

Ordered Objectives in MaxSAT

...or when Core-Based MaxSAT Solvers trivialize

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Pragmatics of SAT 2025

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Motivation

- **MaxSAT** effective optimization paradigm
- Many different optimization algorithms.
 - ▶ **Focus here: core-based algorithms**
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$$\begin{array}{l} \min \sum_{k=1}^n b_k \\ \mathbf{s.t.} \bigwedge_{k=1}^n \text{AsCNF}((z \geq k) \leftrightarrow b_k) \end{array}$$

$$\begin{array}{l} \min \sum_{k=1}^n k \cdot b_k \\ \mathbf{s.t.} \bigwedge_{k=1}^n \text{AsCNF}((z = k) \leftrightarrow b_k) \end{array}$$

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Motivating Example

Cherrypicked instances from MSE 2024

	EvalMaxSAT-SCIP	EvalMaxSAT-No-SCIP	MaxCDCL	Pacose
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TWComp_1dj7_N73.wcnf	1873.42	1979.39	time-out	992.786
TWComp_1en2_N69.wcnf	694.287	737.122	192.768	122.647
TWComp_alarm_N37.wcnf	407.608	407.94	0.8584	0.1516
TWComp_barle_N48.wcnf	422.69	423.961	9.9443	5.7515
TWComp_barley2_N48.wcnf	422.692	424.69	8.7948	5.5337
TWComp_celar02_N100.wcnf	21.4879	61.0337	62.3124	5.8777
TWComp_david_N87.wcnf	49.522	73.1067	59.1008	39.7042
TWComp_david-pp_N29.wcnf	407.066	409.255	2.8107	1.0676
TWComp_hailfinder_N56.wcnf	415.449	418.585	7.7852	0.681
TWComp_mulsol.i.5-pp_N119.wcnf	271.462	356.17	110.219	58.4436
TWComp_myciel4_N23.wcnf	445.474	446.461	18.7783	4.5929
TWComp_oesoca4_N42.wcnf	407.397	408.166	2.4268	0.2316
TWComp_queen5_5_N25.wcnf	3449.75	3277.26	time-out	2615.84
TWComp_ship-ship-pp_N30.wcnf	608.28	611.835	96.8401	28.6641
TWComp_water_N32.wcnf	407.288	412.129	1.2079	1.4856

- **(Almost-)Ordered objectives**

- ▶ Relation to MUSEs and optimal solutions
- ▶ Large prevalence in MSE and literature.
- ▶ Core-based search trivializes in theory
- ▶ ... and in practice

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	Simple-US	EvalNoSCIP	MaxHS	MaxCDCL	Pacose
Treewidth (287)	136	126	133	115	85
Judgment Aggregation (50)	27	19	23	21	13
Graph Coloring (415)	386	387	387	385	380
MSE (weighted) (17)	14	13	14	12	11
MSE (unweighted) (108)	86	83	86	81	70

(Weighted Partial) Maximum Satisfiability

$$\min \sum_i c_i \cdot b_i$$

← objective variable (binary)
← constant

subject to:

$$F \leftarrow \text{CNF-formula}$$

$c_i \cdot b_i$ can be viewed as a soft clause ($\neg b_i$) of weight c_i

Unsatisfiable Core (Clause)

- Clause C is a core if:
 - ▶ C only contains objective variables
 - ▶ $F \models C$, i.e. all solutions of F satisfy C
 - ▶ $F \wedge \bigwedge_{\ell \in C} (\neg \ell)$ is unsatisfiable

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MUS a minimal core

Motivation: Integer Objectives in MaxSAT

General Problem:

min z

subject to:

CONSTRAINTS

$z \in \{0, 1, \dots, n\}$

Example Domains

Graph Coloring, Treewidth, Judgment Aggregation, Clustering, Database Queries, ...

Motivation: Integer Objectives in MaxSAT

General Problem:

min z ← integer variable

subject to:

CONSTRAINTS ← general constraints

$z \in \{0, 1, \dots, n\}$

↙
finite domain

Example Domains

Graph Coloring, Treewidth, Judgment Aggregation, Clustering, Database Queries, ...

