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Subsumed Label Elimination for Maximum Satisfiability

Jeremias Berg and Paul Saikko and Matti Järvisalo

Abstract. We propose subsumed label elimination (SLE), a so-called label-based preprocessing technique for the Boolean optimization paradigm of maximum satisfiability (MaxSAT). We formally show that SLE is orthogonal to previously proposed SAT-based preprocessing techniques for MaxSAT in that it can simplify the underlying minimal unsatisfiable core structure of MaxSAT instances. We also formally show that SLE can considerably reduce the number of internal SAT solver calls within modern core-guided MaxSAT solvers. Empirically, we show that combining SLE with SAT-based preprocessing improves the performance of various state-of-the-art MaxSAT solvers on standard industrial weighted partial MaxSAT benchmarks.

1 INTRODUCTION

Maximum satisfiability (MaxSAT), the optimization counterpart of Boolean satisfiability (SAT), is becoming a competitive approach to solving hard optimization problems due to recent advances in MaxSAT solving [2, 38]. As MaxSAT is finding an increasing number of applications in solving real-world optimization problems—ranging from, e.g., inconsistency analysis, diagnosis, design debugging, and fault localization [15, 14, 4, 32, 44, 30, 39, 27, 35] to further applications in AI, combinatorics, data analysis, and bioinformatics [41, 23, 43, 3, 10, 21, 8, 9, 42]—there is a high demand for new techniques for speeding up MaxSAT solving further.

This paper focuses on improving the efficiency of solving real-world MaxSAT instances via preprocessing the instances before calling a state-of-the-art MaxSAT solver. In particular, effective preprocessing techniques for MaxSAT have the promise of providing solver-independent speeds-up to overall solving times, similarly to SAT where preprocessing is today an integral part of the solving process [20, 29]. This motivates work on MaxSAT-level preprocessing, in hope of bridging the gap between highly successful SAT preprocessing and the currently less studied and understood role of preprocessing for MaxSAT [7, 11, 31, 5, 13].

One approach to MaxSAT preprocessing is to lift commonly applied SAT preprocessing techniques, such as bounded variable elimination [20], self-subsuming resolution, and forms of clause elimination [26], to MaxSAT. Direct applications of such SAT preprocessing techniques are not correct w.r.t. preserving the optimal solutions of MaxSAT instances [7]. However, correct liftings to MaxSAT are enabled by the so-called labelled conjunctive normal form (LCNF) representation [7, 6].

A natural next goal for MaxSAT preprocessing is to go beyond lifting well-known SAT preprocessing techniques, by developing novel MaxSAT-specific LCNF-level preprocessing techniques that can be applied in conjunction with SAT-based preprocessing techniques, ideally with orthogonal simplification properties. In this paper, we address this challenge by proposing label-based preprocessing as a form of native LCNF-level MaxSAT preprocessing. In particular, we propose the preprocessing technique of subsumed label elimination (SLE). The main aim of SLE is, working in conjunction with SAT-based preprocessing on labelled MaxSAT instances, to detect and eliminate redundant labels, i.e., auxiliary variables that are first added to maintain correctness under SAT-based preprocessing, but which can be inferred to be redundant by a simple polynomial-time deduction rule that SLE implements. Arising from deduction rules proposed in the nineties for the so-called binate covering problem [17, 16], a key insight of SLE is that redundant labels can be eliminated by comparing the label-sets $L$ of clauses $C$ on the LCNF level, i.e., regardless of the contents of $C$. While SLE is based on a relatively simple observation, it significantly differs from the earlier proposed SAT-based preprocessing techniques for MaxSAT. In practice it also tends to provide further speed-ups to the MaxSAT solving process for several state-of-the-art MaxSAT solvers.

In more detail, we analyze how known LCNF-lifted SAT preprocessing techniques and SLE modify key properties of MaxSAT instances: the (labelled) minimal unsatisfiable cores (LMUSes) and (labelled) minimal correction sets (LMCSes). We show that SLE is fundamentally different from LCNF-lifted SAT preprocessing. In contrast to SAT preprocessing which is unable to simplify LMUSes and LMCSes, SLE can effectively remove labels from LMUSes. Via a straightforward translation of LCNFs to standard MaxSAT, this implies that SLE can reduce the number of standard MUSes in the resulting MaxSAT instance. This can improve the performance of so-called core-guided MaxSAT solvers, such as [22, 25, 40, 36, 37], as well as those based on the implicit hitting set approach [18, 19, 11].

Giving a concrete witnessing family of LCNF-MaxSAT instances, we show that SLE has the potential to drastically decrease the number of iterations performed by various core-guided MaxSAT solvers. Complementing the theoretical analysis, we show empirically that by combining SLE with LCNF-lifted SAT preprocessing, noticeably more labels (i.e. redundancies) are eliminated than without SLE on weighted partial MaxSAT instances of the industrial track of MaxSAT Evaluation 2015. Further, we show that the additional simplifications translate into runtime improvements for various state-of-the-art MaxSAT solvers on industrial weighted partial instances.

This paper is organized as follows. After preliminaries on labelled CNFs and SAT-based preprocessing for MaxSAT (Section 2), we detail subsumed label elimination (Section 3), and provide a theoretical analysis of SLE both in terms of its effects on the core structure of MaxSAT instances (Section 4) and its potential to speed-up MaxSAT solving (Section 5). Empirical results on simplifications provided by SLE and the impact of SLE on the performance of MaxSAT solvers are provided in Section 6.
2 PRELIMINARIES

Throughout this paper, we work with labelled CNFs (LCNFs) [7, 6] which allow for generalizing MaxSAT and provide a convenient formalism for describing correct liftings of SAT preprocessing techniques to MaxSAT. For an intuitive reading, in LCNF a set of labels is associated with each clause. An empty label-set denotes that the corresponding clause is hard, while a non-empty label-set implies that the corresponding clause is soft. Furthermore, key concepts such as maximum satisfiability, minimal unsatisfiable subsets and minimal correction sets, are defined over the label-sets L of LCNF clauses C\textsuperscript{L} instead of the clauses C.

Before the formal definitions, consider the MaxSAT instance with three unweighted soft clauses shown in Figure 1 (1). As argued in [7], in order to apply e.g. bounded variable elimination (VE) [20] and still maintain the set of optimal solutions, each soft clause C\textsubscript{i} needs to be attached an auxiliary fresh variable I\textsubscript{i} resulting in the instance (Figure 1, 2a). On the level of LCNFs [6], the resulting instance is shown in Figure 1 (2b). Restricting VE from eliminating any of the added variables allows for sound application of most SAT preprocessing techniques in terms of MaxSAT. As an example, first eliminating the variable x and then y gives (possibly among others; here \texttt{\textbackslash l\textsubscript{a}}\textsubscript{x} denotes resolving on x) the clause shown in Figure 1 (3a). Notice how the original one-to-one mapping between the clauses and labels vanishes, as after VE a clause may contain multiple labels. To solve the MaxSAT instance after preprocessing, the clauses obtained by preprocessing are then considered hard, and for each I\textsubscript{i} the unit soft clause (\neg I\textsubscript{i}) with weight inherited from C\textsubscript{i} is added into the instance. On the LCNF level, labelled VE [7] results equivalently in the LCNF instance (3b), explicitly separating original variables and the labels in the labels of the clauses.

