A Davis-Putnam Based Enumeration Algorithm for Linear Pseudo-Boolean Optimization

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MPI-I-95-2-003 January 1995
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Acknowledgements

The author is grateful to Alexander Bockmayr for his valuable comments and fruitful discussions. The author is also grateful to John N. Hooker for his comments on the variable selection heuristics.

This work was supported by the German Ministry for Research and Technology (BMFT) (contract ITS 9103), the ESPRIT Basic Research Project ACCLAIM (contract EP 7195) and the ESPRIT Working Group CCL (contract EP 6028).
Abstract

The Davis-Putnam enumeration method (DP) recently evolved to one of the fastest known methods for solving the clausal satisfiability problem of propositional calculus. We present a generalization of the DP-procedure for linear pseudo-Boolean (or 0-1) inequalities and make use of the achievements for DP. We extend the method to optimize a linear pseudo-Boolean objective function w.r.t. a set of linear pseudo-Boolean inequalities. The algorithm compares well with traditional linear programming based methods on a variety of standard 0-1 integer programming benchmarks.

Keywords

0-1 Integer Programming; Propositional Calculus; Enumeration
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1 Introduction

The Davis-Putnam enumeration method (DP) is widely used in the theorem proving community for solving the clausal satisfiability problem of propositional calculus (SAT) [DP60, Lov78]. In recent years, DP based algorithms have evolved to the fastest known methods for solving SAT [JW90, HHT91, Hoo93, Zha93]. This is due to proper implementation techniques and the development of good variable selection heuristics [JW90, HV94]. We present a generalization of the DP-procedure for solving linear pseudo-Boolean \((0,1)\) optimization problems and so use results from theorem proving on typical Operations Research problems. The method compares well with traditional linear programming based methods on a variety of standard 0-1 integer programming problems found in MIPLIB [BB92].

The generalized DP method for solving linear pseudo-Boolean optimization problems is essentially an implicit enumeration method based on the logical structure of pseudo-Boolean problems. Logic-based methods have been rejected in favor of linear programming based methods, exploiting the polyhedral structure of the problem, years ago. Recently there has been some renewed interest in logic-based methods. Hooker [Hoo94] relates the logic and polyhedral view of pseudo-Boolean problems. He points out that for instance cutting planes are a special class of logical implications and the linear programming relaxation can be replaced by a discrete relaxation. Choosing a discrete relaxation together with an appropriate logic-cut generation method [Hoo92, Hoo94, Bar94] then yields a logic-based branch-and-cut algorithm. In branch-and-cut methods two tasks have to be done. First, a relaxation of the problem has to be solved and a problem has to be split (branch). Second, a problem has be reformulated (strengthened) with an appropriate method if possible (cut).

In this paper we concentrate on solving a discrete relaxation of linear pseudo-Boolean problems, the basic part of any system including branching, and its application inside a pure implicit enumeration method. We consider a weak discrete relaxation, i.e. pseudo-Boolean unit relaxation, which can be efficiently computed and present a branching algorithm based on this relaxation for determining the satisfiability of a set of linear pseudo-Boolean inequalities. The method then is used for optimizing a linear pseudo-Boolean function w.r.t. a set of linear pseudo-Boolean inequalities. We show that a pure branching algorithm based on a discrete relaxation can be comparably efficient w.r.t. linear programming based branch-and-bound methods.

The paper is organized as follows. In Section 2 we give basic definitions and present a normal form for linear pseudo-Boolean inequalities. The DP-procedure for solving SAT is recalled in Section 3. Its generalization to pseudo-Boolean constraints and the application to linear pseudo-Boolean optimization problems is presented in Section 4 and Section 5 respectively. Implementation issues are mentioned in Section 6. We briefly discuss variable selection heuristics in Section 7. Computational results are given in Section 8 followed by the conclusion.

2 Preliminaries

Let \(B := \{X_1, X_2, \ldots, A, B, \ldots\}\) be a finite set of boolean variables, that is the domain of the variables is \(\{0, 1\}\). A literal \(L_i\) is either a boolean variable \(X_j\) (positive literal) or its negation \(\overline{X_j} = 1 - X_j\) (a negative literal). Let \(L\) be the set of all literals. The negation of a negative literal \(\overline{X_j}\) is always simplified to \(X_j\). We denote by \(\text{Var}(X_j) = \text{Var}(\overline{X_j}) = X_j\) the variable of a literal.

A linear pseudo-Boolean term \(c_1 L_1 + \cdots + c_n L_n\) (abbreviated by \(cL\)) is a sum of products \(c_i L_i\), where \(c_i \in \mathbb{Z}\) and \(L_i \in L\). We view \(cL\) also as a set of products. For a set of products \(cL\) we
denote by $\sum c := c_1 + \cdots + c_n$ the sum of the integer coefficients of $cL$. Let $T$ be the set of all linear pseudo-Boolean terms. An assignment is a mapping $\alpha : B \to \{0, 1\}$. An assignment can also be seen as a 0-1 vector of dimension $n$. Assignments are naturally extended to a mapping $\alpha : T \to \mathbb{Z}$.

A linear pseudo-Boolean inequality is of the form $cL \geq d$. An assignment $\alpha$ satisfies a linear pseudo-Boolean inequality $cL \geq d$ if $\alpha(cL) \geq d$. If there is no assignment satisfying $cL \geq d$, we simplify $cL \geq d$ to the contradiction $\perp$. If every assignment satisfies $cL \geq d$ then $cL \geq d$ is a tautology and we simplify it to $\top$. An assignment satisfies a set of linear pseudo-Boolean inequalities if it satisfies each linear pseudo-Boolean inequality in the set. The extension $\text{Ext}(S)$ of a set of linear pseudo-Boolean inequalities is the set of assignments satisfying $S$. A set of linear pseudo-Boolean inequalities $S$ (strictly) dominates a set of linear pseudo-Boolean inequalities $S'$ if $\text{Ext}(S)$ is a (proper) subset of $\text{Ext}(S')$. A linear pseudo-Boolean inequality $cL \geq d$, where $c_i = 1$ for all $1 \leq i \leq n$ is called extended clause and abbreviated by $L \geq d$. If additionally $d = 1$, then we call the linear pseudo-Boolean inequality classical clause. I.e., $L_1 + \cdots + L_n \geq 1$ is equivalent to the disjunction of its literals $L_1 \lor \cdots \lor L_n$. Deciding whether there is an assignment satisfying a set of clauses is called the propositional satisfiability problem (SAT). Next, we define a normal form for linear pseudo-Boolean inequalities.

