Capita Selecta AI - Probabilistic Programming Inference for SRL

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Probabilistic Inference Using Weighted Model Counting

1.1 PGM to CNF

1.1.1 ENC 1

Our ENC1 encoding for the Cancer Bayesian network can be found in appendix 4.1.

1.1.2 ENC 2

Our ENC2 encoding for the Cancer Bayesian network can be found in appendix 4.2.

1.2 SRL to CNF

1.2.1 Encoding of Monty Hall as CNF

An encoding of problog programs can be generated by our program as follows:

python3 scripts/inference.py —problog files/problog/monty_hall.pl

The CNF will be shown using the program's predicates. A version of the CNF in dimacs format will be shown as well. See README.MD for more information.

```
Our CNF encoding for the given Monty Hall ProbLog program is:
         \land (open\_door(2) \lor prize(2) \lor prize(3) \lor \neg p\_open\_door(2)\_0)
         \land (open\_door(2) \lor prize(2) \lor \neg prize(3))
         \land (\neg open\_door(2) \lor \neg prize(2) \lor \neg prize(2))
         \land (\neg open\_door(2) \lor \neg prize(2) \lor prize(3))
         \land (\neg open\_door(2) \lor \neg prize(3) \lor \neg prize(2))
         \land (\neg open\_door(2) \lor \neg prize(3) \lor prize(3))
         \land (\neg open\_door(2) \lor p\_open\_door(2)\_0 \lor \neg prize(2))
         \land (\neg open\_door(2) \lor p\_open\_door(2) \_0 \lor prize(3))
         \land (open\_door(3) \lor prize(2) \lor prize(3) \lor \neg p\_open\_door(3)\_0)
         \land (open\_door(3) \lor prize(3) \lor \neg prize(2))
         \land (\neg open\_door(3) \lor \neg prize(2) \lor \neg prize(3))
         \land (\neg open\_door(3) \lor \neg prize(2) \lor prize(2))
         \land (\neg open\_door(3) \lor \neg prize(3) \lor \neg prize(3))
         \land (\neg open\_door(3) \lor \neg prize(3) \lor prize(2))
         \land (\neg open\_door(3) \lor p\_open\_door(3)\_0 \lor \neg prize(3))
         \land (\neg open\_door(3) \lor p\_open\_door(3)\_0 \lor prize(2))
         \land (win\_keep \lor \neg prize(1))
         \land (\neg win\_keep \lor prize(1))
         \land (win\_switch \lor \neg prize(2) \lor open\_door(2))
         \land (win\_switch \lor \neg prize(3) \lor open\_door(3))
         \land (\neg win\_switch \lor prize(2) \lor prize(3))
         \land (\neg win\_switch \lor prize(2) \lor \neg open\_door(3))
         \land (\neg win\_switch \lor \neg open\_door(2) \lor prize(3))
         \land (\neg win\_switch \lor \neg open\_door(2) \lor \neg open\_door(3))
         \land (\neg prize(1) \lor \neg prize(2))
         \land (\neg prize(1) \lor \neg prize(3))
         \land (\neg prize(2) \lor \neg prize(3))
         \land (prize(1) \lor prize(2) \lor prize(3))
           Weights:
           W(p\_open\_door(2)\_0) = 0.5
           W(p\_open\_door(3)\_0) = 0.5
           W(select\_door(1)) = 1.00
           W(prize(1)) = 0.33
           W(prize(2)) = 0.33
           W(prize(3)) = 0.33
           W(open\_door(2)) = 1.00
           W(open\_door(3)) = 1.00
           W(win\_keep) = 1.00
           W(win\_switch) = 1.00
```

1.3 Weighted Model Counting

1.3.1 Weighted model counters on above CNFs

We will use MiniC2D and Cachet as WMC counters.

MiniC2D

MiniC2D needs to use the -W option to do weighted model counting.

