Generating Random Logic Programs Using Constraint Programming

Paulius Dilkas Vaishak Belle

AIAI Seminar

Probabilistic Logic Programs (ProbLog)

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

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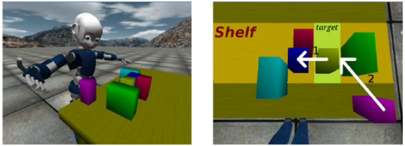
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

Applications



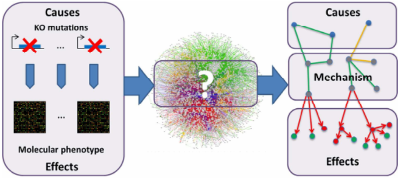
Moldovan et al. 2012

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

4

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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**

1

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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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ProbLog Technology for Inference in a Probabilistic First Order Logic

2

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

Outline

What Characterises a (Probabilistic) Logic Program?

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

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

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

$0.3 :: \texttt{cancer\_smoke}(\mathsf{P}) :\!- \texttt{person}(\mathsf{P}).$

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

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

$\texttt{cancer}(\mathsf{P}) :\!- \texttt{cancer\_spont}(\mathsf{P}).$

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$\texttt{person}(\mathit{michelle}).$

$\texttt{person}(\mathit{timothy}).$

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0.2 :: stress(P) :- person(P).
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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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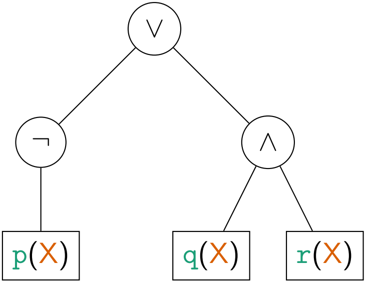
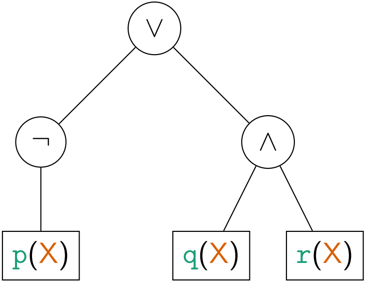


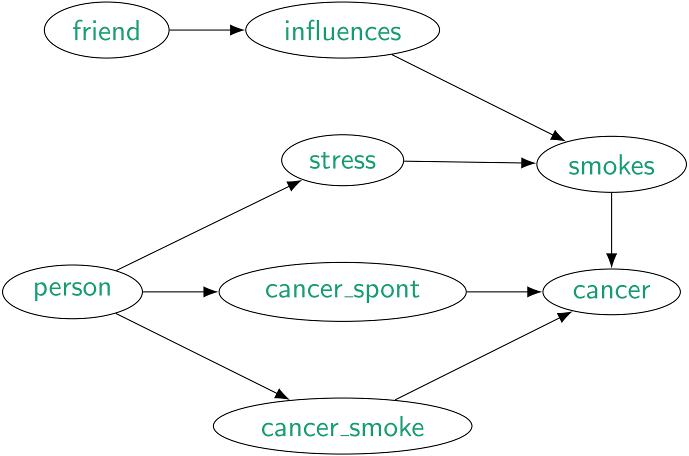
Formulas As Trees

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



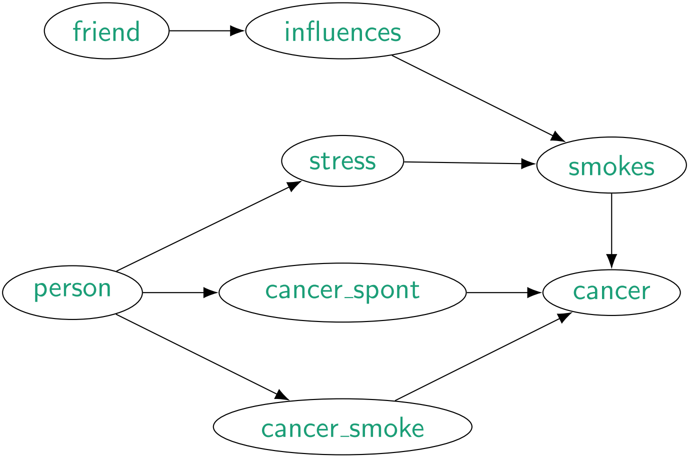
0	0	0	1	2	2
$\lor$	$\neg$	$\land$	p(X)	q(X)	r(X)