**Definition 2.1** A linear pseudo-Boolean inequality $cL \geq d$ is in (pseudo-Boolean) normal form if

$$d \geq c_1 \geq \cdots \geq c_n \geq 1 \text{ and } \text{Var}(L_i) \neq \text{Var}(L_j) \text{ for all } 1 \leq i \neq j \leq n.$$  \hspace{1em} (1)

We assume that $d \geq 1$ because otherwise the pseudo-Boolean inequality in normal form is a tautology, that is it is valid for every assignment $\alpha$ and therefore need not be considered.

**Proposition 2.2** [HR68] For each linear pseudo-Boolean inequality, which is not a tautology, there exists an equivalent linear pseudo-Boolean inequality in normal form.

**Proof:** We constructively describe how to obtain the pseudo-Boolean normal form of a linear pseudo-Boolean inequality. We begin with an arbitrary linear pseudo-Boolean inequality

$$c_1 L_1' + \cdots + c_m L_m' \geq d'$$  \hspace{1em} (2)

First, we apply several arithmetic equivalence transformations. We rewrite (2) such that literals containing the same variable are grouped together and obtain

$$a_1 X_1 + b_1 \overline{X_1} + \cdots + a_n X_n + b_n \overline{X_n} \geq d'$$

where the $X_i$ are pairwise different. For each $i$ such that $a_i = b_i$ we can simplify $a_i X_i + b_i \overline{X_i}$ to the constant $a_i$ and move the constant $a_i$ to the right-hand side. So let us assume that $a_i \neq b_i$ for all $1 \leq i \leq n$. Next, we replace $a_i X_i + b_i \overline{X_i}$ by $c_i' L_i'$, where $c_i' := c_i L_i + c_i' L_i'$, for all $1 \leq i \leq n$ according to

$$c_i' L_i + c_i' L_i := \begin{cases} (a_i - b_i) X_i + b_i & \text{if } a_i > b_i \\ (b_i - a_i) \overline{X_i} + a_i & \text{if } b_i > a_i \end{cases}$$

Note that the $c_i'$ are all positive. Bringing the constants $c_i'$ to the right-hand side gives us the new right-hand side $d = d' - \sum_{i=1}^n c_i'$. After re-indexing according to the ordering restriction we have brought the linear 0-1 inequality into the form

$$c_1 L_1 + \cdots + c_n L_n \geq d'$$  \hspace{1em} (3)
where \( c'_1 \geq \cdots \geq c'_n \geq 1 \) and \( \text{Var}(L_i) \neq \text{Var}(L_j) \) for all \( 1 \leq i < j \leq n \). Note that \( d \geq 1 \), since otherwise (2) is a tautology. So far we have only applied arithmetic equivalence transformations, hence an assignment \( \alpha \) satisfies (2) if and only if \( \alpha \) satisfies (3). When constructing the pseudo-Boolean normal form of a linear pseudo-Boolean inequality we can detect at this point whether we have a tautology or not.

Suppose that \( c'_i > d \) for some \( i \), then every assignment \( \alpha \) with \( \alpha(L_i) = 1 \), maps the left-hand side of (3) to an integer greater than \( d \) and satisfies (3). For all assignments \( \alpha \) with \( \alpha(L_i) = 0 \), the value of the left-hand side is independent of \( c_i \). Hence, we can safely replace each \( c'_i \) by \( d \) if \( c'_i > d \). Formally, we define

\[
c_i := \begin{cases} 
c'_i & \text{if } c'_i \leq d \\
d & \text{if } c'_i > d 
\end{cases}
\]

for all \( 1 \leq i \leq n \), and thereby obtain the pseudo-Boolean normal form

\[
c_1 L_1 + \cdots + c_n L_n \geq d
\]

of (2) with \( d \geq c_1 \geq \cdots \geq c_n \geq 1 \). Obviously, an assignment \( \alpha \) satisfies (2) if and only if \( \alpha \) satisfies (3) if and only if \( \alpha \) satisfies (5).

The last step of the normalization process as described by (4) is also called coefficient reduction [CJP83]. Note that a linear pseudo-Boolean inequality in normal form \( cL \geq d \) is satisfiable if and only if \( \sum c \geq d \), because \( c_i > 0 \) for all \( 1 \leq i \leq n \). Hence, \( cL \geq d \) is unsatisfiable if and only if \( \sum c < d \), and we can easily decide whether \( cL \geq d \) is \( \perp \). From now on we assume that all linear pseudo-Boolean inequalities are brought into pseudo-Boolean normal form.

In optimization problems we want to maximize (resp. minimize) a linear pseudo-Boolean term \( cL \text{ w.r.t. a set of linear pseudo-Boolean inequalities } S \), i.e. we search for a satisfying assignment \( \alpha \) of \( S \) such that \( \alpha(cL) \geq \alpha'(cL) \) (resp. \( \alpha(cL) \leq \alpha'(cL) \)) for all satisfying assignments \( \alpha' \) of \( S \).

### 3 The Classical Davis-Putnam Procedure

First, we recall the classical Davis-Putnam enumeration method (DP) for solving SAT.

