SharpSAT-TD: Improving SharpSAT by Exploiting Tree Decompositions

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SharpSAT-TD

- New modification of SharpSAT [Thurley '06]
    1. Integrates low-width tree decompositions to the variable selection heuristic
    2. Implements new preprocessor
    3. Directly supports weighted model counting

MCC-2021 Results on Public Instances

solver	config	solved
sharp-tw-unweighted	default	83/100
Narsimha	track1_conf2.sh	69/100
Narsimha	track1_conf1.sh	61/100
d4	TRACK1+4_ds_preprocSharpEquiv.sh	59/100
d4	TRACK1+4_ms_preprocSharpEquiv.sh	57/100
TwG	2.sh	38/100

solver	config	solved
sharp-tw-weighted	default	99/100
d4	TRACK2+3ds_preprocEquiv.sh	81/100
d4	TRACK2+3_ms_preprocEquiv.sh	81/100
c2d	default	74/100
Narsimha	track2_conf1.sh	72/100

solver	config	solved
Narsimha	track4_conf2.sh	69/100
sharp-tw-unweighted	default	69/100
Narsimha	track4_conf1.sh	68/100
d4	TRACK1+4_ds_preprocSharpEquiv.sh	57/100
d4	TRACK1+4_ms_preprocSharpEquiv.sh	57/100
dpmc4fix	4	49/100

Overview

Overview of SharpSAT-TD

1. Preprocess
2. Compute a tree decomposition with FlowCutter [Strasser '17]
3. Count using tree decomposition guided variable selection

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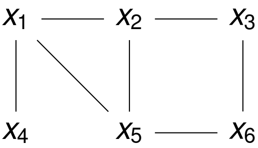
I will first talk about (3), then about (1), and then about other changes compared to SharpSAT

Tree Decompositions

$$(\neg x_2 \vee x_3) \wedge (x_3 \vee \neg x_6) \wedge (x_5 \vee x_6) \wedge (x_1 \vee \neg x_2 \vee x_5) \wedge (x_1 \vee \neg x_4)$$



Primal graph

Tree Decompositions

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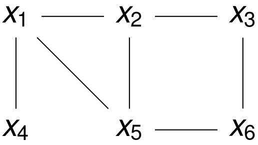
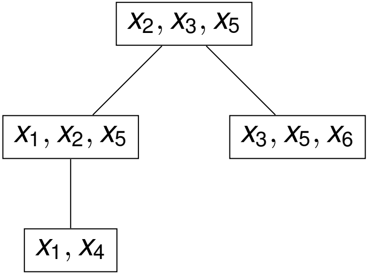


Primal graph



Tree decomposition

Tree Decompositions

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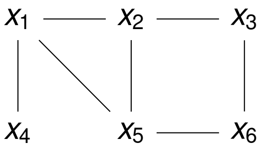
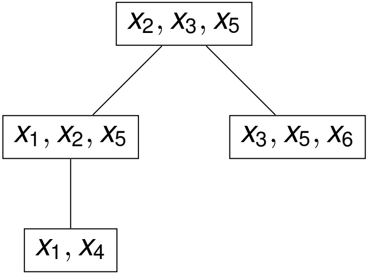


Primal graph



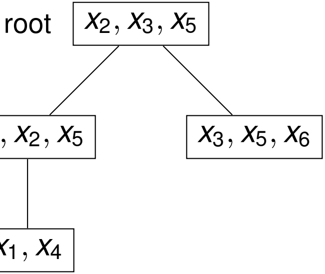
Tree decomposition

- Width of a tree decomposition: Size of the largest bag -1
- Treewidth of a graph/CNF: Minimum width of a tree decomposition

Tree Decomposition Guided Variable Selection

- Select the variable of the active formula that appears the closest to the root in the tree decomposition

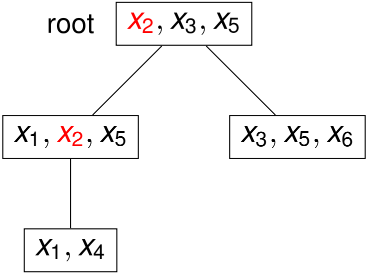
$$(\neg x_2 \vee x_3) \wedge (x_3 \vee \neg x_6) \wedge (x_5 \vee x_6) \wedge (x_1 \vee \neg x_2 \vee x_5) \wedge (x_1 \vee \neg x_4)$$



Tree Decomposition Guided Variable Selection

- Select the variable of the active formula that appears the closest to the root in the tree decomposition

$$(x_3) \land (x_3 \lor \neg x_6) \land (x_5 \lor x_6) \land (x_1 \lor x_5) \land (x_1 \lor \neg x_4)$$



