UpMax: User partitioning for MaxSAT

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Partitioning of MaxSAT Formulae

Hard:	$h_1 : (v_1 \vee v_2)$	$h_2 : (\neg v_2 \vee v_3)$	$h_3 : (\neg v_1 \vee \neg v_3)$	$h_4 : (v_4 \vee v_5)$
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Soft:	$s_1 : (\neg v_1)$	$s_2 : (\neg v_3)$	$s_3 : (\neg v_4)$	$s_4 : (\neg v_6)$

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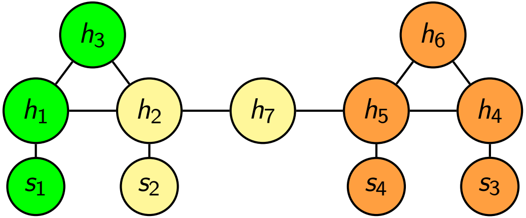
- Instead of dealing with the whole formula at once, some MaxSAT algorithms try to **split the formula into partitions** [Martins et al., 2012].



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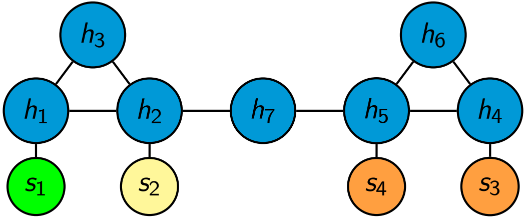
- In particular, the partitioning focuses on **splitting the set of soft clauses into disjoint sets**.



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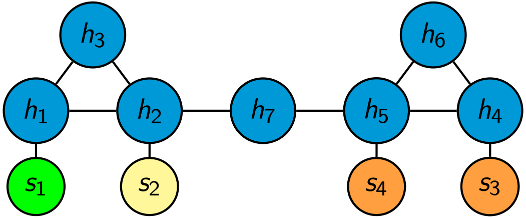
- quickly identify a minimal cost;
- easier to solve;
- faster convergence to the optimum.



Partitioning of MaxSAT Formulae

There have been proposed several types of automatic partitioning methods, such as:

- Partitioning of soft clauses according to their weight [Ansotegui et al., 2012];

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- Partitioning of soft clauses according to their weight [Ansotegui et al., 2012];
- Graph-based partitioning of partial MaxSAT formulae [Neves et al., 2015].

Partitioning of MaxSAT Formulae

Current Drawbacks

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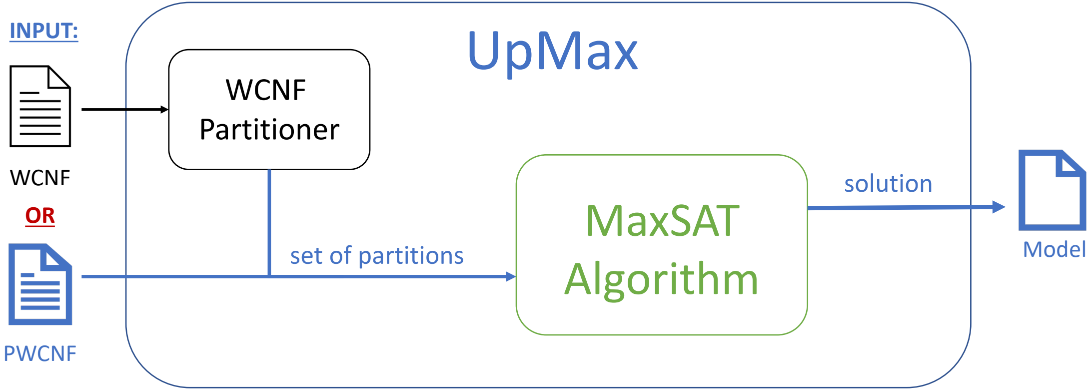
5. The `wcnf` **format does not support the users to provide a partitioning scheme**.


INPUT:
WCNF
OR
PWCNF
UpMax
WCNF
Partitioner
set of partitions
MaxSAT
Algorithm
solution
Model

pwcnf format

- The pwcnf format starts with a header:

```
p pwcnf n_vars n_clauses topw n_part
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- and each line in the body is of the form:

