Generating Random Logic Programs Using Constraint Programming

Paulius Dilkas[1] Vaishak Belle[1,2]

[1]University of Edinburgh, Edinburgh, UK

[2]Alan Turing Institute, London, UK

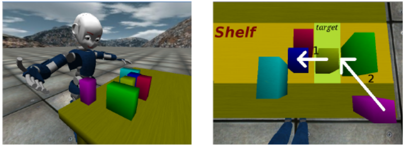
FMAI 2021

Probabilistic Logic Programs (ProbLog)

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

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

Applications



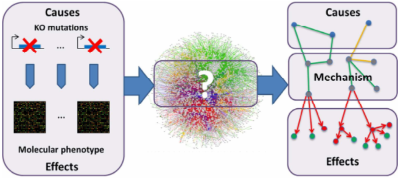
Moldovan et al. 2012

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?

How Many Programs Are Used to Test Algorithms?

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

Jonas Vlasselaer, Guy Van den Broeck, Angelika Kimmig, Wannes Meert, Luc De Raedt
Department of Computer Science
KU Leuven, Belgium
firstname.lastname@cs.kuleuven.be

4

How Many Programs Are Used to Test Algorithms?

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

Jonas Vlasselaer, Guy Van den Broeck, Angelika Kimmig, Wannes Meert, Luc De Raedt
Department of Computer Science
KU Leuven, Belgium
firstname.lastname@cs.kuleuven.be

4

Inference and learning in probabilistic logic programs using weighted Boolean formulas

DAAN FIERENS, GUY VAN DEN BROECK, JORIS RENKENS, DIMITAR SHTERIONOV, BERND GUTMANN, INGO THON, GERDA JANSSENS and LUC DE RAEDT
Department of Computer Science, KU Leuven, Celestijnenlaan 200A, 3001 Heverlee, Belgium
(*e-mail:* FirstName.LastName@cs.kuleuven.be)

3

How Many Programs Are Used to Test Algorithms?

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

4

Jonas Vlasselaer, Guy Van den Broeck, Angelika Kimmig, Wannes Meert, Luc De Raedt
Department of Computer Science
KU Leuven, Belgium
firstname.lastname@cs.kuleuven.be

Inference and learning in probabilistic logic programs using weighted Boolean formulas

3

DAAN FIERENS, GUY VAN DEN BROECK, JORIS RENKENS, DIMITAR SHTERIONOV, BERND GUTMANN, INGO THON, GERDA JANSSENS and LUC DE RAEDT
Department of Computer Science, KU Leuven, Celestijnenlaan 200A, 3001 Heverlee, Belgium
(*e-mail:* FirstName.LastName@cs.kuleuven.be)

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

1

Joris Renkens · Guy Van den Broeck · Siegfried Nijssen

How Many Programs Are Used to Test Algorithms?

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

Jonas Vlasselaer, Guy Van den Broeck, Angelika Kimmig, Wannes Meert, Luc De Raedt
Department of Computer Science
KU Leuven, Belgium
firstname.lastname@cs.kuleuven.be

4

Inference and learning in probabilistic logic programs using weighted Boolean formulas

DAAN FIERENS, GUY VAN DEN BROECK, JORIS RENKENS, DIMITAR SHTERIONOV, BERND GUTMANN, INGO THON, GERDA JANSSENS and LUC DE RAEDT
Department of Computer Science, KU Leuven, Celestijnenlaan 200A, 3001 Heverlee, Belgium
(*e-mail:* FirstName.LastName@cs.kuleuven.be)

3

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

Joris Renkens · Guy Van den Broeck · Siegfried Nijssen

1

On the Efficient Execution of ProbLog Programs

Angelika Kimmig[1], Vítor Santos Costa[2], Ricardo Rocha[2], Bart Demoen[1], and Luc De Raedt[1]

1

How Many Programs Are Used to Test Algorithms?

