Generating Random Logic Programs Using Constraint Programming

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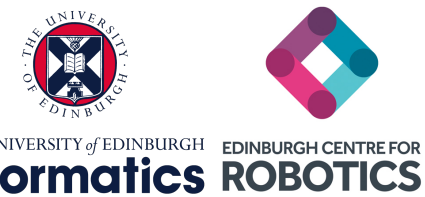
CP 2020



Probabilistic Logic Programs (ProbLog)

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

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How Many Programs Are Used to Test Algorithms?

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Anytime Inference in Probabilistic Logic Programs with T_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

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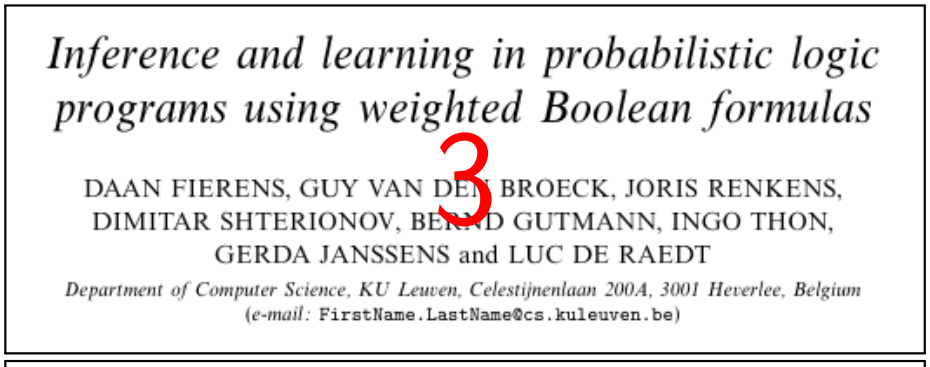

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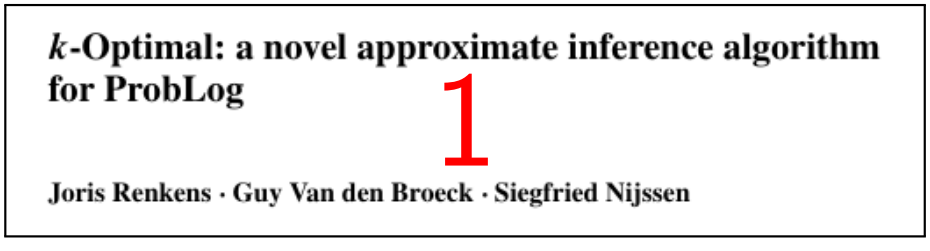

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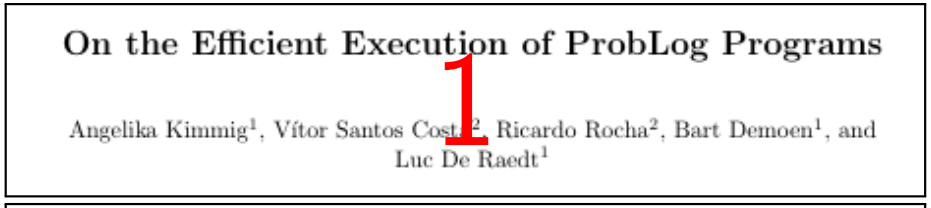

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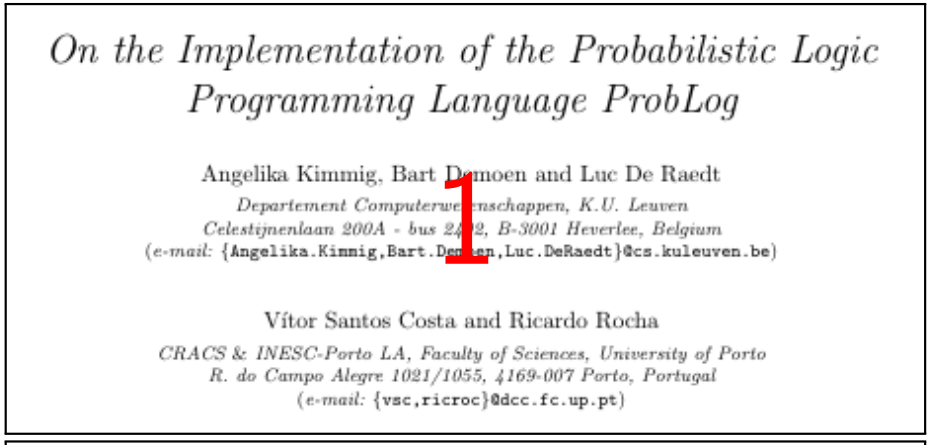

