learning the Structure of PSDDs
Yitao Liang, Jessa Bekker and Guy Van den Broeck
UAI, 2017

Towards Compact Interpretable Models: Learning and Shrinking PSDDs
Yitao Liang and Guy Van den Broeck
IJCAI XAI workshop, 2017

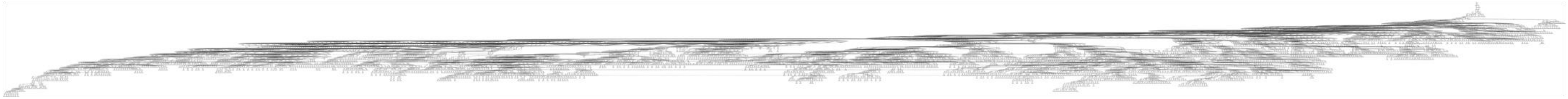
(P)SDDs in Melbourne

- Sunday: Logical Foundations for Uncertainty and Machine Learning Workshop
  - Adnan Darwiche: *"On the Role of Logic in Probabilistic Inference and Machine Learning"*
  - YooJung Choi: *"Optimal Feature Selection for Decision Robustness in Bayesian Networks"*
- Sunday: Explainable AI Workshop
  - Yitao Liang: *"Towards Compact Interpretable Models: Learning and Shrinking PSDDs"*
- Tuesday: IJCAI
  - YooJung Choi (again)

Conclusions



Questions?



PSDD with 15,000 nodes

LearnPSDD code: https://github.com/UCLA-StarAI/LearnPSDD
Other PSDD code: http://reasoning.cs.ucla.edu/psdd/
SDD code: http://reasoning.cs.ucla.edu/sdd/