• ENC1:

Figure 1.1: Grounded problog cnf

• ENC2:

Figure 1.2: Grounded problog cnf

• Monty hall:

Figure 1.3: Grounded problog cnf

•

Cachet

• ENC1:

```
Number of total components

Number of split components

Number of non-split components

Number of non-split components

Number of SAT residual formula

Number of rivial components

Number of changed components

Number of adjusted components

Number of adjusted components

Number of Padjusted components

Number of Padjusted components

Number of Variables

Number of Variables

Number of Variables

Original Num Clauses

Added Conflict Clauses

Oeleted Unrelevant Literals

Number of Implications

Deleted Unrelevant Literals

Number of Implications

Deleted Unrelevant Literals

Number of Implications

Satisfying probability

Number of Solutions

Number of Solutions

Number of Solutions

Satisfying probability

Number of Solutions

93.6645
```

Figure 1.4: Grounded problog cnf

• ENC2:

```
Number of total components

Number of split components

Number of non-split components

Number of non-split components

Number of SAT residual formula

Number of trivial components

Number of changed components

Number of adjusted components

Number of Decisions

Number of Becisions

Number of Decisions

Number of Variables

Original Num Literals

Added Conflict Clauses

Deleted Unrelevant clauses

Deleted Unrelevant clauses

Number of Implications

Total Rum Time

Number of Solutions

Number of Solutions

1.04858e+06
```

Figure 1.5: Grounded problog cnf

• Monty Hall:

For ENC1 we see that with Cachet we get a satisfying probability of almost 0. This is due to the fact that with ENC1 all our negative literals have a weight of 1, while Cachet expects that a literal + its negation = 1.

1.3.2 Difference between the selected WMCs

MiniC2D Vs Cachet

MiniC2D and Cachet are both weighted model counters but how they do this is quite different. MiniC2D is a top down compiler that compiles CNFs into a SDD which results in a faster system but it also uses less space while Cachet is an algorithm that uses formula caching together with clause learning and component analysis. MiniC2D needs vtrees to be able to compile the CNFs into an SDD. TThey, however, both use things from the SAT literature. They both use clause learning and component caching as to be able to reuse components that later appear again in the search. Cachet on the other hand also uses some other things from SAT literature like an explicit on the fly calculation of connected components. This is different in MiniC2D as it uses a vtree to identify disconnected CNF components. [1] [2]

1.3.3 Overview of computational requirements

All the tests can be found in the test folder. We used our scripts to create the dimac files. The input files for our enc1 and enc2 converter ard ".dsc" files which can be found at http://www.bnlearn.com/bnrepository/discrete-small.html#cancer.

Test 1: Cancer network

Table 1.1: My caption

	ENC1				ENC2		
	Prob Memory Runtime			Prob	Memory Runtim		
Minic2d	1.0	0.2 KB	0.155s	1.0	1.0 KB	0.000s	
Cachet	val1	val2	a	b	val3	val4	

Test 2: asia network

Table 1.2: My caption

	ENC1			9 01011	ENC2		
	Prob Memory Runtime			Prob	Memory Runtime		
Minic2d	1.0	0.9 KB	0.145s	1.0	2.0 KB	0.139s	
Cachet	val1	val2	a	b	val3	val4	

Test 3: sachs network

Table 1.3: My caption

	ENC1				ENC2		
	Prob	Memory	Runtime	Prob	Memory	Runtime	
Minic2d	0.99707	14.3 KB	0.184s	1.0	14.5 KB	0.154s	
Cachet	val1	val2	a	b	val3	val4	

Test 4: earthquake network

Table 1.4: My caption

	ENC1			$\mathrm{ENC}2$		
	Prob	Memory	Runtime	Prob	Memory	Runtime
Minic2d	1.0	0.6 KB	0.137s	1.0	1.0 KB	0.153s
Cachet	val1	val2	a	b	val3	val4

Test 5: survey network

Table 1.5: My caption

	ENC1				ENC2		
	Prob	Memory	Runtime	Prob	Memory	Runtime	
Minic2d	1.0	1.6 KB	0.125s	1.0	2.0 KB	0.125s	
Cachet	val1	val2	a	b	val3	val4	

Test 6: alarm network

Table 1.6: My caption

	ENC1			ENC2		
	Prob	Memory	Runtime	Prob	Memory	Runtime
Minic2d	1.0	959.7KB KB	0.268s	1.0	139KB	0.095s
Cachet	val1	val2	a	b	val3	val4

Test 6: andes network

Table 1.7: My caption

		ENC1	, , , , , , , , , , , , , , , , , , ,	ENC2			
	Entor			D 1			
	Prob	Memory	Runtime	Prob	Memory	$\mathbf{Runtime}$	
Minic2d	1.0	2.7GB	122.78s	1.0	139.8MB	6.086s	
Cachet	val1	val2	a	b	val3	val4	

1.4 Knowledge compilation

Vtree with the most compact circuit

During our tests

Pattern for a good vtree

As a vtree is a binary tree, which means that a good vtree is compact. We want thus a vtree that is shallow.

