

# ProbLog: A Probabilistic Prolog and its Application in Link Discovery

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## Paper context

- At the time when the paper was released, there were no programs for modelling the exact inference for discrete variables
- Discrete variables require separate rules than the continuous variables

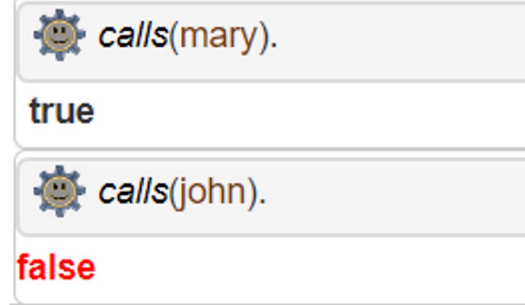
# Intro to Prolog

- Part of the logical programming languages family
- Program consists of a set of definite clauses
- Programs can contain the following: rules, facts and variables
- Clauses can be only True or False

# Prolog example

```
1 burglary.  
2 hears_alarm(mary).  
3  
4 alarm :- burglary.  
5 alarm :- earthquake.  
6  
7 calls(X) :- alarm, hears_alarm(X).  
8 call :- calls(X).  
9
```

- Alarm and calls are called rules
- hears\_alarm, burglary are called facts
- Mary is a variable



The screenshot shows a Prolog interpreter interface with two query boxes. The first box contains the query `calls(mary).` and the result `true`. The second box contains the query `calls(john).` and the result `false`. Each query box has a gear icon on the left.

# Why extending Prolog to Probabilistic Programming?

- Adding probabilities to clauses is closer to real-world problems
- Probabilistic Database is slow -> 10 or more conjuncts are infeasible to compute
- Many practical applications (i.e. life sciences) require computing probabilities in network relations

# Intro to ProbLog

- Built on top of Prolog, both being very similar
- Only major difference: Problog has probabilities of success attached to the clauses
- It has equivalent functions for sample and observe (can you spot them in the next slide?)

# ProbLog example

```
1 1.0:: likes(X,Y):- friendof(X,Y).
2 0.8:: likes(X,Y):- friendof(X,Z), likes(Z,Y).
3 0.5:: friendof(john,mary).
4 0.5:: friendof(mary,pedro).
5 0.5:: friendof(pedro,tom).
6
7 evidence(likes(john, pedro), false).
8
9 query(likes(mary, tom)).|
```

What are sample and observe here?

Query ▼

Location

Probability

likes(mary,tom)

11:7

0.15

Screenshots taken from:

[https://dtai.cs.kuleuven.be/problog/tutorial/basic/02\\_b\\_ayes.html](https://dtai.cs.kuleuven.be/problog/tutorial/basic/02_b_ayes.html) (more examples there as well)

# Computing queries

Two steps:

1. Build monotone DNF formula representing all solutions
2. Compute the probability of this DNF formula

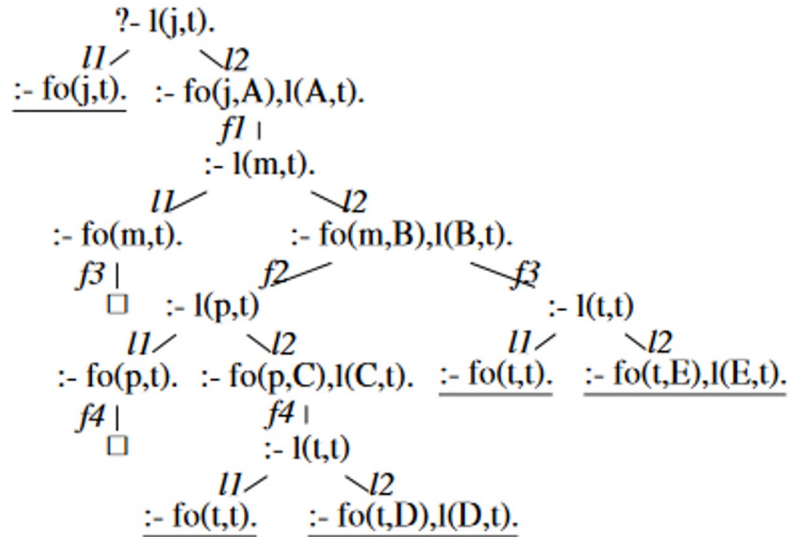


# Computing queries

Two steps:

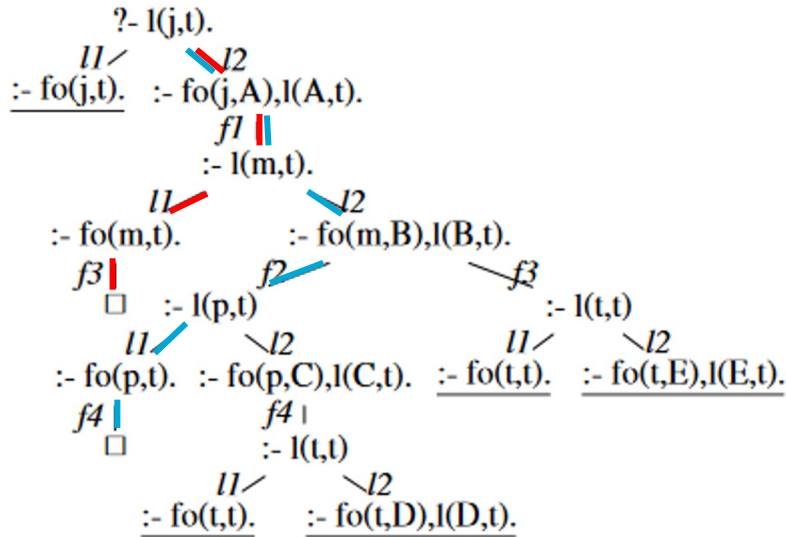
1. Build monotone DNF formula representing all solutions
  - SLD-resolution to transform query into equivalent tree
    - Root is query to be proven
    - Recursively generate subgoals
  - Use the disjunction of proof paths in tree as DNF
2. Compute the probability of this DNF formula

# Computing queries | SLD-resolution example



- 1.0: likes(X,Y):- friendof(X,Y).
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# Computing queries | SLD-resolution example



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$$P(\underbrace{(l_1 \wedge l_2 \wedge f_1 \wedge f_2 \wedge f_4)}_{\text{blue}} \vee \underbrace{(l_1 \wedge l_2 \wedge f_1 \wedge f_3)}_{\text{red}}).$$

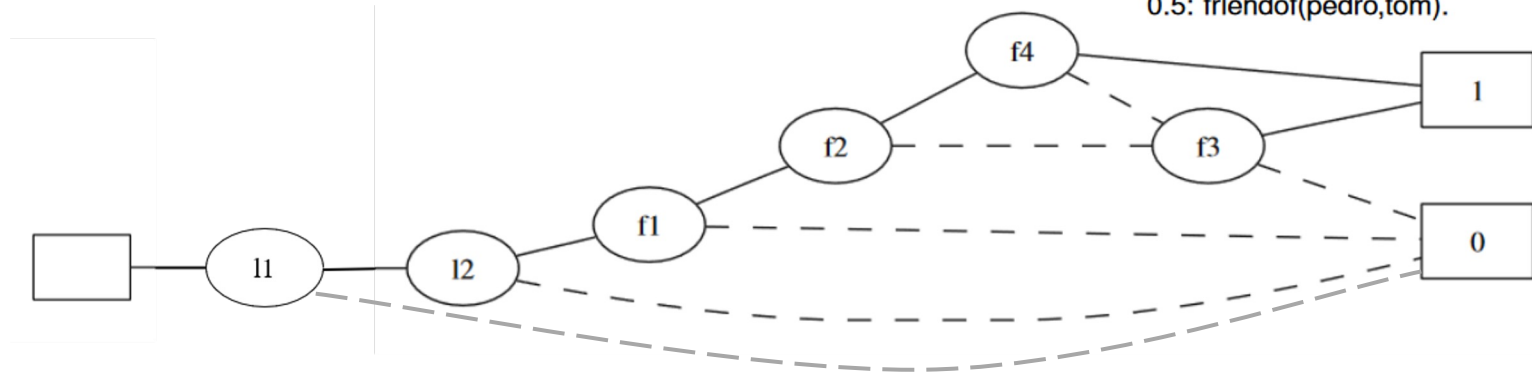
# Computing queries

Two steps:

1. Build monotone DNF formula representing all solutions
2. Compute the probability of this DNF formula
  - Using Binary Decision Diagram (BDD) representation  
Start from full binary tree, merging isomorphic subgraphs and deleting redundant nodes

# Computing queries | BDD calculation example

1.0: likes(X,Y):- friendof(X,Y).  
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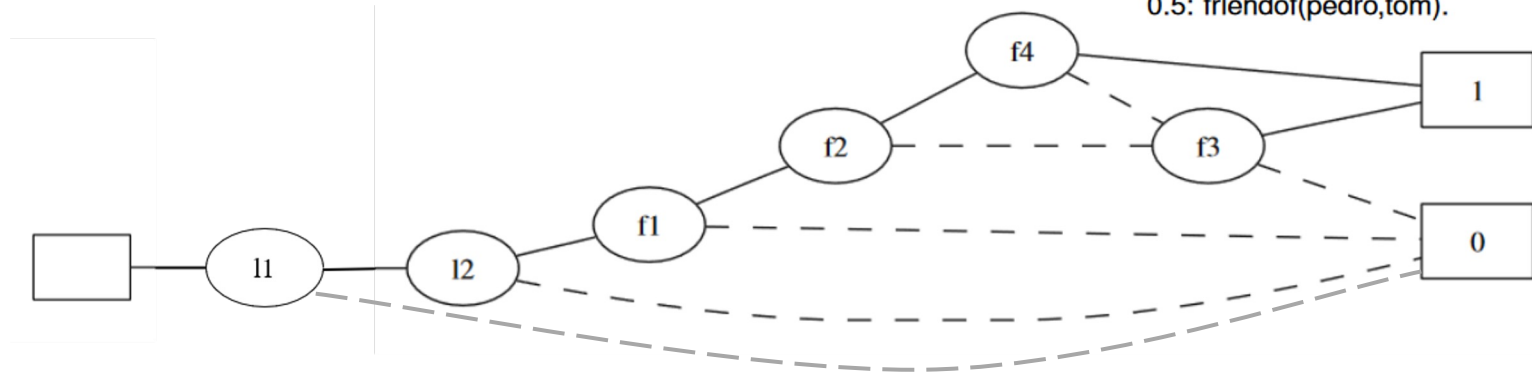
0 1 2 3 4 5

$$P((l_1 \wedge l_2 \wedge f_1 \wedge f_2 \wedge f_4) \vee (l_1 \wedge l_2 \wedge f_1 \wedge f_3)).$$

# Computing queries | BDD calculation example

What node is redundant in this tree?

