Generating Random Logic Programs Using Constraint Programming

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Probabilistic Logic Programs (ProbLog)

The Smokers Network (Domingos et al. 2008)

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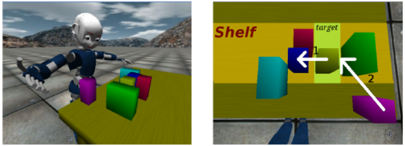

Applications



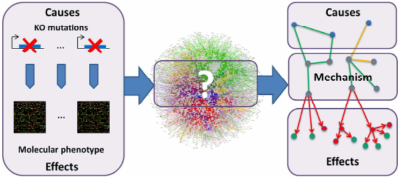
Moldovan et al. 2012

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

Inference Algorithms and Knowledge Compilation Maps

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

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

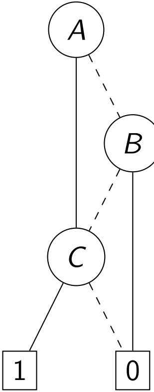


Figure: BDD

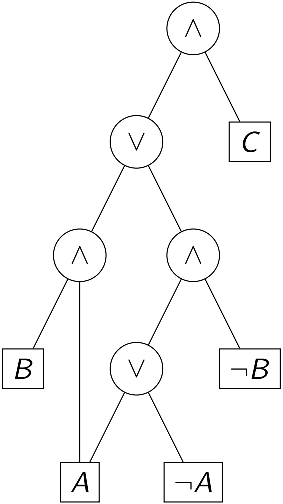


Figure: d-DNNF

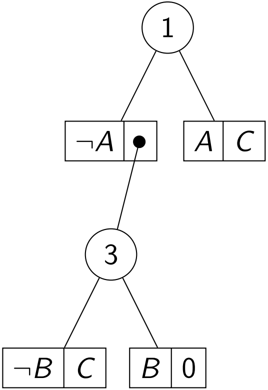


Figure: SDD

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**

1

Joris Renkens · Guy Van den Broeck · Siegfried Nijssen

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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]

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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]

What Characterises a (Probabilistic) Logic Program?

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

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

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

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

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

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

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

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

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- predicates, arities

What Characterises a (Probabilistic) Logic Program?

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- predicates, arities
- variables

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

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$$
\left\{
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\qquad \texttt{cancer}(P) :\text{-}\ \underbrace{\texttt{smokes}(P), \texttt{cancer\_smoke}(P)}.\\
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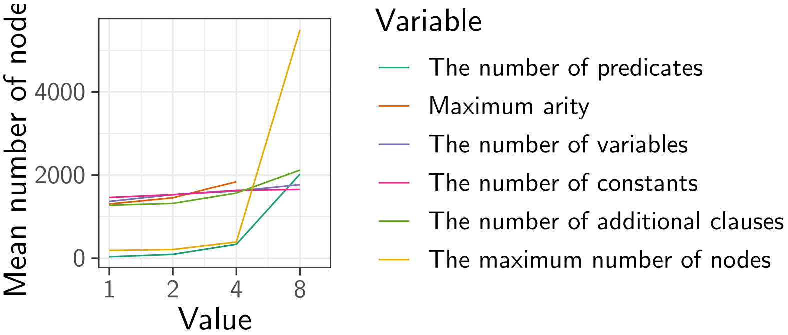
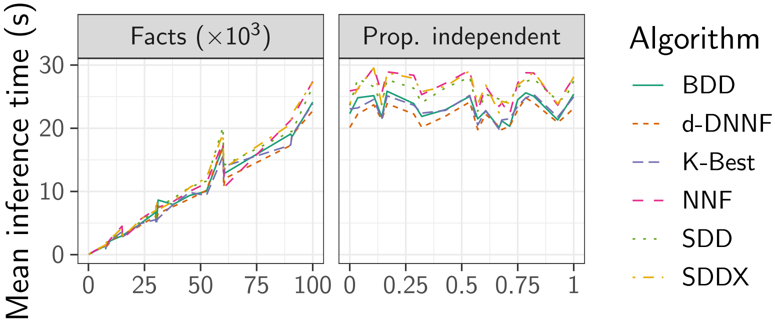
\end{array}
\right.
$$