Build an Inference Engine

2.0.1 Implementation

We have implemented the pipeline using python. Information about it can be found in README.MD.

2.0.2 Pipeline with previous tasks

Cancer Bayesian network

- Probability:
- Total runtime:
- Runtime of the separate parts:
- Number of variables in CNF:
- Number of lines in CNF:
- Depth of vtree:
- Number of edges and nodes in the circuit:

Monty Hall

- Probability:
- Total runtime:
- Runtime of the separate parts:
- Number of variables in CNF:
- Number of lines in CNF:
- Depth of vtree:
- Number of edges and nodes in the circuit:

2.0.3 Pipeline on Bayesian learning example

DAS NEN DIKKE VETTE TODO

- Probability:
- Total runtime:
- Runtime of the separate parts:
- Number of variables in CNF:
- Number of lines in CNF:
- Depth of vtree:
- Number of edges and nodes in the circuit:

2.0.4 Pipeline on alarm Bayesian network

GOD DAMN IT STOM VAK HOE MOETEN WIJ DIT IN 50 UUR DOEN? PROCESS WORDT GEWOON GEKILLED OMDAT DIE CNF GIGANTISCH GROOT WORDT.

- Probability:
- Total runtime:
- Runtime of the separate parts:
- Number of variables in CNF:
- Number of lines in CNF:
- Depth of vtree:
- Number of edges and nodes in the circuit:

Parameter Learning

learning

Appendix

4.1 ENC1

Indicator clauses:

```
 \begin{array}{l} \left( \neg \ \lambda_{PollutionLow} \lor \neg \ \lambda_{PollutionHigh} \right) \land \left( \lambda_{PollutionLow} \lor \lambda_{PollutionHigh} \right) \land \left( \neg \ \lambda_{SmokerTrue} \lor \neg \ \lambda_{SmokerFalse} \right) \land \left( \lambda_{SmokerTrue} \lor \lambda_{SmokerFalse} \right) \land \left( \neg \ \lambda_{CancerTrue} \lor \neg \ \lambda_{CancerFalse} \right) \land \left( \neg \ \lambda_{XrayPositive} \lor \neg \ \lambda_{XrayNegative} \right) \land \left( \lambda_{XrayPositive} \lor \lambda_{XrayNegative} \right) \land \left( \neg \ \lambda_{DyspnoeaTrue} \lor \neg \ \lambda_{DyspnoeaFalse} \right) \land \left( \lambda_{DyspnoeaTrue} \lor \lambda_{DyspnoeaFalse} \right) \end{aligned}
```

