Clause Redundancy and Preprocessing in Maximum Satisfiability

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Motivation

- MaxSAT: declarative optimisation based on propositional logic.
  - compute an assignment to Boolean (0-1) variables that:
    - ★ satisfies a set of (hard) clauses.
    - ★ minimizes a linear objective function (equivalently, minimizes the sum of weights of falsified soft clauses)
- State-of-the-art solvers build on the success of CDCL SAT solvers.
- New application domains and solver improvements annually.

(Recent survey in [Bacchus, Järvisalo, and Martins, 2021])

(Complete) SAT-based MaxSAT solving

Algorithms

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Algorithms

Core-Guided

- Lower-bounding search
- with a SAT solver

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Implicit Hitting Set (IHS)

- Lower-bounding search with a SAT and MIP solver

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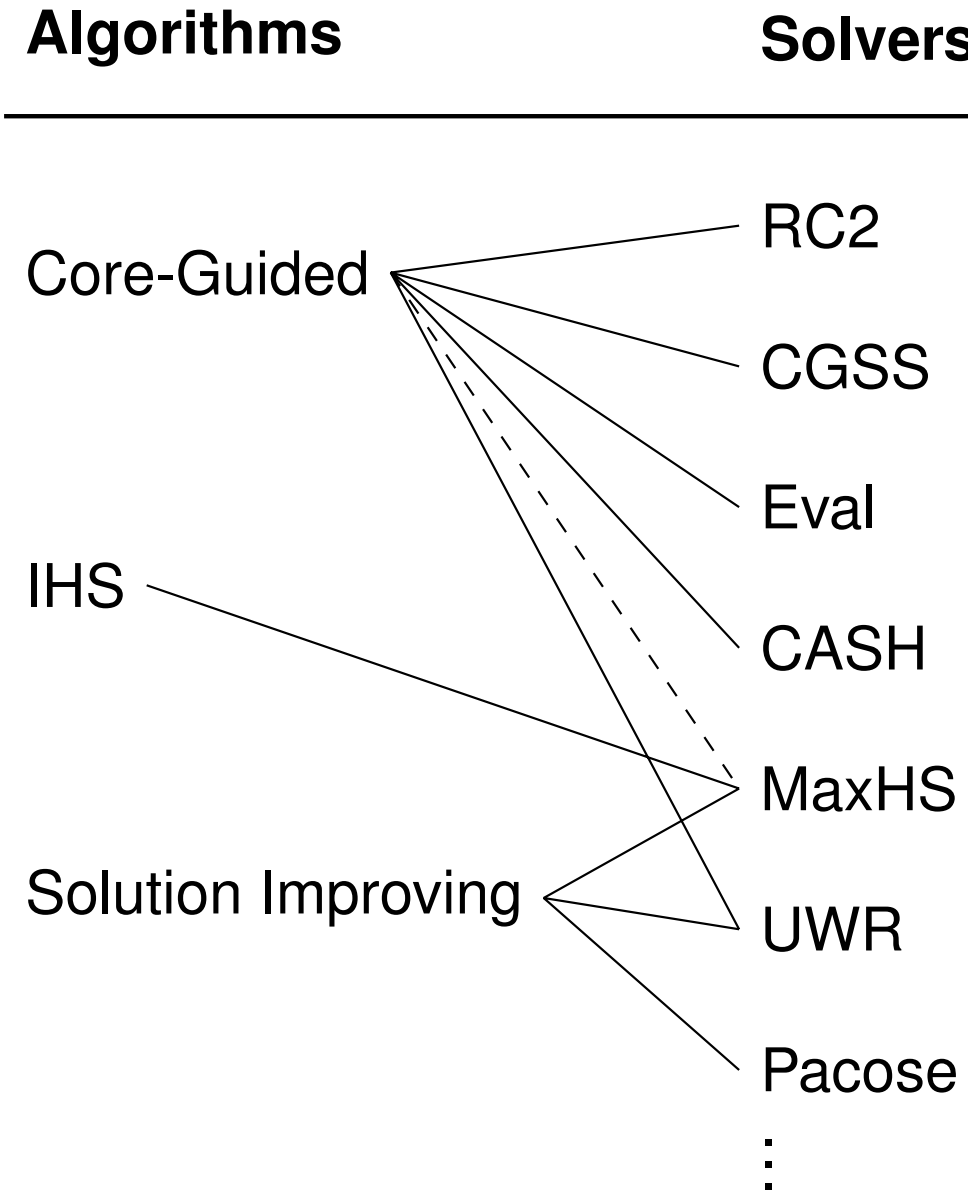
IHS