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

Jonas Vlasselaer, Guy Van den Broeck, Angelika Kimmig, Wannes Meert, Luc De Raedt
Department of Computer Science
KU Leuven, Belgium
firstname.lastname@cs.kuleuven.be

4

Inference and learning in probabilistic logic programs using weighted Boolean formulas

DAAN FIERENS, GUY VAN DEN BROECK, JORIS RENKENS, DIMITAR SHTERIONOV, BERND GUTMANN, INGO THON, GERDA JANSSENS and LUC DE RAEDT
Department of Computer Science, KU Leuven, Celestijnenlaan 200A, 3001 Heverlee, Belgium
(*e-mail:* FirstName.LastName@cs.kuleuven.be)

3

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

Joris Renkens · Guy Van den Broeck · Siegfried Nijssen

1

On the Efficient Execution of ProbLog Programs

Angelika Kimmig[1], Vítor Santos Costa[2], Ricardo Rocha[2], Bart Demoen[1], and Luc De Raedt[1]

1

On the Implementation of the Probabilistic Logic Programming Language ProbLog

Angelika Kimmig, Bart Demoen and Luc De Raedt
Departement Computerwetenschappen, K.U. Leuven
Celestijnenlaan 200A - bus 2402, B-3001 Heverlee, Belgium
(*e-mail:* {Angelika.Kimmig,Bart.Demoen,Luc.DeRaedt}@cs.kuleuven.be)

Vítor Santos Costa and Ricardo Rocha
CRACS & INESC-Porto LA, Faculty of Sciences, University of Porto
R. do Campo Alegre 1021/1055, 4169-007 Porto, Portugal
(*e-mail:* {vsc,ricroc}@dcc.fc.up.pt)

1

How Many Programs Are Used to Test Algorithms?

Anytime Inference in Probabilistic Logic Programs with T_P-Compilation

Jonas Vlasselaer, Guy Van den Broeck, Angelika Kimmig, Wannes Meert, Luc De Raedt
Department of Computer Science
KU Leuven, Belgium
firstname.lastname@cs.kuleuven.be

4

On the Efficient Execution of ProbLog Programs

Angelika Kimmig[1], Vítor Santos Costa[2], Ricardo Rocha[2], Bart Demoen[1], and Luc De Raedt[1]

1

Inference and learning in probabilistic logic programs using weighted Boolean formulas

DAAN FIERENS, GUY VAN DEN BROECK, JORIS RENKENS, DIMITAR SHTERIONOV, BERND GUTMANN, INGO THON, GERDA JANSSENS and LUC DE RAEDT
Department of Computer Science, KU Leuven, Celestijnenlaan 200A, 3001 Heverlee, Belgium
(*e-mail:* FirstName.LastName@cs.kuleuven.be)

3

On the Implementation of the Probabilistic Logic Programming Language ProbLog

Angelika Kimmig, Bart Demoen and Luc De Raedt
Departement Computerwetenschappen, K.U. Leuven
Celestijnenlaan 200A - bus 2402, B-3001 Heverlee, Belgium
(*e-mail:* {Angelika.Kimmig,Bart.Demoen,Luc.DeRaedt}@cs.kuleuven.be)

Vítor Santos Costa and Ricardo Rocha
CRACS & INESC-Porto LA, Faculty of Sciences, University of Porto
R. do Campo Alegre 1021/1055, 4169-007 Porto, Portugal
(*e-mail:* {vsc,ricroc}@dcc.fc.up.pt)

1

k-Optimal: a novel approximate inference algorithm for ProbLog

Joris Renkens · Guy Van den Broeck · Siegfried Nijssen

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 Characterises a (Probabilistic) Logic Program?

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

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

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

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

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

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

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

$\texttt{cancer}(\mathsf{P}) :\!- \texttt{smokes}(\mathsf{P}), \texttt{cancer\_smoke}(\mathsf{P}).$

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

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

$\texttt{friend}(\mathit{timothy}, \mathit{michelle}).$

What Characterises a (Probabilistic) Logic Program?

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

- predicates, arities

What Characterises a (Probabilistic) Logic Program?

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

- predicates, arities
- variables

What Characterises a (Probabilistic) Logic Program?

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

- predicates, arities
- variables
- constants

What Characterises a (Probabilistic) Logic Program?

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

- predicates, arities
- variables
- constants
- probabilities

What Characterises a (Probabilistic) Logic Program?

