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# Inference for SRL Report

Capita Selecta AI (Probabilistic Programming) 2016-2017

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#### I. Probabilistic Inference Using Weighted Model Counting

#### A. PGM to CNF

Table I shows the semantics of the domain variables used for those tasks.

Tables II and III show the logical variables used for encoding the Bayesian Network.

Table IV represents the encoded Bayesian Network using ENC1 and table V contains the corresponding weights.

Likewise, table VI represents the encoded Bayesian Network using ENC2 and table VII contains the corresponding weights.

Table I. VARIABLES AND DOMAIN SEMANTICS

Variable	Domain
B = Burglary	b1 = theres is a burglary
	b2 = theres is no burglary
	e1 = there is a heavy earthquake
E = Earthquake	e2 = there is a mild earthquake
	e3 = there is no earthquake
A = Alarm	a1 = alarm rings
	a2 = alarm does not ring
J = John	j1 = John calls
	j2 = John does not call
M = Mary	m1 = Mary calls
	m2 = Mary does not call

Table II. LOGICAL VARIABLES USING ENC1

Network variables	Indicator Variable	СТР
В	$\lambda_{b1}, \lambda_{b2}$	$\theta_{b1},\theta_{b2}$
Е	$\lambda_{e1}, \lambda_{e2}, \lambda_3$	$\theta_{e1},\theta_{e2},\theta_3$
A	$\lambda_{a1},\lambda_{a2}$	$\begin{array}{c} \theta_{a1 b1,e1},  \theta_{a1 b1,e2}, \theta_{a1 b1,e3}, \\ \theta_{a1 b2,e1},  \theta_{a1 b2,e2},  \theta_{a1 b2,e3}, \\ \theta_{a2 b1,e1},  \theta_{a2 b1,e2}, \theta_{a2 b1,e3}, \\ \theta_{a2 b2,e1},  \theta_{a2 b2,e2},  \theta_{a2 b2,e3} \end{array}$
J	$\lambda_{j1}, \lambda_{j2}$	$\theta_{j1 a1},  \theta_{j2 a1},  \theta_{j1 a2},  \theta_{j2 a2}$
M	$\lambda_{m1}, \lambda_{m2}$	$\theta_{m1 a1}, \theta_{m2 a1}, \theta_{m1 a2}, \theta_{m2 a2}$

Table III. LOGICAL VARIABLES USING ENC2

Variables	Indicator Variable	CTP
В	$\lambda_{b1}, \lambda_{b2}$	$ ho_{b1}$
Е	$\lambda_{e1}, \lambda_{e2}, \lambda_3$	$ ho_{e1}, ho_{e2}$
A	$\lambda_{a1}, \lambda_{a2}$	$\rho_{a1 b1,e1}, \rho_{a1 b1,e2}, \rho_{a1 b1,e3}, \\ \rho_{a1 b2,e1}, \rho_{a1 b2,c2}, \rho_{a1 b2,e3}$
J	$\lambda_{j1}, \lambda_{j2}$	$\rho_{j1 a1}, \rho_{j1 a2}$
M	$\lambda_{m1}, \lambda_{m2}$	$\rho_{m1 a1}, \rho_{m1 a2}$