- Lower-bounding search with a SAT and MIP solver

Solution Improving

- Upper-bounding search with a SAT solver

(Complete) SAT-based MaxSAT solving



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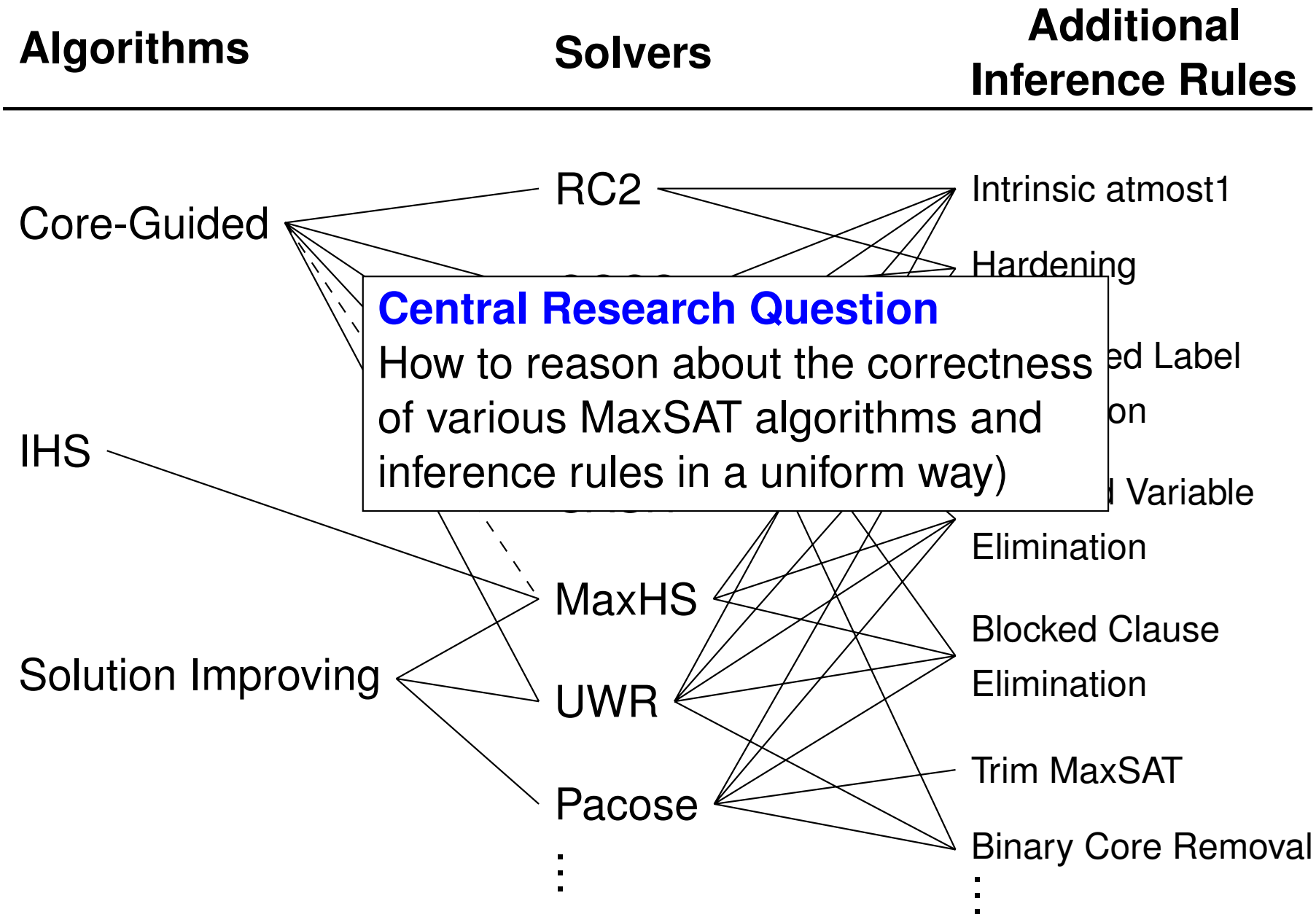

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Clause Redundancy central base for proofs of correctness of SAT solving techniques.