Parameter clauses:

```
(\neg \lambda_{PollutionLow} \lor \theta_{PollutionLow}) \land (\lambda_{PollutionLow} \lor \neg \theta_{PollutionLow}) \land (\neg
   \lambda_{PollutionHigh} \vee \theta_{PollutionHigh}) \wedge (\lambda_{PollutionHigh} \vee \neg \theta_{PollutionHigh}) \wedge (\neg \theta_{PollutionHigh})
        \lambda_{SmokerTrue} \vee \theta_{SmokerTrue}) \wedge (\lambda_{SmokerTrue} \vee \neg \theta_{SmokerTrue}) \wedge (\neg
       \lambda_{SmokerFalse} \vee \theta_{SmokerFalse}) \wedge (\lambda_{SmokerFalse} \vee \neg \theta_{SmokerFalse}) \wedge (\neg \theta_{SmokerFalse})
                       \lambda_{PollutionLow} \vee \neg \lambda_{SmokerTrue} \vee \neg \lambda_{CancerTrue} \vee 
                 \theta_{CancerTrue|PollutionLow,SmokerTrue}) \land (\lambda_{PollutionLow} \lor \neg
                 \theta_{CancerTrue|PollutionLow,SmokerTrue}) \land (\lambda_{SmokerTrue} \lor \neg
                  \theta_{CancerTrue|PollutionLow.SmokerTrue}) \wedge (\lambda_{CancerTrue} \vee \neg
 \theta_{CancerTrue|PollutionLow,SmokerTrue}) \land (\neg \lambda_{PollutionLow} \lor \neg \lambda_{SmokerTrue} \lor \neg
    \lambda_{CancerFalse} \lor \theta_{CancerFalse|PollutionLow,SmokerTrue}) \land (\lambda_{PollutionLow} \lor \neg)
                 \theta_{CancerFalse|PollutionLow,SmokerTrue}) \land (\lambda_{SmokerTrue} \lor \neg
                 \theta_{CancerFalse|PollutionLow,SmokerTrue}) \land (\lambda_{CancerFalse} \lor \lnot
\theta_{CancerFalse|PollutionLow,SmokerTrue}) \land (\neg \lambda_{PollutionLow} \lor \neg \lambda_{SmokerFalse} \lor \neg
     \lambda_{CancerTrue} \lor \theta_{CancerTrue|PollutionLow,SmokerFalse}) \land (\lambda_{PollutionLow} \lor \lnot)
                \theta_{CancerTrue|PollutionLow,SmokerFalse}) \land (\lambda_{SmokerFalse} \lor \neg
                 \theta_{CancerTrue|PollutionLow,SmokerFalse}) \land (\lambda_{CancerTrue} \lor \lnot)
\theta_{CancerTrue|PollutionLow,SmokerFalse}) \land (\neg \lambda_{PollutionLow} \lor \neg \lambda_{SmokerFalse} \lor \neg
    \lambda_{CancerFalse} \lor \theta_{CancerFalse|PollutionLow,SmokerFalse}) \land (\lambda_{PollutionLow} \lor \neg)
                \theta_{CancerFalse|PollutionLow,SmokerFalse}) \land (\lambda_{SmokerFalse} \lor \neg
                \theta_{CancerFalse|PollutionLow,SmokerFalse}) \land (\lambda_{CancerFalse} \lor \neg
\theta_{CancerFalse|PollutionLow,SmokerFalse}) \land (\neg \lambda_{PollutionHigh} \lor \neg \lambda_{SmokerTrue} \lor \neg
    \lambda_{CancerTrue} \lor \theta_{CancerTrue|PollutionHigh,SmokerTrue}) \land (\lambda_{PollutionHigh} \lor \lnot)
                 \theta_{CancerTrue|PollutionHigh,SmokerTrue}) \wedge (\lambda_{SmokerTrue} \vee \neg
                 \theta_{CancerTrue|PollutionHigh,SmokerTrue}) \wedge (\lambda_{CancerTrue} \vee \neg
\theta_{CancerTrue|PollutionHigh,SmokerTrue}) \land (\neg \lambda_{PollutionHigh} \lor \neg \lambda_{SmokerTrue} \lor \neg
   \lambda_{CancerFalse} \lor \theta_{CancerFalse|PollutionHigh,SmokerTrue}) \land (\lambda_{PollutionHigh} \lor \neg)
```

```
\theta_{CancerFalse|PollutionHigh,SmokerTrue}) \land (\lambda_{SmokerTrue} \lor \neg
                                                                               \theta_{CancerFalse|PollutionHigh,SmokerTrue}) \land (\lambda_{CancerFalse} \lor \neg
      	heta_{CancerFalse|PollutionHigh,SmokerTrue}) \land (\lnot \lambda_{PollutionHigh} \lor \lnot \lambda_{SmokerFalse} \lor
          \neg \lambda_{CancerTrue} \lor \theta_{CancerTrue|PollutionHigh,SmokerFalse}) \land (\lambda_{PollutionHigh} \lor \neg
