Stochastic Constraint Propagation for Mining Probabilistic Networks

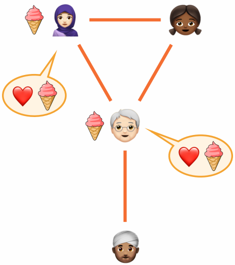
Anna Louise Latour, Behrouz Babaki, Siegfried Nijssen.

Universiteit Leiden The Netherlands

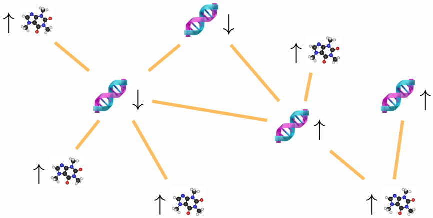
POLYTECHNIQUE MONTRÉAL

UCLouvain

Viral Marketing

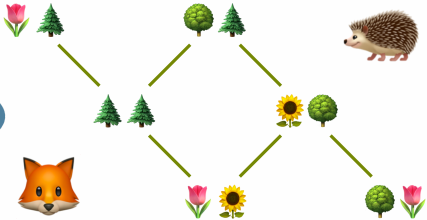


Signalling Regulatory Pathways

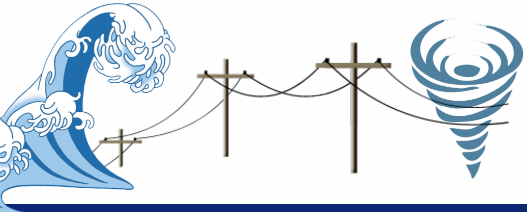


Stochastic **C**onstraint **O**ptimization **P**roblems

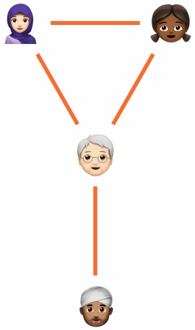
Landscape Connectivity



Powergrid Reliability

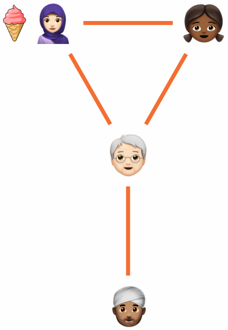


Example: Viral Marketing Problem



David Kempe, Jon Kleinberg, and Éva Tardos
Maximizing the spread of influence through a social network
KDD, 2003

Example: Viral Marketing Problem



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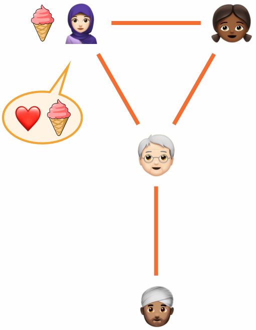

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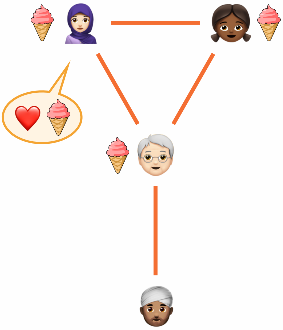

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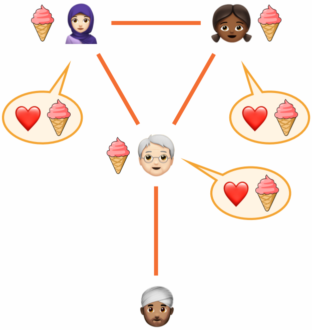

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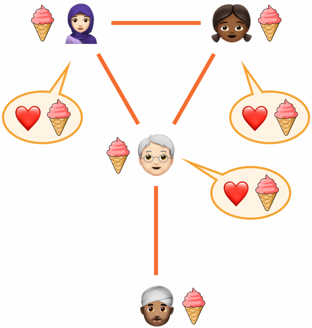

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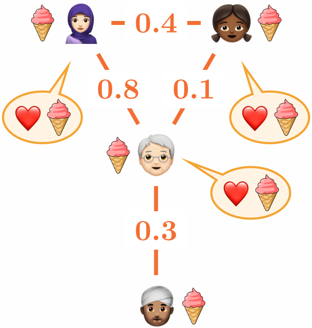