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In this paper we:

- Lift recently proposed redundancy notions from SAT to MaxSAT.
- Reason about the correctness of various solver techniques.
- Analyse the effect of redundant clauses on solutions of MaxSAT instances:
  - Focus especially on the MaxSAT specific concept of minimal correction sets.

[Heule and Kiesl, 2017]
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[Järvisalo, Biere, and Heule, 2012]
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[Biere, Järvisalo, and Kiesl, 2021]
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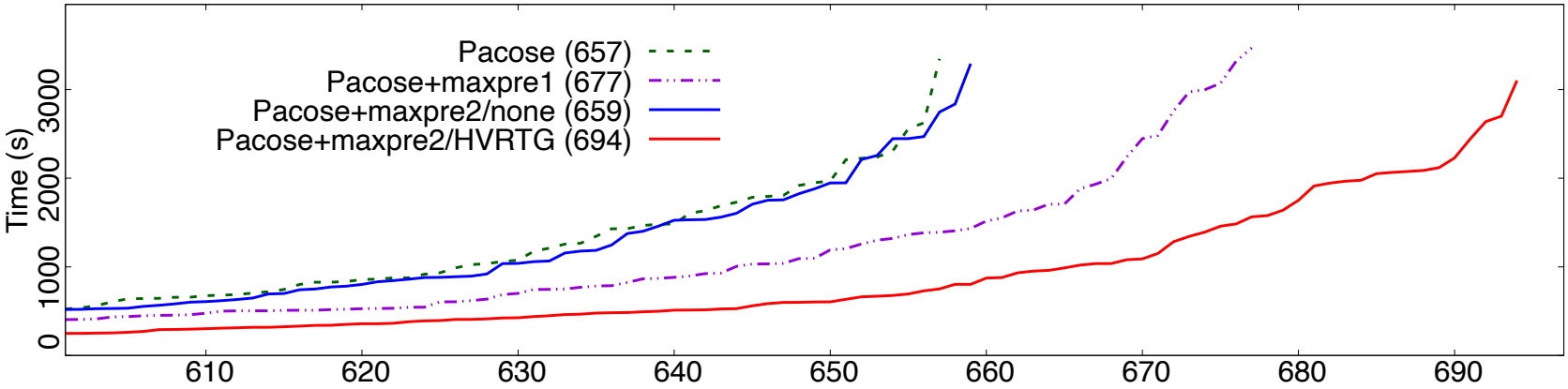
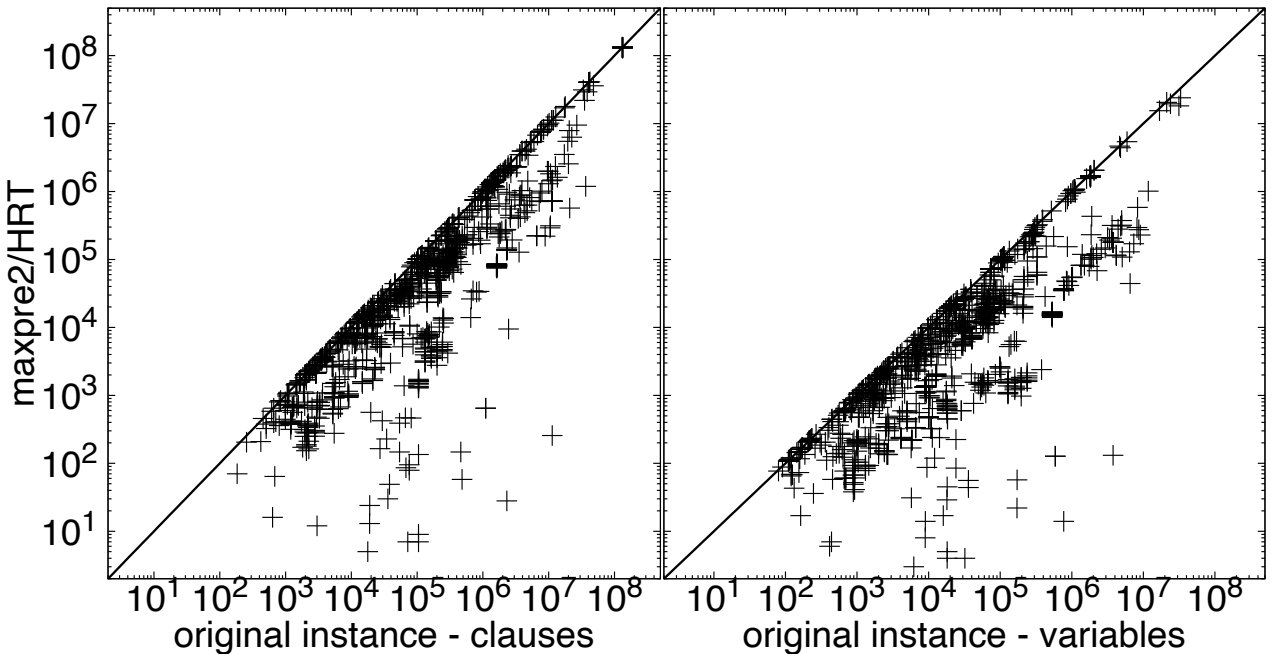
Expressive preprocessing in practice