                                                                            \theta_{CancerTrue|PollutionHigh,SmokerFalse}) \land (\lambda_{SmokerFalse} \lor \neg
                                                                                  \theta_{CancerTrue|PollutionHigh.SmokerFalse}) \land (\lambda_{CancerTrue} \lor \neg
      \theta_{CancerTrue|PollutionHigh,SmokerFalse}) \land (\neg \lambda_{PollutionHigh} \lor \neg \lambda_{SmokerFalse} \lor 
       \neg \lambda_{CancerFalse} \lor \theta_{CancerFalse|PollutionHigh,SmokerFalse}) \land (\lambda_{PollutionHigh} \lor \neg
                                                                            \theta_{CancerFalse|PollutionHigh,SmokerFalse}) \land (\lambda_{SmokerFalse} \lor \neg
                                                                            \theta_{CancerFalse|PollutionHigh,SmokerFalse}) \land (\lambda_{CancerFalse} \lor \neg)
          \theta_{CancerFalse|PollutionHigh,SmokerFalse}) \land (\neg \lambda_{CancerTrue} \lor \neg \lambda_{XrayPositive} \lor \neg \lambda_{
                         \theta_{XrayPositive|CancerTrue}) \wedge (\lambda_{CancerTrue} \vee \neg \theta_{XrayPositive|CancerTrue}) \wedge 
                                                 (\lambda_{XrayPositive} \lor \neg \theta_{XrayPositive|CancerTrue}) \land (\neg \lambda_{CancerTrue} \lor \neg
                                                               \lambda_{XrayNegative} \lor \theta_{XrayNegative|CancerTrue}) \land (\lambda_{CancerTrue} \lor \neg
\theta_{XrayNegative|CancerTrue}) \wedge (\lambda_{XrayNegative} \vee \neg \theta_{XrayNegative|CancerTrue}) \wedge (\neg
\lambda_{CancerFalse} \lor \lnot \lambda_{XrayPositive} \lor \theta_{XrayPositive|CancerFalse}) \land (\lambda_{CancerFalse} \lor \lnot
  \theta_{XrayPositive|CancerFalse}) \land (\lambda_{XrayPositive} \lor \neg \theta_{XrayPositive|CancerFalse}) \land (\neg \theta_{XrayPositive})
 \lambda_{CancerFalse} \lor \neg \lambda_{XrayNegative} \lor \theta_{XrayNegative|CancerFalse}) \land (\lambda_{CancerFalse} \lor \neg \lambda_{XrayNegative} \lor \neg
\neg \theta_{XrayNegative|CancerFalse}) \land (\lambda_{XrayNegative} \lor \neg \theta_{XrayNegative|CancerFalse}) \land (\lambda_{XrayNegative} \lor \neg \theta_{XrayNegative|CancerFalse}) \land (\lambda_{XrayNegative} \lor \neg \theta_{XrayNegative}) \land (\lambda_{XrayNega
  (\neg \lambda_{CancerTrue} \lor \neg \lambda_{DyspnoeaTrue} \lor \theta_{DyspnoeaTrue} | CancerTrue) \land (\lambda_{CancerTrue})
 \vee \neg \theta_{DyspnoeaTrue|CancerTrue}) \wedge (\lambda_{DyspnoeaTrue} \vee \neg \theta_{DyspnoeaTrue|CancerTrue})
                                       \wedge \left( \neg \ \lambda_{CancerTrue} \lor \neg \ \lambda_{DyspnoeaFalse} \lor \ \theta_{DyspnoeaFalse|CancerTrue} \right) \land \\
                                             (\lambda_{CancerTrue} \vee \neg \ \theta_{DyspnoeaFalse|CancerTrue}) \wedge (\lambda_{DyspnoeaFalse} \vee \neg
                                                 \theta_{DyspnoeaFalse|CancerTrue}) \wedge (\neg \lambda_{CancerFalse} \vee \neg \lambda_{DyspnoeaTrue} \vee 
          \theta_{DyspnoeaTrue|CancerFalse}) \wedge (\lambda_{CancerFalse} \vee \neg \theta_{DyspnoeaTrue|CancerFalse}) \wedge (\lambda_{CancerFalse}) \wedge
                                      (\lambda_{DyspnoeaTrue} \lor \neg \theta_{DyspnoeaTrue|CancerFalse}) \land (\neg \lambda_{CancerFalse} \lor \neg
                                                      \lambda_{DyspnoeaFalse} \lor \theta_{DyspnoeaFalse|CancerFalse}) \land (\lambda_{CancerFalse} \lor \lnot)
       \theta_{DyspnoeaFalse|CancerFalse}) \wedge (\lambda_{DyspnoeaFalse} \vee \neg \theta_{DyspnoeaFalse|CancerFalse})
Weights:
```