A classical clause \( L \geq 1 \) with \( |L| = 1 \), i.e. there is only one literal, is called a unit clause. The literal \( L_i \) of a unit clause is called a unit literal. The basic idea of DP is to restrict the resolution rule to the case that at least one of the classical clauses on which resolution is applied, is a unit clause. Such a resolution step is called unit resolution step. The resolvent of a unit clause \( \{L_i\} \geq 1 \) and a classical clause \( L \geq 1 \) is defined by

\[
\text{ures}(\{L_i\} \geq 1, L \geq 1) := \begin{cases} 
L \setminus \overline{\{L_i\}} \geq 1 & \text{if } \overline{L_i} \in L, \\
T & \text{if } L_i \in L, \\
L \geq 1 & \text{otherwise}.
\end{cases}
\]

Since \( \alpha(L_i) = 1 \) for all solutions \( \alpha \) of a SAT-problem containing \( \{L_i\} \geq 1 \), we know that each solution of \( \text{ures}(\{L_i\} \geq 1, L \geq 1), \{L_i\} \geq 1 \) is a solution of \( L \geq 1 \). Therefore, \( L \geq 1 \) is dominated by \( \text{ures}(\{L_i\} \geq 1, L \geq 1), \{L_i\} \geq 1 \) and can be replaced by \( \text{ures}(\{L_i\} \geq 1, L \geq 1) \) in a SAT-problem containing \( \{L_i\} \geq 1 \). For a set of classical clauses \( S \) we define

\[
\text{ures}(\{L_i\} \geq 1, S) := \{\text{ures}(\{L_i\} \geq 1, L \geq 1) | L \geq 1 \in S \text{ and } \text{ures}(\{L_i\} \geq 1, L \geq 1) \neq T \}.
\]
Note that there are no tautologies \( T \) in \( \text{ures}(\{L_i\} \geq 1, S) \). Unit resolution, or clausal chaining, for a set of classical clauses \( S \) then means to apply \( \text{ures} \) as long as there is a unit clause in \( S \).

\[
\frac{\langle S, U \rangle}{\text{ures}(\{L_i\} \geq 1, S), U \cup \{L_i\}} \quad \text{if} \quad \{L_i\} \geq 1 \in S
\] (8)

We denote by \( \langle \text{ur}(S), \text{ul}(S) \rangle \) the normal form obtained by applying the transition rule (8) as long as possible on \( \langle S, \emptyset \rangle \). The set \( \text{ul}(S) \) then contains the set of all literals that occurred in a unit clause during the application of unit resolution. Moreover, \( \text{ur}(S) \) does not contain a unit clause and we have

\[
\text{Ext}(\text{ur}(S) \cup \{\text{ul}(S) \geq \text{ul}(S)\}) = \text{Ext}(S).
\] (9)

If \( \text{ur}(S) \) contains the empty clause \( \bot \), then \( S \) is unsatisfiable and we then say that the unit relaxation of \( S \) is unsatisfiable. On the other hand, we know that \( S \) is satisfiable if and only if \( \text{ur}(S) \) is satisfiable, since each solution \( \alpha \) of \( S \) is a solution of \( \text{ur}(S) \) and \( \alpha(L_i) = 1 \) for all \( L_i \in \text{ul}(S) \). Note that \( \text{Var}(L_i) \neq \text{Var}(L_j) \) for all different \( L_i \) and \( L_j \) in \( \text{ul}(S) \). It is well known that the unit relaxation of \( S \) is unsatisfiable if and only if the linear programming relaxation of \( S \) is unsatisfiable [BJL86].

Given a set of classical clauses \( S \), the DP-procedure solves SAT by searching a solution \( \alpha \) of \( S \) by exploring a search tree, where each node of the tree represents a SAT-problem. Next, we define a transition system that operates on states \( \langle P, \text{Sol} \rangle \). Here, \( P \) is a set of tuples \( \langle S, U \rangle \), where \( S \) is a SAT-problem and \( U \) is a set of literals that are fixed so far, representing the nodes that still need to be explored. We collect the sets of fixed literals that generate an empty SAT-problem as a set of sets of literals \( \text{Sol} \).

\[
\text{dp\_clash} : \frac{\langle S, U \rangle \cup \{P, \text{Sol} \}}{\langle P, \text{Sol} \rangle} \quad \text{if} \quad \bot \in S
\]

\[
\text{dp\_sol} : \frac{\langle S, U \rangle \cup \{P, \text{Sol} \}}{\langle P, \text{Sol} \cup \{U \} \rangle} \quad \text{if} \quad \emptyset = S
\]

\[
\text{dp\_split} : \frac{\langle S, U \rangle \cup \{P, \text{Sol} \}}{\left\{ \langle \text{ur}(S'), \text{ul}(S') \cup U \rangle, \langle \text{ur}(S''), \text{ul}(S'') \cup U \rangle \right\} \cup \{P, \text{Sol} \}} \quad \text{if} \quad \bot \notin S, \{L_i \neq \emptyset, \quad \text{L_i = select literal}(S), \quad S' = S \cup \{\{L_i \geq 1\} \text{ and } S'' = S \cup \{\{\overline{L_i} \geq 1\} \}
\]

In \text{dp\_split} we select a so called switching literal \( L_i \) occurring in a classical clause in the current SAT-problem by a procedure \text{select\_literal}. Applying the transition system defined by the three rules \text{dp\_clash}, \text{dp\_sol} and \text{dp\_split} as long as possible on \( \langle \{\{\text{ur}(S), \text{ul}(S)\}\}, \emptyset \rangle \), where \( S \) is a set of classical clauses, yields the normal form \( \langle \emptyset, \text{Sol} \rangle \). Note that unit resolution applies at least once for each of the two subproblems introduced by \text{dp\_split}, since we add a unit clause. Therefore, the number of literals in each of the two subproblems is smaller than the number of literals in the selected problem. Hence, the above defined transition system always terminates. We know that \( S \) is satisfiable if and only if \( \text{Sol} \neq \emptyset \). From each element \( U \in \text{Sol} \) we can construct a solution \( \alpha \in \text{Ext}(S) \) by defining \( \alpha(L_i) := 1 \) for all \( L_i \in U \) and arbitrary otherwise. The set of all solutions of \( S \) is obtained by building all solutions \( \alpha \) for each \( U \in \text{Sol} \).