Our (Practical) Contributions(2/2)

- **MaxPre 2**: Stand-alone implementation of reasoning techniques previously only appearing in solvers.
- Empirical evaluation on effect of preprocessing on several types of state-of-the-art solvers.

[Korhonen, Berg, Saikko, and Järvisalo, 2017]
[Ansótegui, Bonet, Gabàs, and Levy, 2012]
[Paxian, Raiola, and Becker, 2021]
[Marques-Silva and Planes, 2008]
[Berg, Demirovic, and Stuckey, 2019]
[Morgado, Dodaro, and Marques-Silva, 2014]
[Davies and Bacchus, 2013]
[Martins, Joshi, Manquinho, and Lynce, 2014a]
[Saikko, Berg, and Järvisalo, 2016]
[Martins, Manquinho, and Lynce, 2014b]
[Koshimura, Zhang, Fujita, and Hasegawa, 2012]
[Ignatiev, Morgado, and Marques-Silva, 2019]
[Korhonen, Berg, Saikko, and Järvisalo, 2017]

Outline

1. Definitions.
2. Clause Redundancy in MaxSAT
3. Effects of Redundant Clauses in MaxSAT.
4. Empirical Evaluation.

Preliminaries: Maximum Satisfiability

- Optimisation extension of Boolean Satisfiability (SAT)
- An instance:
  - a set of hard clauses,
  - a linear objective function *cost*
- Find τ that:
  - satisfies all hard clauses and
  - minimizes cost
  - $cost(\mathcal{F})$ = cost of its optimal solutions.
- $\mathcal{F}_B$: set of objective variables.
- **Note:** All results extend to weights!

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

$$cost \equiv b_1 + b_2 + b_3$$

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

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$$cost(\mathcal{F}) = 1$$

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

$$cost \equiv \sum_{b \in \mathcal{F}_B} b$$

$$\mathcal{F}_B = \{b_1, b_2, b_3\}$$

Redundant Clauses in MaxSAT

Clause Redundancy

In MaxSAT

C redundant for $\mathcal{F}$ if

$$cost(\mathcal{F}) = cost(\mathcal{F} \wedge C).$$

where $\mathcal{F} \wedge C = (\mathcal{F}_H \wedge C, \mathcal{F}_B)$

In SAT [Järvisalo, Heule, and Biere, 2012; Heule, Järvisalo, Lonsing, Seidl, and Biere, 2015]

C redundant for F if F and $F \wedge C$ are *equisatisfiable**.

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Note: that the definitions coincide if $\mathcal{F}_B = \emptyset$

Clause Redundancy via Semantic Implication

(Informal) Theorem for SAT [Heule, Kiesl, and Biere, 2020]

Assume $\tau(F) = 1$ and $\tau(C) = 0$.
C is redundant if ω for which $\omega(F \wedge C) = 1$ can be constructed.