(1) MaxSAT instance:
C\textsubscript{1} = (x \lor y \lor z), C\textsubscript{2} = (\neg x \lor \neg a \lor y), C\textsubscript{3} = (\neg y \lor \neg a \lor \neg b)

(2a) After adding labels:

C\textsubscript{1} = (x \lor y \lor z \lor I\textsubscript{1}),
C\textsubscript{2} = (\neg x \lor \neg a \lor y \lor I\textsubscript{2}),
C\textsubscript{3} = (\neg y \lor \neg a \lor \neg b \lor I\textsubscript{3})

(3a) After variable elimination:

C\textsubscript{1} = (x \lor y \lor z),
C\textsubscript{2} = (\neg x \lor \neg a \lor y)

(3b) After labelled variable elimination:

C\textsubscript{1}\textsuperscript{(l\textsubscript{1})},
C\textsubscript{2}\textsuperscript{(l\textsubscript{2})},
C\textsubscript{3}\textsuperscript{(l\textsubscript{3})}

Figure 1: Example of SAT-based preprocessing on the CNF and LCNF level.

2.1 Labelled CNFs and MaxSAT

Assume a countable set Lbl of labels. A labelled clause C\textsuperscript{L} consists of a clause C and a (possibly empty) set L \subseteq Lbl of labels. A LCNF formula \Phi is a set of labelled clauses. Cl(\Phi) and Lbls(\Phi) denote the set of clauses and labels of \Phi, respectively, and LCl(\Phi, l) = \{C\textsuperscript{L} \mid C\textsuperscript{L} \in \Phi, l \in L\} the set of labelled clauses in \Phi that have l in their label-set. A LCNF formula is satisfiable iff Cl(\Phi) (a CNF formula) is satisfiable.

Given a LCNF formula \Phi and a subset M \subseteq Lbls(\Phi) of its labels, the subformula \Phi\mid\text{\_M} of \Phi induced by M is \{C\textsuperscript{L} \in \Phi \mid L \subseteq M\}, i.e., the LCNF formula obtained by removing from \Phi all labelled clauses with at least one label not in M; notice that \Phi\mid\text{\_M}\Phi_{\text{\_M}} = \{C\textsuperscript{L} \in \Phi \mid L \cap M = \emptyset\}. The removal of \texttt{\texttt{\_M}}(\Phi, K) of the label-set K \subseteq Lbls(\Phi) from \Phi gives \{C\textsuperscript{L} \mid C\textsuperscript{L} \notin \Phi\} \in \text{\_M}, i.e., the LCNF formula obtained by removing all labels from \Phi that are in K (note that removal does not remove clauses).

A (labelled) unsatisfiable core of an unsatisfiable LCNF formula \Phi is a label-set L \subseteq Lbls(\Phi) such that \Phi\mid\text{\_L} is unsatisfiable. An unsatisfiable core L is minimal (a LMUS) iff \Phi\mid\_{L'} is satisfiable for all L' \subseteq L. We denote the set of minimal unsatisfiable cores of \Phi by LMUS(\Phi). A (labelled) minimal correction subset (LMCS) of \Phi is a label-set R \subseteq Lbls(\Phi) such that (i) \Phi\mid\text{\_LMCS}(\Phi)\mid\_R is satisfiable, and (ii) \Phi\mid\text{\_LMCS}(\Phi)\mid\_R' is unsatisfiable for all R' \subset R. We denote the set of LMCSes of \Phi by LMCS(\Phi). Hitting set duality, formalizing a connection between LMUSes and LMCSes, is useful in this work.

Theorem 1 (Hitting set duality) [6] A label-set R \subseteq Lbls(\Phi) of a LCNF formula \Phi is a LMCS of \Phi if and only if \Phi\mid\_R is an irreducible hitting set over LMUS(\Phi), i.e., iff R is a hitting set over LMUS(\Phi) and no R' \subset R is a hitting set of LMUS(\Phi).

A LCNF-MaxSAT instance consists of a LCNF formula \Phi, and a weight function w: Lbls(\Phi) \rightarrow \mathbb{N} assigning a positive weight w(l) to each label l \in Lbls(\Phi). The cost of a label-set L \subseteq Lbls(\Phi) is the sum of the weights of the labels in L. Given a LCNF-MaxSAT instance \Phi such that \Phi\mid\_0 is satisfiable, any assignment of truth values to \Phi\mid\_0 is a solution to the LCNF-MaxSAT instance. A solution \sigma is optimal if it satisfies \Phi\mid\text{\_LMCS}(\Phi)\mid\_R for some minimum-cost LMCS R of \Phi. The cost of \sigma is the cost of R. We treat the MaxSAT problem for LCNFs as the problem of computing R. In the rest of the text we will always assume that solutions to (\Phi, w) exist, i.e., that \Phi\mid\_0 is satisfiable.

A (standard/non-labelled) MaxSAT instance F = (F_h, F_s, w) consists of a set F_h of hard and a set F_s of soft clauses, together with a function w: F_s \rightarrow \mathbb{N} assigning a positive weight w(C) to each soft clause C \in F_s. A (standard) minimal correction set (MCS) of F is a subset-minimal subset of F_h whose removal from F_s makes the instance satisfiable. Similarly, a (standard) minimal unsatisfiable core (MUS) of F is a subset-minimal subset F'_h for which F_h \cup F'_s is an unsatisfiable set of clauses. Given a non-labelled MaxSAT instance F, any truth assignment \sigma satisfying all hard clauses is a solution to the instance. A solution \sigma is optimal if the sum of the weights of the soft clauses \sigma satisfies is the maximum over all solutions. Notice that the soft clauses falsified by an optimal solution form a minimum-cost MCS of F.

A MaxSAT instance F = (F_h, F_s, w) can be viewed as a LCNF-MaxSAT instance (\Phi, w) by introducing (i) for each hard clause C \in F_h the labelled clause C\textsuperscript{\Phi}, and (ii) for each soft clause C \in F_s the labelled clause C\textsuperscript{\Phi} \textsuperscript{\texttt{\_l}}\textsuperscript{\texttt{\_c}}\textsuperscript{\texttt{\_b}}\textsuperscript{\texttt{\_b}}, where l\textsubscript{c} is a distinct label for C with weight w(l\textsubscript{c}) = w(C). It is easy to see that any optimal solution to (\Phi, w) is an optimal solution to F, and vice versa. An essential intuition is that LMCSes of (\Phi, w) correspond exactly to the MCSes of (F_h, F_s, w), and LMCSes of (\Phi, w) correspond exactly to the MUSes of (F_h, F_s, w).

