# Improving Unsatisfiability-based Algorithms for Boolean Optimization

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SAT 2010, Edinburgh

#### **Motivation**

- Increasing interest in generalizations of SAT
- SAT techniques extended for MaxSAT, PBO and WBO
- Unsatisfiability-based algorithms have been proposed for Boolean Optimization problems
  - · very effective for several classes of instances
  - can perform poorly on instances that are easy for classical approaches
- Integration of procedures in a unique Boolean optimization framework

#### **Outline**

- Background
  - MaxSAT, PBO and WBO
- Algorithmic Solutions
  - Classical Approaches
  - Unsatisfiability-based approaches
- Improving Unsatisfiability-based algorithms
  - PBO as preprocessing
  - Constraint Branching
- Experimental Results
- Conclusions

# Maximum Satisfiability (MaxSAT)

#### MaxSAT Problem

Given a CNF formula  $\varphi$ , find an assignment to problem variables that maximizes the number of satisfied clauses in  $\varphi$  (or minimizes the number of unsatisfied clauses).

#### Partial MaxSAT Problem

Given a conjunction of two CNF formulas  $\varphi_h$  and  $\varphi_s$ , find an assignment to problem variables that satisfies all hard clauses  $(\varphi_h)$  and maximizes the number of satisfied soft clauses  $(\varphi_s)$ .

# Maximum Satisfiability (MaxSAT)

#### Weighted CNF Formula

- set of weighted clauses
- weighted clause: pair  $(\omega,c)$  where  $\omega$  is a clause and  $c\in\mathbb{N}$  is a positive cost of unsatisfying  $\omega$

#### Weighted MaxSAT Problem

Given a weighted CNF formula  $\varphi_{s,c}$ , find an assignment to problem variables that minimizes the total cost of unsatisfied clauses.

#### Weighted Partial MaxSAT Problem

Given a weighted CNF formula  $\varphi_{s,c}$  and a classical CNF formula  $\varphi_h$ , find an assignment to problem variables that satisfies all hard clauses  $(\varphi_h)$  and minimizes the total cost of unsatisfied soft clauses in  $\varphi_{s,c}$ .

# Pseudo-Boolean Optimization (PBO)

#### **Pseudo-Boolean Optimization**

$$\begin{array}{ll} \text{minimize} & \sum\limits_{j=1}^{n} c_{j} \cdot x_{j} \\ \text{subject to} & \sum\limits_{j=1}^{n} a_{ij} \cdot l_{j} \geq b_{i}, \\ & l_{j} \in \{x_{j}, \overline{x}_{j}\}, x_{j} \in \{0, 1\}, \\ & a_{ij}, b_{i}, c_{j} \in \mathbb{N}_{0}^{+} \end{array}$$

# Weighted Boolean Optimization (WBO)

#### **WBO Formula**

Weighted Boolean Optimization formula is composed of two pseudo-Boolean constraint sets  $(\varphi_h, \varphi_s)$ :

- $\varphi_h$ : set of hard pseudo-Boolean constraints
- $\varphi_s$ : set of soft weighted pseudo-Boolean constraints
- Soft pseudo-Boolean constraint  $(\omega, c)$ :
  - ω: pseudo-Boolean constraint
  - ullet there is an integer weight c representing the cost of not satisfying  $\omega$

#### **WBO Problem**

Given a WBO formula, find an assignment to problem variables that satisfies all hard constraints  $(\varphi_h)$  and minimizes the total cost of unsatisfied soft constraints  $(\varphi_s)$ .

### WBO (Example)

#### Weighted Boolean Optimization instance

$$\varphi_{h} = \{x_{1} + x_{2} + x_{3} \ge 2, \quad 2\overline{x}_{1} + \overline{x}_{2} + x_{3} \ge 2\} 
\varphi_{s} = \{(x_{1} + \overline{x}_{2} \ge 1, 2), \quad (\overline{x}_{1} + \overline{x}_{3} \ge 1, 3)\}$$

- Assignments that satisfy all hard constraints:
  - (1)  $x_1 = x_3 = 1$ ;  $x_2 = 0$ ;  $\sum c_i = 3$
  - (2)  $x_1 = 0$ ;  $x_2 = x_3 = 1$ ;  $\sum c_i = 2$  (solution)

#### **Encode MaxSAT as WBO**

- For each hard clause  $(l_1 \lor l_2 \lor \cdots \lor l_k)$ 
  - define a hard PB constraint as  $l_1 + l_2 + \cdots + l_k \ge 1$
- For each weighted soft clause  $(\omega, c)$  where  $\omega = (I_1 \vee I_2 \vee \cdots \vee I_k)$ 
  - define a soft PB constraint as  $l_1 + l_2 + \cdots + l_k \ge 1$  with weight c