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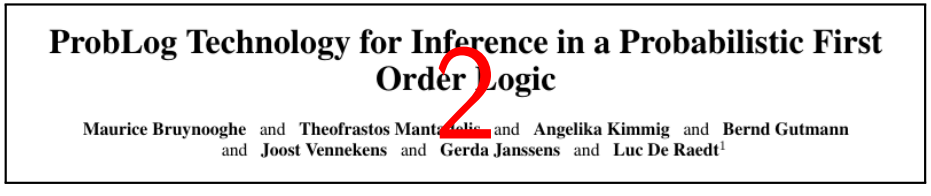

ProbLog Technology for Inference in a Probabilistic First Order Logic

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

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What Characterises a (Probabilistic) Logic Program?

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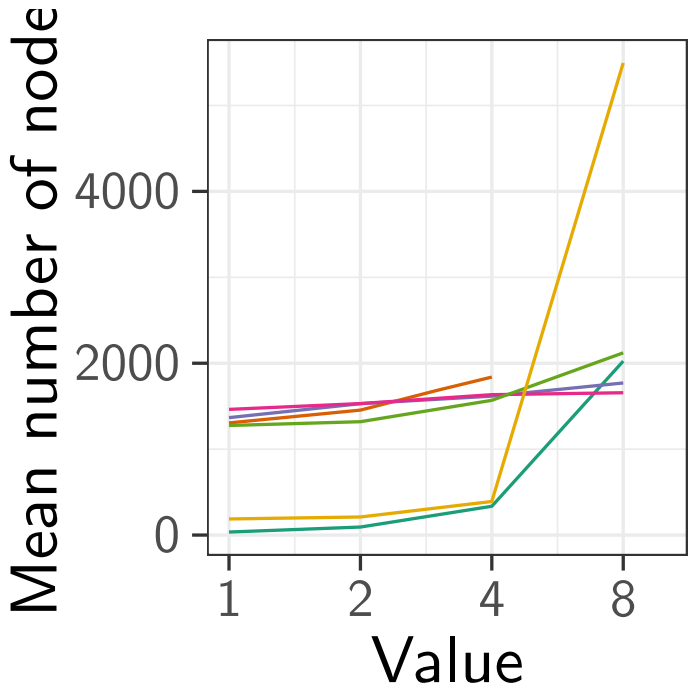
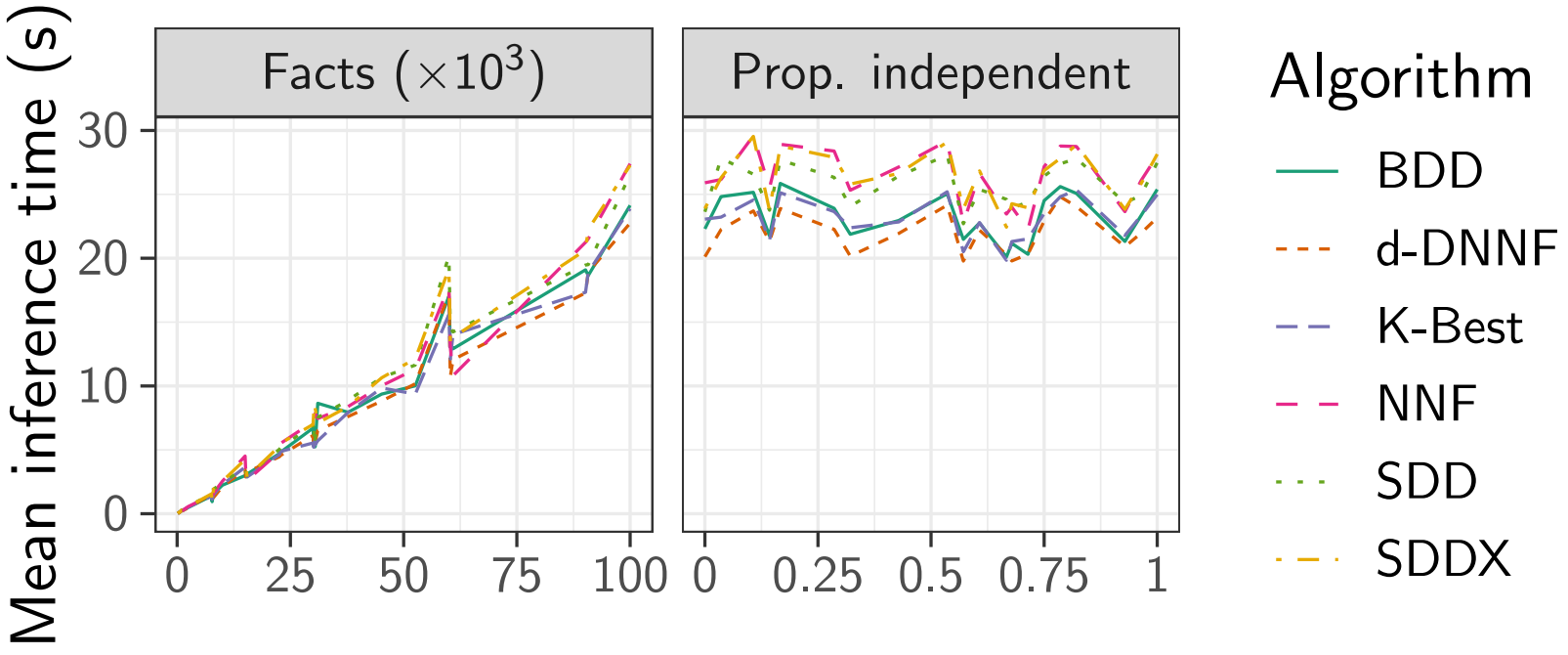
Scalability