For efficiency reasons the search tree is typically explored depth first, i.e. the set of subproblems is implemented as a “Last In, First Out” (LIFO) data structure. Since we are only interested
in whether the SAT-problem is satisfiable or not, we stop the transition system whenever the first solution is found. We define
\[
dp(S) := \begin{cases} 
(T, U) & \text{if } S \text{ is satisfiable and } U \in \text{Sol} \\
(\bot, \emptyset) & \text{otherwise}
\end{cases}
\tag{10}
\]
which yields \((T, U)\) if and only if \(S\) is satisfiable and \(U\) is the first set of literals that is added to \(\text{Sol}\).

4 Davis-Putnam for Linear Pseudo-Boolean Inequalities

We generalize the DP-procedure for solving the satisfiability problem of a set of linear pseudo-Boolean inequalities by generalizing unit resolution to pseudo-Boolean unit resolution. The key idea of the unit resolution procedure is to fix a literal to one value and then to make obvious inferences, i.e. fixing other literals and detection of (un)satisfiability. First, we need to determine whether a linear pseudo-Boolean inequality implies fixing of a literal.

**Lemma 4.1** A linear pseudo-Boolean inequality \(cL \geq d\) dominates \(\{L_i\} \geq 1\) if and only if \(c_i L_i \in cL\) and \(\sum c - c_i < d\), where \(\sum c\) denotes the sum over all coefficients of \(c\).

**Proof:** Let \(c'L'\) be \(cL \setminus \{c_i L_i\}\) and \(\alpha\) be a solution of \(cL \geq d\). Then \(\alpha(c_i L_i) + \alpha(c'L') \geq d\) and \(\sum c' = \sum c - c_i\).

\(\Leftarrow\): Suppose that \(\sum c' < d\). Because \(\alpha(c'L') \leq \sum c' < d\), we must have \(\alpha(c_i L_i) > 0\) and thus \(\alpha(L_i) = 1\). Hence, \(\{L_i\} \geq 1\) is dominated by \(cL \geq d\).

\(\Rightarrow\): We assume that \(\sum c' \geq d\) and show that then \(\{L_i\} \geq 1\) is not dominated by \(cL \geq d\). Let \(\alpha(L_i) = 0\) and \(\alpha(L_j) = 1\) for all \(L_j \in L'\), then \(\alpha(cL) = \alpha(c_i L_i) + \alpha(c'L') = \sum c' \geq d\). Hence, \(\alpha\) is a solution of \(cL \geq d\), but not of \(\{L_i\} \geq 1\). \(\square\)

If a linear pseudo-Boolean inequality \(cL \geq d\) dominates \(\{L_i\} \geq 1\), we call \(L_i\) unit literal of \(cL \geq d\).

**Lemma 4.2** If a linear pseudo-Boolean inequality \(cL \geq d\) dominates \(\{L_i\} \geq 1\) with \(c_i L_i \in cL\), then \(cL \geq d\) dominates \(\{L_j\} \geq 1\) for all \(c_j L_j \in cL\) with \(c_j \geq c_i\).

**Proof:** If \(\sum c - c_i < d\) then \(\sum c - c_j < d\), because \(c_j \geq c_i\) and therefore Lemma 4.1 applies. But then we know that \(cL \geq d\) dominates \(\{L_j\} \geq 1\). \(\square\)

Using Lemma 4.2, we see that a linear pseudo-Boolean inequality \(cL \geq d\) dominates \(\{L_i\} \geq 1\) for some \(L_i\) if and only if \(cL \geq d\) dominates \(\{L_1\} \geq 1\), since \(L_i\) is a literal with the largest coefficient in a linear pseudo-Boolean inequality \(cL \geq d\) in normal form. We define
\[
\text{fixed}(cL \geq d) := \begin{cases} 
L_1 & \text{if } \sum c - c_i < d \\
\bot & \text{otherwise}
\end{cases}
\tag{11}
\]
and we have \(\text{fixed}(cL \geq d) = L_1\) if and only if \(cL \geq d\) dominates \(\{L_1\} \geq 1\). Moreover, if \(\text{fixed}(cL \geq d) = \bot\), then \(cL \geq d\) does not dominate any unit clause. Given a unit clause \(\{L_i\} \geq 1\), we can simplify a linear pseudo-Boolean inequality \(cL \geq d\) relative to the unit literal \(L_i\). We replace the literal \(L_i\) by 1 and bring the constant \(c_i\) to the right-hand side. Special
cases arise when the linear pseudo-Boolean inequality becomes tautologous after fixing (T) or unsatisfiable (⊥). We define
\[
\text{fix}(L_i, cL \geq d) := \begin{cases} 
T & \text{if } d - c_i \leq 0 \text{ and } c_i L_i \in cL, \\
cL \setminus \{c_i L_i\} \geq d - c_i & \text{if } d - c_i > 0 \text{ and } c_i L_i \in cL, \\
\bot & \text{if } \sum c - c_i < d \text{ and } c_i L_i \in cL, \\
cL \setminus \{c_i L_i\} \geq d & \text{if } \sum c - c_i \geq d \text{ and } c_i L_i \in cL, \\
cL \geq d & \text{if neither } L_i \text{ nor } \overline{L_i} \text{ in } cL, 
\end{cases}
\] (12)
and have
\[
\text{Ext}(\{cL \geq d, \{L_i\} \geq 1\}) = \{\text{fix}(L_i, cL \geq d), \{L_i\} \geq 1\}.
\]