Table IV. CNF representation of Bayesian network using ENC1

Variables		CNF
В	$\begin{array}{c} \lambda_{b1} \vee \lambda_{b2} \\ \neg \lambda_{b1} \vee \neg \lambda_{b2} \end{array}$	$ \lambda_{b1} \Leftrightarrow \theta_{b1} \\ \lambda_{b2} \Leftrightarrow \theta_{b2} $
Е	$\lambda_{e1} \lor \lambda_{e2} \lor \lambda_{e3}$ $\neg \lambda_{e1} \lor \neg \lambda_{e2}$ $\neg \lambda_{e1} \lor \neg \lambda_{e3}$ $\neg \lambda_{e2} \lor \neg \lambda_{e3}$	$\lambda_{e1} \Leftrightarrow \theta_{e1}$ $\lambda_{e2} \Leftrightarrow \theta_{e2}$ $\lambda_{e3} \Leftrightarrow \theta_{e3}$
A	$\lambda_{a1} \vee \lambda_{a2}$ $\neg \lambda_{a1} \vee \neg \lambda_{a2}$	$\begin{array}{c} \lambda_{a1} \wedge \lambda_{b1} \wedge \lambda_{e1} \Leftrightarrow \theta_{a1 b1,e1} \\ \lambda_{a1} \wedge \lambda_{b1} \wedge \lambda_{e2} \Leftrightarrow \theta_{a1 b1,e2} \\ \lambda_{a1} \wedge \lambda_{b1} \wedge \lambda_{e3} \Leftrightarrow \theta_{a1 b1,e3} \\ \lambda_{a1} \wedge \lambda_{b2} \wedge \lambda_{e1} \Leftrightarrow \theta_{a1 b2,e1} \\ \lambda_{a1} \wedge \lambda_{b2} \wedge \lambda_{e2} \Leftrightarrow \theta_{a1 b2,e2} \\ \lambda_{a1} \wedge \lambda_{b2} \wedge \lambda_{e3} \Leftrightarrow \theta_{a1 b2,e3} \\ \lambda_{a2} \wedge \lambda_{b1} \wedge \lambda_{e1} \Leftrightarrow \theta_{a2 b1,e1} \\ \lambda_{a2} \wedge \lambda_{b1} \wedge \lambda_{e2} \Leftrightarrow \theta_{a2 b1,e2} \\ \lambda_{a2} \wedge \lambda_{b1} \wedge \lambda_{e3} \Leftrightarrow \theta_{a2 b1,e3} \\ \lambda_{a2} \wedge \lambda_{b2} \wedge \lambda_{e1} \Leftrightarrow \theta_{a2 b2,e1} \\ \lambda_{a2} \wedge \lambda_{b2} \wedge \lambda_{e2} \Leftrightarrow \theta_{a2 b2,e2} \\ \lambda_{a2} \wedge \lambda_{b2} \wedge \lambda_{e3} \Leftrightarrow \theta_{a2 b2,e2} \\ \lambda_{a2} \wedge \lambda_{b2} \wedge \lambda_{e3} \Leftrightarrow \theta_{a2 b2,e3} \end{array}$
J	$\begin{array}{c} \lambda_{j1} \vee \lambda_{j2} \\ \neg \lambda_{j1} \vee \neg \lambda_{j2} \end{array}$	$\lambda_{j1} \wedge \lambda_{a1} \Leftrightarrow \theta_{j1 a1}$ $\lambda_{j1} \wedge \lambda_{a2} \Leftrightarrow \theta_{j1 a2}$ $\lambda_{j2} \wedge \lambda_{a1} \Leftrightarrow \theta_{j2 a1}$ $\lambda_{j2} \wedge \lambda_{a2} \Leftrightarrow \theta_{j2 a2}$
М	$\lambda_{m1} \vee \lambda_{m2} \\ \neg \lambda_{m1} \vee \neg \lambda_{m2}$	$\lambda_{m1} \wedge \lambda_{a1} \Leftrightarrow \theta_{m1 a1}$ $\lambda_{m1} \wedge \lambda_{a2} \Leftrightarrow \theta_{m1 a2}$ $\lambda_{m2} \wedge \lambda_{a1} \Leftrightarrow \theta_{m2 a1}$ $\lambda_{m2} \wedge \lambda_{a2} \Leftrightarrow \theta_{m2 a2}$

Table V. WEIGHTS ASSOCIATION USING ENC1

Weights	Value
$W(\theta_{b1})$	0.7
$W(\theta_{b2})$	0.3
$W(\theta_{e1})$	0.01
$W(\theta_{e2})$	0.19
$W(\theta_{e3})$	0.80
$W(\theta_{a1 b1,e1})$	0.90
$W(\theta_{a1 b1.e2})$	0.85
$W(\theta_{a1 b1,e3})$	0.80
$W(\theta_{a1 b2,e1})$	0.30
$W(\theta_{a1 b2,e2})$	0.10
$W(\theta_{a1 b2,e3})$	0.00
$W(\theta_{a2 b1,e1})$	0.10
$W(\theta_{a2 b1.e2})$	0.15
$W(\theta_{a2 b1,e3})$	0.20
$W(\theta_{a2 b2,e1})$	0.70
$\mathrm{W}(\theta_{a2 b2,e2})$	0.90
$W(\theta_{a2 b2,e3})$	1.00
$W(\theta_{j1 a1})$	0.80
$W(\theta_{j1 a2})$	0.10
$W(\theta_{j2 a1})$	0.20
$W(\theta_{j2 a2})$	0.90
$W(\theta_{m1 a1})$	0.80
$W(\theta_{m1 a2})$	0.10
$W(\theta_{m2 a1})$	0.20
$W(\theta_{m2 a2})$	0.90