 $W(\lambda_{PollutionLow}) = 1.00$ $W(\neg \lambda_{PollutionLow}) = 1.00$ $W(\lambda_{PollutionHigh}) = 1.00$ $W(\neg \lambda_{PollutionHigh}) = 1.00$ $W(\lambda_{SmokerTrue}) = 1.00$ $W(\neg \lambda_{SmokerTrue}) = 1.00$ $W(\lambda_{SmokerFalse}) = 1.00$ $W(\neg \lambda_{SmokerFalse}) = 1.00$ $W(\lambda_{CancerTrue}) = 1.00$ $W(\neg \lambda_{CancerTrue}) = 1.00$ $W(\lambda_{CancerFalse}) = 1.00$ $W(\neg \lambda_{CancerFalse}) = 1.00$ $W(\lambda_{XrayPositive}) = 1.00$ $W(\neg \lambda_{XrayPositive}) = 1.00$ $W(\lambda_{XrayNegative}) = 1.00$ $W(\neg \lambda_{XrayNegative}) = 1.00$ $W(\lambda_{DyspnoeaTrue}) = 1.00$ $W(\neg \lambda_{DyspnoeaTrue}) = 1.00$ $W(\lambda_{DyspnoeaFalse}) = 1.00$ $W(\neg \lambda_{DyspnoeaFalse}) = 1.00$

```
W(\theta_{PollutionLow}) = 0.90
W(\neg \theta_{PollutionLow}) = 1.00
W(\theta_{PollutionHigh}) = 0.10
W(\neg \theta_{PollutionHigh}) = 1.00
W(\theta_{SmokerTrue}) = 0.30
W(\neg \theta_{SmokerTrue}) = 1.00
W(\theta_{SmokerFalse}) = 0.70
W(\neg \theta_{SmokerFalse}) = 1.00
W(\theta_{CancerTrue|PollutionLow,SmokerTrue}) = 0.03
W(\neg \theta_{CancerTrue|PollutionLow,SmokerTrue}) = 1.00
W(\theta_{CancerFalse|PollutionLow,SmokerTrue}) = 0.97
W(\neg \theta_{CancerFalse|PollutionLow,SmokerTrue}) = 1.00
W(\theta_{CancerTrue|PollutionLow,SmokerFalse}) = 0.00
W(\neg \theta_{CancerTrue|PollutionLow,SmokerFalse}) = 1.00
W(\theta_{CancerFalse|PollutionLow,SmokerFalse}) = 1.00
W(\neg \theta_{CancerFalse|PollutionLow,SmokerFalse}) = 1.00
W(\theta_{CancerTrue|PollutionHigh,SmokerTrue}) = 0.05
W(\neg \theta_{CancerTrue|PollutionHigh,SmokerTrue}) = 1.00
W(\theta_{CancerFalse|PollutionHigh,SmokerTrue}) = 0.95
W(\neg \theta_{CancerFalse|PollutionHigh,SmokerTrue}) = 1.00
W(\theta_{CancerTrue|PollutionHigh,SmokerFalse}) = 0.02
W(\neg \theta_{CancerTrue|PollutionHigh,SmokerFalse}) = 1.00
W(\theta_{CancerFalse|PollutionHigh,SmokerFalse}) = 0.98
W(\neg \theta_{CancerFalse|PollutionHigh,SmokerFalse}) = 1.00
W(\theta_{XrayPositive|CancerTrue}) = 0.90
W(\neg \theta_{XrayPositive|CancerTrue}) = 1.00
W(\theta_{XrayNegative|CancerTrue}) = 0.10
W(\neg \theta_{XrayNegative|CancerTrue}) = 1.00
W(\theta_{XrayPositive|CancerFalse}) = 0.20
W(\neg \theta_{XrayPositive|CancerFalse}) = 1.00
W(\theta_{XrayNegative|CancerFalse}) = 0.80
W(\neg \theta_{XrayNegative|CancerFalse}) = 1.00
W(\theta_{DyspnoeaTrue|CancerTrue}) = 0.65
W(\neg \theta_{DyspnoeaTrue|CancerTrue}) = 1.00
W(\theta_{DyspnoeaFalse|CancerTrue}) = 0.35
W(\neg \theta_{DyspnoeaFalse|CancerTrue}) = 1.00
W(\theta_{DyspnoeaTrue|CancerFalse}) = 0.30
W(\neg \theta_{DyspnoeaTrue|CancerFalse}) = 1.00
W(\theta_{DyspnoeaFalse|CancerFalse}) = 0.70
W(\neg \theta_{DyspnoeaFalse|CancerFalse}) = 1.00
```