# **Encode MaxSAT as WBO (Example)**

Weighted Partial MaxSAT instance

$$\varphi_h = \{x_1 \lor x_2 \lor \overline{x}_3, \quad \overline{x}_2 \lor x_3, \quad \overline{x}_1 \lor x_3\}$$
  
$$\varphi_s = \{(\overline{x}_3, 5), \quad (x_1 \lor x_2, 3), \quad (x_1 \lor x_3, 2)\}$$

Corresponding WBO instance

$$\begin{array}{lll} \varphi_h &= \{x_1 + x_2 + \overline{x}_3 \geq 1, & \overline{x}_2 + x_3 \geq 1, & \overline{x}_1 + x_3 \geq 1\} \\ \varphi_s &= \{(\overline{x}_3 \geq 1, 5), & (x_1 + x_2 \geq 1, 3), & (x_1 + x_3 \geq 1, 2)\} \end{array}$$

#### **Encode PBO as WBO**

- ullet For each pseudo-Boolean constraint  $\sum\limits_{j=1}^n a_{ij} l_j \geq b_i$ 
  - add this PB constraint to the set of hard PB constraints
- For each term  $c_i \cdot x_i$  in the objective function
  - ullet add a weighted soft PB constraint of the form  $((\overline{x}_j \geq 1), c_j)$

### **Encode PBO as WBO (Example)**

#### Pseudo-Boolean Optimization instance

minimize 
$$4x_1 + 2x_2 + x_3$$
  
subject to  $2x_1 + 3x_2 + 5x_3 \ge 5$   
 $\overline{x}_1 + \overline{x}_2 \ge 1$   
 $x_1 + x_2 + x_3 \ge 2$ 

#### Corresponding WBO instance

$$\begin{array}{lll} \varphi_h &= \{2x_1 + 3x_2 + 5x_3 \geq 5, & \overline{x}_1 + \overline{x}_2 \geq 1, & x_1 + x_2 + x_3 \geq 2\} \\ \varphi_s &= \{(\overline{x}_1 \geq 1, 4), & (\overline{x}_2 \geq 1, 2), & (\overline{x}_3 \geq 1, 1)\} \end{array}$$

### **Algorithmic Solutions (Classical Approaches)**

- Branch and bound:
  - e.g. MaxSatz, MiniMaxSAT
- Iteration of the upper bound:
  - e.g. Pueblo, minisat+
- Conversions from one Boolean formalism to another:
  - e.g. minisat+, SAT4J MS

### **Unsatisfiability-based MaxSAT**

#### Original algorithm proposed by Fu&Malik [SAT 2006]:

- (1) Identify unsatisfiable sub-formula of an UNSAT formula
  - SAT solver able to generate an UNSAT core
- (2) For each unsatisfiable sub-formula  $\varphi_C$ :
  - Relax all soft clauses in  $\varphi_{\mathcal{C}}$  by adding a new relaxation variable to each clause
  - Add a new constraint such that at most 1 relaxation variable is assigned value 1
- (3) When the resulting CNF formula is SAT, the solver terminates
- (4) Otherwise, go back to 1

### **Unsatisfiability-based MaxSAT**

```
\varphi_W \leftarrow \varphi
       while (\varphi_W is UNSAT)
 3
                do Let \varphi_C be an unsatisfiable sub-formula of \varphi_W
                      V_P \leftarrow \emptyset
 5
                      for each soft clause \omega \in \varphi_C
 6
                              do \omega_R \leftarrow \omega \cup \{r\}
                                   \varphi_W \leftarrow \varphi_W - \{\omega\} \cup \{\omega_R\}
 8
                                    V_R \leftarrow V_R \cup \{r\}
                      \varphi_R \leftarrow \mathsf{CNF}(\sum_{r \in V_P} r = 1) > Equals1 constraint
 9
                      \varphi_W \leftarrow \varphi_W \cup \varphi_R \quad \triangleright \text{ Clauses in } \varphi_R \text{ are declared hard}
10
       return |\varphi| – number of relaxation variables assigned to 1
11
```