Table VI. CNF REPRESENTATION OF BAYESIAN NETWORK USING ENC2

Variables		CNF
В	$\begin{array}{c} \lambda_{b1} \vee \lambda_{b2} \\ \neg \lambda_{b1} \vee \neg \lambda_{b2} \end{array}$	$ \begin{array}{c} \rho_{b1} \Rightarrow \lambda_{b1} \\ \neg \rho_{b1} \Rightarrow \lambda_{b2} \end{array} $
E	$\lambda_{e1} \lor \lambda_{e2} \lor \lambda_{e3}$ $\neg \lambda_{e1} \lor \neg \lambda_{e2}$ $\neg \lambda_{e1} \lor \neg \lambda_{e3}$ $\neg \lambda_{e2} \lor \neg \lambda_{e3}$	$ \rho_{e1} \Rightarrow \lambda_{e1}  \neg \rho_{e1} \wedge \rho_{e2} \Rightarrow \lambda_{e2}  \neg \rho_{e1} \wedge \neg \rho_{e2} \Rightarrow \lambda_{e3} $
A	$\lambda_{a1} \vee \lambda_{a2}$ $\neg \lambda_{a1} \vee \neg \lambda_{a2}$	$\begin{array}{c} \lambda_{b1} \wedge \lambda_{e1} \wedge \rho_{a1 b1,e1} \Rightarrow \lambda_{a1} \\ \lambda_{b1} \wedge \lambda_{e2} \wedge \rho_{a1 b1,e2} \Rightarrow \lambda_{a1} \\ \lambda_{b1} \wedge \lambda_{e3} \wedge \rho_{a1 b1,e3} \Rightarrow \lambda_{a1} \\ \lambda_{b2} \wedge \lambda_{e1} \wedge \rho_{a1 b2,e1} \Rightarrow \lambda_{a1} \\ \lambda_{b2} \wedge \lambda_{e2} \wedge \rho_{a1 b2,e2} \Rightarrow \lambda_{a1} \\ \lambda_{b2} \wedge \lambda_{e3} \wedge \rho_{a1 b2,e3} \Rightarrow \lambda_{a1} \\ \lambda_{b1} \wedge \lambda_{e3} \wedge \rho_{a1 b1,e1} \Rightarrow \lambda_{a2} \\ \lambda_{b1} \wedge \lambda_{e2} \wedge -\rho_{a1 b1,e2} \Rightarrow \lambda_{a2} \\ \lambda_{b1} \wedge \lambda_{e2} \wedge -\rho_{a1 b1,e2} \Rightarrow \lambda_{a2} \\ \lambda_{b1} \wedge \lambda_{e3} \wedge -\rho_{a1 b1,e3} \Rightarrow \lambda_{a2} \\ \lambda_{b2} \wedge \lambda_{e1} \wedge -\rho_{a1 b2,e1} \Rightarrow \lambda_{a2} \\ \lambda_{b2} \wedge \lambda_{e2} \wedge -\rho_{a1 b2,e2} \Rightarrow \lambda_{a2} \\ \lambda_{b2} \wedge \lambda_{e3} \wedge -\rho_{a1 b2,e3} \Rightarrow \lambda_{a2} \\ \lambda_{b2} \wedge \lambda_{e3} \wedge -\rho_{a1 b2,e3} \Rightarrow \lambda_{a2} \end{array}$
J	$\begin{array}{c} \lambda_{j1} \vee \lambda_{j2} \\ \neg \lambda_{j1} \vee \neg \lambda_{j2} \end{array}$	$\lambda_{a1} \wedge \rho_{j1 a1} \Rightarrow \lambda_{j1}$ $\lambda_{a2} \wedge \rho_{j1 a2} \Rightarrow \lambda_{j1}$ $\lambda_{a1} \wedge \neg \rho_{j1 a1} \Rightarrow \lambda_{j2}$ $\lambda_{a2} \wedge \neg \rho_{j1 a2} \Rightarrow \lambda_{j2}$
М	$\lambda_{m1} \vee \lambda_{m2}$ $\neg \lambda_{m1} \vee \neg \lambda_{m2}$	$\lambda_{a1} \wedge \rho_{m1 a1} \Rightarrow \lambda_{m1}$ $\lambda_{a2} \wedge \rho_{m1 a2} \Rightarrow \lambda_{m1}$ $\lambda_{a1} \wedge \neg \rho_{m1 a1} \Rightarrow \lambda_{m2}$ $\lambda_{a2} \wedge \neg \rho_{m1 a2} \Rightarrow \lambda_{m2}$