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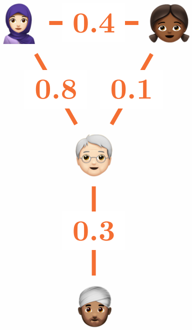

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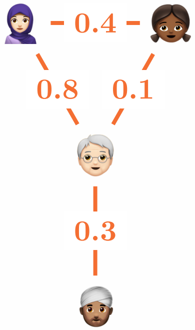

Properties

- **Probabilistic** influence;

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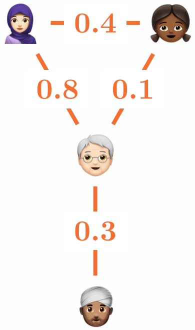

Properties

- **Probabilistic** influence;
- limited **budget** of free samples ;

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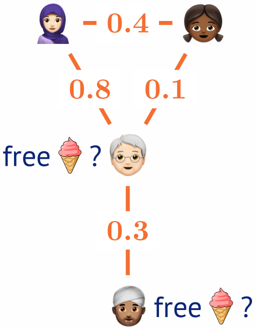

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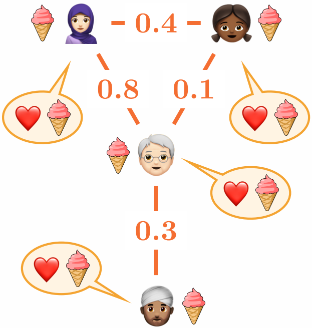

Properties

- **Probabilistic** influence;
- limited **budget** of free samples 🍦🍦;
- **maximize** expected # people buying your ice cream.

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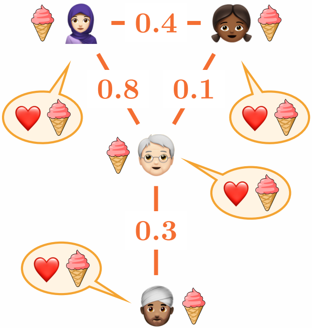

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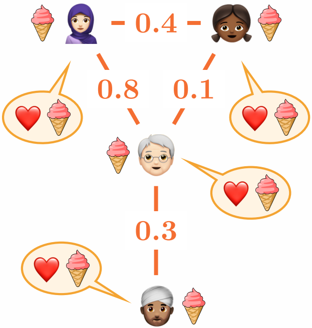

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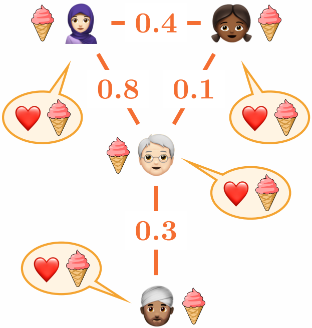

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Exact solving is **NP-hard**

- Exponential # of **strategies**;
- **Probabilistic inference** is **#P-complete**.

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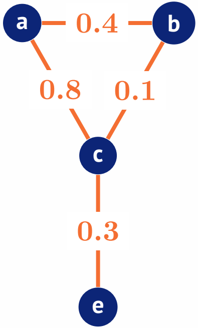
KDD, 2003

Dan Roth
The hardness of approximate reasoning
Artif. Intell., 1996

Example: Viral Marketing Problem



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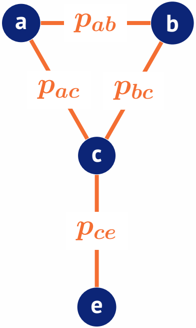

$$P(t_{xy} = 1) = p_{xy}$$
$$P(t_{xy} = 0) = (1 - p_{xy})$$

Boolean influence relationships are **independent**.

