# Generating Random WMC Instances An Empirical Analysis with Varying Primal Treewidth

#### Paulius Dilkas

National University of Singapore, Singapore

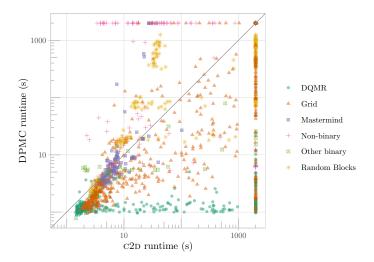
30th May 2024







# Which Algorithm Is Better? It Depends on the Data



The runtime data is from Dilkas and Belle (2021): various Bayesian networks encoded using the approach by Darwiche (2002)

# The Problem: Weighted Model Counting (WMC)

- A generalisation of propositional model counting (#SAT)
- Applications:
  - graphical models
  - probabilistic programming
  - neuro-symbolic Al
- WMC algorithms use:
  - dynamic programming
  - knowledge compilation
  - SAT solvers

## 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)
  - a SAT solver with clause learning and 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 and tree decomposition based planning

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- Q: Why am I giving a talk about this now?



#### Formula in CNF:

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

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### Its primal graph:

$$\begin{array}{c|c} x_1 & - & x_2 \\ & & & \\ x_3 & - & x_4 \end{array}$$

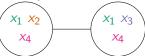
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## Its primal graph:

$$X_1 \longrightarrow X_2$$
 $X_3 \longrightarrow X_4$ 

# Its minimum-width tree decomposition:



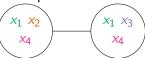
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## Its primal graph:

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

Its minimum-width tree decomposition:



 $\therefore$  the primal treewidth of  $\phi$  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

## From Random SAT to Random WMC

We introduce parameter  $\rho \in [0,1]$  that biases the probability distribution towards adding variables that would introduce fewer new edges to the primal graph.

Example partially-filled formula:

$$(\neg x_5 \lor x_2 \lor x_1) \land (x_5 \lor ? \lor ?)$$





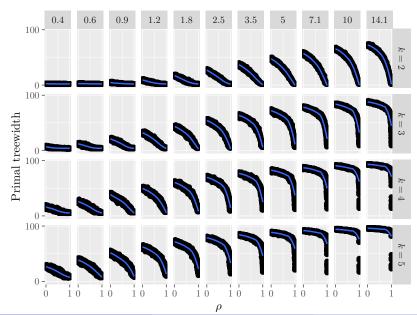
## The probability distribution for the next variable

Base probability of each variable being chosen:

$$\frac{1-\rho}{4}$$

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 $\rho$ and Primal Treewidth



## Peak Hardness w.r.t. Density

Let  $\mu$  denote the density, i.e., the number of clauses divided by the number of variables.

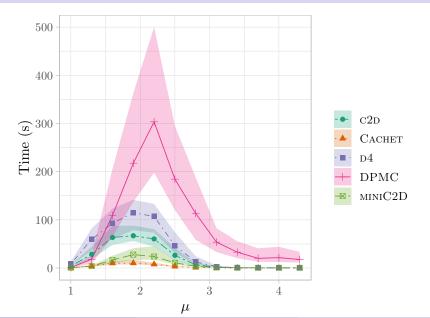
- CACHET is known to peak at  $\mu = 1.8$  (Sang et al. 2004)
- $\bullet$  Bayardo Jr. and Pehoushek (2000) show some #SAT algorithms to peak at  $\mu=1.2$  and  $\mu=1.9$

# Peak Hardness w.r.t. Density

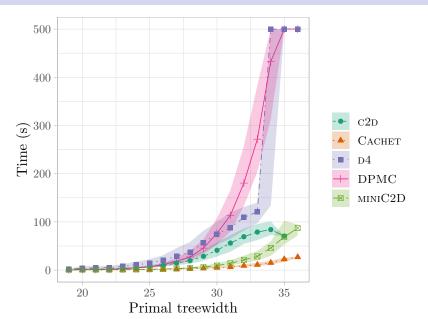
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- In our experiments:
  - DPMC peaks at  $\mu = 2.2$
  - ullet all other algorithms peak at  $\mu=1.9$

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



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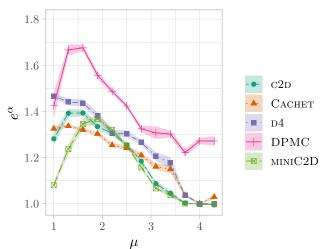
Let us fit the model  $\ln t \sim \alpha w + \beta$ , i.e.,  $t \sim e^{\beta} (e^{\alpha})^{w}$ , where t is runtime, and w is primal treewidth

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
3.8-	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	Саснет	D4	DPMC	MINIC2D

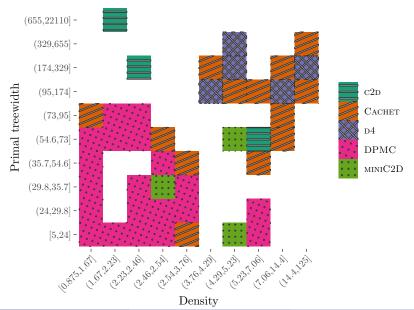
$$R^2$$
 0.25 0.50 0.75 1.00

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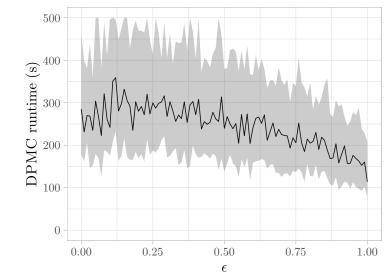


## Does Real Data Confirm Our Observations?



# Bonus: How DPMC Reacts to Redundancy in Weights

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



## Summary

- This work introduced a random model for WMC instances with a parameter that indirectly controls primal treewidth
- 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
- Future work:
  - ullet A theoretical relationship between ho and primal treewidth
  - Non-k-CNF instances
  - Algorithm portfolios for WMC

# Generating Random WMC Instances: The Algorithm

```
\phi \leftarrow \text{empty CNF formula};
G \leftarrow \text{empty graph};
for i \leftarrow 1 to m do \leftarrow ----- • the number of
                               X \leftarrow \emptyset:
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  clauses
                             for i \leftarrow 1 to k do \leftarrow
                                                            x \leftarrow \text{newVariable}(X, G); \leftarrow 
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             clause width
                                                           \mathcal{V}(G) \leftarrow \mathcal{V}(G) \cup \{x\};
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  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 \leadsto \mathcal{U}\{x, \neg x\} \mid x \in X\}\}\}
```

## 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):

```
\begin{split} & N \leftarrow \{\, e \in \mathcal{E}(G) \mid |e \cap X| = 1 \,\}; \\ & \text{if } N = \emptyset \text{ then return } x \leadsto \mathcal{U}(\{\, x_1, x_2, \ldots, x_n \,\} \setminus X); \\ & \text{return} \\ & x \leadsto \left( \{\, x_1, x_2, \ldots, 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); \end{split}
```