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

- predicates, arities
- variables
- constants
- probabilities
- length

What Characterises a (Probabilistic) Logic Program?

```
0.2::stress(P) :- person(P).
0.3::influences(P1, P2) :- friend(P1, P2).
0.1::cancer_spont(P) :- person(P).
0.3::cancer_smoke(P) :- person(P).
     smokes(X) :- stress(X).
     smokes(X) :- smokes(Y), influences(Y, X).
     cancer(P) :- cancer_spont(P).
     cancer(P) :- smokes(P), cancer_smoke(P).
     person(michelle).
     person(timothy).
     friend(timothy, michelle).
```

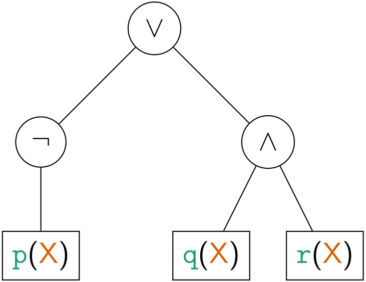
- predicates, arities
- variables
- constants
- probabilities
- length
- complexity

Formulas As Trees

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

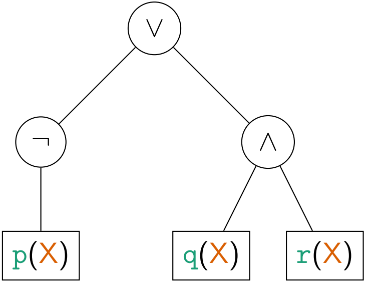
Formulas As Trees

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



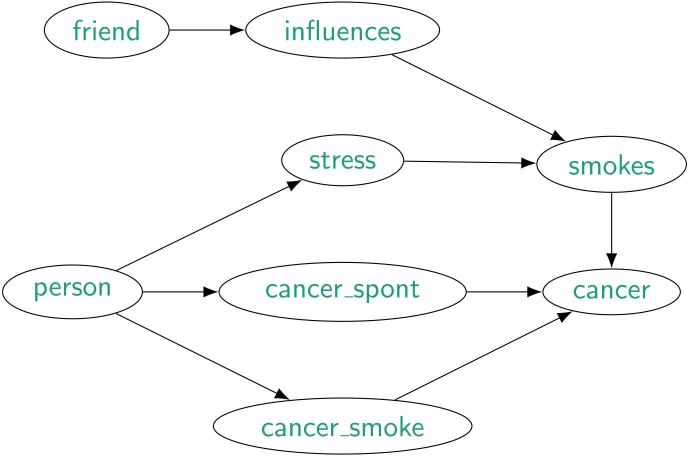
Formulas As Trees

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



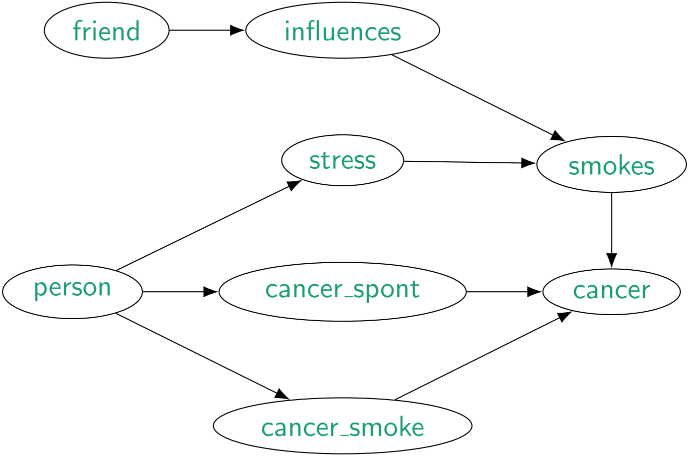
0	0	0	1	2	2
$\lor$	$\neg$	$\land$	p(X)	q(X)	r(X)

Predicate Dependency Graph



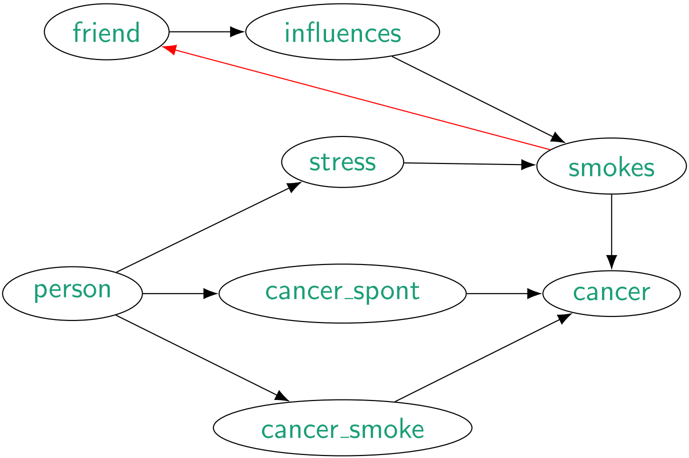
Stratification and Negative Cycles

```
0.1::friend(X,Y) :- \+ smokes(Y).
```