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General Problem:

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subject to:

CONSTRAINTS

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As MaxSAT:

$$\min \sum_{k=1}^n b_k \leftarrow \text{binary variable}$$

subject to:

$$\bigwedge_{k=1}^n \text{ASCNF}((z \geq k) \leftrightarrow b_k)$$

$$\text{ASCNF}(\text{CONSTRAINTS})$$

↑
CNF formulas

Example Domains

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Ordered Objectives

Definition

- Solutions order objective.
 - ▶ $b_k \rightarrow b_{k-1}$ for all solutions.

Properties

- MUSes are units.
- MUSes are ordered.

$$\min \sum_{k=1}^n b_k$$

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- MUSes are ordered.
 - ▶ if (b_k) is an MUS, so is (b_{k-1}) .

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Motivation: Integer Encodings with Implications

General Problem:

$$\min z$$

subject to:

CONSTRAINTS

$$z \in \{0, 1, \dots, n\}$$

As MaxSAT (in theory):

$$\min \sum_{k=1}^n b_k$$

subject to:

equivalence



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$$\text{ASCNF}(\text{CONSTRAINTS})$$

Motivation: Integer Encodings with Implications

General Problem:

$$\min z$$

subject to:

CONSTRAINTS

$$z \in \{0, 1, \dots, n\}$$

As MaxSAT (in practice):

$$\min \sum_{k=1}^n b_k$$

subject to:

implication



$$\bigwedge_{k=1}^n \text{ASCNF}((z \geq k) \rightarrow b_k)$$
$$\text{ASCNF}(\text{CONSTRAINTS})$$

Almost-Ordered Objectives

Definition

- Optimal solutions order objective.
 - ▶ $b_k \rightarrow b_{k-1}$ for all opt. sols.

Properties

- All solutions assign the objective the same way.

$$\min \sum_{k=1}^n b_k$$

subject to:

$$\bigwedge_{k=1}^n \text{ASCNF}((z \geq k) \rightarrow b_k)$$

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Almost-Ordered Objectives

Definition

- Optimal solutions order objective.
 - ▶ $b_k \rightarrow b_{k-1}$ for all opt. sols.

Properties

- All solutions assign the objective the same way.
 - ▶ no opt sol assigns $b_2 = 1$ and $b_1 = 0$.

$$\min \sum_{k=1}^n b_k$$

subject to:

$$\bigwedge_{k=1}^n \text{AsCNF}((z \geq k) \rightarrow b_k)$$

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Summary: (Almost-)Ordered Objectives

Ordered Objective

$(F, \sum_i c_i b_i)$ has an ordered objective if:

- all solutions of F satisfy $(b_i \rightarrow b_{i-1})$

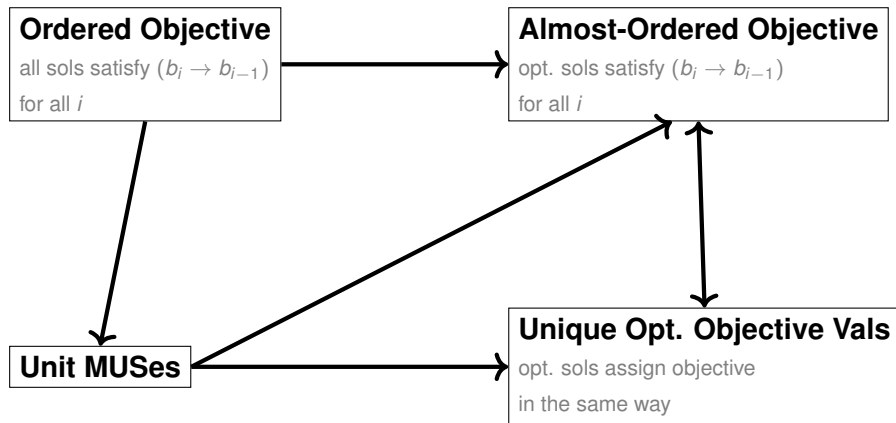
Almost Ordered Objective

$(F, \sum_i c_i b_i)$ has an almost-ordered objective if:

- every optimal solution satisfies $(b_i \rightarrow b_{i-1})$

Summary: Properties of (Almost-)Ordered Objectives

Formula F , objective $\sum_i c_i b_i$



Prevalence of Ordered Objectives

Instances of MSE 22-24

Algorithmic Detection

- **Ordered:** Exhaustive search or UP-based lookahead.
- **Almost-Ordered:** Enumerating MUSes or optimal solutions.