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

Scalability



Properties of Programs vs. Inference Algorithms



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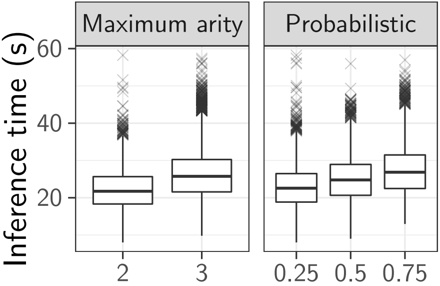

Overview

General parameters

- maximum number of solutions
- `maxNumNodes` (in the tree representation of a clause)
- list of predicates with their variables
- maximum number of clauses
- option to forbid all cycles or just negative cycles
- list of probabilities that are randomly assigned to clauses: $\{0.1, 0.2, \dots, 0.9, 1, 1, 1, 1, 1, 1\}$

Decision variables

- `IntVar[] clauseAssignments`: a predicate or disabled
- `Clause[] clauses`

Constraints

Each predicate should get at least one constraint

- `numDisabledClauses`: defined by a count constraint
- $\texttt{numDistinctValues} = \begin{cases} \texttt{numPredicates} + 1 & \text{if } \texttt{numDisabledValues} > 0 \\ \texttt{numPredicates} & \text{otherwise.} \end{cases}$
  - also constrained using the `nValues` constraint

Miscellaneous

- `clauseAssignments` are sorted.
- If $\texttt{clauseAssignments}[i-1] = \texttt{clauseAssignments}[i]$,
  - then $\texttt{clause}[i-1] \preceq \texttt{clause}[i]$.

Clauses

A clause is defined by...

- `IntVar[] treeStructure`
  - $\texttt{treeStructure}[i] = i$: the i-th node is a root.
  - $\texttt{treeStructure}[i] = j$: the i-th node's parent is node j.
- `IntVar[] treeValues`: $\neg$, $\wedge$, $\vee$, $\top$, and any predefined predicates with variables.

Auxiliary variables

- $\texttt{numNodes}, \texttt{numTrees} \in \{1, \ldots, \texttt{maxNumNodes}\}$

Clause constraints

- $\texttt{treeStructure}$ represents $\texttt{numTrees}$ trees.
- $\texttt{treeStructure}[0] = 0$
- $\texttt{numTrees} + \texttt{numNodes} = \texttt{maxNumNodes} + 1$
- $\texttt{treeStructure}$ is sorted
- For $i = 0, \ldots, \texttt{maxNumNodes} - 1$,
  - If $\texttt{numNodes} \leq i$,
  - then $\texttt{treeStructure}[i] = i$ and $\texttt{treeValues}[i] = \top$,
  - else $\texttt{treeStructure}[i] < \texttt{numNodes}$.
  - has 0 children $\iff$ $\texttt{treeValues}[i]$ is a predicate
  - has 1 child $\iff$ $\texttt{treeValues}[i] = \neg$
  - has > 1 child $\iff$ $\texttt{treeValues}[i] \in \{\wedge, \vee\}$
  - $\texttt{treeStructure}[i] \neq i \implies \texttt{treeValues}[i] \neq \top$
- If the clause should be disabled, $\texttt{numNodes} = 1$ and $\texttt{treeValues}[0] = \top$.

Adjacency matrix representation

$A[i][j] = 0 \iff \nexists k : \texttt{clauseAssignments}[k] = j$ and $i \in \texttt{clauses}[k].\texttt{treeValues}$

New constraints

- No (negative) cycles
  - No clever propagation, just entailment checking.
- Independence. Propagation:
  - Two types of dependencies: determined and one-undetermined-edge-away-from-being-determined.
  - Look up the dependencies of both predicates. For each pair of matching dependencies:
    - If both are determined, fail.
    - If one is determined, the selected edge of the other must not exist.
- Conditional independence
  - Same propagation, but with a ‘filter’ that masks out the expression that the independence is conditioned on.