Generating Random Logic Programs Using Constraint Programming

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UKRI Engineering and Physical Sciences Research Council

Probabilistic Logic Programs (ProbLog)

"Smokers" (Domingos et al. 2008; Fierens et al. 2015)

$$
\begin{aligned}
0.2 &:: \texttt{stress}(P) :- \texttt{person}(P).\\
0.3 &:: \texttt{influences}(P_1, P_2) :- \texttt{friend}(P_1, P_2).\\
0.1 &:: \texttt{cancer\_spont}(P) :- \texttt{person}(P).\\
0.3 &:: \texttt{cancer\_smoke}(P) :- \texttt{person}(P).\\
&\texttt{smokes}(X) :- \texttt{stress}(X).\\
&\texttt{smokes}(X) :- \texttt{smokes}(Y), \texttt{influences}(Y, X).\\
&\texttt{cancer}(P) :- \texttt{cancer\_spont}(P).\\
&\texttt{cancer}(P) :- \texttt{smokes}(P), \texttt{cancer\_smoke}(P).\\
&\texttt{person}(\mathit{michelle}).\\
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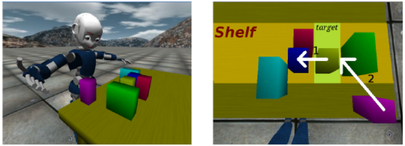
&\texttt{friend}(\mathit{timothy}, \mathit{michelle}).
\end{aligned}
$$

Applications



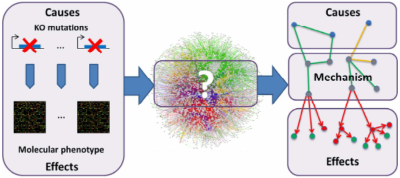
Moldovan et al. 2012

Q1: In a group of 10 people, 60 percent have brown eyes. Two people are to be selected at random from the group. What is the probability that neither person selected will have brown eyes?
Q2: Mike has a bag of marbles with 4 white, 8 blue, and 6 red marbles. He pulls out one marble from the bag and it is red. What is the probability that the second marble he pulls out of the bag is white?

Dries et al. 2017

```
is_malignant(Case):-
        biopsyProcedure(Case,usCore),
        changes_Sizeinc(Case,missing),
        feature_shape(Case).
is_malignant(Case):-
        assoFinding(Case,asymmetry),
        breastDensity(Case,scatteredFDensities),
        vacuumAssisted(Case,yes).
is_malignant(Case):-
        needleGauge(Case,9),
        offset(Case,14),
        vacuumAssisted(Case,yes).
```

Côrte-Real, Dutra, and Rocha 2017



De Maeyer et al. 2013

How Many Programs Are Used to Test Algorithms?

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Anytime Inference in Probabilistic Logic Programs with $T_\mathcal{P}$-Compilation

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Inference and learning in probabilistic logic programs using weighted Boolean formulas

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***k*-Optimal: a novel approximate inference algorithm for ProbLog**

Joris Renkens · Guy Van den Broeck · Siegfried Nijssen

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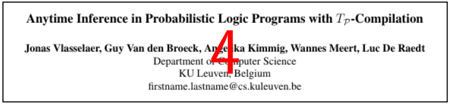

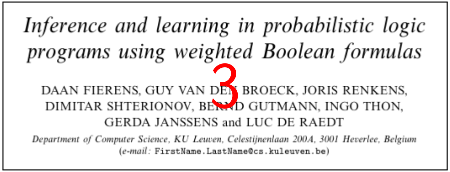

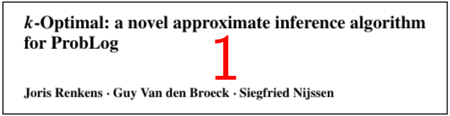

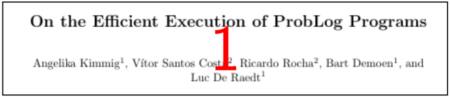

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On the Efficient Execution of ProbLog Programs

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On the Implementation of the Probabilistic Logic Programming Language ProbLog

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1

ProbLog Technology for Inference in a Probabilistic First Order Logic

Maurice Bruynooghe and **Theofrastos Mantadelis** and **Angelika Kimmig** and **Bernd Gutmann** and **Joost Vennekens** and **Gerda Janssens** and **Luc De Raedt**[1]

2

Outline

What Characterizes a (Probabilistic) Logic Program?