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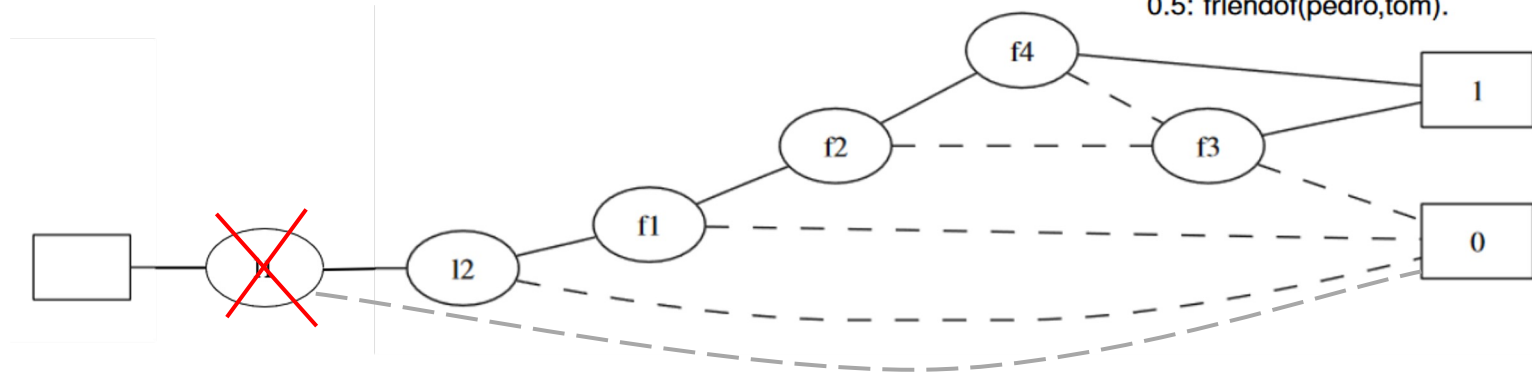
0 1 2 3 4 5

$$P((l_1 \wedge l_2 \wedge f_1 \wedge f_2 \wedge f_4) \vee (l_1 \wedge l_2 \wedge f_1 \wedge f_3)).$$

# Computing queries | BDD calculation example

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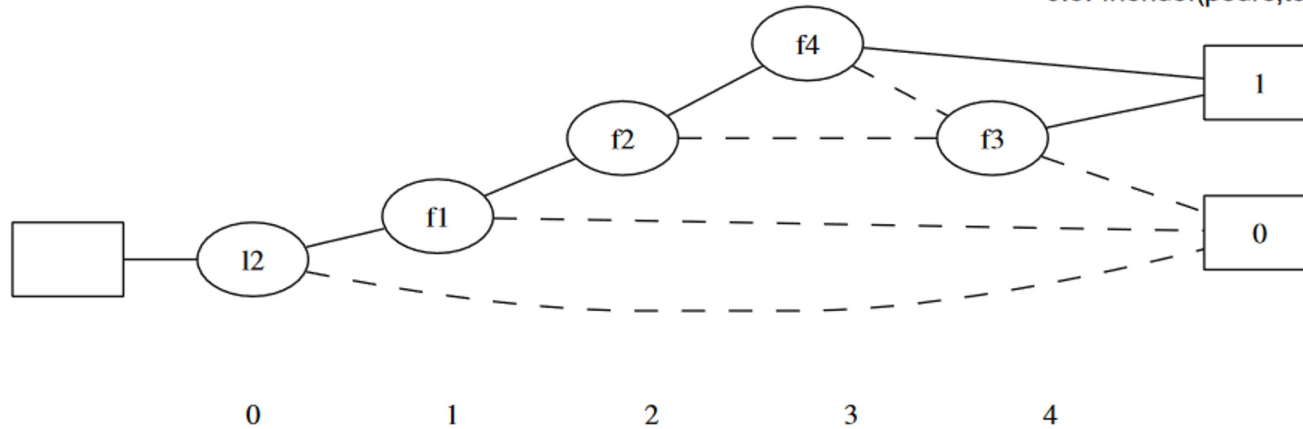


0 1 2 3 4 5

$$P((l_1 \wedge l_2 \wedge f_1 \wedge f_2 \wedge f_4) \vee (l_1 \wedge l_2 \wedge f_1 \wedge f_3)).$$

# Computing queries | BDD calculation example

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0.5: friendof(mary,tom).  
0.5: friendof(pedro,tom).