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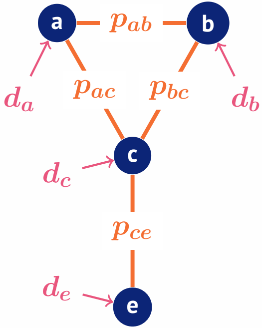

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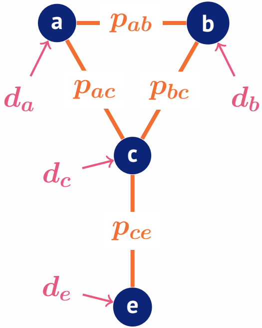

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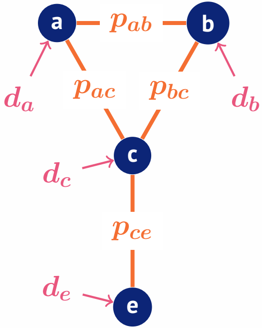

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- influence relationships are symmetric;

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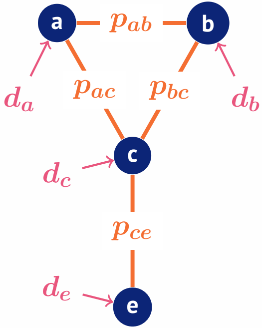

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- if person i gets a free sample ($d_i = 1$), they will buy it in the future;

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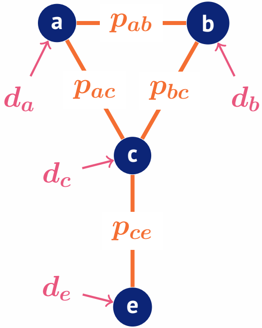

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Boolean influence relationships are **independent**.

Simplifying assumptions

- influence relationships are symmetric;
- if person i gets a free sample ($d_i = 1$), they will buy it in the future;
- if person i buys ice cream and they have influence over j ($t_{ij} = 1$), then j will buy ice cream.

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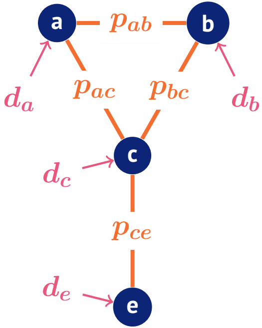

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Person e buys ice cream:

$$\phi_e =$$

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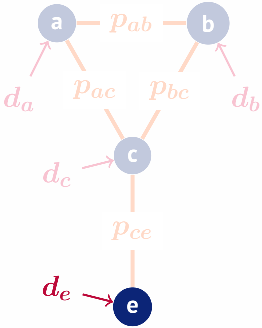

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$$\phi_e = d_e \vee$$

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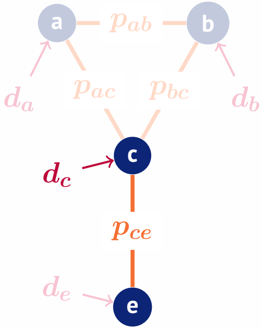

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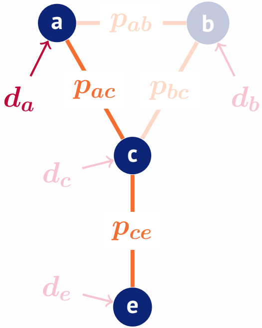

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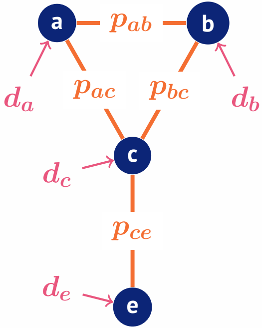

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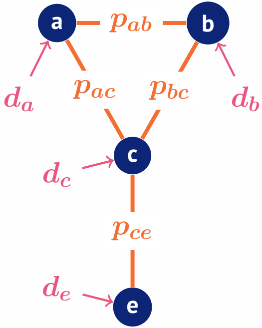

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$$\arg\max_{\sigma} \sum_{i \in \{a,b,c,e\}} P(\phi_i \mid \sigma)$$

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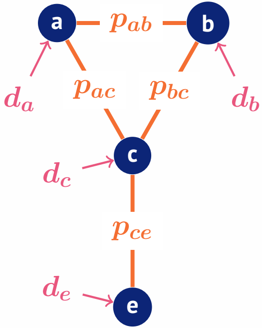

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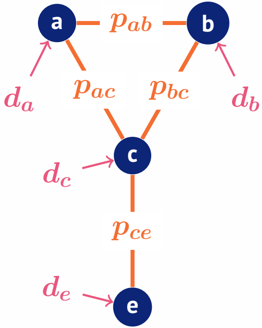