Note that fixing a literal \( L_i \) in a linear pseudo-Boolean inequality \( cL \geq d \) may only produce a tautology if \( L_i \in L \) and may only produce a contradiction if \( \overline{L_i} \in L \). Given a set of linear pseudo-Boolean inequalities \( S \), we denote by \( \text{fix}(L_i, S) \) the set of all linear pseudo-Boolean inequalities \( \text{fix}(L_i, cL \geq d) \neq T \) with \( cL \geq d \in S \). Note that no tautologies are in \( \text{fix}(L_i, S) \). Next, we define pseudo-Boolean unit resolution for a set of linear pseudo-Boolean inequalities \( S \), the generalization of the unit resolution procedure for classical clauses to the pseudo-Boolean case.

\[
\frac{(S, U)}{\{\text{fix}(L_i, S), U \cup \{L_i\}\}} \text{ if } cL \geq d \in S \text{ and } L_i = \text{fixed}(cL \geq d)(\neq \bot) \quad (13)
\]

We denote by \( \{\text{pbur}(S), \text{pbu1}(S)\} \) the normal form obtained by applying the transition rule (13) as long as possible on \( (S, \emptyset) \). The set \( \text{pbu1}(S) \) then contains the set of all unit literals detected by \( \text{fix} \) during the application of pseudo-Boolean unit resolution. Moreover, \( \text{pbur}(S) \) does not contain a linear pseudo-Boolean inequality \( cL \geq d \) with \( \text{fixed}(cL \geq d) \neq \bot \) and we have
\[
\text{Ext}(\text{pbur}(S) \cup \{\text{pbu1}(S) \geq |\text{pbu1}(S)|\}) = \text{Ext}(S). \quad (14)
\]

The pseudo-Boolean unit relaxation of \( S \) is the set of all assignments \( \alpha \) such that \( \alpha(L_i) = 1 \) for all \( L_i \in \text{pbu1}(U) \) if \( \bot \notin \text{pbur}(S) \) and \( \emptyset \) otherwise. If \( \bot \notin \text{pbur}(S) \), then we say that the pseudo-Boolean unit relaxation of \( S \) is unsatisfiable. On the other hand, \( S \) is satisfiable if and only if \( \text{pbur}(S) \) is satisfiable, since each solution \( \alpha \) of \( S \) is a solution of \( \text{pbur}(S) \) and \( \alpha(L_i) = 1 \) for all \( L_i \in \text{pbu1}(S) \). If \( S \) contains only classical clauses, then \( \text{ur}(S) = \text{pbur}(S) \) and therefore \( \bot \notin \text{pbur}(S) \) if and only if \( \bot \notin \text{ur}(S) \). If the pseudo-Boolean unit relaxation of \( S \) is unsatisfiable, then the linear programming relaxation of \( S \) is unsatisfiable. The converse no longer holds. For example, consider
\[
S = \{1 \cdot A + 1 \cdot B + 1 \cdot C \geq 2, 1 \cdot \overline{A} + 1 \cdot \overline{B} + 1 \cdot \overline{C} \geq 2\}. \quad (15)
\]

Since \( \text{fixed}(1 \cdot A + 1 \cdot B + 1 \cdot C \geq 2) = \text{fixed}(1 \cdot \overline{A} + 1 \cdot \overline{B} + 1 \cdot \overline{C} \geq 2) = \bot \), we have \( \text{pbur}(S) = S \) and \( \text{pbu1}(S) = \emptyset \), thus \( \bot \notin \text{pbur}(S) \). On the other hand, the sum of both linear pseudo-Boolean inequalities simplifies to \( 3 \geq 4 \) and therefore the linear programming relaxation is unsatisfiable.

Next, we generalize DP to the pseudo-Boolean case. Again, we define a transition system that operates on states \( (P, \text{Sol}) \), but here \( P \) is a set of tuples \( (S, U) \), where \( S \) is a set of linear pseudo-Boolean inequalities. For the sake of completeness we include the transition system, which is almost identical to the one for classical clauses.

\[
\text{pbdp-clash: } \frac{(S, U) \cup P, \text{Sol}}{P, \text{Sol}} \text{ if } \bot \in S
\]

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\[ \text{pbdp\_sol: } \frac{\langle S, U \cup P, \text{Sol} \rangle}{\langle P, \text{Sol} \cup \{U\} \rangle} \text{ if } S = \emptyset \]

\[ \text{pbdp\_split: } \frac{\langle S, U \cup P, \text{Sol} \rangle}{\langle \{\text{pbur}(S'), \text{pbul}(S') \cup U\}, \{\text{pbur}(S''), \text{pbul}(S'') \cup U\} \cup P, \text{Sol} \rangle} \text{ if } \begin{array}{ll} \bot \not\in S, S \neq \emptyset, & L_i = \text{select\_literal}(S), \\ S' = S \cup \{L_i\} \geq 1 \text{ and } \\ S'' = S \cup \{\overline{L_i}\} \geq 1 \end{array} \]

Just the unit resolution procedure is replaced by its generalization to the pseudo-Boolean case. Applying the transition system defined by the three rules \text{pbdp\_flash}, \text{pbdp\_sol} and \text{pbdp\_split} as long as possible on \langle \{\text{pbur}(S), \text{pbul}(S)\}, \emptyset \rangle, where \( S \) is a set of linear pseudo-Boolean inequalities, yields the normal form \langle \emptyset, \text{Sol} \rangle and Sol represents the set of all solutions of \( S \). We define

\[ \text{pbdp}(S) := \begin{cases} (T, U) & \text{if } S \text{ is satisfiable and } U \in \text{Sol} \\ (\bot, \emptyset) & \text{otherwise} \end{cases} \tag{16} \]

which yields \((T, U)\) if and only if \( S \) is satisfiable and \( U \) is the first set of literals that is added to \( \text{Sol} \) when exploring the search tree depth first and stopping after the first solution has been found.