To the other direction, a LCNF-MaxSAT instance (\Phi, w) can be viewed as a MaxSAT instance F_h by associating with each label l\textsubscript{i} \in Lbls(\Phi) a distinct variable a\textsubscript{i}, and introducing (i) for each labelled clause C\textsuperscript{\Phi} \in \Phi a hard clause C \lor_{l\textsubscript{i} \in Lbls(\Phi)} a\textsubscript{i}, and (ii) for each l\textsubscript{i} \in Lbls(\Phi), a soft clause (\neg a\textsubscript{i}) with weight w(\neg a\textsubscript{i}) = w(l\textsubscript{i}), where w(l\textsubscript{i}) is the weight of the label l\textsubscript{i}. Again, using this reduction, LMUSes and LMCSes of (\Phi, w) correspond exactly to the MUSes
and MCSes of $F_b$. Importantly for this work, especially the discussion in Section 5, this reduction allows one to treat any standard MaxSAT solver as a LCNF-MaxSAT solver.

**Example 2** Consider the MaxSAT instance $F_{ex} = (F_b, F_s, w)$ with $w(C) = 1$ for all $C \in F_s$. $F_b = \{(x \lor y), (\neg x \lor \neg z), (\neg y \lor z), (z \lor t)\}$, and $F_s = \{(\neg x), (y \lor t), (z \lor v \lor x)\}$. The assignment $\tau$ for which $\tau(t) = 0$ and $\tau(y) = \tau(z) = 1$ is an optimal solution to $F_{ex}$ with cost 1. The LCNF-MaxSAT instance $\Phi_{F_{ex}}$ corresponding to $F_{ex}$ is

\[ \Phi_{F_{ex}} = \{ (x \lor y)^0, (\neg x \lor \neg z)^0, (\neg y \lor z)^0, (z \lor t)^0, (\neg z)^{11}, (x)^{12}, (y \lor t)^{11}, (z \lor v \lor x)^{14} \} \]

with $w(l_i) = 1$ for $i = 1, 4$. Now $\text{CIL}(\Phi_{F_{ex}}) = F_b \cup F_s$, and $\text{LBSs}(\Phi_{F_{ex}}) = \{ l_1, l_2, l_3, l_4 \}$. The label-set $L = \{ l_1, l_2 \}$ is an LMUS of $\Phi_{F_{ex}}$ as

\[ \Phi_{F_{ex}} | L = \{ (x \lor y)^0, (\neg x \lor \neg z)^0, (\neg y \lor z)^0, (z \lor t)^0, (\neg z)^{11}, (x)^{12} \} \]

is unsatisfiable. The sets $R_1 = \{ l_1 \}$ and $R_2 = \{ l_2 \}$ are examples of (minimum-cost) LMCSEs of $\Phi_{F_{ex}}$. The fact that $\tau$ is an optimal solution to the LCNF-MaxSAT instance $\Phi_{F_{ex}}$ can be verified by checking that $\tau$ satisfies $\Phi_{F_{ex}} | Lb(\Phi_{F_{ex}}) \setminus R_2$. Converting $\Phi_{F_{ex}}$ back to MaxSAT results in the instance $F' = (F'_b, F'_s, w)$ with

\[ F'_b = \{ (x \lor y), (\neg x \lor \neg z), (\neg y \lor z), (z \lor t), (\neg x \lor a_1), (x \lor a_2), (y \lor t \lor a_3), (z \lor x \lor a_4) \} \quad \text{and} \quad F'_s = \{ (\neg a_1), (\neg a_2), (\neg a_3), (\neg a_4) \} \]

2.2 SAT-based Preprocessing for LCNFs

A motivation for viewing MaxSAT instances as LCNF in [7] was to develop sound applications of SAT preprocessing techniques for MaxSAT. Many important SAT preprocessing techniques, including bounded variable elimination (VE) [20], self-subsuming resolution (SSR), and subsumption elimination (SE), cannot be used directly on MaxSAT instances [7]. However, the techniques can be applied on LCNFs by taking into account the natural restrictions implied by the SAT-level techniques on the label-sets of labelled clauses. With this intuition, the following LCNF-liftings of VE, SSR, and SE were proposed [7].

- **LCNF-lifting of the resolution rule:** The resolvent of two labelled clauses $(x \lor A)^{L_1}$ and $(\neg x \lor B)^{L_2}$ w.r.t. $x$ is $(x \lor A)^{L_1 \setminus x} \lor (\neg x \lor B)^{L_2}$.

- **LCNF-lifting of VE (LVE):** Let $\Phi_x$ and $\Phi_{\neg x}$, resp., denote the sets of labelled clauses that contain the literal $x$ and the literal $\neg x$, resp. LVE allows for replacing $\Phi_x \cup \Phi_{\neg x}$ with $\Phi_x \cup \Phi_{\neg x} \cup A \lor B$ non-tautologically given that $|\Phi_x \cup \Phi_{\neg x} \cup A \lor B| > |\Phi_x \cup \Phi_{\neg x}|$.

- **LCNF-lifting of SE (LSE):** A labelled clause $A^L_{\lor} L_1$ subsumes $B^L_{\lor} L_2$ if $A \subseteq B$ and $L_1 \subseteq L_2$. LSE allows for removing subsumes clauses.

- **LCNF-lifting of SSR (LSSR):**

**Blocked clause elimination (BCE):** [28] is sound for MaxSAT [7], and could as such be directly applied on MaxSAT instances. However, for a uniform presentation, it makes sense to consider a straightforward lifting of BCE.

- **LCNF-lifting of BCE (LBCE):** A labelled clause $C^{L_z}$ is blocked in $\Phi$ if $C$ is blocked in $CIL(\Phi)$. LBCE allows for removing blocked clauses.

**Example 3** Consider the LCNF-MaxSAT instance $\Phi_{F_{ex}}$ from Example 2. Applying LSE to remove $(z \lor v \lor x)^{14}$ and LVE to eliminate $x$ and $t$ results in the formula

\[ \{ (y)^{11}, (\neg z \lor v)^0, (\neg y \lor z)^0, (l_1, l_2), (y \lor z)^{11} \} \]

Removing $(y \lor z)^{11}$ by LSE and eliminating $z$ by LVE results in the preprocessed formula $\Phi_{F_{ex}}^\text{pre} = \{ (y)^{11}, (l_1, l_2) \}$. LVE, LSSR, LSE, and LBCE are correct due to the following.

