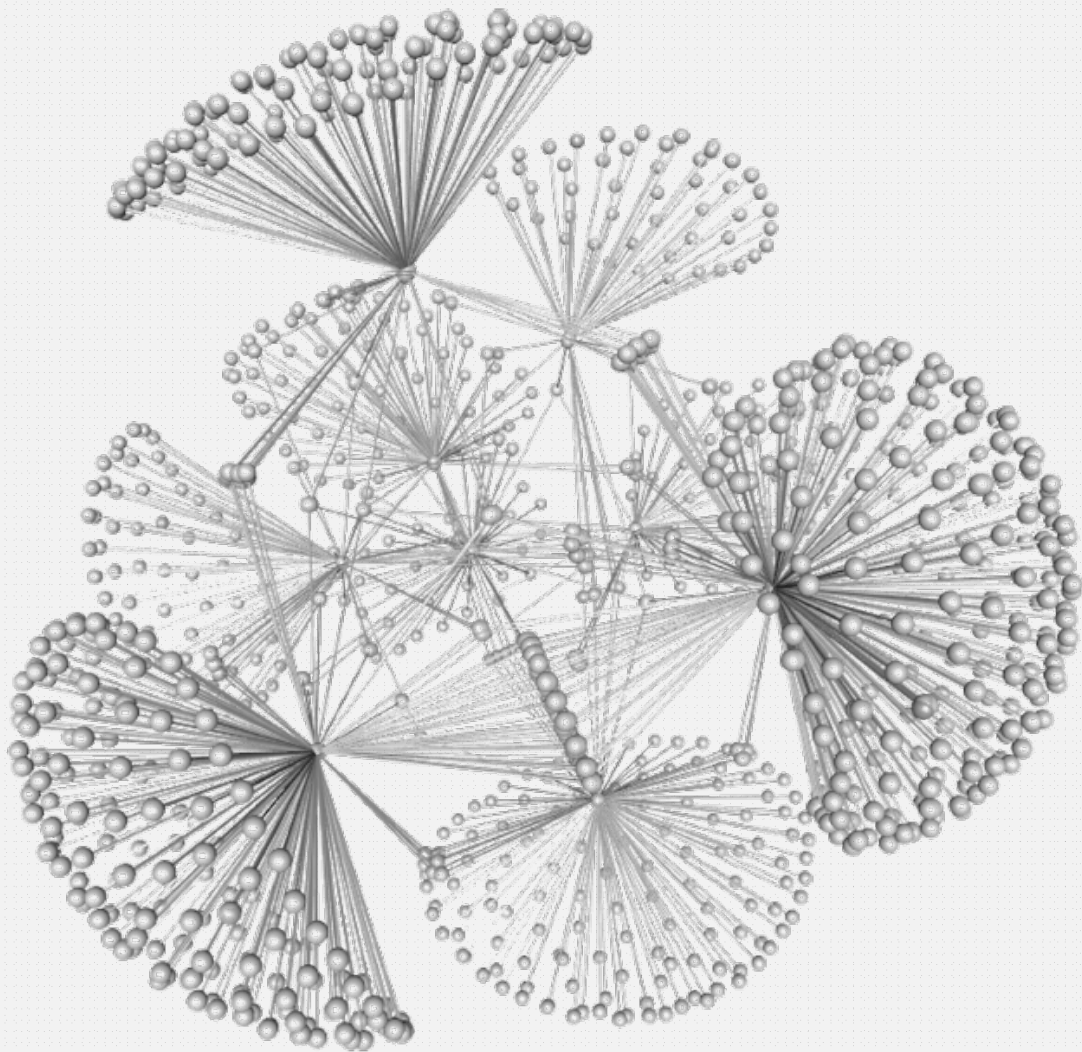


Probabilistic Programming

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INTELLIGENCE

Contents

Probabilistic Inference Using Weighted Model Counting	1
1.1 SRL to CNF	1
1.2 SRL to PGM	4
1.3 PGM to CNF	4
1.4 Weighted Model Counting	4
Lifted Inference	4
Parameter Learning	4

Below's our solution for the given challenges. The questions in each section of the original assignment are answered in a section having the same title.

```
1 person(a).
2 person(b).
3 person(c).
4 0.2::stress(X) :- person(X).
5 0.1::friends(X,Y) :- person(X), person(Y).
6 0.3::smokes(X) :- stress(X).
7 0.4::smokes(X) :- friends(X,Y), smokes(Y).
8 query(smokes(a)).
```

Code snippet 1: PROLOG program used throughout the first two chapters of the report.