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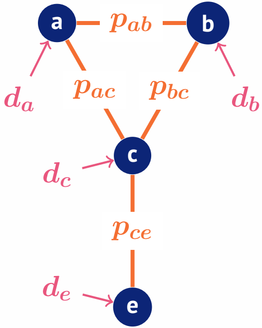

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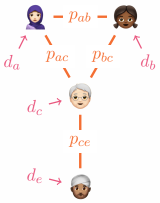

A.L.D. Latour, B. Babaki, A. Dries, A. Kimmig, G. Van den Broeck, S. Nijssen.
Combining Stochastic Constraint Optimization and Probabilistic Programming: From Knowledge Compilation to Constraint Solving. CP, 2017

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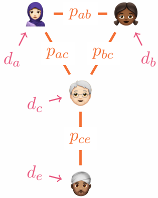

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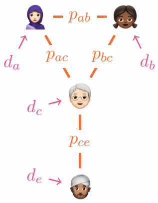

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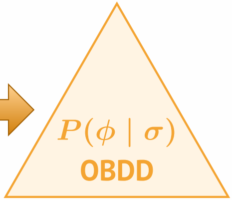

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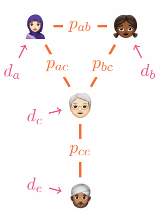

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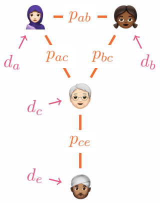
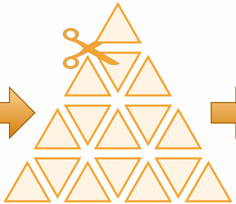


$$\phi_e = d_e \lor (d_c \land t_{ce}) \lor (d_a \land t_{ac} \land t_{ce}) \lor (d_b \land t_{bc} \land t_{ce}) \lor (d_a \land t_{ab} \land t_{bc} \land t_{ce}) \lor (d_b \land t_{ab} \land t_{ac} \land t_{ce})$$

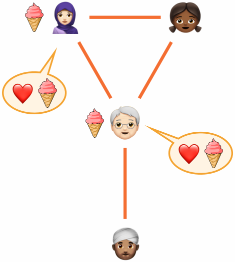


CP
or
MIP

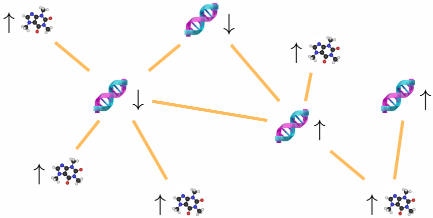
A.L.D. Latour, B. Babaki, A. Dries, A. Kimmig, G. Van den Broeck, S. Nijssen. *Combining Stochastic Constraint Optimization and Probabilistic Programming: From Knowledge Compilation to Constraint Solving.* CP, 2017

Observation 1: existing method does **not guarantee** Generalized Arc Consistency (**GAC**) $\longrightarrow$ **inefficient**;

Viral Marketing

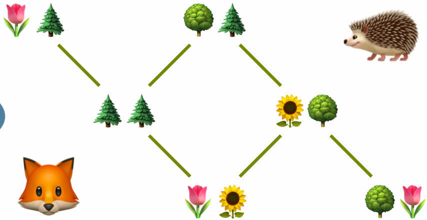


Signalling Regulatory Pathways

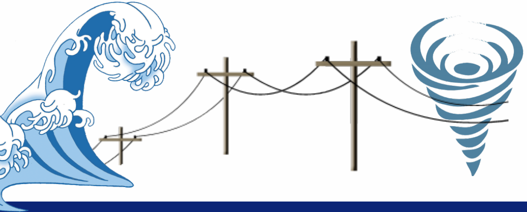


monotonic distributions

Landscape Connectivity



Powergrid Reliability



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GOAL: create constraint propagation algorithm for Stochastic Constraints on Monotonic Distributions (SCMDs), which guarantees GAC.