**Proposition 4** ([7]) Let $\Phi$ be a LCNF-MaxSAT instance and $\Phi^\text{pre}$ the LCNF-MaxSAT instance resulting from an application of LVE, LSSR, LSE, and LBCE on $\Phi$. Then $\text{LMUS}(\Phi^\text{pre}) = \text{LMUS}(\Phi^\text{pre})$ and, by Theorem 1, LMCS$(\Phi) = \text{LMCS}(\Phi^\text{pre})$.

3 SUBSUMED LABEL ELIMINATION

We propose and analyze subsumed label elimination (SLE), a labelled-preprocessing technique for MaxSAT. The primary goal of SLE is to provide further simplifications when applied in conjunction with SAT-based preprocessing; SLE focuses on removing labels from non-singleton label-sets (produced starting from non-labelled MaxSAT instances mainly by LVE). Before a formal definition of SLE, we begin with an example to illustrate some of the shortcomings of SAT-based preprocessing for MaxSAT that SLE seeks to address.

**Example 5** Consider the MaxSAT instance $F = (F_b, F_s, w)$ with $w(C) = 1$ for all $C \in F_s$ and

\[ F_b = \{ (x \lor y) \} \quad \text{and} \quad F_s = \{ (\neg x), (\neg y) \} \]

Converting $F$ to LCNF gives the instance $\Phi^F = \{ (x \lor y)^0, (\neg x)^{11}, (\neg y)^{12} \}$. Applying LVE to eliminate both $x$ and $y$ results in the LCNF-MaxSAT instance $\text{pre}(\Phi^F) = \{ (l_1, l_2) \}$. Finally, converting $\text{pre}(\Phi^F)$ back to MaxSAT gives the MaxSAT instance $F' = (F'_b, F'_s, w)$ with

\[ F'_b = \{ (a_1 \lor a_2) \} \quad \text{and} \quad F'_s = \{ (\neg a_1), (\neg a_2) \} \]

i.e., the exact same instance as $F$ modulo variable naming. In other words, LVE (or LSSR, LSE, and LBCE) is unable to simplify $F$. Furthermore, notice that $F$ contains exactly one MUS: $\{ (\neg x), (\neg y) \}$. As the clauses $(\neg x)$ and $(\neg y)$ occur in exactly the same MUSes, no optimal solution to $F$ falsifies both of them. As an alternative view, no MCS of $F$ contains both $(\neg x)$ and $(\neg y)$, which means that either clause could be hardened, i.e., changed to a hard clause, without removing all of the optimal solutions of the instance. As we will see, SLE captures this simplification on the LCNF-level.

More concretely, consider a LCNF-MaxSAT instance $\Phi$. SLE is based on the following observation. Consider two labels $l_1, l_2 \in \text{Lbs}(\Phi)$ such that $w(l_1) \leq w(l_2)$, and let $l_1$ appear in at least the same LMUSes of $\Phi$ as $l_2$. Then $l_2$ is redundant in that $l_2$ can be replaced by $l_1$ in any LMCS $R$ of $\Phi$ without increasing the cost of $R$. Hence $l_2$ can be removed from $\Phi$ while maintaining at least one minimum-cost LMCS. This is more formally stated as Theorem 6.

**Theorem 6** Let $l_1, l_2 \in \text{Lbs}(\Phi)$ and $\Phi^\text{pre} = \text{REMOVE}(\Phi, \{ l_2 \})$. Assume that, for all $L \in \text{LMUS}(\Phi)$, $l_2 \in L$ implies $l_1 \in L$. Then $\emptyset \neq \text{LMCS}(\Phi^\text{pre}) \subseteq \text{LMCS}(\Phi)$. 
Proof. \(\Phi^{\text{pre}}|_{Lbs(\Phi^{\text{pre}})} \models R = \Phi|_{Lbs(\Phi)} \models R\) for any label-set \(R \subseteq Lbs(\Phi^{\text{pre}})\). Hence it suffices to show that there is an \(R \in \text{LMCS}(\Phi)\) s.t. \(R \subseteq Lbs(\Phi^{\text{pre}})\). This can be verified by viewing \(R\) as an irreducible hitting set of LMUS(\(\Phi\)). If \(R \not\subseteq Lbs(\Phi^{\text{pre}})\), then \(l_2 \not\in R\). By assumption, \(R' = (R \setminus \{l_2\}) \cup \{l_1\}\), a subset of \(Lbs(\Phi^{\text{pre}})\), is also an irreducible hitting set of LMUS(\(\Phi\)) and hence a LMCS of \(\Phi\). \(\square\)

While the assumption in Theorem 6 is likely not checkable in polynomial time, a stricter, easier-to-check version of the assumption, formalized in Proposition 7, gives the basis for SLE. In words, let \(L\) be any label-set and \(C^{\text{L}}\) any labelled clause of \(\Phi\). If \(L'\) contains labels \(l_1\) and \(l_2\) such that \(l_2 \not\in L\) but \(l_1 \not\in L\), then \(C^{\text{L'}}\) is not a member of the formula \(\Phi|_{L_1}\). This is specifically true for any LMUS of \(\Phi\).

Proposition 7 Let \(l_1, l_2 \in Lbs(\Phi)\) and \(LCI(\Phi, l_2) \subseteq LCI(\Phi, l_1)\). Then, for all \(L \in \text{LMUS}(\Phi)\), \(l_2 \in L\) implies \(l_1 \in L\).

Proof. Let \(L\) be a label-set such that \(l_2 \in L\) and \(l_1 \not\in L\). We show that \(L\) is not a LMUS of \(\Phi\). From the assumption \(LCI(\Phi, l_2) \subseteq LCI(\Phi, l_1)\) it follows that, if \(C^{\text{L}}\) is a labelled clause for which \(l_2 \not\in L'\), then \(l_1 \not\in L'\). Thus \(C^{\text{L'}}\) \(\not\models \Phi|_{L'}\), and hence \(\Phi|_{L} = \Phi|_{L_1}(l_2)\). As such \(L \not\in \text{LMUS}(\Phi)\) as either \(\Phi|_{L}\) is satisfiable or \(\Phi|_{L_1}\) is unsatisfiable for \(l_1 = L \setminus \{l_2\} \subseteq L\). \(\square\)

The final part in the formalization of SLE ensures that the removal of \(l_2\) preserves at least one minimum-cost LMCS of the instance. This follows by adding an assumption on the weights of \(l_1\) and \(l_2\).

Proposition 8 Let \(l_1, l_2 \in Lbs(\Phi)\) and \(\Phi^{\text{pre}} = \text{REMOVE}(\Phi, \{l_2\})\). Assume that, for all \(L \in \text{LMUS}(\Phi)\), \(l_2 \in L\) implies \(l_1 \in L\), and \(w(l_1) \leq w(l_2)\). Then all minimum-cost LMCSes of \(\Phi^{\text{pre}}\) are also minimum-cost LMCSes of \(\Phi\).