4.2 ENC2

Indicator clauses

```
 (\neg \lambda_{PollutionLow} \lor \neg \lambda_{PollutionHigh}) \land (\lambda_{PollutionLow} \lor \lambda_{PollutionHigh}) \land (\neg \lambda_{SmokerTrue} \lor \neg \lambda_{SmokerFalse}) \land (\lambda_{SmokerTrue} \lor \lambda_{SmokerFalse}) \land (\neg \lambda_{Smo
```

```
\lambda_{CancerTrue} \vee \neg \lambda_{CancerFalse}) \wedge (\lambda_{CancerTrue} \vee \lambda_{CancerFalse}) \wedge (\neg \lambda_{XrayPositive} \vee \neg \lambda_{XrayNegative}) \wedge (\lambda_{XrayPositive} \vee \lambda_{XrayNegative}) \wedge (\neg \lambda_{DyspnoeaTrue} \vee \neg \lambda_{DyspnoeaFalse}) \wedge (\lambda_{DyspnoeaTrue} \vee \lambda_{DyspnoeaFalse})
```

Parameter clauses

```
(\neg \rho_{PollutionLow} \lor \lambda_{PollutionLow}) \land (\rho_{PollutionLow} \lor \lambda_{PollutionHigh}) \land (\neg
        \rho_{SmokerTrue} \lor \lambda_{SmokerTrue}) \land (\rho_{SmokerTrue} \lor \lambda_{SmokerFalse}) \land (\neg
  \lambda_{PollutionLow} \vee \neg \lambda_{SmokerTrue} \vee \neg \rho_{CancerTrue|PollutionLow,SmokerTrue} \vee 
                   \lambda_{CancerTrue}) \wedge (\neg \lambda_{PollutionLow} \vee \neg \lambda_{SmokerTrue} \vee 
\rho_{CancerTrue|PollutionLow,SmokerTrue} \lor \lambda_{CancerFalse}) \land (\lnot \lambda_{PollutionLow} \lor \lnot
 \lambda_{SmokerFalse} \lor \neg \rho_{CancerTrue|PollutionLow,SmokerFalse} \lor \lambda_{CancerTrue}) \land (\neg
   \lambda_{PollutionLow} \vee \neg \lambda_{SmokerFalse} \vee \rho_{CancerTrue|PollutionLow,SmokerFalse} \vee
                \lambda_{CancerFalse}) \wedge (\neg \lambda_{PollutionHigh} \vee \neg \lambda_{SmokerTrue} \vee \neg
\rho_{CancerTrue|PollutionHigh,SmokerTrue} \lor \lambda_{CancerTrue}) \land (\neg \lambda_{PollutionHigh} \lor \neg
  \lambda_{SmokerTrue} \lor \rho_{CancerTrue|PollutionHigh,SmokerTrue} \lor \lambda_{CancerFalse}) \land (\lnot
\lambda_{PollutionHigh} \lor \lnot \lambda_{SmokerFalse} \lor \lnot \rho_{CancerTrue|PollutionHigh,SmokerFalse} \lor
                  \lambda_{CancerTrue}) \wedge (\neg \lambda_{PollutionHigh} \vee \neg \lambda_{SmokerFalse} \vee \neg \lambda_{SmokerFalse})
\rho_{CancerTrue|PollutionHigh,SmokerFalse} \lor \lambda_{CancerFalse}) \land (\lnot \lambda_{CancerTrue} \lor \lnot 
            \rho_{XrayPositive|CancerTrue} \lor \lambda_{XrayPositive}) \land (\neg \lambda_{CancerTrue} \lor )
         \rho_{XrayPositive|CancerTrue} \lor \lambda_{XrayNegative}) \land (\lnot \lambda_{CancerFalse} \lor \lnot
           \rho_{XrayPositive|CancerFalse} \vee \lambda_{XrayPositive}) \wedge (\neg \lambda_{CancerFalse} \vee
         \rho_{XrayPositive|CancerFalse} \vee \lambda_{XrayNegative}) \wedge (\neg \lambda_{CancerTrue} \vee \neg
          \rho_{DyspnoeaTrue|CancerTrue} \vee \lambda_{DyspnoeaTrue}) \wedge (\neg \lambda_{CancerTrue} \vee )
        \rho_{DyspnoeaTrue|CancerTrue} \lor \lambda_{DyspnoeaFalse}) \land (\lnot \lambda_{CancerFalse} \lor \lnot
         \rho_{DyspnoeaTrue|CancerFalse} \lor \lambda_{DyspnoeaTrue}) \land (\lnot \lambda_{CancerFalse} \lor )
                         \rho_{DyspnoeaTrue|CancerFalse} \lor \lambda_{DyspnoeaFalse})
```