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OscaR: Scala in OR, 2012
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leverage structure (global propagator)

OscaR: Scala in OR, 2012
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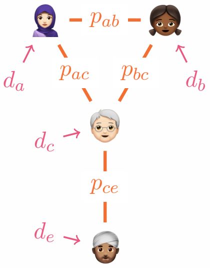
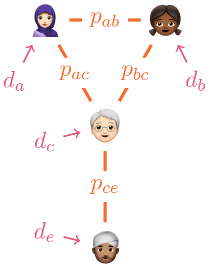

p_{ab}
d_a
p_{ac}
p_{bc}
d_b
d_c
p_{ce}
d_e



$$
\begin{aligned}
\phi_e = d_e \vee (d_c \wedge t_{ce}) \vee \\
(d_a \wedge t_{ac} \wedge t_{ce}) \vee \\
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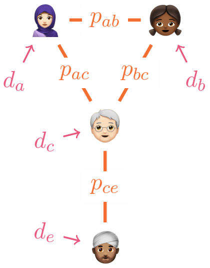
\end{aligned}
$$

$$P\left(\phi_e \mid \sigma = \{d_a, d_c\}\right) \geq \theta$$



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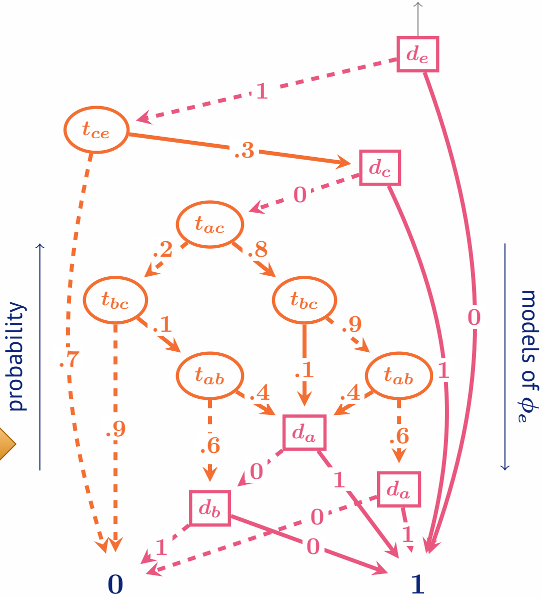

Ordered Binary Decision Diagram (**OBDD**) encodes **probability distribution**

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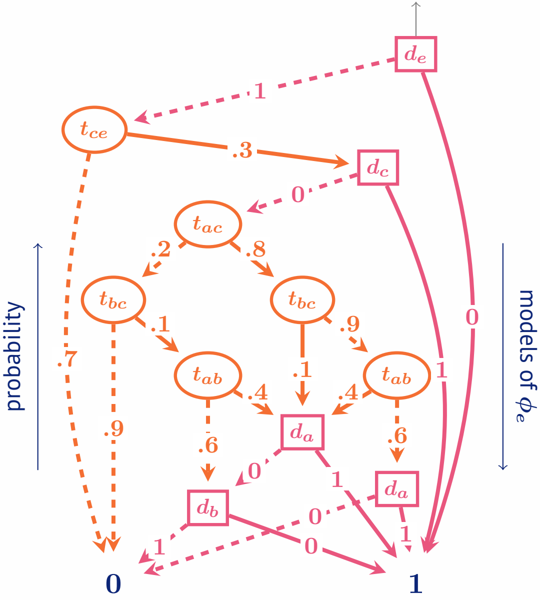

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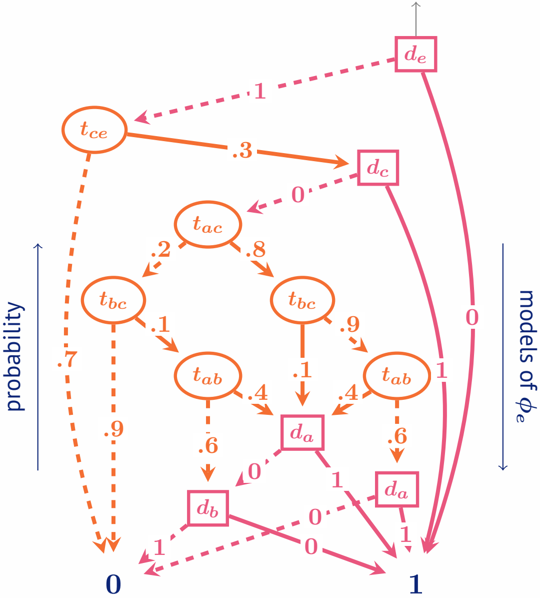