### **Unsatisfiability-based Weighted MaxSAT**

```
\varphi_W \leftarrow \varphi
 2 cost_{lb} \leftarrow 0
       while (\varphi_W is UNSAT)
                 do Let \varphi_C be an unsatisfiable sub-formula of \varphi_W
 4
                       min_c \leftarrow min_{\omega \in \varphi_c \wedge \neg hard(\omega)} cost(\omega)
 5
 6
                       cost_{1b} \leftarrow cost_{1b} + min_c
 7
                        V_R \leftarrow \emptyset
 8
                       for each soft clause \omega \in \varphi_C
 9
                                do \omega_R \leftarrow \omega \cup \{r\}
10
                                      cost(\omega_R) \leftarrow min_c
                                      if cost(\omega) > min_c
11
12
                                          then \varphi_W \leftarrow \varphi_W \cup \{\omega_R\}
                                                    cost(\omega) \leftarrow cost(\omega) - min_c
13
14
                                          else \varphi_W \leftarrow \varphi_W - \{\omega\} \cup \{\omega_R\}
15
                                      V_R \leftarrow V_R \cup \{r\}
                       \varphi_W \leftarrow \varphi_W \cup \mathsf{CNF}(\sum_{r \in V_n} r = 1)
16
17
        return cost is
```

### **Unsatisfiability-based Weighted MaxSAT**

Weighted MaxSAT instance

$$\varphi_h = \{x_1 \lor x_2 \lor \overline{x}_3, \quad \overline{x}_2 \lor x_3, \quad \overline{x}_1 \lor x_3\}$$
  
$$\varphi_s = \{(\overline{x}_3, 5), \quad (x_1 \lor x_2, 3), \quad (x_1 \lor x_3, 2)\}$$

Unsatisfiable sub-formula:

$$\varphi_{\mathcal{C}} = \{ \overline{x}_2 \lor x_3, \overline{x}_1 \lor x_3, (\overline{x}_3, 5), (x_1 \lor x_2, 3) \}$$

- $min_C = 3$
- Relax  $(x_1 \lor x_2, 3)$  to  $(r_1 \lor x_1 \lor x_2, 3)$
- Split  $(\overline{x}_3,5)$  into  $(\overline{x}_3,2)$  and  $(r_2 \vee \overline{x}_3,3)$
- Add CNF $(r_1 + r_2 = 1)$  to  $\varphi_h$

### **Unsatisfiability-based Weighted MaxSAT**

#### Weighted MaxSAT instance

$$\begin{array}{lll} \varphi_h &= \{x_1 \vee x_2 \vee \overline{x}_3, & \overline{x}_2 \vee x_3, & \overline{x}_1 \vee x_3\} \\ \varphi_s &= \{(\overline{x}_3, 5), & (x_1 \vee x_2, 3), & (x_1 \vee x_3, 2)\} \end{array}$$

Results in a new formula:

$$\begin{array}{lll} \varphi_h &= \{x_1 \vee x_2 \vee \overline{x}_3, & \overline{x}_2 \vee x_3, & \overline{x}_1 \vee x_3, & \mathsf{CNF}(r_1 + r_2 = 1)\} \\ \varphi_{\mathfrak{s}} &= \{(\overline{x}_3, 2), & (r_2 \vee \overline{x}_3, 3), & (r_1 \vee x_1 \vee x_2, 3), & (x_1 \vee x_3, 2)\} \end{array}$$

### Algorithm for Weighted Boolean Optimization

- Follows the same approach as Unsatisfiability-Based Weighted MaxSAT algorithm
- Instead of SAT solver, uses Pseudo-Boolean solver enhanced with unsatisfiable sub-formula extraction
- Relaxation of pseudo-Boolean constraints  $\sum a_j l_j \geq b$ 
  - $b \cdot r + \sum a_j I_j \ge b$
- No need to encode constraint  $\sum_{r \in V_R} r = 1$  into CNF

### **Improving Unsatisfiability-based Algorithms**

- Unsatisfiability-based algorithms search on the lower bound. Sometimes is better to search on the upper bound:
  - (1) PBO as Preprocessing
- The number of relaxation variables grows significantly at each step:
  - (2) Constraint Branching

#### **Encode WBO as PBO**

- For each hard PB constraint  $\sum_{i=1}^{n} a_{ij} l_j \geq b_i$ 
  - add this PB constraint to the set of constraints
- For each weighted soft PB constraint  $\sum_{j=1}^{n} a_{ij} l_j \geq b_i$  with cost  $c_j$ 
  - define a PB constraint with a new relaxation variable r  $b_i r + \sum\limits_{j=1}^n a_{ij} l_j \geq b_i$
  - add  $c_j \cdot r$  to the objective function

### **Encode WBO as PBO (Example)**

Weighted Boolean Optimization instance

$$\begin{array}{ll} \varphi_h &= \{x_1 + x_2 + x_3 \geq 2, \quad 2\overline{x}_1 + \overline{x}_2 + x_3 \geq 2, \quad x_1 + x_4 \geq 1\} \\ \varphi_s &= \{(x_1 + \overline{x}_2 \geq 1, 2), \quad (\overline{x}_1 + \overline{x}_3 \geq 1, 3), \quad (\overline{x}_4 \geq 1, 4)\} \end{array}$$