```
[part] [weight] [literals*] 0
```

Use Cases

Use Case: Minimum Sum Coloring (MSC)

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  - Each vertex should be assigned exactly one color;
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- **Goal:** minimize the number of different colors in the graph.

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- X_c^v is true if color c is assigned to vertex v.
- **Goal (soft clauses):** Maximize $\neg X_c^v$ (weight $= c$).

Use Case: Minimum Sum Coloring (MSC)

Example

Given a graph G with 4 vertices, $v_1, \ldots, v_4$, and 4 different colors available $c_1, \ldots, c_4$.

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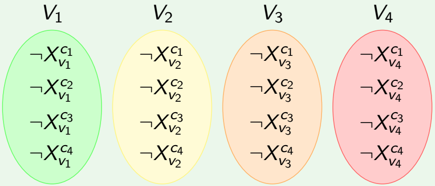
VERTEX-based



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COLOR-based

C_1	C_2	C_3	C_4
$\neg X_{v_1}^{c_1}$	$\neg X_{v_1}^{c_2}$	$\neg X_{v_1}^{c_3}$	$\neg X_{v_1}^{c_4}$
$\neg X_{v_2}^{c_1}$	$\neg X_{v_2}^{c_2}$	$\neg X_{v_2}^{c_3}$	$\neg X_{v_2}^{c_4}$
$\neg X_{v_3}^{c_1}$	$\neg X_{v_3}^{c_2}$	$\neg X_{v_3}^{c_3}$	$\neg X_{v_3}^{c_4}$
$\neg X_{v_4}^{c_1}$	$\neg X_{v_4}^{c_2}$	$\neg X_{v_4}^{c_3}$	$\neg X_{v_4}^{c_4}$

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We want to seat persons at tables such that the following properties are met:

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Goal: minimize the number of different tags between all persons seated at the same table.

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Consider that a user wants to seat 5 persons, $p_1, \ldots, p_5$, in two tables t_1, t_2. Moreover, the set of different tags is $\{$A, B, C$\}$.

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TAGS-based

A	B	C
$\neg Y^{A}_{t_1}$	$\neg Y^{B}_{t_1}$	$\neg Y^{C}_{t_1}$
$\neg Y^{A}_{t_2}$	$\neg Y^{B}_{t_2}$	$\neg Y^{C}_{t_2}$

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TABLES-based

t_1	t_2
$\neg Y_{t_1}^{A}$	$\neg Y_{t_2}^{A}$
$\neg Y_{t_1}^{B}$	$\neg Y_{t_2}^{B}$
$\neg Y_{t_1}^{C}$	$\neg Y_{t_2}^{C}$

Implementation

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- UpMax supports the new format `pwcnf` for user-based partitioning.
- It can also take as **input a `wcnf`** formula and **output a `pwcnf`** formula using an automatic partitioning strategy based on:
  - VIG;
  - CVIG;
  - RES;
  - randomly splitting the formula into k partitions.

UpMax

- UpMax currently supports **three UNSAT-based algorithms** (**WBO** [Manquinho et al., 2009], **OLL** [Morgado et al., 2014], and **MSU3** [Martins et al., 2014 (b)]) for both unweighted and weighted problems that take advantage of the partitions;