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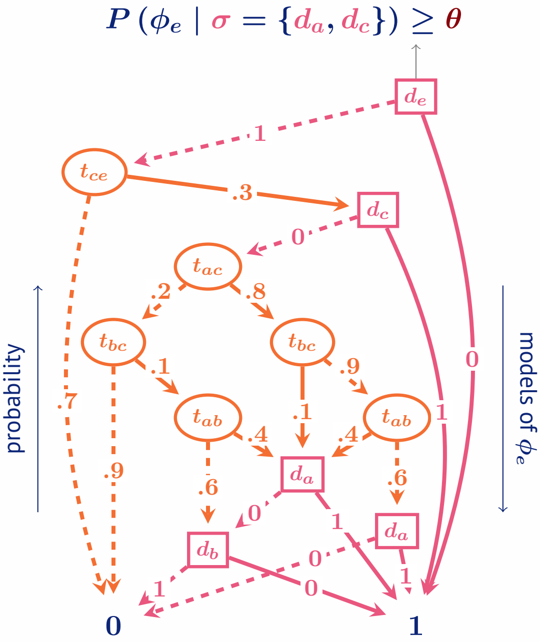
solve $\sum_{\phi \in \Phi} P(\phi \mid \sigma) \geq \theta$



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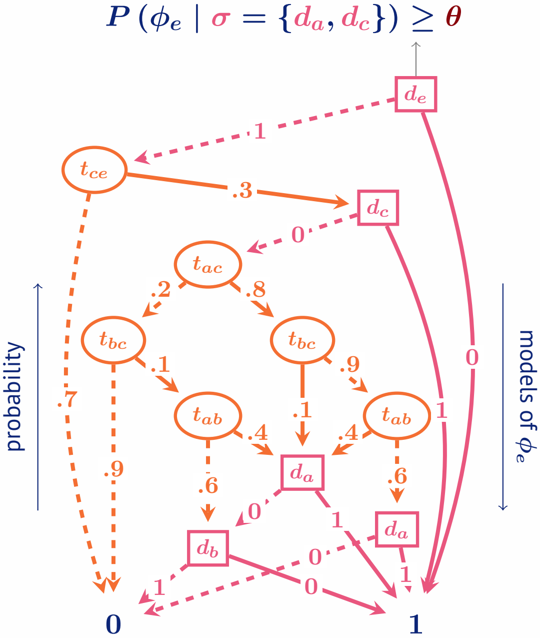
Use OBDD to evaluate **strategy σ**. **Complexity** of one sweep: $O(m)$, with $m = |\text{OBDD}|$.



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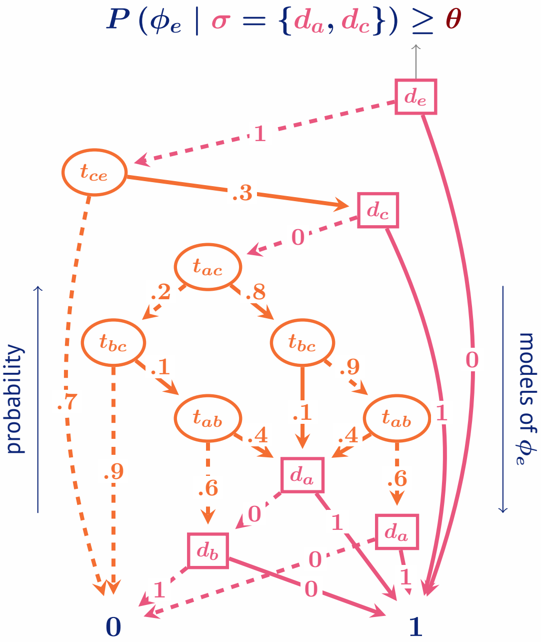
Naïve method has complexity $O(m \cdot n)$, where n is the number of unbound variables