Formally, if an ω for which $\omega(C) = 1$, and $\mathcal{F}_H\big|_{\neg C} \models \mathcal{F}_H\big|_{\omega}$ exists.

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Our extension for MaxSAT

Assume $\tau(\mathcal{F}_H) = 1$ and $\tau(C) = 0$.
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More specifically C is:

- cost literal propagation redundant (CLPR) if
  ω flips a single $l \in C \setminus \mathcal{F}_B$.
- cost set propagation redundant (CSPR) if
  ω flips a subset $L \subset C \setminus \mathcal{F}_B$.
- cost propagation redundant (CPR) if
  ω is constructed based on a given third assignment δ.

Example

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

$$\mathcal{F}_B = \{b_1, b_2, b_3\}$$

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$(\neg x \vee \neg b_1)$

1. $(\neg x \vee \neg b_1)$ is redundant,
2. $(\neg b_1)$ is redundant,
3. $(\neg b_2)$ is not redundant since the witness would have higher cost

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$$\omega(b_2) = \omega(x) = 1$$
$$\omega(b_1) = \omega(b_3) = \omega(y) = 0$$
$$cost(\omega) = 1 \leq 2 = cost(\tau)$$

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$$\omega(b_1) = 0$$

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Example

$$\mathcal{F}_H = \{(b_1 \vee x), (\neg x \vee b_2), (b_2 \vee y), (\neg y \vee b_3)\} \qquad (\neg b_2)$$

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Why does this matter?

Example: Bounded Variable Elimination

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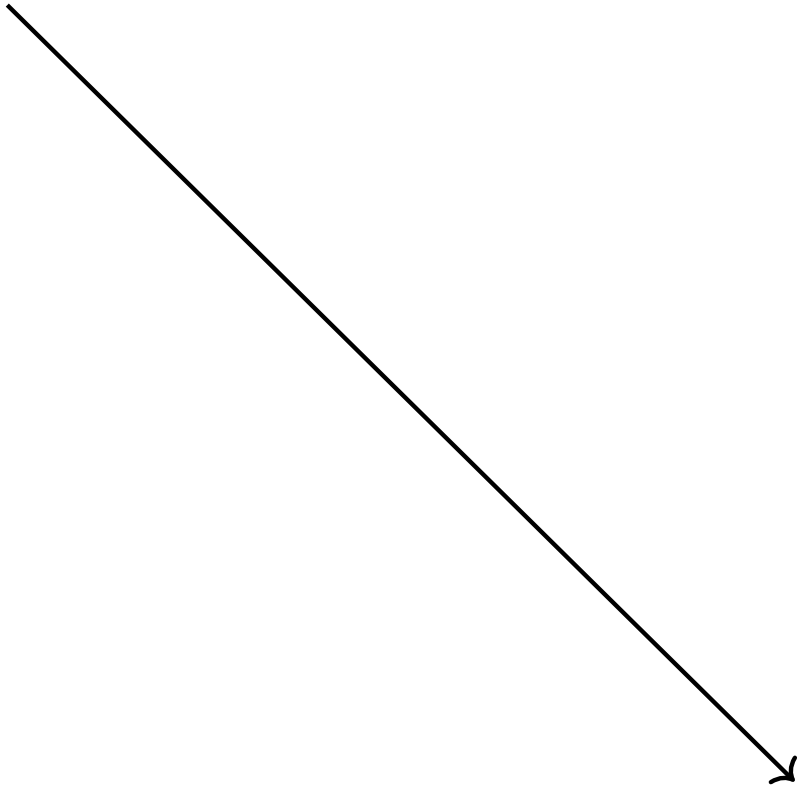

$$\mathcal{F}_H^P = \{(b_1 \vee b_2), (b_2 \vee b_3)\}$$

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Example: Bounded Variable Elimination

$$\mathcal{F}_H = \{(b_1 \vee x), (\neg x \vee b_2), (b_2 \vee y), (\neg y, b_3)\} \longrightarrow \mathcal{F}_H^1 = \{(b_1 \vee x), (\neg x \vee b_2), (b_2 \vee y), (\neg y \vee b_3), (b_1 \vee b_2)\}$$

