Preprocessing in Incomplete MaxSAT Solving

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Contributions

- We analyse the effects of preprocessing on (incomplete) MaxSAT solving.
  - Using preprocessing results in solvers misinterpreting cost of *non-optimal solutions* both in theory and practice.
- Propose *locally minimal solutions*
  - A sufficient criterion for avoiding misinterpretation of cost.
- Develop stochastic local search (SLS) over locally minimal solutions
  - Searching over locally minimal solutions improves performance in practice.

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Outline

- Motivation - MaxSAT
- Preprocessing and Cost Preservation
- Locally Minimal Solutions
- Locally Minimal Solutions in SLS MaxSAT solving
- Empirical Evaluation

Motivation: MaxSAT

- A declarative optimisation paradigm based on propositional logic.
- Various types of efficient MaxSAT solvers have been developed.
- Enable efficiently solving various NP-hard optimization problems via *encode-and-solve*.
  - Applications in:
    - AI & ML
    - Data Analysis
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Ghosh and Meel [2019]
Chen et al. [2010]
Zhang and Bacchus [2012]
Berg and Järvisalo [2017]
Demirovic et al. [2019]
Hosokawa et al. [2019]
Bacchus et al. [2019]
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Motivation: MaxSAT

- Solving a MaxSAT instance $\mathcal{F}$
  - Find truth assignment that satisfies all hard clauses in $\mathcal{F}_H$ and maximises the number of satisfied soft clauses in $\mathcal{F}_S$.
  - Can have weights on soft clauses.

$$\mathcal{F}_H = \{(b_1 \vee b_2), (b_2 \vee b_3)\}$$

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$$\mathcal{F}_H = \{(b_1 \vee b_2), (b_2 \vee b_3)\}$$

$$\mathcal{F}_S = \{(\neg b_1), (\neg b_2), (\neg b_3)\}$$

$$\tau = \{\neg b_1, b_2, \neg b_3\}$$

$$cost(\tau) = \mathbf{1}$$

Two Topical Research Directions

Incomplete Solving

Aim at quickly computing a solution that is as good as possible (not necessarily an optimal one)

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Focus on understanding how costs of non-optimal solutions are influenced by preprocessing

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Note

Non-optimal solutions encountered both in complete, and incomplete solving

MaxSAT Preprocessing

Preprocessing an instance $\mathcal{F}$:

$$\mathcal{F}_H = \{ \quad (x \vee \neg y), (\neg x \vee y) \quad \}$$
$$\mathcal{F}_S = \{ \quad (\neg x) \quad \}$$

MaxSAT Preprocessing

Preprocessing an instance $\mathcal{F}$:

1. Apply preprocessing rules to form $\textsc{Pre}(\mathcal{F})$
2. Solve $\textsc{Pre}(\mathcal{F})$
3. Reconstruct a solution to $\mathcal{F}$

$\mathcal{F}_H = \{ \ (x \vee \neg y), (\neg x \vee y) \ \}$
$\mathcal{F}_S = \{ \ (\neg x) \ \}$

$\textsc{Pre}(\mathcal{F}_H) = \{ \ (x \vee \neg y) \ \}$
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$\textsc{Rec}(\tau) = \{\neg x, \neg y\}$

$\tau = \{\neg x, \neg y\}$

MaxSAT Preprocessing

Definition:
Preprocessing is sound if
$cost(\tau) = cost(\text{REC}(\tau))$
for any optimal solution to $\text{PRE}(\mathcal{F})$.

$\mathcal{F}_H = \{ \quad (x \vee \neg y), (\neg x \vee y) \quad \}$
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$\text{REC}(\tau) = \{\neg x, \neg y\}$
$cost(\text{REC}(\tau)) = 0$

$\tau = \{\neg x, \neg y\}$
$cost(\tau) = 0$

MaxSAT Preprocessing

Take-Home Message 1
Existing proofs of soundness only apply to optimal solutions.

$\mathcal{F}_H = \{ \quad (x \vee \neg y), (\neg x \vee y) \quad \}$
$\mathcal{F}_S = \{ \quad (\neg x) \quad \}$