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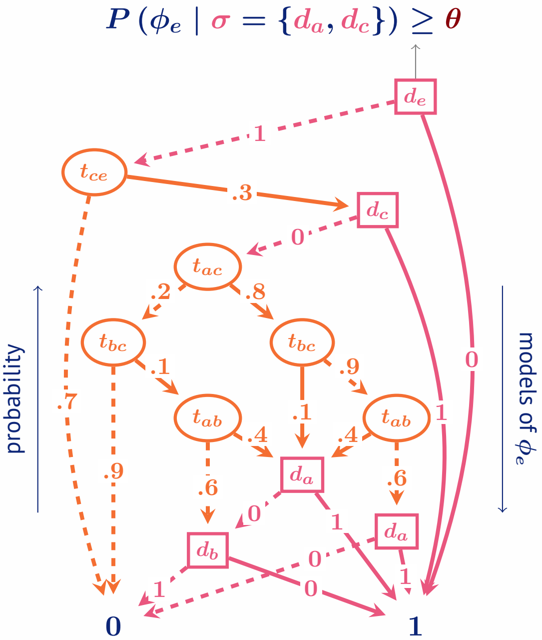
Use OBDD to evaluate **strategy σ**. **Complexity** of one sweep: $O(m)$, with $m = |\text{OBDD}|$.

Smart, incremental method has complexity $O(m + n)$, using **derivatives**.



Adnan Darwiche.
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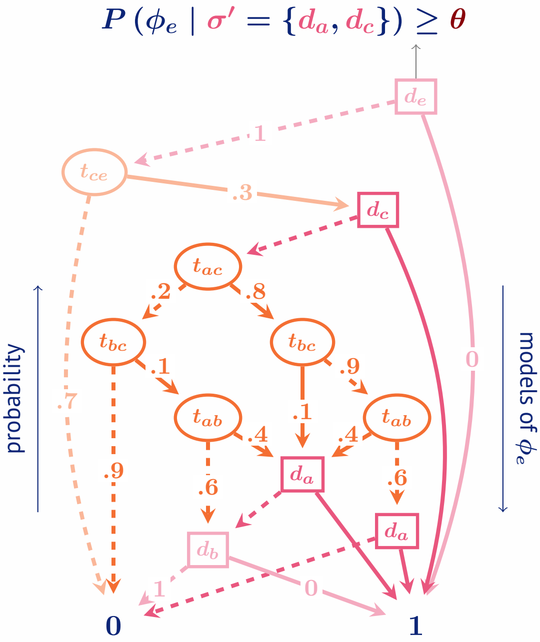

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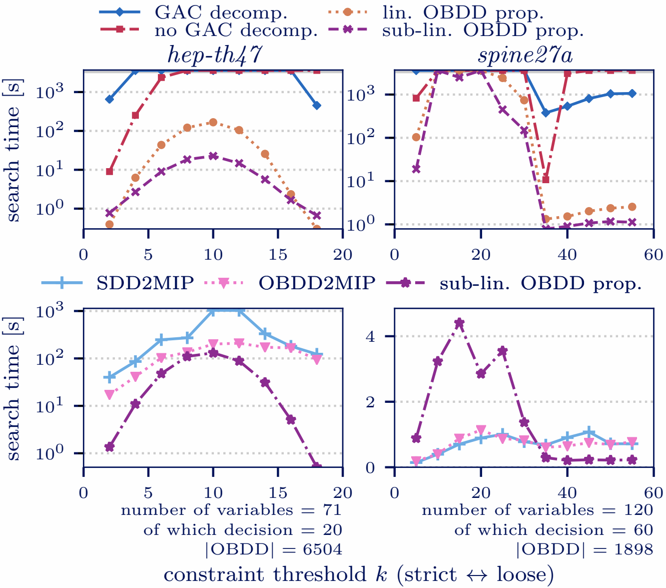
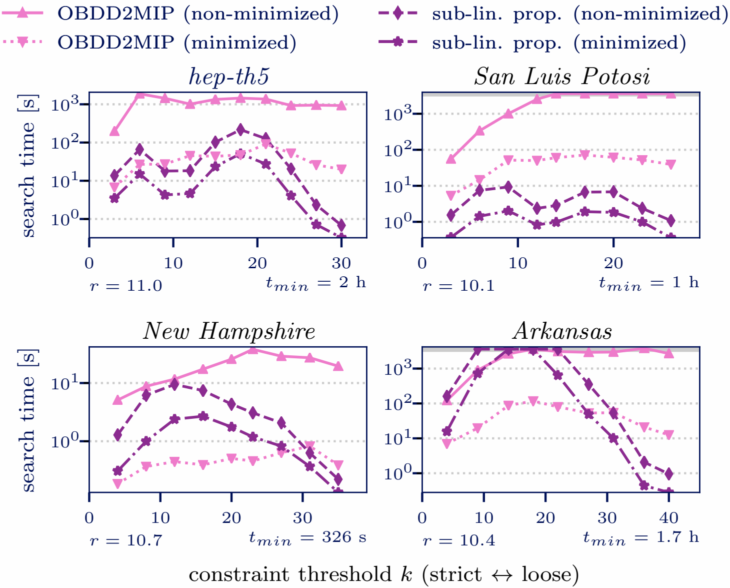
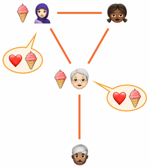
SCMD propagator vs existing methods