5 Optimizing with Pseudo-Boolean Davis-Putnam

Optimizing a linear pseudo-Boolean term \( c'L' \) subject to a set of linear pseudo-Boolean inequalities \( S \) can be done by solving a sequence of pseudo-Boolean satisfiability problems. We consider the problem of maximizing \( c'L' \) subject to \( S \). Minimization works in a similar way.

The goal is to find a solution \( \alpha \) of \( S \) such that \( \alpha(c'L') \geq \alpha'(c'L') \) for all solutions \( \alpha' \) of \( S \). We will find such an assignment by solving a sequence of satisfiability problems of the form \( S_i := S \cup \{c'L' \geq \max_i\} \), where only \( \max_i \) differs from problem to problem. We call \( c'L' \geq \max_i \) objective function inequality. Suppose that we have \( \max_0 \) such that \( c'L' \geq \max_0 \) is a tautology. Solving \( S_0 \) yields a solution \( \alpha_0 \) of \( S_0 \) and therefore of \( S \). A lower bound of the optimum then is \( \alpha_0(c'L') \). We define \( \max_{i+1} := \max_i + 1 \) and so exclude assignments yielding no better lower bounds than the current one. Obviously, we have \( \alpha_{i+1}(c'L') > \alpha_i(c'L') \) for all satisfying assignments \( \alpha_i \) of \( S_i \) and \( \alpha_{i+1} \) of \( S_{i+1} \). If \( S_i \) is satisfiable and \( S_{i+1} \) is unsatisfiable, then \( \alpha_{i+1}(c'L') \) is the desired maximum.

We can incorporate this idea into \text{pbdp} by replacing just the rule \text{pbdp\_sol}. Instead of adding a computed solution that fixes the literals \( U \), we construct a solution \( \alpha \) such that \( \alpha(L_i) = 1 \) for all \( L_i \in U \cup \{L' \setminus \overline{U}\} \). Then \( \alpha(c'L') \) is the maximal value of \( \max c'L' \) subject to \( \{U \geq |U|\} \). We then add to the remaining satisfiability problems the linear pseudo-Boolean inequality \( c'L' \geq \alpha(c'L') + 1 \). Therefore, we make certain that for each further solution the value of the objective function is larger. If there are no remaining nodes, then the last computed \( \alpha(c'L') \) was optimal.

Let \( c'L' \) be a linear pseudo-Boolean term with \( c_i > 0 \) for all \( c_i \in c' \). We define a transition system that operates on states \( \langle P, \text{max} \rangle \), where \( P \) is a set of tuples \( \langle S, U \rangle \), \( S \) is a set of linear pseudo-Boolean inequalities, and \( U \) is a set of literals that are fixed so far. The current lower bound of the optimization problem is \( \text{max} \).

\[ \text{opbdp\_flash: } \frac{\langle S, U \cup P, \text{max} \rangle}{\langle P, \text{max} \rangle} \text{ if } \bot \in S \]
\[
\text{opbdp\_climb: } \begin{cases} 
\langle\langle S, U \rangle \not\equiv P, \max \rangle & \text{if } \forall L_i \in U \cup (L' \setminus \overline{U}) : \alpha'(L_i) = 1 \text{ and } \\
\langle\langle \text{propagate}(P, \max' + 1), \max' \rangle & \end{cases}
\]

\[
\text{opbdp\_split: } \begin{cases} 
\langle\langle S, U \rangle \not\equiv P, \max \rangle & \text{if } \\
\left\{ \begin{array}{l}
\langle\text{pbur}(S'), \text{pbul}(S') \cup U \rangle, \\
\langle\text{pbur}(S'), \text{pbul}(S') \cup U \rangle
\end{array} \right\} \cup P, \max & 
\end{cases}
\]

It remains to define \text{propagate}, which updates the remaining satisfiability problems such that only better lower bounds are generated.

\[
\text{propagate}(\langle\langle S, U \rangle \not\equiv P, \max \rangle) := \{ \langle\text{pbur}(S \cup \{c' L' \geq \max\}), \text{pbul}(S \cup \{c' L' \geq \max\}) \cup U \} \\
\cup \text{propagate}(P, \max)
\]

\[
\text{propagate}(\emptyset, \max) := \emptyset
\]

Applying the transition system defined by the three rules \text{opbdp\_clash}, \text{opbdp\_climb}, and \text{opbdp\_split} as long as possible on \langle\langle \{\text{pbur}(S), \text{pbul}(S)\}, \neg 1 \rangle \rangle yields the normal form \langle\emptyset, \max \rangle, where \max \geq \alpha(c' L') for all \alpha \in \text{Ext}(S) and \max = -1 if and only if \emptyset is unsatisfiable. We define the optimization procedure \text{opbdp}(S, c' L') := \max, where max is the value computed by the above given transition system.

It is no restriction to require that \(c' L'\) contains only positive coefficients. Each term \(c_i L_i\) with \(c_i < 0\) is equivalent to \(c_i + |c_i| \overline{L_i}\), since

\[
\begin{align*}
c_i L_i &= c_i - c_i + c_i L_i \\
&= c_i - c_i \cdot (1 - L_i) \\
&= c_i - c_i \overline{L_i}.
\end{align*}
\]

Optimizing a linear pseudo-Boolean term \(\sum_{i=1}^{n} c_i L_i\) containing also negative coefficients is done by optimizing \(\sum_{i=1}^{n} |c_i| L'_i\), where \(L'_i = L_i\) if \(c_i > 0\) and \(\overline{L_i}\) otherwise, and adding the sum over the negative coefficients \(c_i\) to the positive result of \text{opbdp}.