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Instances	#	Ord.	Not Ord.	AO	Not AO
Unweighted	1558	134	1266	589	556
Weighted	1545	29	1421	616	439

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Over a third of instances determined to have an almost-ordered objective

Solving instances with an ordered objective

Intuition

- optimal solutions set $b_1 = b_2 = \dots = b_t = 1$ and rest to 0.
- suffices to find t .

Simple-US

```
1 Simple-US( $F, \sum_i c_i b_i$ )
2   for  $i=1, \dots, n$  do
3      $(sat?, \alpha) \leftarrow$  SAT-Solve-w-Assums( $F, \{b_i = 0\}$ );
4     if  $sat?$  then return  $\alpha$ ;
```

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```

Core-Guided MaxSAT

```
1 Core-Guided ( $F, O$ )
2    $(F^W, O^W) \leftarrow (F, O)$ 
3   while TRUE do
4      $\mathcal{A} \leftarrow \{\neg b \mid c \cdot b \in O^W\}$ 
5      $(sat?, \alpha, C) \leftarrow \text{ExtractCore-w-SAT-solver}(F^W, \mathcal{A})$ 
6     if  $sat?$  then return  $\alpha$ ;
7      $(F^W, O^W) \leftarrow \text{Relax}(F^W, O^W, C)$ 
```

Intuition for this talk

- Least number of iterations when extracting MUSes.
- Unit cores fixed.

State-of-the-art Core-Based MaxSAT

On ordered objectives

Informal Theorem

Simple-US simulates best-case of state-of-the-art core-guided and IHS MaxSAT solvers.

Simple-US

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2   for  $i=1, \dots, n$  do
3      $(sat?, \alpha) \leftarrow \text{SAT-Solve-w-Assums}(F, \{b_i = 0\});$ 
4     if  $sat?$  then return  $\alpha;$ 
   /* Else  $F \leftarrow F \wedge (b_i)$  */
```

Back to this Table

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Conclusions

(Almost-)Ordered Objectives

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Take Home Message:

If your encoding results in an ordered objective, core-based solvers are (probably) not the best idea.

Details on Runtime of Empirical Solvers

Solver	UW (108)		W (17)		Col (415)		JA AO (50)		JA O (50)		TW AO (287)		TW O (287)	
	#	PAR-2	#	PAR-2	#	PAR-2	#	PAR-2	#	PAR-2	#	PAR-2	#	PAR-2
Simple-SIS	88	1780.3	13	2360.7	387	497.1	27	3819.5	27	3826.1	142	3818.9	143	3807.5
Simple-US	86	1950.0	14	1760.1	386	510.6	20	4827.9	27	4067.0	142	3864.1	136	3990.6
EvalSCIP	84	2248.1	12	2468.4	392	481.9	18	5160.3	19	5031.4	121	4441.8	123	4415.3
EvalNoSCIP	83	2135.0	13	2271.6	387	498.8	20	4940.8	19	4962.6	124	4228.2	126	4183.9
MaxHS	86	1959.1	14	1985.2	387	501.6	12	5777.3	23	4442.7	125	4233.0	133	4027.5
MaxCDCL	81	2360.4	12	2628.6	385	606.6	21	5099.3	21	4949.1	108	4660.4	115	4502.4
Pacose	70	2876.5	11	3304.3	380	637.5	12	5862.8	13	5663.0	77	5417.4	85	5167.0
Virtual Best	89	1720.4	14	1603.5	393	388.3	28	3733.2	28	3692.8	143	3793.4	143	3792.6

Overhead on Clean Reimplementations

	Col (415)		JA AO (50)		JA O (50)		TW AO (287)		TW O (287)	
	Non-unit	Overh.	Non-unit	Overh	Non-unit	Overh	Non-unit	Overh	Non-unit	Overh
IHS	140/383	1.2	5/5	9.2	6/6	2.6	43/65	1.2	41/66	1.2
OLL	0/387	0	21/21	41	27/27	6	66/125	10	59/135	1

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		UP	Total		UMUS	Unique	
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