Variable

- The number of predicates
- Maximum arity
- The number of variables
- The number of constants
- The number of additional clauses
- The maximum number of nodes

Properties of Programs vs. Inference Algorithms



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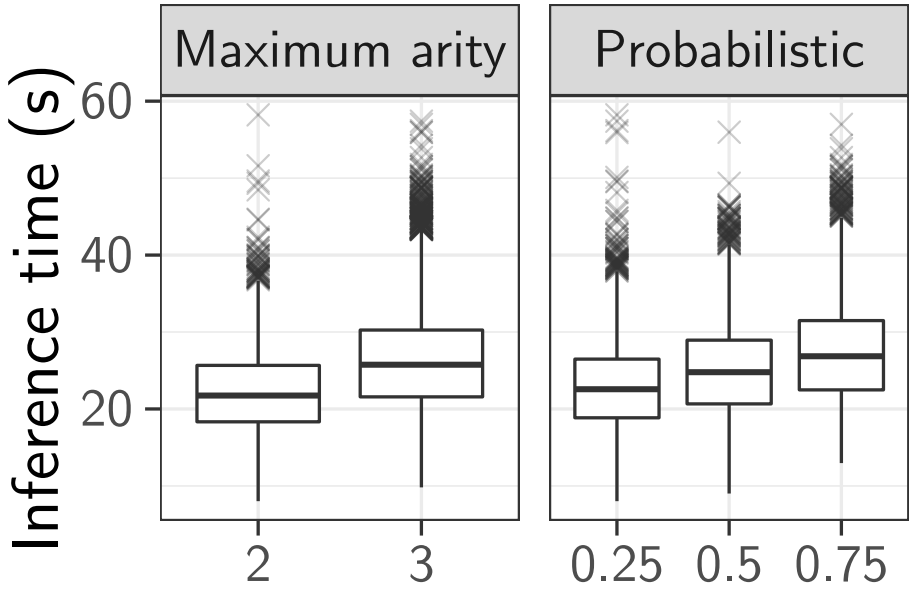

Overview

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: $\{0.1, 0.2, \ldots, 0.9, 1, 1, 1, 1, 1, 1\}$

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`
  - `treeStructure`$[i] = i$: the i-th node is a root.
  - `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.