6 Implementation

Proper implementation and the use of appropriate data structures are important factors of the efficiency of the DP-procedure [Hoo93, HHT91, Zha93]. In a naive implementation of \text{dp}, a satisfiability problem has to be copied at each node which may require excessive storage. We use the following data structure for implementing \text{dp}. Given a set of clauses \(S\) and the set of variables \(V\) occurring in \(S\), we compute in advance the following index data structures. Each classical clause can be referenced by a unique identifier \(\text{cid}\). The set of literals in a classical clause with identifier \(\text{cid}\) can be referenced by \(\text{lids}(\text{cid})\). We can obtain a list of clause identifiers, where a literal \(L_i\) occurs by \(\text{cids}(L_i)\). We represent a sub-problem of \(S\) by a list of active variables \(\text{av}\), i.e. variables that are not yet fixed, and a list of clause states, where a clause state is a clause identifier and the number of literals \(nl\) currently active in that classical clause. Applying unit resolution for the literal \(L_i\) is done by

- deleting each element in the clause state list, where the identifier in the clause state is in \(\text{cids}(L_i)\)
- and decreasing \(nl\) by one if the identifier in the clause state is in \(\text{cids}(\overline{L_i})\).
We obtain a unit clause if \( nl \) is set to 1. The new unit literal then is determined by \( \text{ids}(\text{cid}) \cap (\text{av} \cup \overline{\text{av}}) \) and its variable is deleted from \( \text{av} \). The empty clause is derived if \( nl \) is set to 0. Copying a sub-problem is now done by just copying the active clause list and the clause state list. The advantage of this data structure is that the index data structure does not change while exploring the search tree. The representation of the sub-problem in a node is very compact and detection of unit literals is straightforward.

For \text{pbdp} each linear pseudo-Boolean inequality can be referenced by a unique inequality identifier \( \text{iid} \). Given a literal \( L_i \), we can obtain a list of inequality identifiers \( \text{ids}(L_i) \), where \( L_i \) occurs. We need an additional index data structure to access the coefficient \( c_i = \text{coeff}(L_i, \text{iid}) \) of a given literal \( L_i \) and an inequality identifier \( \text{iid} \). A sub-problem is represented by a list of active variables \( \text{av} \) and a list of inequality states. An inequality state consists of an inequality identifier \( \text{iid} \), a current right-hand side \( d \) of the linear pseudo-Boolean inequality and a current sum \( \sum c \) over all coefficients of the active literals of the linear pseudo-Boolean inequality. For applying pseudo-Boolean unit resolution for the literal \( L_i \) we do the following for all inequality states, where the inequality identifier \( \text{iid} \) is in \( \text{ids}(L_i) \):

- Delete the inequality state if \( \text{coeff}(L_i, \text{iid}) \geq d \) (eliminate tautologies).
- Otherwise decrease the current right-hand side \( d \) and the current sum over all coefficients \( \sum c \) by \( \text{coeff}(L_i, \text{iid}) \).

For all inequality states, where the inequality identifier \( \text{iid} \) is in \( \text{ids}(\overline{L_i}) \) we do the following:

- Decrease the sum over all coefficients \( \sum c \) by \( \text{coeff}(\overline{L_i}, \text{iid}) \). If \( \sum c \) is smaller than the current right-hand side, then the sub-problem is unsatisfiable.
- Compute the active literal \( L_{j} \in \text{av} \) for which \( \text{coeff}(L_{j}, \text{iid}) \) is maximal. \( L_{j} \) is a new unit literal if \( \sum c - \text{coeff}(L_{j}, \text{iid}) < d \).

For large linear pseudo-Boolean inequalities computing the active literal \( L_{j} \in \text{av} \cup \overline{\text{av}} \) for which \( \text{coeff}(L_{j}, \text{iid}) \) is maximal will often yield the same literal. One improvement is to store the maximal coefficient with its literal in the inequality state and to update it only if this literal is fixed.

We implement \text{opbdp} as a slight variation of \text{pbdp}. When a satisfiable solution is found (i.e. an empty inequality state list) we do not return \( \top \), but calculate the maximal value \( \max \) of the objective function under the current assignment. We then change destructively all copied right-hand sides \( d \) of the objective function inequality states to the new value \( d - (\max + 1 - \max') \) where \( \max' \) is the previous calculated maximal value. The current node then is found to be unsatisfiable and we backtrack until the objective function constraint is no longer violated. Then standard \text{pbdp} depth first search is continued. We follow roughly the ideas presented by Hooker [Hoo93] for incrementally solving SAT.

7 Heuristics

The selection of the branching literal [JW90, HHT91, HV94] is the other important factor for the efficiency of the DP-procedure. Good literal selection heuristics can reduce the number of explored nodes by an order of magnitude. Hooker et. al [HV94] investigate several branching heuristics for the clausal case. The “Two-Sided Jereslow-Wang” rule has been justified by a Markov chain analysis of a simplification model that selects the literal \( L_i \) when \( \text{pbur}(S \cup \{L_i\}) \)
is the *mostly simplified* problem [HV94]. The rule says we should branch on the variable \( X_i \) which maximizes \( J(X_i) + J(\overline{X_i}) \) with

\[
J(L_i) := \sum_{L \in S : L_i \in L} 2^{-|L|} .
\]  

(17)

If \( J(X_i) \geq J(\overline{X_i}) \), then \( X_i \) should be selected, otherwise \( \overline{X_i} \). The intention of the rule is that we branch on a variable that occurs often in short clauses and so get a small sub-problem with an increasing probability that unit literals occur.