$$\mathcal{F}_H^2 = \{\cancel{(b_1 \vee x)}, (\neg x \vee b_2), (b_2 \vee y), (\neg y \vee b_3), (b_1 \vee b_2)\} \longrightarrow \mathcal{F}_H^3 = \{\cancel{(b_1 \vee x)}, \cancel{(\neg x \vee b_2)}, (b_2 \vee y), (\neg y \vee b_3), (b_1 \vee b_2)\}$$

$$\ldots \longrightarrow \mathcal{F}_H^P = \{(b_1 \vee b_2), (b_2 \vee b_3)\}$$

Effect of Redundant Clauses in MaxSAT

Definition: MCSes

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

$$cost \equiv b_1 + b_2 + b_3$$

- MCS: subset-minimal set of blocking variables set to 1 by some solution.
  - equivalently, a minimal set of soft clauses falsified by some solution.
- Tight connections between MCSes and MaxSAT solutions.
- MCS($\mathcal{F}$): set of all MCSes of $\mathcal{F}$.

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$hs^1 = \{b_1, b_3\}$ $(\equiv \{(\neg b_1), (\neg b_3)\})$

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Effect of redundant Clauses on MCSes

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$$\mathcal{F}_B = \{b_1, b_2, b_3\}$$

$$\mathsf{MCS}(\mathcal{F}) = \{\{b_1, b_3\}, \{b_2\}\}$$

- Adding CLPR clause $(\neg x \vee \neg b_1)$ does not affect MCSes.
- Adding CPR clause $(\neg b_1)$ does.

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Analysis of Redundant Clauses

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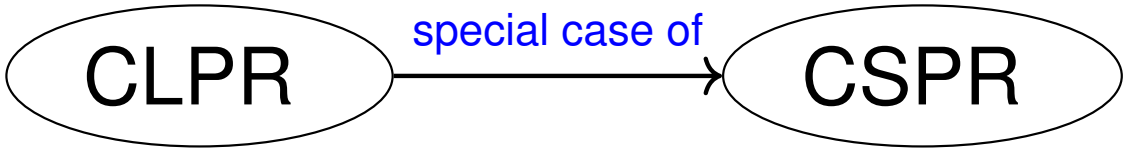

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- Adding or removing preserves all MCSes
- Adding or removing is guaranteed to only preserve one minimum cost MCS

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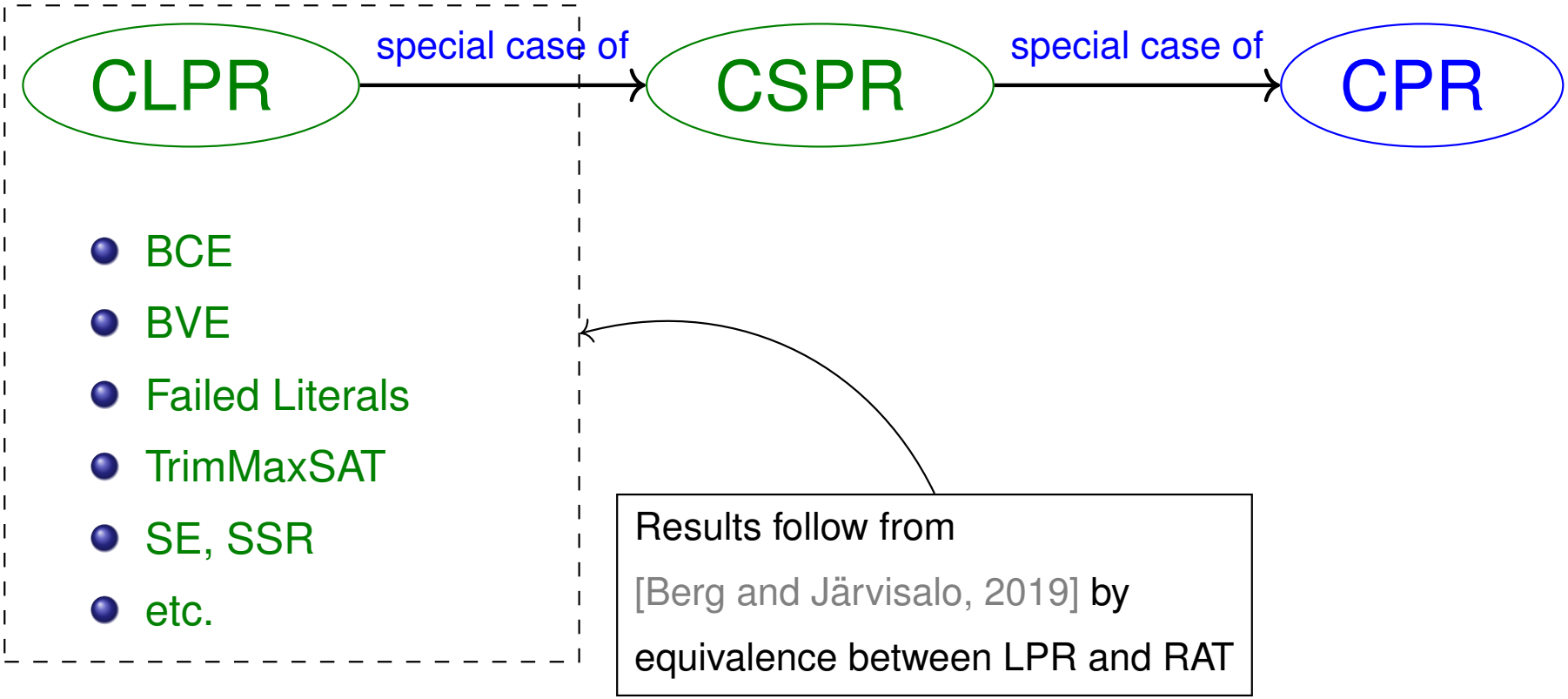