Predicate Dependency Graph



Stratification and Negative Cycles

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



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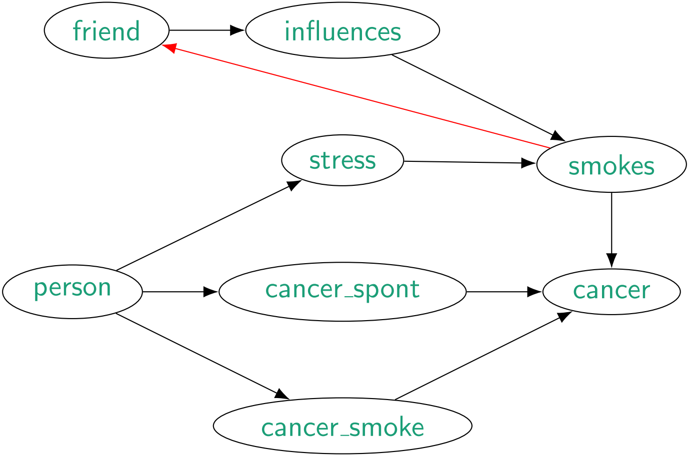
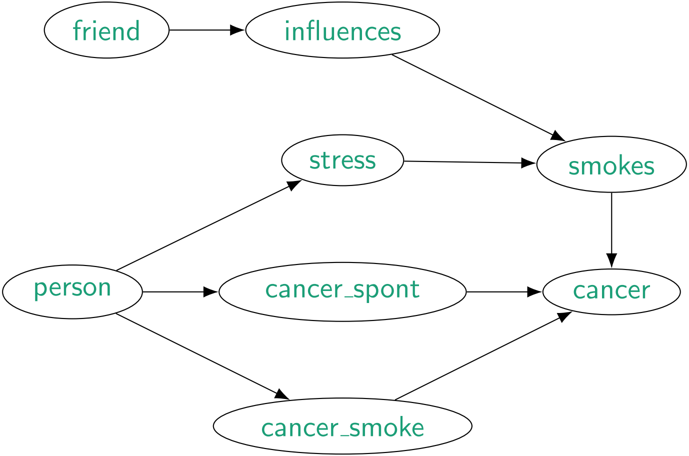


Predicate Independence: $\text{friend} \perp\!\!\!\perp \text{stress}$



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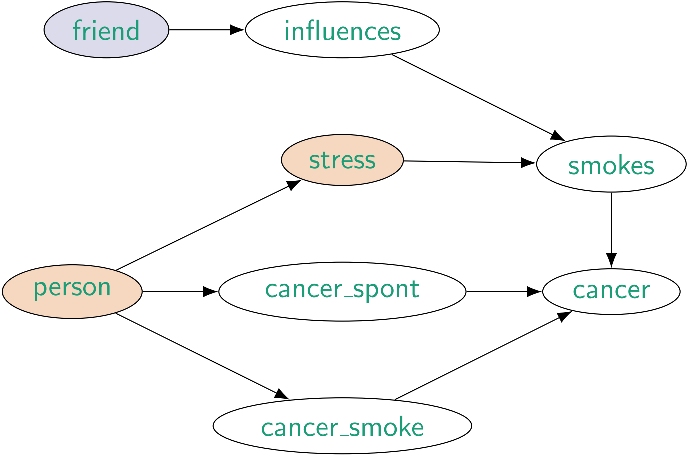

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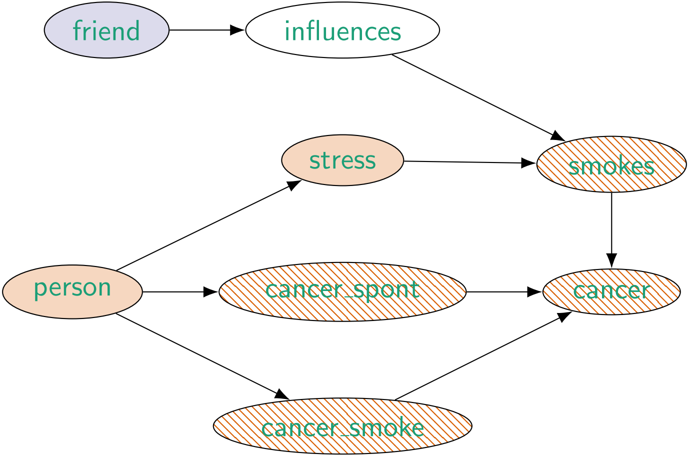
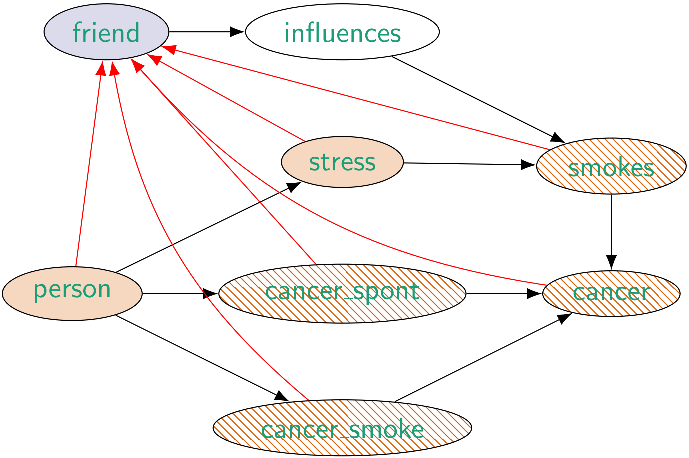