For linear pseudo-Boolean inequalities we adapt the two-sided Jeroslow-Wang rule and branch on a variable \( X_i \) that maximizes \( PBJ(X_i) + PBJ(\overline{X_i}) \) with

\[
PBJ(L_i) = \sum_{c_L \geq d \in S : c_i \in c L \in L} \frac{c_i}{c - d} \cdot 2^{-\lfloor c/d \rfloor} .
\]  

(18)

If \( PBJ(X_i) \geq PBJ(\overline{X_i}) \), then \( X_i \) is selected, otherwise \( \overline{X_i} \). We replace \(|L|\), which is a measure of the length of a clause, by \(|\sum c/d|\), which reduces to the length if we have classical clauses and is so a straightforward generalization. The idea is that we prefer linear pseudo-Boolean inequalities, where many of the coefficients are needed in order to satisfy the linear pseudo-Boolean inequality. We weight this preference by multiplying \( 2^{-\lfloor c/d \rfloor} \) by \( c_i/(\sum c - d) \) and so take into account the relative improvement of reaching the right-hand side when fixing the literal to 1. Further analysis is required in order to obtain a more efficient branching heuristic. For \texttt{opbdp} we use as alternative a greedy-like heuristic depending only on the objective function. We simply select the literal \( L_i \) with the maximal coefficient in the objective function. The idea is, that a better approximation of the optimal value is obtained earlier. A better literal selection heuristic that takes into account the goal of maximizing an objective function and reducing the search space needs to be found.

8 Computational Results

A prototype of \texttt{opbdp} has been implemented in C++\(^1\). In Figure 1 we present computational results for using \texttt{opbdp} on a variety of pure 0-1 integer programming problems found in MIPLIB [BB92]. In column “Name” we give the name of the problem. In “# V” we mention the number of variables and in “# F” the number of inequalities of the problem. “Nodes” is the number of nodes explored for solving the problem and “Time” is the user cpu time used for solving the problem with \texttt{opbdp} on a SPARC-10/31. In the “DS-JW” column we use \texttt{opbdp} with the adapted two sided Jeroslow Wang heuristic and in the columns “OF” we select the literal with the largest coefficient in the objective function. The columns “...(opt)” describe when the optimal value is found and the columns “...(V)” describe when the optimal result is verified and \texttt{opbdp} terminates. In Figure 2 we solve the selected 0-1 integer optimization problems with CPLEX 3.0. CPLEX is a commercial mixed integer solver based on the simplex algorithm. Integer problems are solved by branch-and-bound. CPLEX offers the possibility to additionally generate cutting planes (e.g. clique inequalities and lifted knapsack covers) at each node if possible, yielding a branch-and-cut algorithm. For CPLEX the time when the optimal solution was found is not given. The other columns in Figure 2 are similar to Figure 1. We solve all problems first by branch-and-bound (B&B) and then with branch-and-cut (B&C). On some problems, i.e. p0201, the cutting plane generation gives a significant speedup.

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& : aborted after 30000 seconds

Figure 1: 0-1 Integer Optimization Problems from MIPLIB with opbdp

The presented opbdp procedure compares well w.r.t. the linear programming based solver CPLEX. Especially enigma and the stein-problems are solved much faster by opbdp. On other problems, i.e. lseu and the air-problems, the linear programming based method is faster. i.e. problems, where the optimal value of the linear programming relaxation is already near the integer optimal value, but the number of variables is very high (the air-problems), are better attacked by linear programming based methods. It is interesting to note that exploiting the logical structure of a problem, i.e. using opbdp, yields good performance on problems where exploiting the polyhedral structure seems to be inefficient and vice versa. Hence, there is no “better” approach, but problem specific characteristics that can be explored. An integration of both approaches and systems that exploit either structure need to be investigated and will lead to more powerful optimization algorithms.

Note that in all but one of the problems the optimal solution was found relatively early when using the greedy like heuristics. Unfortunately, the number of evaluated nodes does not decrease significantly when using the adapted Two-Sided Jeroslow-Wang heuristics, which indicates that better heuristics need to be developed. Special handling of equality constraints are further possibilities to improve the presented algorithm. Note that all occurring linear pseudo-Boolean equalities \( cL = d \) have been replaced by the two linear pseudo-Boolean inequalities \( cL \leq d \) and \( cL \geq d \). Therefore, the column “# 1” may differ from the column “ROWS” found in MIPLIB. Direct use of the equality constraints would reduce the problem size and might help to decrease the number of explored nodes.

We currently require that all the coefficients are integer. The results still hold when rational coefficients are allowed in the constraint inequalities and adapting the presented method is easy. This has not yet been done and therefore some problems (mod008, mod010, pipex) have not been considered. Furthermore, we have not considered some problems with a very large number of variables. We believe that a version of opbdp using preprocessing techniques and logic-cut generation techniques [Bar94] could also be applied on larger problems like the air-problems.
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Figure 2: 0-1 Integer Optimization Problems from MIPLIB with CPLEX

9 Conclusion

Branching methods based on a discrete relaxation can be comparably efficient w.r.t. branching methods based on the linear programming relaxation for solving linear pseudo-Boolean optimization problems. By choosing a straightforward generalization of unit relaxation in propositional calculus to the pseudo-Boolean case, implementation techniques of clausal satisfiability provers can be used. The next step towards an efficient logic-based branch-and-cut method is the incorporation of logic-cut generation methods [Hoo92, Bar94] in opbdp.
References


Below you find a list of the most recent technical reports of the research group *Logic of Programming* at the Max-Planck-Institut für Informatik. They are available by anonymous ftp from our ftp server ftp.mpi-sb.mpg.de under the directory pub/papers/reports. Most of the reports are also accessible via WWW using the URL http://www.mpi-sb.mpg.de. If you have any questions concerning ftp or WWW access, please contact reports@mpi-sb.mpg.de. Paper copies (which are not necessarily free of charge) can be ordered either by regular mail or by e-mail at the address below.

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<td>F. Baader, H.-J. Ohlbach</td>
<td>A Multi-Dimensional Terminological Knowledge Representation Language</td>
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<td>S. Vorobyov</td>
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