$0.2 :: \mathtt{stress}(\mathsf{P}) \mathrel{:\!-} \mathtt{person}(\mathsf{P}).$

$0.3 :: \mathtt{influences}(\mathsf{P}_1, \mathsf{P}_2) \mathrel{:\!-} \mathtt{friend}(\mathsf{P}_1, \mathsf{P}_2).$

$0.1 :: \mathtt{cancer\_spont}(\mathsf{P}) \mathrel{:\!-} \mathtt{person}(\mathsf{P}).$

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$\mathtt{smokes}(\mathsf{X}) \mathrel{:\!-} \mathtt{stress}(\mathsf{X}).$

$\mathtt{smokes}(\mathsf{X}) \mathrel{:\!-} \mathtt{smokes}(\mathsf{Y}), \mathtt{influences}(\mathsf{Y}, \mathsf{X}).$

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0.1::cancer_spont(P) :- person(P).
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     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
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- predicates, arities

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- complexity

Formulas As Trees

$$\neg \mathtt{p}(X) \vee (\mathtt{q}(X) \wedge \mathtt{r}(X))$$

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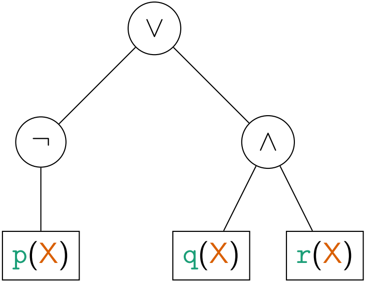
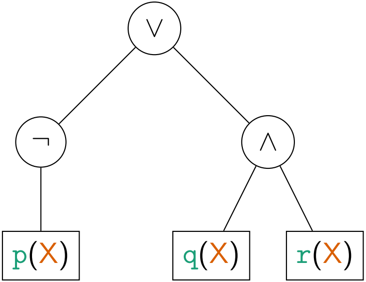


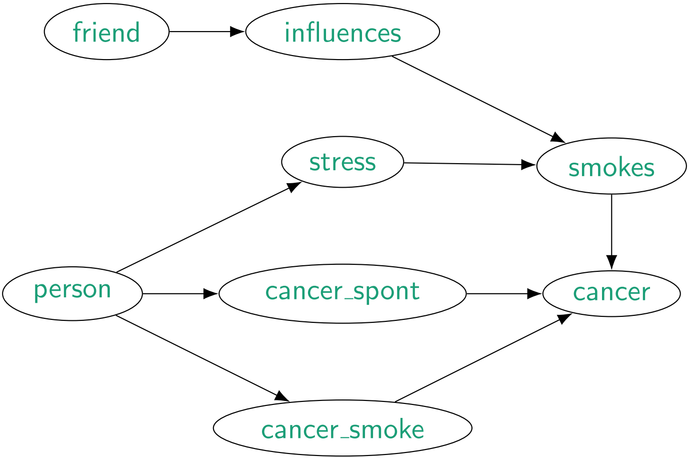
Formulas As Trees

$$\neg p(X) \lor (q(X) \land r(X))$$

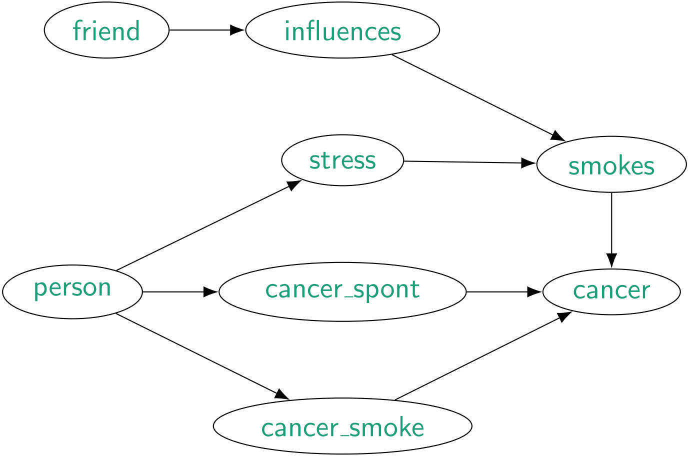


0	0	0	1	2	2
$\lor$	$\neg$	$\land$	p(X)	q(X)	r(X)

Predicate Dependency Graph



Independence: $\mathrm{friend} \perp\!\!\!\perp \mathrm{stress}$



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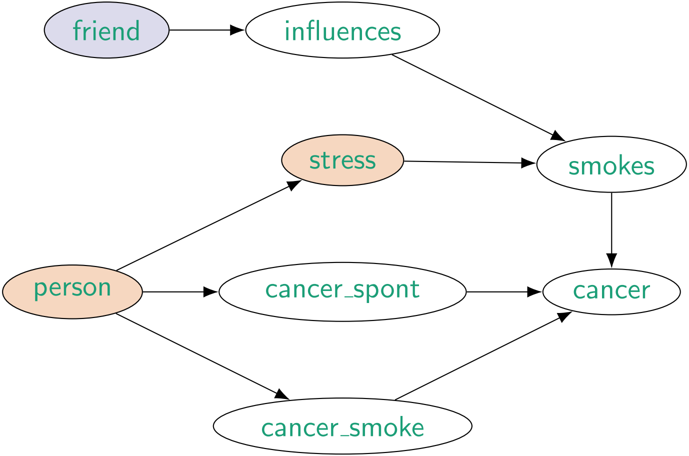