$\textsc{Pre}(\mathcal{F}_H) = \{ \quad (x \vee \neg y) \quad \}$
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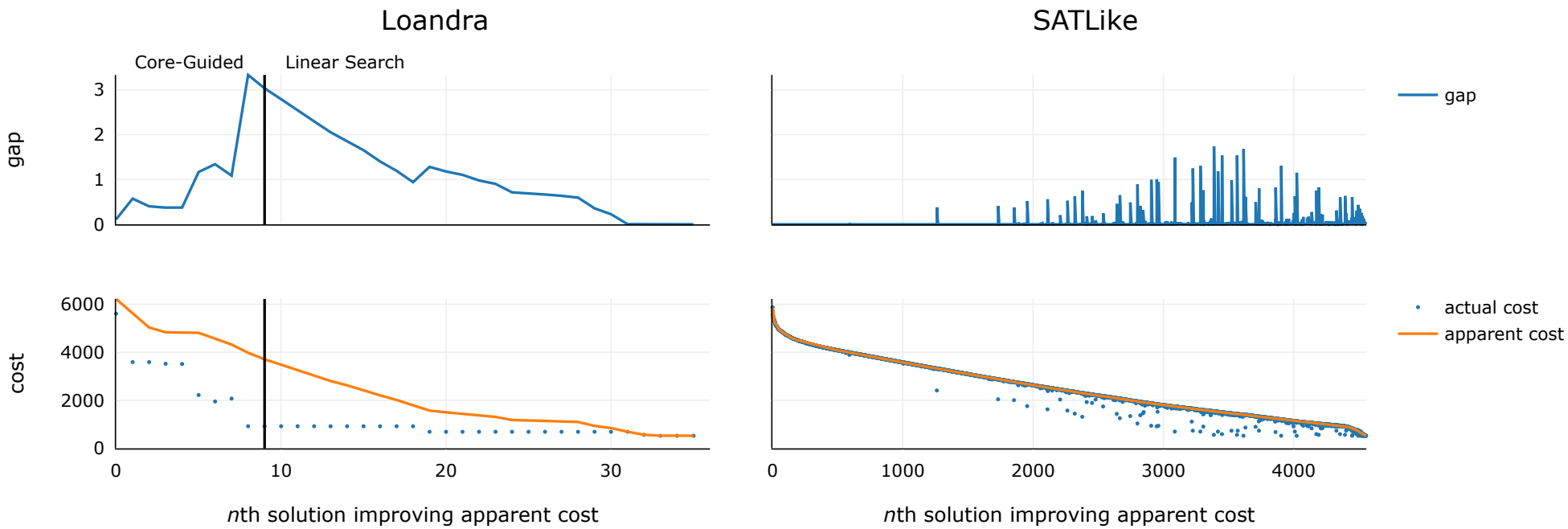
$\textsc{Rec}(\tau) = \{\neg \mathbf{x}, \neg \mathbf{y}\}$
$\mathit{cost}(\textsc{Rec}(\tau)) = 0$

$\tau = \{\mathbf{x}, \neg \mathbf{y}\}$
$\mathit{cost}(\tau) = 1$

And in practice...

Loandra: Berg et al. [2019], SAT-Like: Lei and Cai [2018]



- Actual Cost $\rightarrow$ $cost(\text{REC}(\tau))$
- Apparent Cost $\rightarrow$ $cost(\tau)$

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Take-Home Message 2

Preprocessing can lead to misinterpreted costs of non-optimal solutions both in theory and practice

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Take-Home Message 2

Preprocessing can lead to misinterpreted costs of non-optimal solutions both in theory and practice

Recall

Non-optimal solutions encountered both in complete and incomplete search

Solution:

Locally Minimal Solutions

Solutions where no falsified soft clause can be ”trivially” satisfied.

Example

We show:

The cost of locally minimal solutions is not misrepresented during search.

Solution:

Locally Minimal Solutions

Solutions where no falsified soft clause can be ”trivially” satisfied.

Example

$\textsc{Pre}(\mathcal{F}_H) = \{(x \vee y)\}$
$\textsc{Pre}(\mathcal{F}_S) = \{(\neg x)\}$
$\tau = \{x, y\}$

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More details in the paper

Stochastic Local Search over Locally Minimal Solutions

Key Ideas

- Build on top of the state-of-the-art local search approach SATLike
- Group clauses after preprocessing.
  - put two clauses into the same group if they ”originate” from the same soft clause.
- Direct search toward satisfying groups instead of clauses.
- Greedily minimize solutions obtained during search to guarantee local minimality.

Experiments

Setup

Benchmarks: The 297 weighted instances (from 26 domains) of MaxSAT Evaluation 2019.

Solver variants:

- NO-PREPRO : no preprocessing.
- PREPRO-NOLOCMIN : only preprocessing.
- DEFAULT : preprocessing and searching over locally minimal solutions.

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High-level results

DEFAULT $\xrightarrow{\text{wins } \mathbf{23} \text{ domains over}}$ NO-PREPRO $\xrightarrow{\text{wins } \mathbf{15} \text{ domains over}}$ PREPRO-NOLOCMIN

See paper for detailed results!

Experiments

Take-Home Message 3

Searching over locally minimal solutions is crucial for effective use of preprocessing.

Conclusions

In this paper, we:

- show that preprocessing can mislead several different types of complete and incomplete solvers;
- propose locally minimal solutions as a possible fix;
- propose an SLS algorithm that only searches over locally minimal solutions; and
- show that incorporating locally minimal solutions to search improves the empirical performance.

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In the future we aim to:

- Use locally minimal solutions to improve complete algorithms.

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