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Analysis of Redundant Clauses

Summary

- BCE
- BVE
- Failed Literals
- TrimMaxSAT
- SE, SSR
- etc.

- Group Subsumed Label Elimination
- Hardening
- etc.

- Adding or removing preserves all MCSes
- Adding or removing is guaranteed to only preserve one minimum cost MCS

MaxPre 2 - Expressive preprocessing in practice

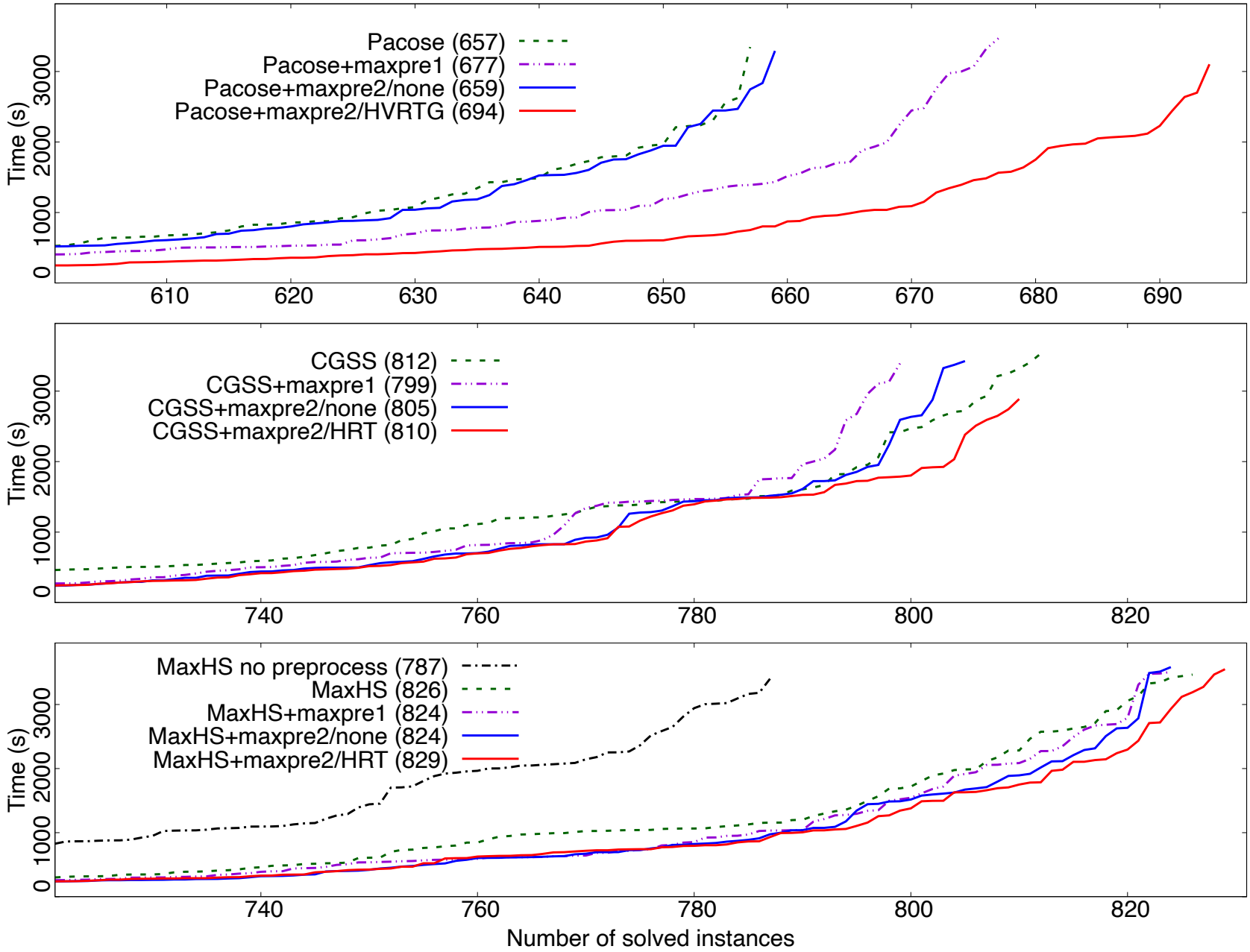
MaxPre 2

- Stand-alone tool implementing several heuristics previously only appearing in solvers.
- Allows applying heuristics as a separate solving step.
- Available in open source
  `https://bitbucket.org/coreo-group/maxpre2/`

Set Up of Experiments

- All distinct weighted benchmarks from MaxSAT Evaluations 2020 and 2021.
- Experiments with three state-of-the-art complete solvers representing the three types of algorithms:
  - Core guided: CGSS
  - IHS-based: MaxHS
  - Model improving: Pacose
- Also experiments with incomplete Loandra

Complete Solving



Incomplete Solving

#Wins	base (maxpre1)	no-prepro	maxpre2/ none	maxpre2/ VG
base (maxpre1)	—			
no-prepro		—		
maxpre2/none			—	
maxpre2/VG				—
Score:	0.852	0.840	0.863	0.870

- Results for the state-of-the-art Loandra solver.
- Wins = #instances on which found solution has lower cost.
- Score = average ratio between best-known cost and cost of found solution.

Incomplete Solving

#Wins	base (maxpre1)	no-prepro	maxpre2/ none	maxpre2/ VG
base (maxpre1)	—		135	
no-prepro		—		