Probabilistic Inference Using Weighted Model Counting

SRL to CNF

First the program is grounded. This is a matter of collecting all atoms involved in all proofs of the query.

```
1 0.2::stress(a).
2 0.2::stress(b).
3 0.2::stress(c).
4
5 0.1::friends(a,a).
6 0.1::friends(a,b).
7 0.1::friends(a,c).
8
9 0.1::friends(b,a).
10 0.1::friends(b,b).
11 0.1::friends(b,c).
12
13 0.1::friends(c,a).
14 0.1::friends(c,b).
15 0.1::friends(c,c).
16
17 0.3::smokes(a) :- stress(a).
18 0.3::smokes(b) :- stress(b).
19 0.3::smokes(c) :- stress(c).
20 0.4::smokes(a) :- friends(a,a), smokes(a).
```

```
21 0.4::smokes(a) :- friends(a,b), smokes(b).
22 0.4::smokes(a) :- friends(a,c), smokes(c).
23 0.4::smokes(b) :- friends(b,a), smokes(a).
24 0.4::smokes(b) :- friends(b,b), smokes(b).
25 0.4::smokes(b) :- friends(b,c), smokes(c).
26
27 0.4::smokes(c) :- friends(c,a), smokes(a).
28 0.4::smokes(c) :- friends(c,b), smokes(b).
29 0.4::smokes(c) :- friends(c,c), smokes(c).
```

Code snippet 2: Relevant ground program.

The proofs of the query make for a trie as shown in figure 1, where colourings indicate the presence of cycles. Any proof involving an atom `friends(X,X)` or `friends(Y,a)` (with $Y \in \{b,c\}$) is non-minimal and doesn't affect the final probability. These atoms are disregarded. For the remaining cycles (involving `friends(b,c)` and `friends(c,b)`) auxiliary variables can be used to obtain a cycle-free program without intensional probabilistic facts :

```
1 0.2::stress(a).
2 0.2::stress(b).
3 0.2::stress(c).
4
5 0.1::friends(a,b).
6 0.1::friends(a,c).
```

7	0.1::friends(b,c).	$\wedge (\neg \text{smokes}(a) \vee p(a) \vee p(a,b) \vee p(a,c))$
8	0.1::friends(c,b).	$\wedge (\neg \text{stress}(a) \vee \neg p(a) \vee \text{smokes}(a))$
9		$\wedge (\neg \text{friends}(a,b) \vee \neg \text{smokes}(b) \vee \neg p(a,b) \vee \text{smokes}(a))$
10	0.3::p(a).	$\wedge (\neg \text{friends}(a,c) \vee \neg \text{smokes}(c) \vee \neg p(a,c) \vee \text{smokes}(a))$
11	0.3::p(b).	$\wedge (\neg \text{smokes}(b) \vee \text{stress}(b) \vee \text{friends}(b,c))$
12	0.3::p(c).	$\wedge (\neg \text{smokes}(b) \vee \text{stress}(b) \vee \text{stress}(c))$
13		$\wedge (\neg \text{smokes}(b) \vee \text{stress}(b) \vee p(c))$
14	0.4::p(a,b).	$\wedge (\neg \text{smokes}(b) \vee \text{stress}(b) \vee p(b,c))$
15	0.4::p(a,c).	$\wedge (\neg \text{smokes}(b) \vee p(b) \vee \text{friends}(b,c))$
16	0.4::p(b,c).	$\wedge (\neg \text{smokes}(b) \vee p(b) \vee \text{stress}(c))$
17	0.4::p(c,b).	$\wedge (\neg \text{smokes}(b) \vee p(b) \vee p(c))$
18		$\wedge (\neg \text{smokes}(b) \vee p(b) \vee p(b,c))$
19	smokes(a) :- stress(a), p(a).	$\wedge (\neg \text{stress}(b) \vee \neg p(b) \vee \text{smokes}(b))$
20	smokes(b) :- stress(b), p(b).	$\wedge (\neg \text{friends}(b,c) \vee \neg \text{stress}(c) \vee \neg p(c) \vee \neg p(b,c) \vee \text{smokes}(b))$
21	smokes(c) :- stress(c), p(c).	$\wedge (\neg \text{smokes}(c) \vee \text{stress}(c) \vee \text{friends}(c,b))$
22		$\wedge (\neg \text{smokes}(c) \vee \text{stress}(c) \vee \text{stress}(b))$
23	smokes(a) :-	$\wedge (\neg \text{smokes}(c) \vee \text{stress}(c) \vee p(b))$
24	friends(a,b), smokes(b), p(a,b).	$\wedge (\neg \text{smokes}(c) \vee \text{stress}(c) \vee p(c,b))$
25	smokes(a) :-	$\wedge (\neg \text{smokes}(c) \vee p(c) \vee \text{friends}(c,b))$
26	friends(a,c), smokes(c), p(a,c).	$\wedge (\neg \text{smokes}(c) \vee p(c) \vee \text{stress}(b))$
27	smokes(b) :-	$\wedge (\neg \text{smokes}(c) \vee p(c) \vee p(b))$
28	friends(b,c), stress(c), p(c), p(b,c).	$\wedge (\neg \text{smokes}(c) \vee p(c) \vee p(c,b))$
29	smokes(c) :-	$\wedge (\neg \text{stress}(c) \vee \neg p(c) \vee \text{smokes}(c))$
30	friends(c,b), stress(b), p(b), p(c,b).	$\wedge (\neg \text{friends}(c,b) \vee \neg \text{stress}(b) \vee \neg p(b) \vee \neg p(c,b) \vee \text{smokes}(c))$
31		
32	query(smokes(a)).	

