Generating Random WMC Instances An Empirical Analysis with Varying Primal Treewidth

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Weighted Model Counting (WMC)

 A generalisation of propositional model counting (#SAT)

Example

$$w(x) = 0.3, w(\neg x) = 0.7,$$

 $w(y) = 0.2, w(\neg y) = 0.8$

WMC(
$$x \lor y$$
) = $w(x)w(y)$ +
 $w(x)w(\neg y) + w(\neg x)w(y) = 0.44$

Weighted Model Counting (WMC)

- A generalisation of propositional model counting (#SAT)
- Applications:
 - graphical models
 - probabilistic programming
 - neural-symbolic artificial intelligence

Example

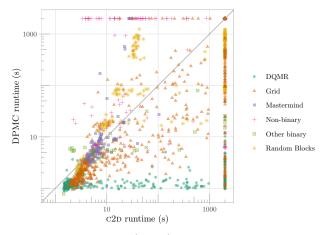
$$w(x) = 0.3, \ w(\neg x) = 0.7, w(y) = 0.2, \ w(\neg y) = 0.8$$

$$WMC(x \lor y) = w(x)w(y) + w(x)w(\neg y) + w(\neg x)w(y) = 0.44$$

(Some of the) WMC Algorithms

- ► CACHET (Sang et al. 2004)
 - component caching
- ► C2D (Darwiche 2004)
 - knowledge compilation to d-DNNF
- ▶ D4 (Lagniez and Marquis 2017)
 - knowledge compilation to decision-DNNF
- MINIC2D (Oztok and Darwiche 2015)
 - knowledge compilation to decision sentential decision diagrams
- ▶ DPMC (Dudek, Phan and Vardi 2020)
 - dynamic programming with algebraic decision diagrams (ADDs) and tree decomposition based planning

The Performance Characteristics of WMC Algorithms



Data from Dilkas and Belle (2021): various Bayesian networks encoded using the method by Darwiche (2002)

Formula in CNF:

$$\phi = (\mathbf{x_4} \vee \neg \mathbf{x_3} \vee \mathbf{x_1}) \wedge (\neg \mathbf{x_2} \vee \mathbf{x_4}) \wedge (\neg \mathbf{x_1} \vee \mathbf{x_2} \vee \mathbf{x_4})$$

Formula in CNF:

$$\phi = (x_4 \vee \neg x_3 \vee x_1) \wedge (\neg x_2 \vee x_4) \wedge (\neg x_1 \vee x_2 \vee x_4)$$

Its primal graph:

$$X_1 - X_2$$
 $X_3 - X_4$

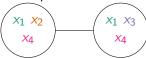
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Its primal graph:



Its minimum-width tree decomposition:



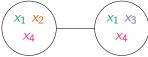
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Its primal graph:



Its minimum-width tree decomposition:



 \therefore the primal treewidth of ϕ is 2

The Parameterised Complexity of WMC Algorithms

Let n be the number of variables and m be the number of clauses.

- ► Component caching (used in CACHET) is $2^{\mathcal{O}(w)}n^{\mathcal{O}(1)}$, where w is the branchwidth of the underlying hypergraph (Bacchus, Dalmao and Pitassi 2009)
 - Branchwidth is within a constant factor of primal treewidth
- ▶ C2D is based on an algorithm, which is $\mathcal{O}(2^w mw)$, where w is at most primal treewidth (Darwiche 2001; Darwiche 2004)
- ▶ DPMC can be shown to be $\mathcal{O}(4^w mn)$, where w is an upper bound on primal treewidth

Generating Random WMC Instances: The Algorithm

```
\phi \leftarrow \text{empty CNF formula};
  G \leftarrow \text{empty graph};
X \leftarrow \emptyset:
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            clauses
                               x \leftarrow \text{newVariable}(X, G); \leftarrow 
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         a function to
                                                            \mathcal{V}(G) \leftarrow \mathcal{V}(G) \cup \{x\}:
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            pick a variable
                                                         \mathcal{E}(G) \leftarrow \mathcal{E}(G) \cup \{\{x,y\} \mid y \in X\};
                                                                                                                                                                                                                                                                                                                                                                                                               → a (fair) coin flip
                                        X \leftarrow X \cup \{x\};

\phi \leftarrow \phi \cup \{\{I \hookleftarrow \mathcal{U}\{x, \neg x\} \mid x \in X\}\}; \checkmark
```

How to Pick a Variable

Parameter $\rho \in [0,1]$ biases the probability distribution towards adding variables that would introduce fewer new edges.

Function newVariable(set of variables X, primal graph G):

```
N \leftarrow \{e \in \mathcal{E}(G) \mid |e \cap X| = 1\};
if N = \emptyset then return x \hookleftarrow \mathcal{U}(\{x_1, x_2, \dots, x_n\} \setminus X);
return
x \hookleftarrow \left(\{x_1, x_2, \dots, x_n\} \setminus X, y \mapsto \frac{1-\rho}{n-|X|} + \rho \frac{|\{z \in X \mid \{y,z\} \in \mathcal{E}(G)\}|}{|N|}\right);
```

An Example

Setup

Let n = 5, k = 3, and $\rho = 0.3$.

