

Improvements to Core-Guided Binary Search for MaxSAT

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Outline

Motivation

Previous Algorithms - Overview

BCD2

Optimizations

Results

Conclusions

MaxSAT

Maximum Satisfiability (MaxSAT) Given a propositional formula in Conjunctive Normal Form (CNF), compute an assignment to the variables that **maximizes** the number of **satisfied clauses**

$$(x_1) \wedge (\neg x_1 \vee \neg x_2) \wedge (x_2)$$

The instance is unsatisfiable, and the MaxSAT solution is **2**

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There are 3 variants of the MaxSAT problem

MaxSAT Variants

- **Partial MaxSAT**
 - Set of clauses divided in two:
 - ▶ Hard clauses - have to be satisfied
 - ▶ Soft clauses - satisfied or not
 - Objective: Minimize the number of falsified soft clauses while satisfying all hard clauses
- **Weighted MaxSAT**
 - Clauses have weights associated that represent the cost of falsifying the clause
 - Objective: Minimize the sum of the weights of the falsified clauses
- **Weighted Partial MaxSAT**
 - Combines the previous two
 - Objective: Minimize the sum of the weights of the falsified soft clauses while satisfying all the hard clauses

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MaxSAT Problem

- Complexity:
 - Decision version of MaxSAT is NP-Complete
 - MaxSAT is Δ_2^P -complete

- Many optimization problems can be modeled as MaxSAT: Bayesian Networks, Physics (Spinglass), Bioinformatics (haplotyping, protein alignment), Circuit Debugging, Fault Localization, Graph problems (Max-Cut, Max-Clique), etc.

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 - **Binary Search** requires a **linear** number of calls to the SAT solver

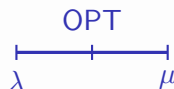
[fm-SAT06]

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 - most of them require an exponential number of calls to the SAT solver
 - **Binary Search** requires a **linear** number of calls to the SAT solver
[fm-SAT06]
- Extend binary search for MaxSAT:
 - **BC** - **Core-guided binary search**: Relax soft clauses on demand as dictated by the unsatisfiable cores found so far [hmms-AAAI11]
 - **BCD** - **Core-guided binary search with disjoint cores**: Maintaining disjoint cores allows adding smaller constraints [hmms-AAAI11]
 - **BCD2** - Improvement of BCD: New bounds, better maintenance of the bounds [mhms-SAT12]

Computing a MaxSAT Solution - Notation

- φ - **Unsatisfiable** Weighted CNF Formula:
(c_i, w_i) weighted clause:
 - c_i is a clause
 - w_i is a non-negative integer or \top ;
cost of falsifying c_i
- \mathcal{A} - Complete Assignment: $\mathcal{A} = \{x_1 = 1, x_2 = 0, \dots\}$
Cost of assignment: Sum of weights of falsified clauses
- **OPT** - Optimum cost: **Minimum** cost
- μ - Upper Bound: Cost **not lower** than OPT
- λ - Lower Bound: Value **lower** than OPT



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Binary Search (1/2)

Proposed by Fu&Malik SAT2006

(c_i, w_i)

$((x_1), 2) \quad ((x_2), 5)$
 $((\neg x_1 \vee \neg x_2), \top)$

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If $\mathcal{A} \not\models c_i$ then $\mathcal{A} \models r_i$

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If $\mathcal{A} \not\models c_i$ then $\mathcal{A} \models r_i$

Minimize sum of weights of true relaxation variables

\Leftrightarrow

Minimize sum of weights of falsified soft clauses

Binary Search (2/2)

In each iteration:

- Consider τ - maximum allowed sum of weights of true r.v.