Code snippet 3: Relevant ground program without cycles.

The probabilistic literals in the CNF are assigned weights (derived literals get a weight of 1) :

The above logic program is equivalent to the following propositional formula :

$$\begin{aligned}
& (\text{smokes}(a) \leftrightarrow (\text{stress}(a) \wedge p(a)) \\
& \quad \vee (\text{friends}(a,b) \wedge \text{smokes}(b) \wedge p(a,b)) \\
& \quad \vee (\text{friends}(a,c) \wedge \text{smokes}(c) \wedge p(a,c))) \\
& \quad \wedge \\
& (\text{smokes}(b) \leftrightarrow (\text{stress}(b) \wedge p(b)) \\
& \quad \vee (\text{friends}(b,c) \wedge \text{stress}(c) \wedge p(c) \wedge p(b,c))) \\
& \quad \wedge \\
& (\text{smokes}(c) \leftrightarrow (\text{stress}(c) \wedge p(c)) \\
& \quad \vee (\text{friends}(c,b) \wedge \text{stress}(b) \wedge p(b) \wedge p(c,b)))
\end{aligned}$$

Which corresponds to the following CNF :

$$\begin{aligned}
& (\neg \text{smokes}(a) \vee \text{stress}(a) \vee \text{friends}(a,b) \vee \text{friends}(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee \text{friends}(a,b) \vee \text{smokes}(c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee \text{friends}(a,b) \vee p(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee \text{smokes}(b) \vee \text{friends}(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee \text{smokes}(b) \vee \text{smokes}(c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee \text{smokes}(b) \vee p(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee p(a,b) \vee \text{friends}(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee p(a,b) \vee \text{smokes}(c)) \\
& \wedge (\neg \text{smokes}(a) \vee \text{stress}(a) \vee p(a,b) \vee p(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee \text{friends}(a,b) \vee \text{friends}(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee \text{friends}(a,b) \vee \text{smokes}(c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee \text{friends}(a,b) \vee p(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee \text{smokes}(b) \vee \text{friends}(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee \text{smokes}(b) \vee \text{smokes}(c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee \text{smokes}(b) \vee p(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee p(a,b) \vee \text{friends}(a,c)) \\
& \wedge (\neg \text{smokes}(a) \vee p(a) \vee p(a,b) \vee \text{smokes}(c))
\end{aligned}$$

Literal	Weight
stress(a)	0.2
¬stress(a)	0.8
stress(b)	0.2
¬stress(b)	0.8
stress(c)	0.2
¬stress(c)	0.8
friends(a,b)	0.1
¬friends(a,b)	0.9
friends(a,c)	0.1
¬friends(a,c)	0.9
friends(b,c)	0.1
¬friends(b,c)	0.9
friends(c,b)	0.1
¬friends(c,b)	0.9
p(a)	0.3
¬p(a)	0.7
p(b)	0.3
¬p(b)	0.7
p(c)	0.3
¬p(c)	0.7
p(a,b)	0.4
¬p(a,b)	0.6
p(a,c)	0.4
¬p(a,c)	0.6
p(b,c)	0.4
¬p(b,c)	0.6
p(c,b)	0.4
¬p(c,b)	0.6