maxpre2/none	105		—	
maxpre2/VG				—
Score:	0.852	0.840	0.863	0.870

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- Score = average ratio between best-known cost and cost of found solution.

Incomplete Solving

#Wins	base (maxpre1)	no-prepro	maxpre2/ none	maxpre2/ VG
base (maxpre1)	—		135	152
no-prepro		—		
maxpre2/none	105		—	
maxpre2/VG	110			—
Score:	0.852	0.840	0.863	0.870

- Results for the state-of-the-art Loandra solver.
- Wins = #instances on which found solution has lower cost.
- Score = average ratio between best-known cost and cost of found solution.

Incomplete Solving

#Wins	base (maxpre1)	no-prepro	maxpre2/ none	maxpre2/ VG
base (maxpre1)	—	154	135	152
no-prepro	208	—	216	218
maxpre2/none	105	143	—	77
maxpre2/VG	110	140	80	—
Score:	0.852	0.840	0.863	0.870

- Results for the state-of-the-art Loandra solver.
- Wins = #instances on which found solution has lower cost.
- Score = average ratio between best-known cost and cost of found solution.

Conclusions

- Lift recently proposed clause redundancy notions from SAT to MaxSAT
- Complete analysis on the effect of redundant clauses on MCSes
- Provide empirical evaluation on the effect of preprocessing on state-of-the-art MaxSAT solvers.

Future Work

- Develop new inference rules based on the redundancy notions.
  - Especially rules on the ”CPR level”.
- Further extend framework to include e.g. core-guided reasoning

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