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- We have also extended **RC2** [Ignatiev et al., 2019] and **Hitman** [Moreno-Centeno et al., 2013], available in PySAT [Ignatiev et al., 2018], to use our `pwcnf` formulae.

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- Partitioning strategies used:
  - Graph-based partitions (VIG, CVIG, RES);
  - Random partitioning strategy ($k = 16$);
  - User-based partitions (UP):
    - *VERTEX/COLOR-based* partitions (MSC);
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- All of the experiments were run on StarExec [Stump et al., 2014], with a timeout of 1800 seconds and a memory limit of 32 GB.

Use Case: Minimum Sum Coloring

Table: Number of solved instances for the Minimum Sum Coloring (MSC) problem.

		User Part.		Graph Part.			
Solver	**No Part.**	**Vertex**	**Color**	**VIG**	**CVIG**	**RES**	**Random**
MSU3	245	758	770	774	770	775	**776**
OLL	796	863	594	945	944	**947**	756
WBO	483	622	314	745	750	**755**	493
Hitman	610	613	471	605	**614**	609	592
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MaxSAT Eval 2022:

- EvalMaxSAT: 729; MaxHS: 873; CASHWMaxSAT: 993;
- UWrMaxSat: 994; **MaxCDCL: 995**.

Use Case: Seating Assignment

Table: Number of solved instances for the Seating Assignment problem.

		User Part.		Graph Part.			
Solver	**No Part.**	**Table**	**Tag**	**VIG**	**CVIG**	**RES**	**Random**
MSU3	558	**671**	639	659	641	640	565
OLL	526	**634**	624	627	599	608	528
WBO	306	400	**536**	400	385	386	360
Hitman	420	403	**510**	406	425	420	440
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- UpMax allows users to specify how to **partition MaxSAT formulae based on their domain knowledge** with the `pwcnf` format.
- Experimental results with two use cases with 5 algorithms (MSU3, WBO, OLL, RC2, Hitman), show that **partitioning can improve the performance of MaxSAT algorithms**.

To conclude

- In this paper, we propose UpMax, a new framework that decouples the partition generation from the MaxSAT solving.
- UpMax allows users to specify how to **partition MaxSAT formulae based on their domain knowledge** with the `pwcnf` format.
- Experimental results with two use cases with 5 algorithms (MSU3, WBO, OLL, RC2, Hitman), show that **partitioning can improve the performance of MaxSAT algorithms**.
- Check **Alloy$^{\text{Max}}$ [Zhang et al., 2021]** paper for UpMax's results on other application domains.

UpMax

GitHub

arXiv

UpMax

GitHub

arXiv

Thank you!

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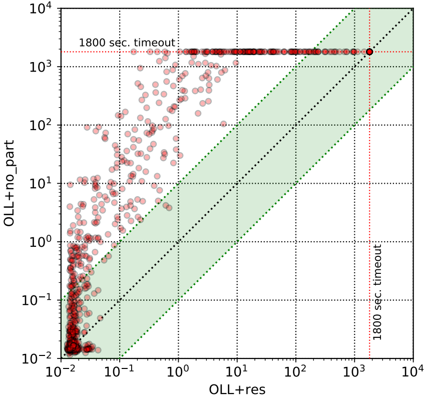
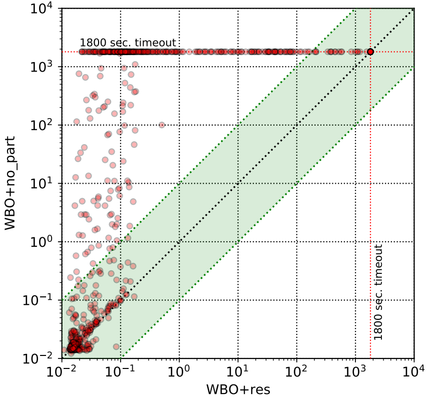
Appendix

MSC: Scatter plots