Predicate Independence: friend $\perp\!\!\!\perp$ stress



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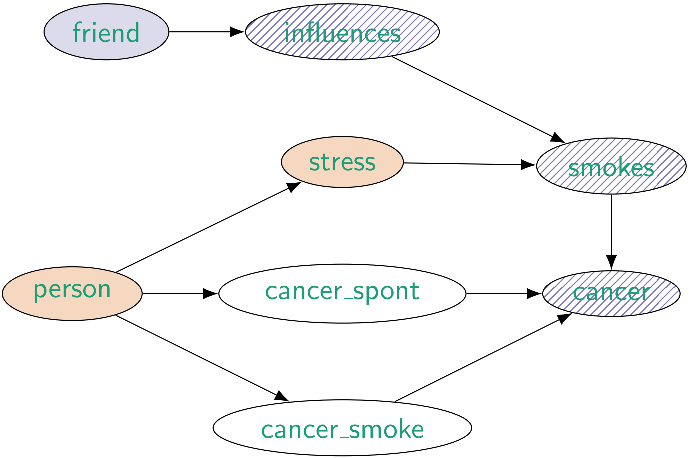

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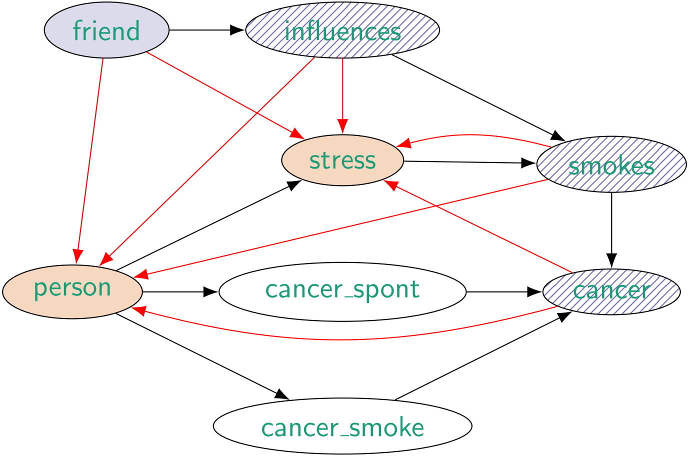


Inference and Knowledge Compilation

NNF	negation normal form
d-DNNF	deterministic decomposable negation normal form
BDD	binary decision diagrams
SDD	sentential decision diagrams

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

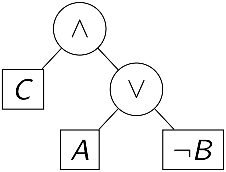


Figure: NNF

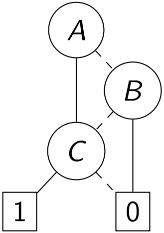


Figure: BDD

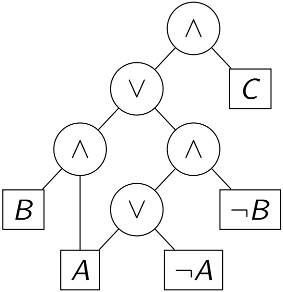


Figure: d-DNNF

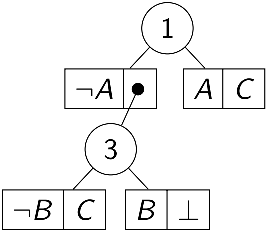
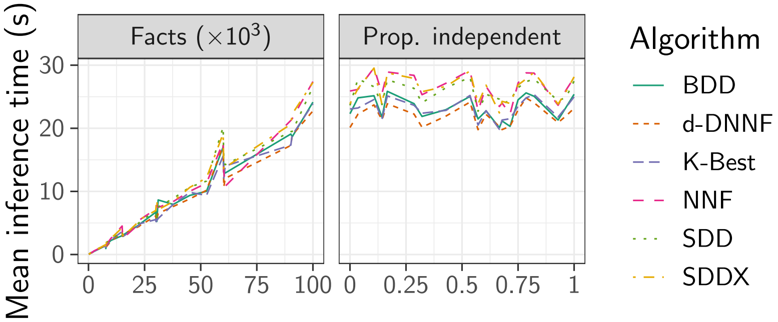


Figure: SDD

Properties of Programs vs. Inference Algorithms

Facts: friend(*timothy*, *michelle*).

Rules: 0.2 :: stress(P) :- person(P).



Summary

- The model can generate (approximately) realistic instances of reasonable size.
- Open questions for future work:
  - Can we ensure uniform sampling?
  - Why do all of the algorithms behave so similarly?
  - Why does independence have no effect on inference time?