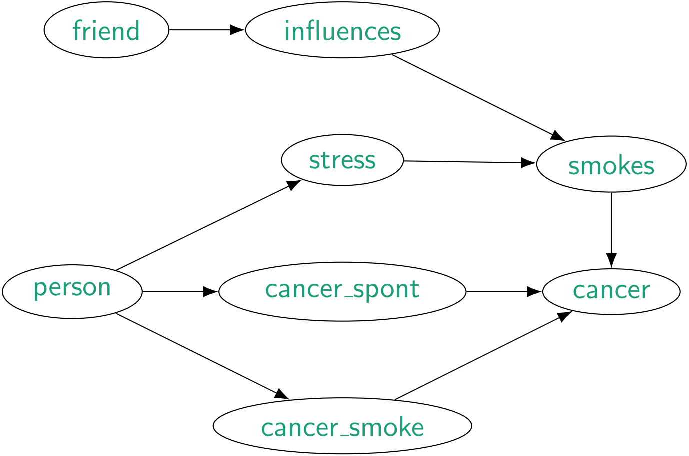


Stratification and Negative Cycles

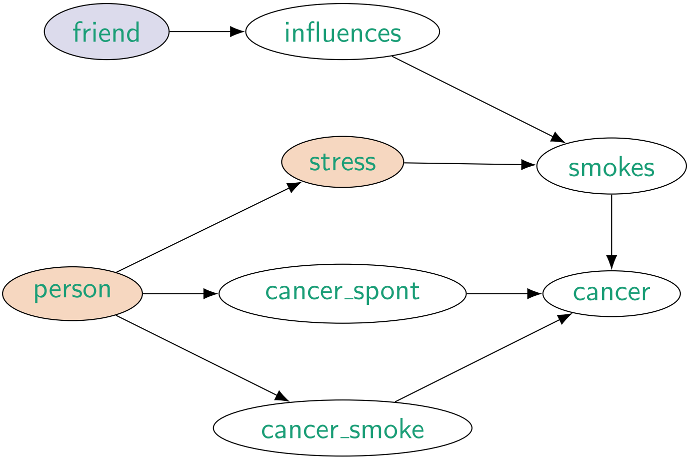
```
0.1::friend(X, Y) :- \+ smokes(Y).
```



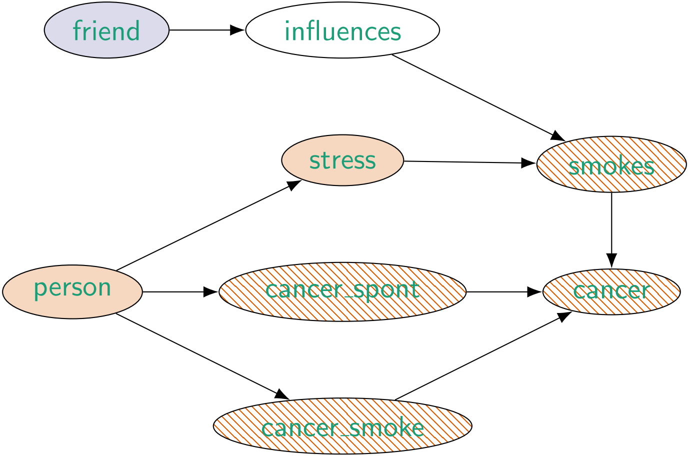
Predicate Independence: $\text{friend} \perp\!\!\!\perp \text{stress}$



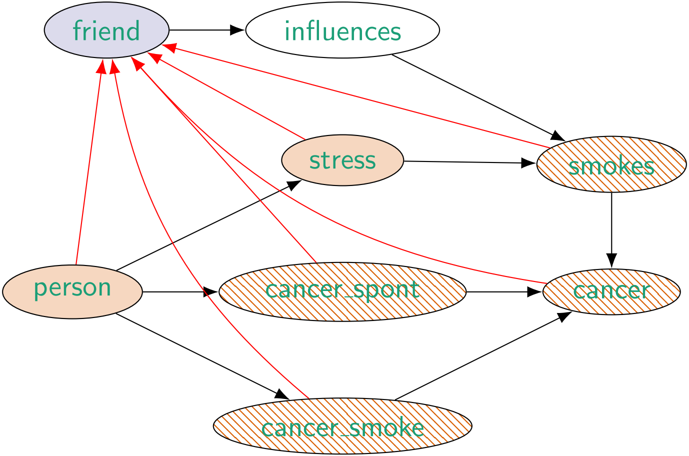
Predicate Independence: $\mathrm{friend} \perp\!\!\!\perp \mathrm{stress}$