Proof. Following the proof of Theorem 6 let \(R' = (R \setminus \{l_2\}) \cup \{l_1\}\) be the LMCS of \(\Phi\) constructed in order to replace the LMCS \(R \subseteq Lbs(\Phi^{\text{pre}})\). The extra assumption on the weights guarantees that the cost of \(R'\) is not higher than the cost of \(R\). \(\square\)

Putting these results together gives SLE. Informally, SLE removes subsumed labels \(l_2\), or, more formally, converts \(\Phi\) into \(\text{REMOVE}(\Phi, \{l_2\})\).

Definition 9 (Subsumed Label Elimination (SLE)) Let \(\Phi\) be a LCNF-MaxSAT instance and \(l_1, l_2 \in Lbs(\Phi)\). We say that \(l_1\) subsumes \(l_2\) if (i) \(LCI(\Phi, l_2) \subseteq LCI(\Phi, l_1)\), and (ii) \(w(l_1) \leq w(l_2)\). SLE allows for removing subsumed labels from LCNF-MaxSAT instances.

Example 10 Consider the LCNF-MaxSAT instance
\[
\Phi = \{(x_i \lor y_i)^{0} | i = 1..4\} \cup \{(\neg x_i \lor \neg x_3)^{0}, (\neg x_i \lor \neg x_4)^{0} | i = 1, 2\} \cup \{(\neg y_i)^{(i)} | i = 1..4\}
\]
with \(w(l) = 1\) and \(w(l_1) = w(l_2) = 2\) for all \(l\). First note that LVE, LSSR, LSE, and LBCE cannot simplify \(\Phi\). Specifically, as every variable appears both negatively and positively at least twice and no produced resolvents are tautologies, LVE cannot eliminate any variables. However, \(l\) subsumes all of the other labels, and hence applying SLE gives
\[
\{(x_i \lor y_i)^{0} | i, j = 1..4\} \cup \{(\neg x_i \lor \neg x_3)^{0}, (\neg x_i \lor \neg x_4)^{0} | i = 1, 2\} \cup \{(\neg y_i)^{(i)} | i = 1..4\}.
\]
Each \(y_i\) appears negatively only in a single clause and can hence be eliminated by LVE, resulting in
\[
\{(x_i)^{(i)} | i = 1..4\} \cup \{(\neg x_i \lor \neg x_3)^{0}, (\neg x_i \lor \neg x_4)^{0} | i = 1, 2\}.
\]
Now each \(x_i\) only appears positively in a single clause. LVE then gives \(\Phi^{\text{pre}} = \{(i)^{(i)}\}\).

Remark 1 While the main focus of this work is on understanding the effect of SLE on the core structure of MaxSAT instances and the potential of SLE for speed up state-of-the-art MaxSAT solvers, we note that SLE (for MaxSAT) can be viewed as the counterpart of the so-called dominance rule proposed in the early 90s in conjunction with branch-and-bound approaches for the so-called binary covering problem [17, 16] with applications in logic synthesis. More details on this connection are provided in Appendix A. To the best of our knowledge, however, SLE has not been previously proposed, analyzed, or empirically evaluated in the context of MaxSAT.

4 EFFECTS OF SLE

We continue by analyzing SLE in terms of how it simplifies LCNFs. We show that SLE is orthogonal to the LCNF-lifted SAT-based preprocessing techniques in terms of the LMUSes and LMCSes—and hence MaxSAT solutions—preserved under simplification.

We start with relatively simple corollaries of the definition. First, we observe that subsumed labels remain subsumed after applications of SAT-based preprocessing.

Proposition 11 Let \(l \in Lbs(\Phi)\) and assume that SLE can eliminate \(l\) from \(\Phi\). Let \(\Phi^{\text{pre}} = \Phi\) after applying LVE, LSSR, LSE, or LBCE. Then SLE can eliminate \(l\) from \(\Phi^{\text{pre}}\).

Proof. Let \(l_1\) be a label that subsumes \(l\) in \(\Phi\). It suffices to show that the preconditions of SLE are satisfied in \(\Phi^{\text{pre}}\). First, the precondition \(w(l_1) \leq w(l)\) is trivially satisfied as none of the techniques alter the weights of labels. For the second precondition, \(LCI(\Phi^{\text{pre}}, l) \subseteq LCI(\Phi^{\text{pre}}, l_1)\), the non-trivial case is \(LCI(\Phi^{\text{pre}}, l) \neq \emptyset\). As \(LCI(\Phi, l) \subseteq LCI(\Phi, l_1)\), it is enough to verify that none of the SAT-based preprocessing techniques introduce a labelled clause \(C^{\text{L'}}\) in \(\Phi^{\text{pre}}\) with \(l \in L\) and \(l_1 \notin L\). This is trivially true for LSE and LBCE as they only remove clauses. This is also true for LSSR as it only removes literals, not labels. Finally, LVE cannot produce resolvents which contain \(l\) but not \(l_1\), since there are no labelled clauses \(C^{\text{L'}}\) in \(\Phi\) with \(l \in L'\) and \(l_1 \notin L'\). Thus the label-set of any resolvent produced by LVE, which is a union of label-sets in \(\Phi\), contains either both or neither of \(l_1\) and \(l\). \(\square\)

Thus it makes sense to incorporate SLE into the preprocessing loop together with LVE, LSSR, LSE, and LBCE. In analogy with Proposition 11, subsumed labels remain subsumed also under SLE steps quite generally. An exception comes from cases in which two labels \(l_1\) and \(l_2\) subsume each other, i.e., when \(l_1\) and \(l_2\) occur in exactly the same label-sets and \(w(l_2) = w(l_1)\). Note also that, generally, if \(l_1\) subsumes \(l_2\), and \(l_2\) subsumes \(l_3\), then \(l_1\) subsumes \(l_3\).

Turning to comparing SLE and SAT-based preprocessing, Propositions 4 and 12 together illustrate fundamental differences between SLE and LVE, LSSR, LSE, and LBCE. By Proposition 4, LVE, LSSR, LSE, and LBCE preserve the LMUSes of LCNF-MaxSAT instances. This is not true for SLE. Instead, SLE guarantees (only) that at least one minimum-cost (optimal) LMCS and, as such, that at least one optimal solution of the instance is preserved.
Proposition 12 SLE does not in general preserve LMUSes (or LMCSes) of LCNF-MaxSAT instances.