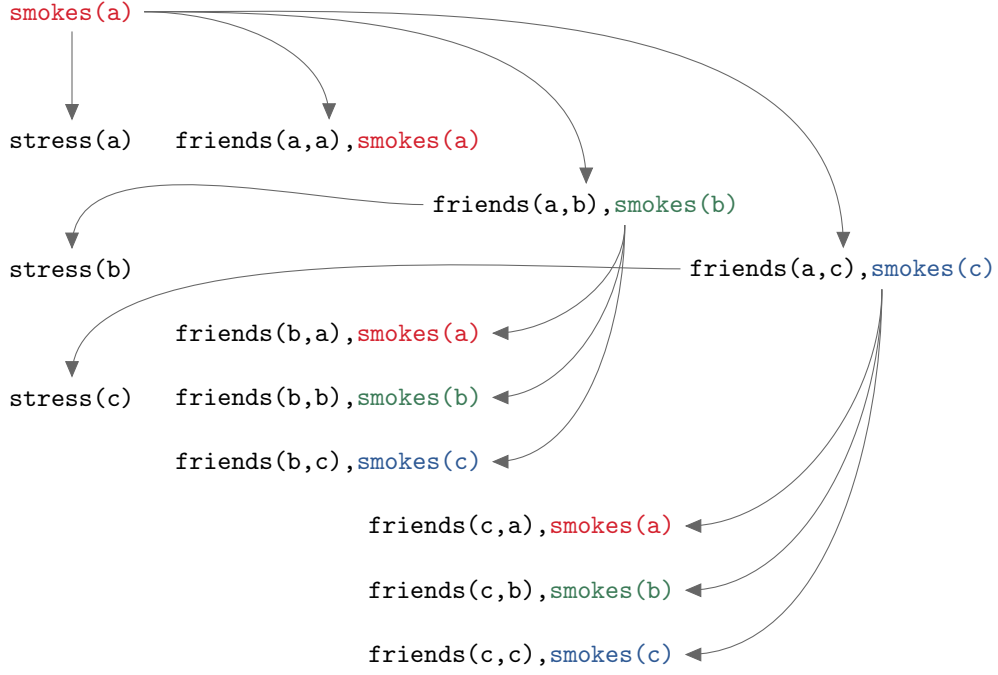


Figure 1: Trie representing proofs of the query. Coloured atoms indicate the presence of cycles.