Partial formula: $(\neg x_5 \lor x_2 \lor x_1) \land (x_5 \lor ?)$.



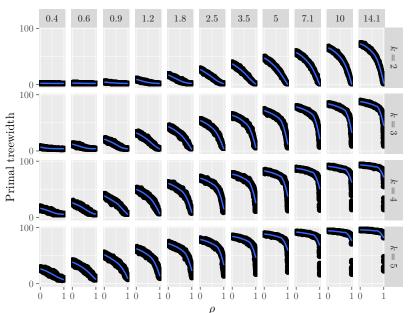
The probability distribution for the next variable

Base probability of each variable being chosen:

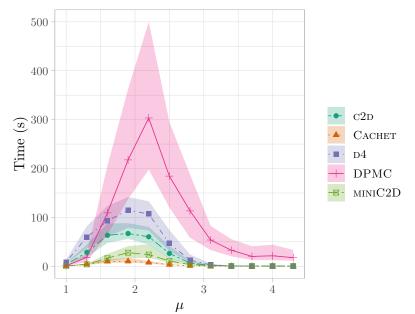
$$\frac{1-\rho}{n-|X|} = \frac{1-0.3}{5-1} = 0.175.$$

Both x_1 and x_2 get a bonus probability of $\rho/2$ for each being the endpoint of one out of the two neighbourhood edges.

The Relationship Between ρ and Primal Treewidth



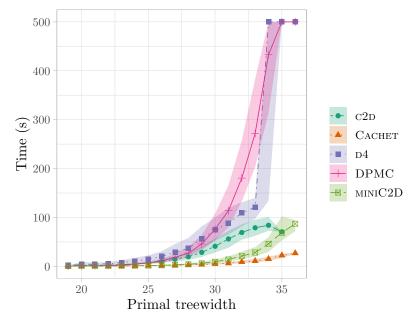
Hardness w.r.t. Density (when $\rho = 0$)



Peak Hardness w.r.t. Density

- In our experiments:
 - ▶ DPMC peaks at $\mu = 2.2$
 - \blacktriangleright all other algorithms peak at $\mu=1.9$
- ► CACHET is known to peak at $\mu = 1.8$ (Sang et al. 2004)
- ▶ Bayardo Jr. and Pehoushek (2000) show some #SAT algorithms to peak at $\mu=1.2$ and $\mu=1.9$

Hardness w.r.t. Primal Treewidth (when $\mu=1.9$)



Is The Relationship Exponential?

Let us fit the model $\ln t \sim \alpha w + \beta$, i.e., $t \sim e^{\beta} (e^{\alpha})^w$, where t is runtime, and w is primal treewidth

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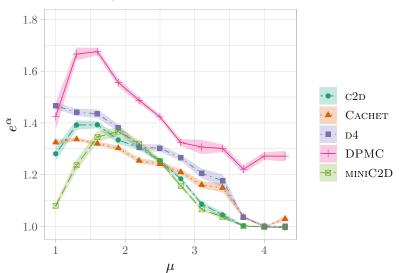
Let us fit the model $\ln t \sim \alpha w + \beta$, i.e., $t \sim e^{\beta} (e^{\alpha})^w$, where t is runtime, and w is primal treewidth

4.3 -	0.62	0.33	1	0.94	0.53
4 -	0.19	0.49	0	0.97	0.43
3.7 -	0.57	0.71	0.83	0.94	0.18
3.4 -	0.47	0.85	0.8	0.97	0.53
3.1 -	0.88	0.92	0.91	0.91	0.9
2.8-	0.97	0.96	0.98	0.98	0.95
2.5 -	0.98	0.98	0.97	1	0.98
2.2 -	0.99	0.98	0.98	0.99	0.98
1.9 -	0.98	0.99	0.98	0.99	0.98
1.6 -	0.99	0.99	0.98	1	0.96
1.3 -	0.98	1	0.99	0.99	0.9
1 -	0.91	0.99	0.99	0.87	0.79
	c2d	Cachet	D4	DPMC	MINIC2D



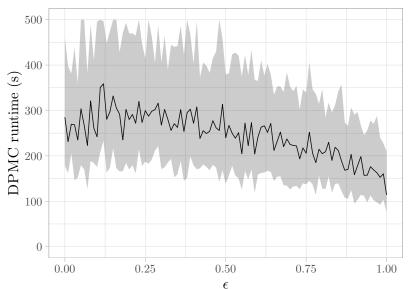
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Bonus: How DPMC Reacts to Redundancy in Weights

Let ϵ be the proportion of variables x s.t. $w(x) = w(\neg x) = 0.5$



Summary

Observations

- ► All algorithms scale exponentially w.r.t. primal treewidth
- ► The running time of DPMC peaks at a higher density and scales worse w.r.t. primal treewidth
- ► MINIC2D seems to be best on low density high primal treewidth instances

Future work

- \triangleright A theoretical relationship between ρ and primal treewidth
- ▶ Non-k-CNF instances
- Algorithm portfolios for WMC