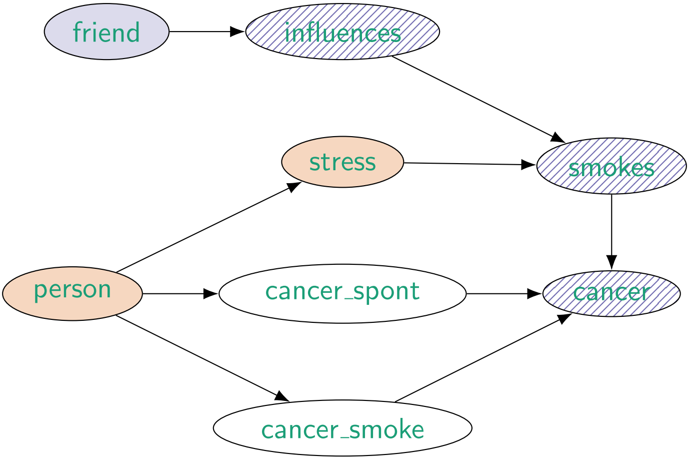
Predicate Independence: $\text{friend} \perp\!\!\!\perp \text{stress}$



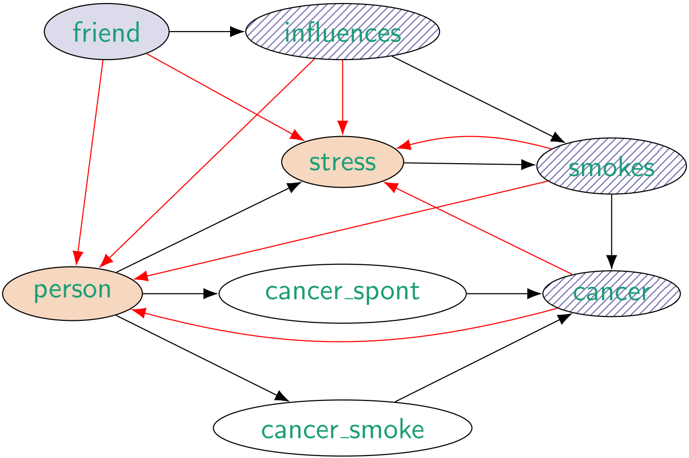
Predicate Independence: $\mathrm{friend} \perp\!\!\!\perp \mathrm{stress}$



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



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



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 $C \wedge (A \vee \neg B)$

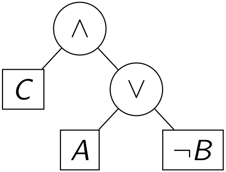


Figure: NNF

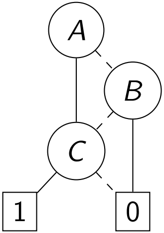


Figure: BDD

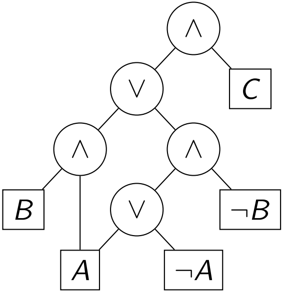


Figure: d-DNNF

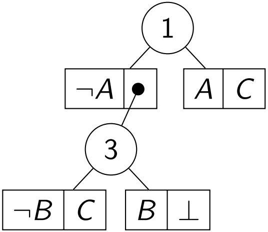
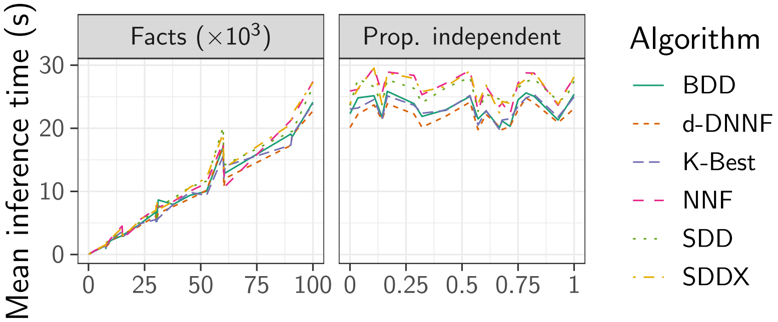


Figure: SDD

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?