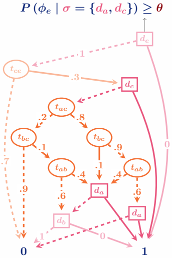


Scalability of SCMD propagator vs MIP



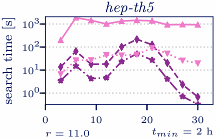
Main contribution





A new global constraint propagator for Stochastic Constraints on Monotonic Distributions (SCMDs) which:

- guarantees GAC;
- has linear complexity;
- outperforms existing CP-based methods and complements MIP-based methods;
- scales better with OBDD size than existing MIP-based methods.



contact: `a.l.d.latour@liacs.leidenuniv.nl`

code & more **results**: `github.com/latower/SCMD`

new work: D. Fokkinga, A.L.D. Latour, M. Anastacio, S. Nijssen, H. Hoos. *Programming a Stochastic Constraint Optimisation Algorithm, by Optimisation.* IJCAI Data Science meets Optimization workshop, 2019.

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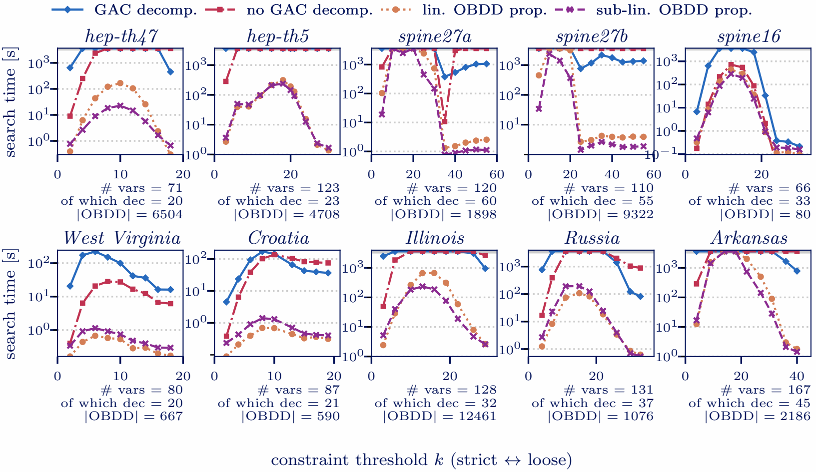
Theme by Joost Schalken. Updated by Pepijn van Heiningen & Anna Latour.

Acknowledgements

We thank Hélène Verhaeghe for her input and suggestions. This work was supported by the Netherlands Organisation for Scientific Research (NWO). Behrouz Babaki is supported by a postdoctoral scholarship from IVADO through the Canada First Research Excellence Fund (CFREF) grant.

SCMD propagator vs existing CP methods



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