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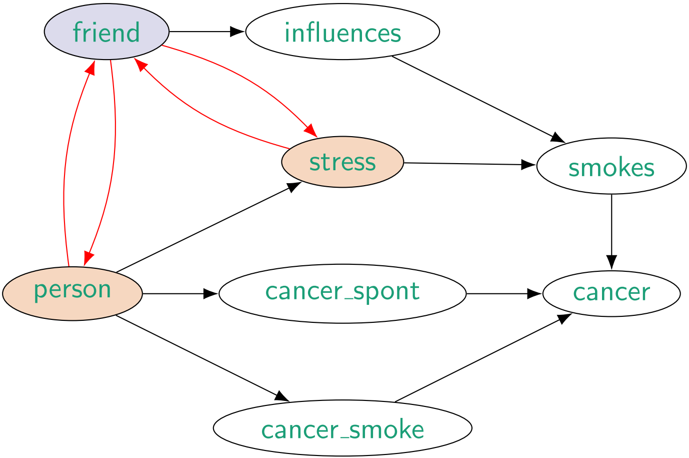
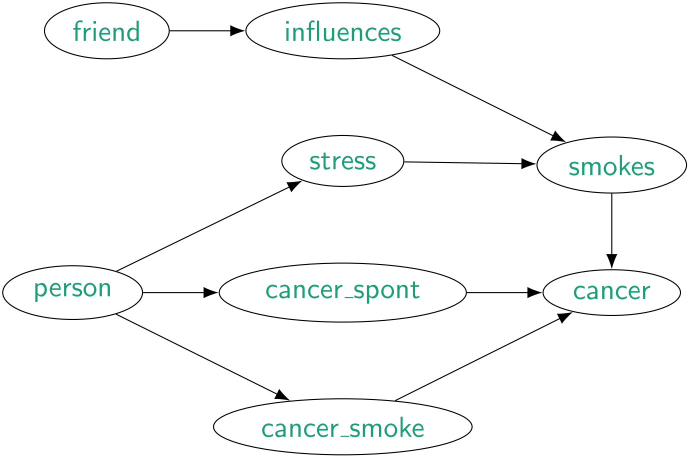


Stratification and Negative Cycles

$\texttt{0.1::friend(X, Y):-\textbackslash+ smokes(Y).}$



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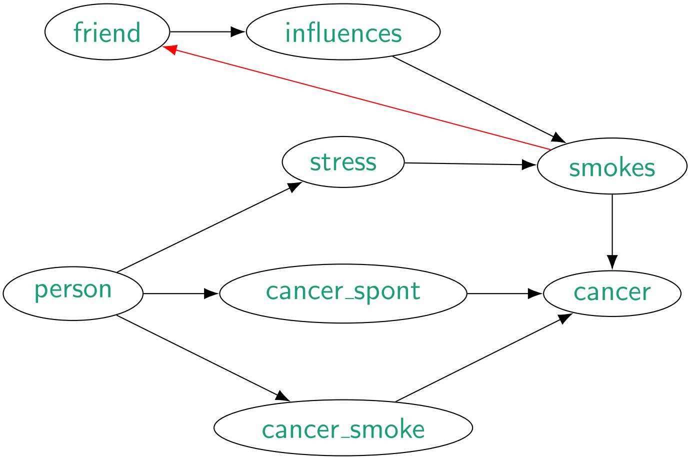

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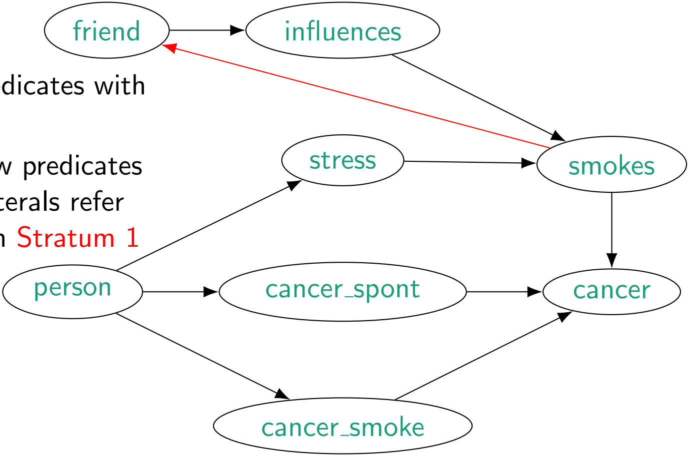
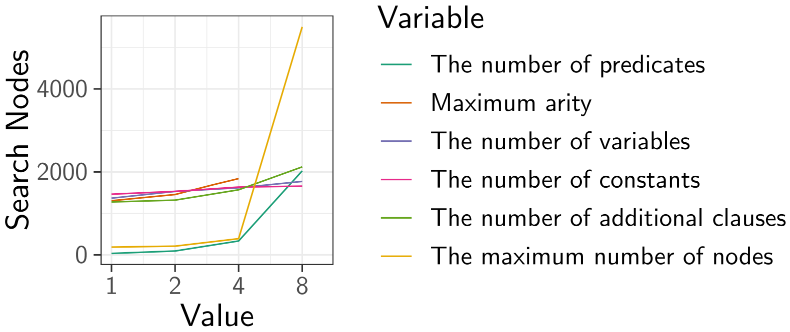