Proof. Consider the instances \( \Phi \) and \( \Phi^{pre} \) from Example 10. The sets \( \{ i, i \} \) and \( \{ i, i \} \) are LMUSes of \( \Phi \) for all \( i \) but not of \( \Phi^{pre} \). \( \square \)

An alternative way of stating Proposition 12 is that applying SLE does not in general preserve all optimal solutions to LCNF-MaxSAT instances. For a simple example, consider the LCNF-MaxSAT instance \( \Phi = \{ (x(\bar{1}), -x(\bar{2})) \} \) with unit-weighted labels. There are two optimal solutions to \( \Phi \): \( \tau_1(x) = 1 \) satisfying \( \Phi|_{L_{bls}(\Phi)\{\bar{1}\}} \), and \( \tau_2(x) = 0 \) satisfying \( \Phi|_{L_{bls}(\Phi)\{\bar{1}\}} \). However, by LVE, we can simplify \( \Phi \) to \( \{ (\bar{1}) \} \) and by SLE further to \( \{ (\bar{1}) \} \). Only LMCS of the simplified instance is \( \{ i \} \), corresponding to the solution \( \tau_2 \).

Instead of preserving LMUSes, SLE could be seen as a form of LMUS minimization in the sense that all LMUSes remaining after SLE are projections of LMUSes of the original LCNF onto the remaining set of labels.

Theorem 13 Let \( \Phi \) be a LCNF-MaxSAT instance and \( l \in L_{blds}(\Phi) \) a subsumed label. Let \( \Phi^{pre} = \text{REMOVE}(\Phi, \{ l \}) \), i.e., the formula after eliminating \( l \) by SLE from \( \Phi \). Then all LMUSes \( L^p \) of \( \Phi^{pre} \) are of the form \( L^p = L \cap L_{blds}(\Phi^{pre}) \) for some LMUS \( L \) of \( \Phi \).

Proof. First notice that \( \Phi|_{L_{bls}(\Phi^{pre})L} \subseteq \Phi^{pre}|_{L_{bls}(\Phi^{pre})L} \) as the restriction operator only removes labels from label sets, not clauses. If \( \Phi|_{L_{bls}(\Phi^{pre})L} = \Phi^{pre}|_{L_{bls}(\Phi^{pre})L} \), then the same will be true for any \( L^p \subseteq L \), so \( L^p \) itself is an LMUS of \( \Phi \). Otherwise, the reason for a labelled clause \( C_l \) to be in \( \Phi^{pre}|_{L_{bls}(\Phi^{pre})L} \) but not in \( \Phi|_{L_{bls}(\Phi^{pre})L} \) is that the eliminated label \( l \) was in \( L \), i.e., \( C_l \notin \Phi \) but \( C_l|_{L_{bls}(\Phi^{pre})L} \). Hence \( \Phi|_{L_{blds}(\Phi^{pre})(l)} = \Phi^{pre}|_{L_{blds}(\Phi^{pre})L} \), and \( L \cup \{ l \} \) is a LMUS of \( \Phi \).

For further differences between SLE and LVE, LSSR, LSE, and LBCE, consider a SAT instance \( F \) and a soft clause \( C \in F_s \). Let \( \Phi_F \) be the LCNF-MaxSAT instance corresponding to \( F \) and let \( l_C \) the label for which \( C_l \in \Phi_F \). A simple application of Theorem 4 gives that if \( l_C \) is removed from \( \Phi_F \) by LVE, LSSR, LSE, or LBCE, then any optimal solution to \( \Phi_F \), which is also an optimal solution to \( F \), will satisfy \( C \).

Proposition 14 Let \( \Phi^{pre}_F \) be the instance resulting after an application of LVE, LSSR, LSE, or LBCE on \( \Phi_F \). If \( l_C \notin L_{bls}(\Phi^{pre}_F) \), then any optimal solution \( \tau \) to \( \Phi_F \), which is also an optimal solution to \( F \), will satisfy \( C \).

Proof. Since \( \tau \) is optimal, it satisfies \( \Phi_F|_{L_{blds}(\Phi_F)\{l_C\}} \) for some minimum-cost LMCS \( R \) of \( \Phi_F \). By Theorem 4, \( l_C \notin R \), and thus \( C \in C(\Phi_F|_{L_{blds}(\Phi_F)\{l_C\}}) \).

Informally, it could be said that SAT-based preprocessing can only remove labels that are “uninteresting” in terms of LMCS computation. In contrast, elimination of \( l_C \) by SLE means that some (but not necessarily all) optimal solutions of \( F \) satisfy \( C \), as shown next.

Proposition 15 Let \( \Phi^{pre}_F \) be the instance resulting from an application of SLE on \( \Phi_F \). If \( l_C \notin L_{blds}(\Phi^{pre}_F) \), then there is an optimal solution \( \tau \) to \( \Phi_F \) and \( F \) that satisfies \( C \). Furthermore, there may exist optimal solutions to \( \Phi_F \) that do not satisfy \( C \).

Proof. By the assumption that \( l_C \) is subsumed, it follows from Theorem 6 and Proposition 8 that there is a minimum-cost LMCS \( R \) of \( \Phi_F \) for which \( l_C \notin R \). The first part of the claim follows by observing that \( \Phi_F|_{L_{blds}(\Phi_F)\{l_C\}} \) is satisfiable and \( C \in C(\Phi_F|_{L_{blds}(\Phi_F)\{l_C\}}) \).

Algorithm 1: CG-MaxSAT

5 SLE and Core-Guided Solvers

We now show that SLE has the potential to considerably lower the number of iterations made by so-called core-guided MaxSAT solvers, one of the most successful current MaxSAT solving approaches. The core-guided approach has several variants, e.g., [2, 38, 22, 25, 40, 36, 37, 18, 19]. In this work, we study the effect of SLE on two different types of core-guided solvers through generic abstractions. The first one, CG-MaxSAT (Algorithm 1), iteratively employs a SAT solver to extract unsatisfiable cores and rules out each of the found cores from the formula by a clause replication and relaxation step. Several algorithms that fit the CG-MaxSAT abstraction have been proposed [22, 25, 40, 36, 37]. The second one, MaxHS (Algorithm 2), is an abstraction of the implicit hitting set approach to MaxSAT [18, 19], iteratively using a SAT solver to extract unsatisfiable cores, and an exact minimum-cost hitting set algorithm to compute hitting sets over the found cores.

In more detail, at each iteration \( i \), CG-MaxSAT invokes a SAT solver on the clauses of a working formula \( F_i \) (initialized as all clauses of the MaxSAT instance viewed as hard). If the working formula is satisfiable, CG-MaxSAT terminates and returns the satisfying assignment returned by the SAT solver. Otherwise, the SAT solver returns an unsatisfiable core \( \kappa \) of \( F_i \). CG-MaxSAT then duplicates the clauses in \( \kappa \) to create two sets \( \kappa' \) and \( \kappa'' \). Both sets contain exactly the same clauses as \( \kappa \); each clause \( C \in \kappa \) is duplicated into two: \( C' \in \kappa' \) and \( C'' \in \kappa'' \). The weight of \( C' \) is set to \( w_m \), the minimum weight over the clauses in the core, and the weight of \( C'' \) to \( w(C) - w_m \). The clauses of \( \kappa'' \) are added to the working formula unaltered. Finally, the working formula is updated by relaxing the clauses in \( \kappa'' \). The method of relaxation varies between core-guided solvers. For our analysis, the important consequences of relaxation are that the (possibly altered) clauses of \( \kappa'' \) do not appear as a core in future iterations, and that the optimal cost of \( F_i+1 \) (when viewed as a MaxSAT instance) is exactly \( w_m \) lower than the optimal cost of \( F_i \).