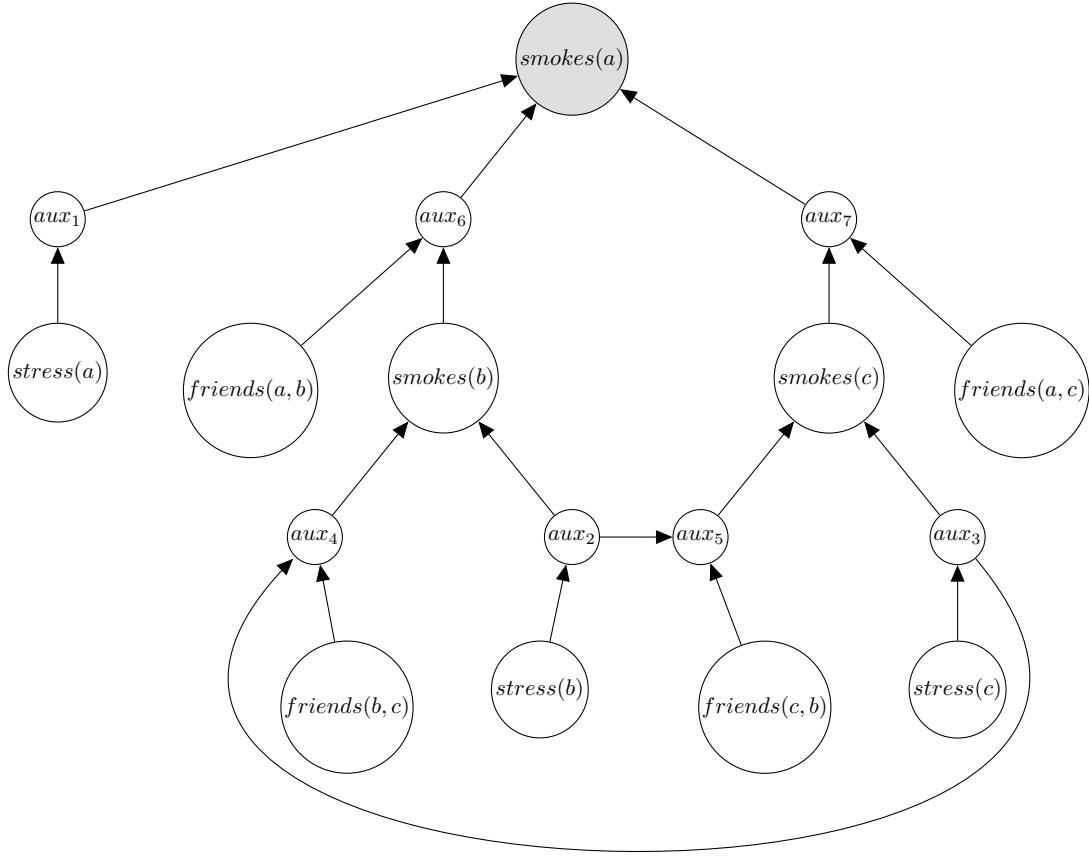


Figure 2: Bayesian network corresponding to the ground acyclic program.

SRL to PGM

A Bayesian network is shown in figure 2. The conditional probability tables (CPTs) for the nodes are given below. Note that every table represents multiple identical tables in the network (like those of the $stress(a)$, $stress(b)$ and $stress(c)$ nodes for example).

\top	$\frac{stress(\{a,b,c\})}{0.2}$	\top	$\frac{friends(\{a,b,c\},\{b,c\})}{0.1}$
\perp	$\frac{0.8}{0.8}$	\perp	$\frac{0.9}{0.9}$

$\frac{stress(\{a,b,c\})}{\top}$	$\frac{aux_{\{1,2,3\}}}{\top}$	$\frac{0.3}{0.7}$
\perp	$\frac{0.0}{1.0}$	$\frac{1.0}{1.0}$

$\frac{friends(\{b,c\},\{c,b\})}{\top}$	$\frac{aux_{2,3}}{\top}$	$\frac{aux_{4,5}}{\top}$	$\frac{0.4}{0.6}$
\perp	$\frac{0.0}{1.0}$	$\frac{0.0}{1.0}$	$\frac{1.0}{1.0}$

$\frac{friends(\{a\},\{b,c\})}{\top}$	$\frac{smokes(\{b,c\})}{\top}$	$\frac{aux_{6,7}}{\top}$	$\frac{0.4}{0.6}$
\perp	$\frac{0.0}{1.0}$	$\frac{0.0}{1.0}$	$\frac{1.0}{1.0}$

$\frac{aux_{4,5}}{\top}$	$\frac{aux_{2,3}}{\top}$	$\frac{smokes(\{b,c\})}{\top}$	$\frac{1.0}{0.0}$
\perp	$\frac{0.0}{1.0}$	$\frac{0.0}{1.0}$	$\frac{1.0}{1.0}$

$\frac{aux_1}{\top}$	$\frac{smokes(b)}{\top}$	$\frac{smokes(c)}{\top}$	$\frac{smokes(a)}{\top}$	$\frac{1.0}{0.0}$
\perp	$\frac{0.0}{1.0}$	$\frac{0.0}{1.0}$	$\frac{0.0}{1.0}$	$\frac{1.0}{1.0}$

In ENC1 each row in each CPT is encoded by a parameter clause.

In ENC2 an order is assumed over each variable's values. Then, each row of each CPT is encoded by an equivalence.

For both of these a Python script was written to automate the creation of CNF files, since manual conversion to a CNF turned out to be cumbersome. The script also produces L^AT_EX output which is added to the appendix.

Since the noisy OR relations end up being encoded naively by considering each row of the CPT separately, a more compact encoding is obtained by replacing this part of the encoding with a one-liner. For example :

$$smokes(a) \Leftrightarrow aux_1 \vee aux_6 \vee aux_7$$

This can be converted to a CNF in the usual way :

$$\begin{aligned} & smokes(a) \vee \neg aux_1 \vee \neg aux_6 \vee \neg aux_7 \\ & \wedge (\neg smokes(a) \vee aux_1) \\ & \wedge (\neg smokes(a) \vee aux_6) \\ & \wedge (\neg smokes(a) \vee aux_7) \end{aligned}$$

Weighted Model Counting

Lifted Inference

Parameter Learning

PGM to CNF

The Bayesian network can be encoded as a logical formula. Encodings ENC1 and ENC2 discussed [1] both make use of the same indicator variables such as $\lambda_{stress(a)=true}$ and $\lambda_{stress(a)=false}$ (which introduces redundancy considering the fact that all network variables are boolean).

References

- [1] Mark Chavira and Adnan Darwiche. On probabilistic inference by weighted model counting. *Artificial Intelligence*, 172(6):772 – 799, 2008.