- Stratum 1: predicates with no negation
- Stratum 2: new predicates s.t. negative literals refer to predicates in Stratum 1

Scalability



Inference Algorithms and Knowledge Compilation Maps

NNF	negation normal form
BDD	binary decision diagrams
SDD	sentential decision diagrams
k-Best	only use the *k* most probable proofs
d-DNNF	deterministic decomposable negation normal form

Inference Algorithms and Knowledge Compilation Maps

- **NNF** negation normal form
- **BDD** binary decision diagrams
- **SDD** sentential decision diagrams
- ***k*-Best** only use the k most probable proofs
- **d-DNNF** deterministic decomposable negation normal form
  - for every pair $\alpha \vee \beta$, we have $\alpha \wedge \beta = \perp$
  - for every pair $\alpha \wedge \beta$, no atoms are shared between α and β

Example Diagrams for $C \wedge (A \vee \neg B)$

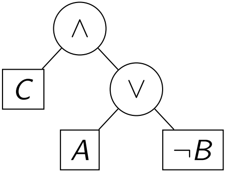


Figure: NNF

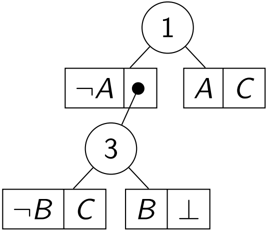


Figure: SDD

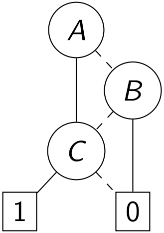


Figure: BDD

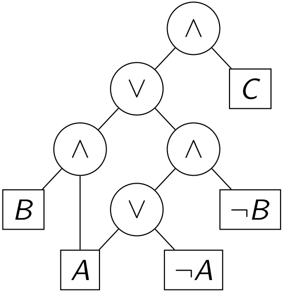


Figure: d-DNNF

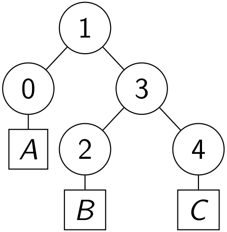
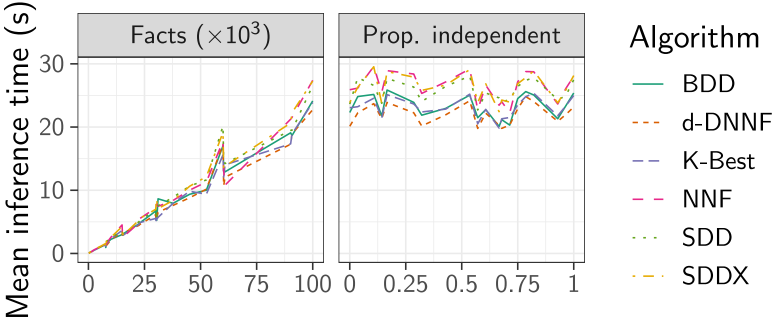


Figure: vtree

Properties of Programs vs. Inference Algorithms



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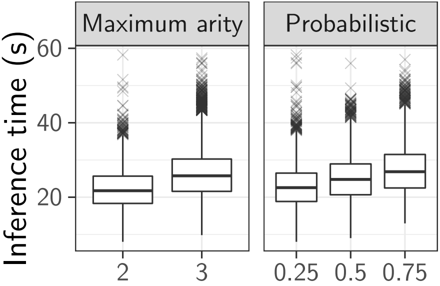

Summary

- The model can generate (approximately) realistic instances of reasonable size
- The main performance bottleneck can be addressed by generating programs with a simpler structure
- Open questions and future work
  - Can the model be used to ensure uniform sampling?
  - What is the reason behind all algorithms behaving similarly?
  - Why does independence have no effect on inference time?
  - Can random program generation be useful in, e.g., learning?

The implementation of the model is available at

`https://github.com/dilkas/random-logic-programs`