$$P((l_2 \wedge f_1 \wedge f_2 \wedge f_4) \vee (l_2 \wedge f_1 \wedge f_3))$$



# Computing queries

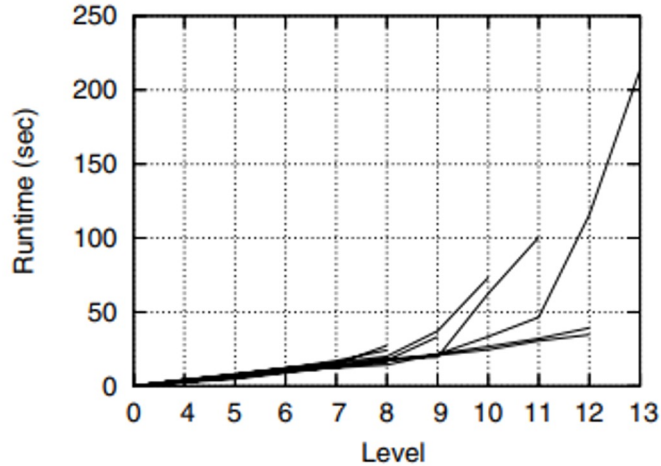
Two steps:

1. Build monotone DNF formula representing all solutions
2. Compute the probability of this DNF formula
  - Using Binary Decision Diagram (BDD) representation
    - Start from full binary tree, merging isomorphic subgraphs and deleting redundant nodes
  - Heuristically determine variable order in SOTA BDD algorithms
  - Reusable BDD for different queries

# Approximating the success probability

- Why approximate?
- Iterative deepening to compute SLD-tree
- Use incomplete SLD-tree to derive upper and lower bound
  - Lower bound encodes successful proofs found so far
  - Upper bound encodes all proofs all proofs found so far
  - Keep growing tree until upper and lower bound are sufficiently close

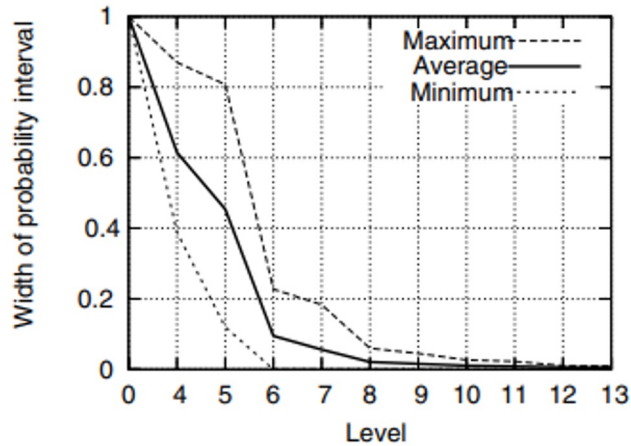
# Results



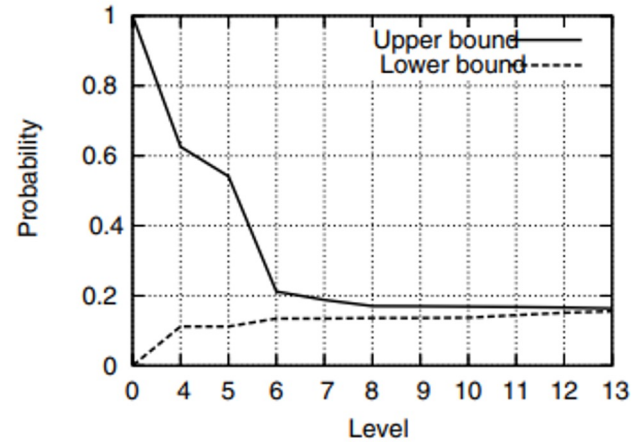
Running times for 10 test graphs with 1400 edges.

- Good runtime in terms of level depthness
- Can deal with many conjuncts, up to 100k.
- Probability is converging to the true one after the 6th depth level
- Bounds are converging to  $\sim 0.2$  after the 6th depth level.

# Results



Convergence of the probability interval for 10 test graphs with 1400 edges.



Convergence of bounds for one graph with 1800 edges, as a function of the search level.

# Questions

- What is the addition of ProbLog to Prolog?

# Questions

- What is the addition of ProbLog to Prolog?
- What other probabilistic programming languages also have inherently included upper and lower bounds?

Thank you for your attention!

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