Termination of CG-MaxSAT is guaranteed by the fact that \( w_m > 0 \) on all iterations and that a MaxSAT instance of cost 0 is satisfiable as a SAT instance. For a concrete example of a relaxation step, consider the classical Fu-Malkil algorithm [22] and its extensions to the weighted case [33, 1]. These algorithms augments each \( C_i \in \kappa' \) with a fresh relaxation variable \( r_i \), creating the clause \( C_i \lor r_i \), and additionally adds a hard exactly-one constraint \( \sum r_i = 1 \) over the relaxation variables. The intuition behind this step is that assigning a relaxation variable to 1 effectively removes the corresponding clause from the formula, hence removing the core \( \kappa'' \). Additionally,
Input: MaxSAT instance $F = (F_h, F_s, w)$.
Output: An optimal solution $\tau$ for $F$.

$K \leftarrow \emptyset$ // set of found unsat cores of $F$

$F_w \leftarrow (F_h \cup F_s)$

while true do
  $H \leftarrow \text{MINCOSTHITTINGSET}(K)$
  $F_w \leftarrow F_h \cup (F_s \setminus H)$
  (result, $\kappa$, $\tau$) $\leftarrow$ SATSOLVE($F_w$)
  if result="satisfiable" then
    return $\tau$ // optimal solution
  else
    $K \leftarrow K \cup \{\kappa\}$ // SAT solver returned unsat core
  end
end

Algorithm 2: MaxHS

the exactly-one constraint ensures that the cost is lowered exactly by $w_m$.

MaxHS is a hybrid algorithm that uses a SAT solver for core extraction
over a working formula $F_w$ (initialized as all clauses of the input instance viewed as hard).
Given a collection $K$ of extracted cores, MaxHS uses an exact algorithm (integer programming solver
in practice) to find a minimum-cost hitting set $hs$ over $K$. The working formula is then
updated to contain all clauses of $F$ except for the soft clauses in $hs$,
and the SAT solver is invoked again. If the working formula is satisfiable,
the satisfying assignment obtained is
an optimal solution to $F$. Otherwise another core is obtained and the
search continues again with hitting set computation.

The main result of this section is that there are families of LCNF-
MaxSAT instances on which SLE can significantly decrease the number
of SAT solver calls and clause replication when subsequently
solving the instances with CG-MaxSAT or MaxHS.

Proposition 16 For $A \in \{\text{CG-MaxSAT, MaxHS}\}$, there is a family
of LCNF-MaxSAT instances $\Phi_N$, with $\Theta(N)$ different labels, on
which

(i) $A$ requires $\Theta(N)$ calls to its SAT solver; and, for $A = \text{CG-
MaxSAT}$, $A$ requires $\Theta(N)$ clause replication steps, on $\Theta(N)$
different executions; while

(ii) $A$ is guaranteed to require only two (one unsatisfiable and one
satisfiable) SAT solver calls if SLE is applied on $\Phi_N$ before
$A$ under the assumption that the internal SAT solver is guaranteed
to return minimal unsatisfiable cores.

Proof: The family of LCNF-MaxSAT instances witnessing the claim
is the same for CG-MaxSAT and MaxHS. Let $N$ be sufficiently large
and define

$$\Phi_N := \bigcup_{i=1}^{2N-2} P_i \cup \bigcup_{i=1}^{N-1} H_i,$$

where

$$P_i = \bigcup_{j=1}^{N} \{\neg p_i^k \lor \neg p_j^k \} \mid k = (i+1) \ldots (2N-1)$$

and

$$H_i = \left\{ \left( \bigwedge_{j=1}^{N} p_j^k \right) \mid \tau = (i) \right\},$$

with $w(l) = w(l_{N-1}) = N$ and $w(l_i) = 1$ for all other labels $l_i$.
Notice that $\Phi_N$ contains $N-1$ LMUSes of the form $\{l_i, l_{i+1}\}$
for all $1 \leq i \leq N-1$. Hence, the only minimum-cost LMCS of $\Phi_N$ is

$\{\}$. Furthermore, refuting any of the LMUSes requires proving
the unsatisfiability of the formula $\Phi_N \setminus \{l_i, l_{i+1}\}$, which
corresponds to an instance of the pigeonhole principle; meaning that the extraction any
of the LMUSes of $\Phi_N$ requires an exponentially long SAT solver
call [24]. Next we sketch the executions of both CG-MaxSAT and
MaxHS that require $\Theta(N)$ SAT-solver calls when solving $\Phi_N$.

Conversion of $\Phi_N$ to MaxSAT results in the formula $F = (F_h, F_s, w)$, where

$$F_h = \bigcup_{i=1}^{2N-2} \bigcup_{j=1}^{N} \{\neg p_i^k \lor \neg p_j^k \} \mid k = i \ldots (2N-1)$$

and $F_s = \left\{ \left( \bigwedge_{i=1}^{N-1} \neg a_i \right) \right\}$

with $w(\neg a_i) = w(\neg a_{N-1}) = N$ and $w(C) = 1$ for all other
$C \in F_s$. The MUSes of $F$ correspond exactly to the LMUSes of $\Phi_N$
and are of the form $\left\{ \neg a_i, \neg a_{i+1} \right\}$ for all $i = 1 \ldots N-1$.
For an intu-
6 EXPERIMENTS

Complementing the theoretical analysis, we evaluate the practical effects of SLE on the 2015 MaxSAT Evaluation benchmarks (http://www.maxsat.udl.cat/15/). We observe that SLE is beneficial especially on industrial weighted partial benchmark instances. When applying SLE in conjunction with the LCNF-lifted SAT-based preprocessing techniques (LVE, LSSR, LSE, LBCE), noticeably more labels can be removed than without applying SLE. Furthermore, SLE improves the overall performance of various state-of-the-art MaxSAT solvers on industrial weighted partial benchmarks.

All reported solving times include the time spent in preprocessing as well as in the actual MaxSAT solving. The experiments were run on 2.53-GHz Intel Xeon quad-core machines with 32-GB RAM under Linux. A per-instance timeout of 1800 seconds and a memory limit of 30 GB were enforced.