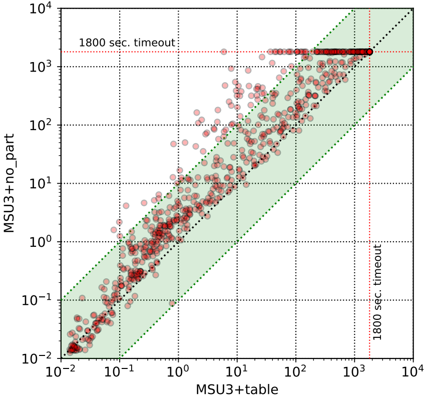
(a) MSC - OLL RES VS No Part.



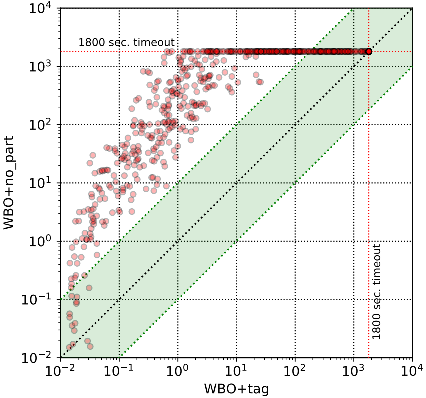
(b) MSC - WBO RES VS No Part.

Figure: Scatter plots comparing different MaxSAT algorithms and respective partitioning schemes for the Minimum Sum Coloring (MSC) problem.

SA: Scatter plots



(a) SA - MSU3 Table VS No Part.



(b) SA - WBO Tag VS No Part.

Figure: Scatter plots comparing different MaxSAT algorithms and respective partitioning schemes for the Seating Assignment (SA) problem.

MSC: Cactus plot

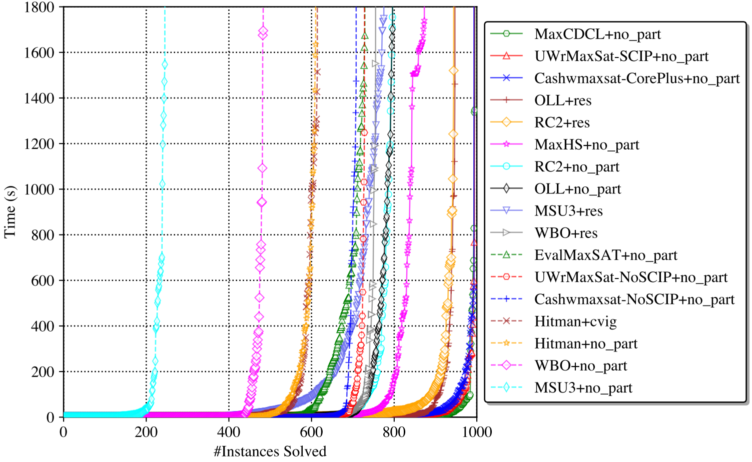


Figure: Cactus plot - The number of instances solved for the MSC problem for each MaxSAT algorithm and partitioning scheme.

SA: Cactus plot

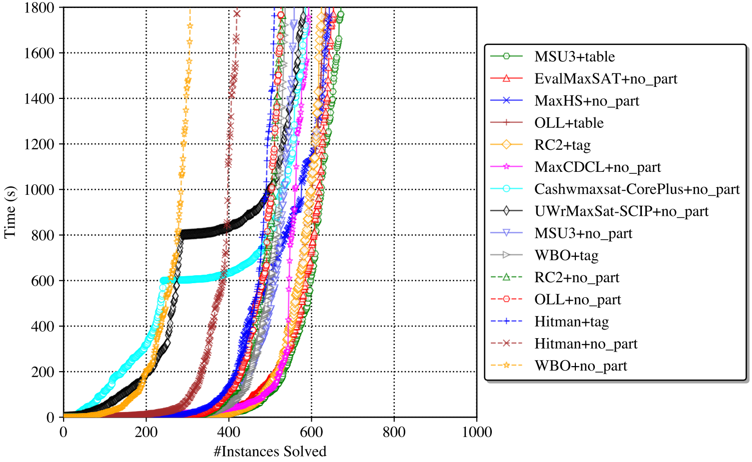


Figure: Cactus plot - The number of instances solved for the Seating Assignment problem for each MaxSAT algorithm and partitioning scheme.

Variable Incidence Graph (VIG)

Hard:	$h_1 : (v_1 \lor v_2)$	$h_2 : (\neg v_2 \lor v_3)$	$h_3 : (\neg v_1 \lor \neg v_3)$	$h_4 : (v_4 \lor v_5)$
	$h_5 : (\neg v_5 \lor v_6)$	$h_6 : (\neg v_4 \lor \neg v_6)$	$h_7 : (\neg v_3 \lor \neg v_6)$	
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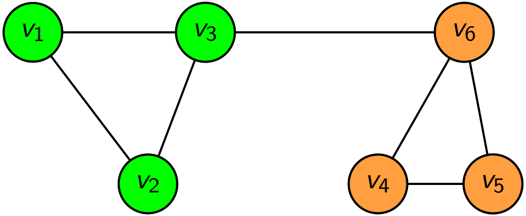

Clause-Variable Incidence Graph (CVIG)

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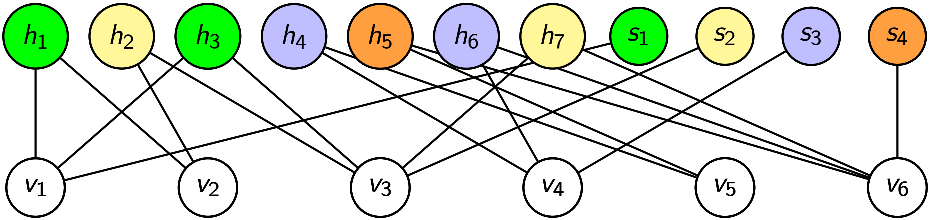

Resolution-based Graphs (RES)

Hard: $h_1 : (v_1 \vee v_2)$ $h_2 : (\neg v_2 \vee v_3)$ $h_3 : (\neg v_1 \vee \neg v_3)$ $h_4 : (v_4 \vee v_5)$
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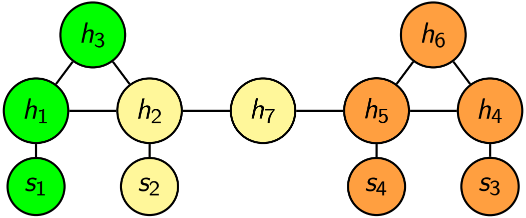

The Boolean Satisfiability Problem

Given a CNF formula ϕ, the Satisfiability (SAT) problem corresponds to decide if there is an assignment such that ϕ is satisfied or prove that no such assignment exists.

$$\phi: \quad c_1 : (v_1 \vee v_2) \qquad c_2 : (\neg v_2 \vee v_3) \qquad c_3 : (\neg v_1 \vee \neg v_3)$$

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The Maximum Satisfiability Problem

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Soft:	$s_1 : (\neg v_1)$	$s_2 : (\neg v_3)$	

The Maximum Satisfiability Problem

- The Maximum Satisfiability (MaxSAT) is an optimization version of the SAT problem.
- In partial MaxSAT, clauses in ϕ are split in hard and soft clauses.
- Given a formula ϕ, the goal is to find an assignment that satisfies all hard clauses while minimizing the number of unsatisfied soft clauses.

Hard:	$h_1 : (v_1 \vee v_2)$	$h_2 : (\neg v_2 \vee v_3)$	$h_3 : (\neg v_1 \vee \neg v_3)$
Soft:	$s_1 : (\neg v_1)$	$s_2 : (\neg v_3)$	
Solution :	v_1	$\neg v_2$	$\neg v_3$

$s_1 \vee s_2 \longrightarrow \text{Cost} = 1$