Corresponding PBO instance

minimize 
$$2r_1 + 3r_2 + 4r_3$$
  
subject to  $x_1 + x_2 + x_3 \ge 2$   
 $2\overline{x}_1 + \overline{x}_2 + x_3 \ge 2$   
 $x_1 + x_4 \ge 1$   
 $r_1 + x_1 + \overline{x}_2 \ge 1$   
 $r_2 + \overline{x}_1 + \overline{x}_3 \ge 1$   
 $r_3 + \overline{x}_4 \ge 1$ 

### **PBO** as Preprocessing

- (1) Simplification techniques are used in the PBO formula:
  - a generalization of Hypre for PB formulas is used
- (2) The PBO formula is solved using tight limits:
  - PB solver is used for 10% of the time limit
  - If optimality is not proved, the formula is translated back to WBO
  - Small learnt clauses are kept in the WBO formula as hard clauses

### **Using Constraint Branching**

- Consider the following Equals1 constraint:  $\sum_{i=1}^{k} r_i = 1$ :
  - If  $r_i$  is assigned to 1, all other variables  $r_i \neq r_i$  must be 0
  - However, if  $r_i$  is assigned to 0, no propagation occurs
- Assigning value 1 to any of these variables produces very different search trees

# **Using Constraint Branching**

- Constraint Branching:
  - Instead of assigning one variables, half of the variables are assigned:

$$\omega_{c1}:\sum_{i=1}^{k/2}r_i=0$$

- If  $\varphi \cup \{\omega_{c1}\}$  is unsatisfiable then:
  - $\exists_i r_i = 1$ , with  $1 \le i \le \frac{k}{2}$
  - we can infer  $\omega_{c2}$  :  $\sum_{i=k/2+1}^{k} r_i = 0$

# **Computing Cores with Constraint Branching**

```
COMPUTE_CORE(\varphi)
       if (no large Equals1 constraint exist in \varphi)
            then (st, \varphi_C) \leftarrow PB(\varphi)
  3
                     return (st, \varphi_C)
            else Select a large Equals1 constraint \omega from \varphi
  5
                     k = size(\omega)
                     \omega_{c1}: \sum_{i=1}^{k/2} r_i = 0
  6
                     (st, \varphi_{C1}) \leftarrow COMPUTE\_CORE(\varphi \cup \{\omega_{c1}\})
  8
                     if (st = SAT \vee \omega_{c1} \notin \varphi_{C1})
                         then return (st, \varphi_{C1})
 9
                        else \omega_{c2} : \sum_{i=k/2+1}^{k} r_i = 0
10
                                 (st, \varphi_{C2}) \leftarrow COMPUTE\_CORE(\varphi \cup \{\omega_{c2}\})
11
                                 if (st = SAT \vee \omega_{c2} \notin \varphi_{C2})
12
13
                                     then return (st, \varphi_{C2})
                                     else return (st, \varphi_{C1} \cup \varphi_{C2})
14
```

#### **Experimental Results**

- Industrial benchmark sets of the partial MaxSAT problem
- The most effective MaxSAT solvers from the MaxSAT evaluation of 2009 were considered: MSUncore, SAT4J (MS), pm2
- Timeout: 1800 seconds
- Intel Xeon 5160 server with 3GB RAM

### **Experimental Results**

#### • Solved Instances for Industrial Partial MaxSAT:

Benchmark set	#I	MSUncore	SAT4J (MS)	pm2	wbo1.0	wbo1.2
bcp-fir	59	49	10	58	40	47
bcp-hipp-yRa1	176	139	140	166	144	137
bcp-msp	148	121	95	93	26	95
bcp-mtg	215	173	196	215	181	207
bcp-syn	74	32	21	39	34	33
CircuitTraceCompaction	4	0	4	4	0	4
HaplotypeAssembly	6	5	0	5	5	5
pbo-mqc	256	119	250	217	131	210
pbo-routing	15	15	13	15	15	15
PROTEIN_INS	12	0	2	3	1	2
Total	965	553	731	815	577	755

#### **Conclusions**

- PBO solvers can be used as a preprocessing step such that:
  - 1) inference preprocessing techniques are used;
  - 2a) some problems are easily solved with a search on the upper bound;
  - 2b) restrict the search space by learning hard constraints.
- Constraint branching can improve the effectiveness of the solver
- Experimental results show that these techniques significantly improve the performance of wbo
- These results provide a strong stimulus for further integration of other Boolean optimization techniques