$x_2 = 1,$

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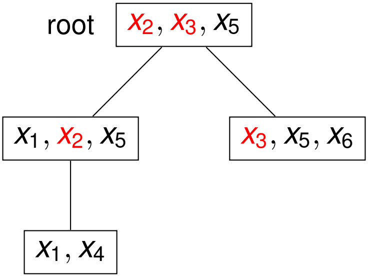
$$(x_5 \vee x_6) \wedge (x_1 \vee \neg x_2 \vee x_5) \wedge (x_1 \vee \neg x_4)$$



$x_2 = 1, \quad x_3 = 1,$

Tree Decomposition Guided Variable Selection

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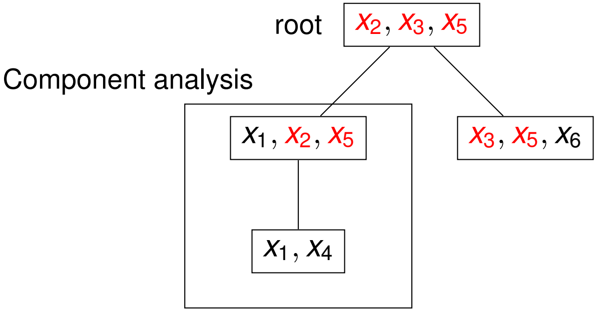
$$(x_1 \vee \neg x_4)$$



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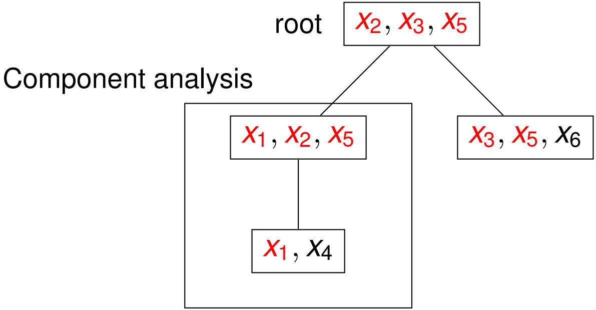

$x_2 = 1, \quad x_3 = 1, \quad x_5 = 1, \quad x_1 = 1$

Theoretical Background

Proposition ([BDP03, Dar01])

Standard #DPLL algorithm, with component analysis and component caching, works in $2^w \mathrm{poly}(|\phi|)$ time when using a tree decomposition of width w for variable selection.

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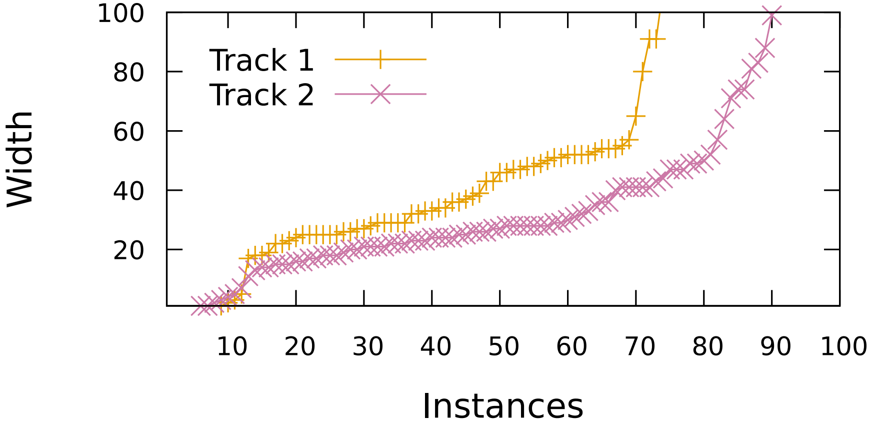

Implementation of Variable Selection

Variable x with highest $\texttt{score}(x)$ is selected.

Standard SharpSAT:

$$\texttt{score}(x) = \texttt{act}(x) + \texttt{freq}(x)$$

Where

- $\texttt{act}(x)$ is VSIDS-like activity score
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SharpSAT-TD:

$$\mathtt{score}(x) = \mathtt{act}(x) + \mathtt{freq}(x) - C \cdot d(x)$$

Where

- $\mathtt{act}(x)$ is VSIDS-like activity score
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- $d(x)$ is the distance from root of tree decomposition to closest bag containing x
- C is some positive constant

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  - C chosen per-instance based on the width of the tree decomposition

Preprocessing

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1. Complete vivification (minimalize each clause, with SAT solver)
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3. Equivalent variable merging (treewidth-aware)
4. Re-implementation of B+E [LLM16] (treewidth-aware)

Other Modifications

- “Implicit BCP” disabled
- LBD learned clause scoring scheme [AS09]
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- Probabilistic component caching [SRSM19]
- Extension to weighted model counting via template parameters – easily extensible to model counting over any semiring

The end

Thank you for your attention!

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