Weights

 $W(\lambda_{PollutionLow}) = 1.00$ $W(\neg \lambda_{PollutionLow}) = 1.00$ $W(\lambda_{PollutionHigh}) = 1.00$ $W(\neg \lambda_{PollutionHigh}) = 1.00$ $W(\lambda_{SmokerTrue}) = 1.00$ $W(\neg \lambda_{SmokerTrue}) = 1.00$ $W(\lambda_{SmokerFalse}) = 1.00$ $W(\neg \lambda_{SmokerFalse}) = 1.00$ $W(\lambda_{CancerTrue}) = 1.00$ $W(\neg \lambda_{CancerTrue}) = 1.00$ $W(\lambda_{CancerFalse}) = 1.00$ $W(\neg \lambda_{CancerFalse}) = 1.00$ $W(\lambda_{XrayPositive}) = 1.00$ $W(\neg \lambda_{XrayPositive}) = 1.00$ $W(\lambda_{XrayNegative}) = 1.00$ $W(\neg \lambda_{XrayNegative}) = 1.00$ $W(\lambda_{DyspnoeaTrue}) = 1.00$ $W(\neg \lambda_{DyspnoeaTrue}) = 1.00$ $W(\lambda_{DyspnoeaFalse}) = 1.00$ $W(\neg \lambda_{DyspnoeaFalse}) = 1.00$ $W(\rho_{PollutionLow}) = 0.90$ $W(\neg \rho_{PollutionLow}) = 0.10$

```
W(\rho_{SmokerTrue}) = 0.30
W(\neg \rho_{SmokerTrue}) = 0.70
W(\rho_{CancerTrue|PollutionLow,SmokerTrue}) = 0.03
W(\neg \rho_{CancerTrue|PollutionLow,SmokerTrue}) = 0.97
W(\rho_{CancerTrue|PollutionLow,SmokerFalse}) = 0.00
W(\neg \rho_{CancerTrue|PollutionLow,SmokerFalse}) = 1.00
W(\rho_{CancerTrue|PollutionHigh,SmokerTrue}) = 0.05
W(\neg \rho_{CancerTrue|PollutionHigh,SmokerTrue}) = 0.95
W(\rho_{CancerTrue|PollutionHigh,SmokerFalse}) = 0.02
W(\neg \rho_{CancerTrue|PollutionHigh,SmokerFalse}) = 0.98
W(\rho_{XrayPositive|CancerTrue}) = 0.90
W(\neg \rho_{XrayPositive|CancerTrue}) = 0.10
W(\rho_{XrayPositive|CancerFalse}) = 0.20
W(\neg \rho_{XrayPositive|CancerFalse}) = 0.80
W(\rho_{DyspnoeaTrue|CancerTrue}) = 0.65
W(\neg \rho_{DyspnoeaTrue|CancerTrue}) = 0.35
```

 $W(\rho_{DyspnoeaTrue|CancerFalse}) = 0.30$ $W(\neg \rho_{DyspnoeaTrue|CancerFalse}) = 0.70$

Bibliography

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