We implemented SLE by extending the Coprocessor 2.0 SAT preprocessor [34] in the following way. Given a MaxSAT instance as input, we convert the instance to LCNF, apply Coprocessor to preprocess the LCNF, and then convert the preprocessed LCNF back to a MaxSAT instance. LVE, LSSR LSE, LSSR, and LBCE are realized by representing a labelled clause \( C_L \) as \( C \lor \bigvee_{i \in L} a_i \) in Coprocessor, applying the existing implementations of VE, SSR, SE and BCE, while forbidding the elimination of any of the \( a_i \) variables corresponding to the labels.

A simple way of implementing SLE consists of explicitly checking for each label \( l \) whether or not \( l \) is subsumed. A potentially more efficient way of implementing SLE would be to track the resolvents produced by LVE and only check labels that have appeared in resolvents produced. However, as shown in Figure 3, even the simple implementation appears to be sufficient; we did not observe any significant increase in total preprocessing time (w/\( \text{pre+SL} \)) compared to not using SLE (w/\( \text{pre} \)). We also note that SLE does not increase overall memory consumption w.r.t SAT-based preprocessing.

The fraction of labels (i.e. soft clauses) remaining after preprocessing with and without SLE (applying in both cases LVE, LSSR, LSE, and LBCE) is shown in Figure 2 for both unweighted and weighted partial industrial and crafted instances. SLE is effective in removing additional labels in particular on the industrial weighted partial instances. For example, for one third of the instances (\( x = 0.3 \)), with SLE close to 80\% of the labels are eliminated (\( y \approx 0.2 \), i.e., some 20\% of the labels remain afterwards); in comparison, without SLE only \( \approx 45\% \) are eliminated. As a side-note, when examining the instance families in more detail, we found that out of the 172 industrial benchmarks in which no labels were removable by preprocessing, 151 were new instances in the 2015 evaluation. In fact, when preprocessing the 2014 evaluation instances—which are a subset of the 2015 evaluation instances—using SLE, at least 80\% of the labels are eliminated from over 50\% of the instances. This suggests that, in terms of SLE, the instances added for 2015 are structurally different from the ones from 2014.

The additional simplifications obtained via SLE are also reflected in the total number of solved instances and solver runtimes on industrial weighted partial instances. Results are shown in Table 1 for the state-of-the-art MaxSAT solvers Eva [40], core-guided, best industrial weighted partial solver in 2014; LMHS [11], one of the best crafted and industrial weighted partial solvers in 2015, a labelled lifting of the SAT-IP hybrid MaxSAT solver MaxHS [18]; OpenWBO [36], one of the best industrial unweighted solvers in 2015; and Primal-Dual [12], a new core-guided solver from 2015. SAT-based preprocessing together with SLE results in the highest number of solved instances for each of the solvers. The increase in the number of solved instances is especially noticeable for LMHS. SLE also decreases the total runtime over all solved instances for each of the solvers. For example, for both Eva and Primal-Dual, using SLE improves further on applying only SAT-based preprocessing by decreasing the total runtime by approximately 10\%, at the same time enabling Primal-Dual and Eva to solve one and two more instances, respectively. Finally, Figure 4 shows a comparison of the running times of the individual instances with the solvers are presented in the order LMHS (first column), Eva (second), Open-WBO (third), and Primal-Dual (fourth column). For each solver, we compare runtimes on logscale when applying SLE together with LVE, LSSR, LSE, and LBCE (\( \text{w/pre+SLE} \)) to (i) without preprocessing (\( \text{w/pre} \)), (ii) preprocessing only with LVE, LSSR, LSE, and LBCE (\( \text{w/pre} \), right). For a majority of the instances, SLE improves the total solving time of each of the solvers both compared to using no preprocessing, and only using LVE, LSSR, LSE and LBCE.
7 CONCLUSIONS

We proposed subsumed label elimination (SLE) as a MaxSAT preprocessing technique that is beneficial to apply in conjunction with SAT-based preprocessing techniques before MaxSAT solving. SLE is orthogonal to SAT-based preprocessing in that SLE can eliminate redundant auxiliary variables (labels) from clauses irrespective of the original variables occurring in clauses. On the level of labelled CNFs, this accounts to removing redundant labels from LMUSes, thereby resulting in cases in a decrease in the number and sizes of MUSes of MaxSAT instances. Furthermore, SLE has the potential to drastically reduce the number of iterations performed by core-guided MaxSAT solvers, currently one of the important classes of MaxSAT solvers. Applying SLE further improves the running times of various state-of-the-art MaxSAT solvers on standard industrial weighted partial benchmarks. For future work, we aim to study more general notions of redundancies over labels in LCNFs to obtain further label-based preprocessing techniques for MaxSAT, as well as to study potential applications in MUS extraction.

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A SLE and Dominance in Binate Covering

SLE (for MaxSAT) can be viewed as the counterpart of the so-called dominance rule proposed in the early 90s in conjunction with branch-and-bound approaches for the so-called binate covering problem [17, 16] with applications in logic synthesis. In short, in the binate covering problem, we are given a Boolean function \( f : \{0, 1\}^n \to \{0, 1\} \) over the variables \( x_1, \ldots, x_n \), and a function \( \text{cost} : \{1..n\} \to \mathbb{N} \) assigning a non-negative cost \( \text{cost}(i) \) to each variable \( x_i \). The task is to find a truth assignment \( \tau \) over \( x_1, \ldots, x_n \) that minimizes \( \sum_{i=1}^n \tau(x_i) \cdot \text{cost}(i) \) subject to \( f(\tau(x_1), \ldots, \tau(x_n)) = 1 \). The dominance rule for binate covering is described in [17] for the so-called modified covering matrix representation of binate covering for Boolean functions in CNF. We interpret the rule directly on the definition as follows: variable \( x_i \) dominates \( x_j \) if (i) the literal \( x_j \) occurs in a clause \( C \) whenever the literal \( x_i \) occurs in \( C \); (ii) \( \neg x_j \) occurs in a clause \( C \) whenever \( \neg x_i \) occurs in \( C \); and (iii) \( \text{cost}(x_i) \leq \text{cost}(x_j) \). A dominated variable can be assigned to 0.

A LCNF-MaxSAT instance \((\Phi, w)\) can be viewed as an instance of binate covering by viewing each labelled clause \( C^L \in \Phi \) as the clause \( C \lor \), and letting \( \text{cost}(l) = w(l) \) for each \( l \in \text{Lbls}(\Phi) \) and \( \text{cost}(x) = 0 \) for each variable in \( \bigcup C(\Phi) \). After this reduction, one can observe that, for any label \( l \in \text{Lbls}(\Phi) \), it holds that \( l \) is dominated in the resulting binate covering instance if and only if SLE can eliminate \( l \) from \((\Phi, w)\).
REFERENCES