Table VII. WEIGHTS ASSOCIATION USING ENC2

Weights	Value
$W(\rho_{b1})$	0.7
$W(\neg \rho_{b1})$	0.3
$W(\rho_{e1})$	0.01
$W(\rho_{e2})$	0.19
$W(\neg \rho_{e1})$	1-0.01 = 0.99
$W(\neg \rho_{e2})$	1-0.19 = 0.81
$W(\rho_{a1 b1,e1})$	0.90
$W(\neg \rho_{a1 b1,e1})$	1-0.90=0.10
$W(\rho_{a1 b1,e2})$	0.85
$W(\neg \rho_{a1 b1,e2})$	1-0.85=0.15
$W(\rho_{a1 b1,e3})$	0.80
$W(\neg \rho_{a1 b1,e3})$	1-0.80=0.20
$W(\rho_{a1 b2,e1})$	0.30
$W(\neg \rho_{a1 b2,e1})$	1-0.30=0.70
$W(\rho_{a1 b2,e2})$	0.10
$W(\neg \rho_{a1 b2,e2})$	1-0-10=0.90
$W(\rho_{a1 b2,e3})$	0
$W(\neg \rho_{a1 b2,e3})$	1-0=1
$W(\rho_{j1 a1})$	0.80
$W(\neg \rho_{j1 a1})$	1-0.80=0.20
$W(\rho_{j1 a2})$	0.10
$W(\neg \rho_{j1 a2})$	1-0.10=0.90

### B. SRL to CNF

First the program must be grounded, while taking into account  $\mathbf{Q}$  and  $\mathbf{E}$ . In this case the evidence set  $\mathbf{E}$  is empty (there is no evidence available). The grounding process of the queries will be described step-by-step in listings 1 and 2. If only  $\mathbf{query}(\mathbf{path}(1,5))$  was considered, then  $\mathbf{edge}(5,6)$  and  $\mathbf{edge}(2,6)$  would have been irrelevant. With the inclusion of  $\mathbf{query}(\mathbf{path}(1,6))$  all edges become relevant.

```
% grounding path(1,5) becomes:
path(1,5) := edge(1,3), 5 = 3, path(3,5).
path(1,5) := edge(1,2), 5 = 2, path(2,5).
% grounding path(3,5)
path(3,5) := edge(3,4), 5 = 4, path(4,5).
% grounding path (4,5).
path(4,5) :- edge(4,5).
% grounding path (2,5)
path(2,5) := edge(2,5).
% putting the results together (and resolving the inequalities) gives:
path (1,5): - edge (1,3), edge (3,4), edge (4,5).
path (1,5): - edge (1,2), edge (2,5).
                     Listing 1: Grounding of path(1,5)
% grounding path(1,6) becomes:
path(1,6) := edge(1,3), 6 = 3, path(3,6).
path(1,6) := edge(1,2), 6 = 2, path(2,6).
% grounding path (3,6)
path(3,6) := edge(3,4), 6 = 4, path(4,6).
% grounding path (4,6).
path(4,6) := edge(4,5), 6 = 5, path(5,6).
% grounding path (5,6)
path (5,6): - edge (5,6).
% grounding path (2,6)
path(2,6) :- edge(2,6).
path(2,6) := edge(5,6), 6 = 5, path(5,6).
% path(5,6) has already been grounded
% putting the results together (and resolving the inequalities) gives:
path(1,6) := edge(1,3), edge(3,4), edge(4,5), edge(5,6).
path(1,6) := edge(1,2), edge(2,5), edge(5,6).
path(1,6) := edge(1,2), edge(2,6).
```

Listing 2: Grounding of path(1,6)