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$$CNF(\sum w_i r_i \leq \tau)$$

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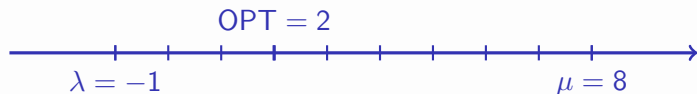
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$$((x_1 \vee r_1), 2) \quad ((x_2 \vee r_2), 5) \\ ((\neg x_1 \vee \neg x_2), \top)$$

$$\mu_0 = 8 \quad \lambda_0 = -1$$



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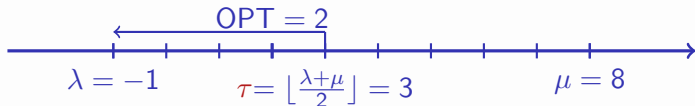
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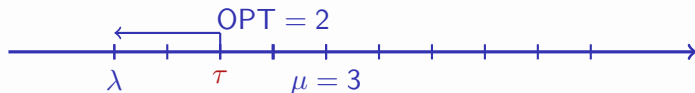
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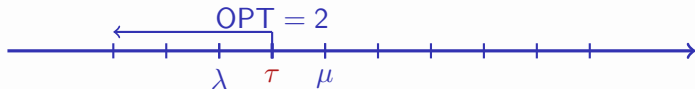
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$$((x_1 \vee r_1), 2) \quad ((x_2 \vee r_2), 5) \\ ((\neg x_1 \vee \neg x_2), \top)$$

$$\mu_2 = 3 \quad \lambda_2 = 1$$



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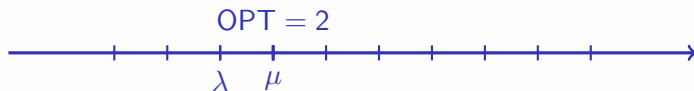
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$$\mu_3 = 2 \quad \lambda_3 = 1$$



BC - Core-Guided Binary Search

- Binary Search relaxes **all** soft clauses
- State of the art SAT solvers report **Unsatisfiable Cores** on **unsatisfiable formulas**
 - φ_C - Unsatisfiable Core: subset of unsatisfiable clauses

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BCD/BCD2 - Core-Guided Binary Search with Disjoint Cores

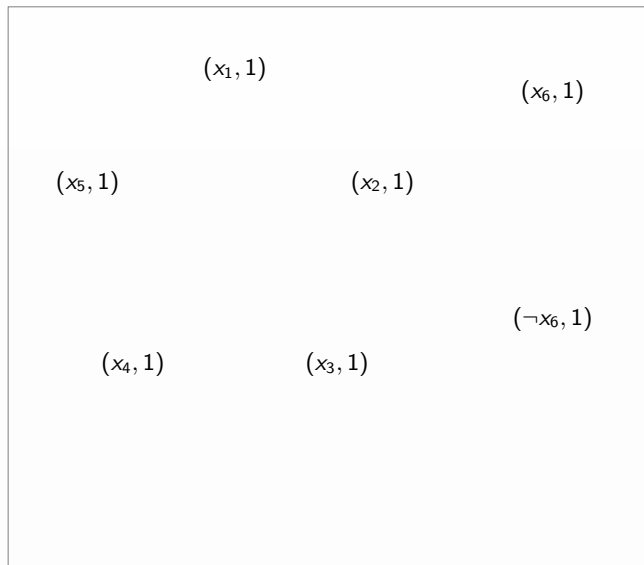
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BCD/BCD2 - Core-Guided Binary Search with Disjoint Cores

- BC maintains **one “large”** PB-constraint
- Some cores do not intersect other cores throughout the iterations
- BCD/BCD2 maintain disjoint cores separate:
 - Each disjoint core C_i is a core with its own:
 - ▶ μ_i - upper bound
 - ▶ λ_i - lower bound
 - ▶ R_i - set of relaxation variables
 - ▶ τ_i - middle value
 - Each disjoint core C_i adds a PB-constraint to the formula

$$CNF\left(\sum_{r_j \in R_i} w_j r_j \leq \tau_i\right)$$

BCD/BCD2 on Example



$$(\neg x_1 \vee \neg x_2, \top)$$

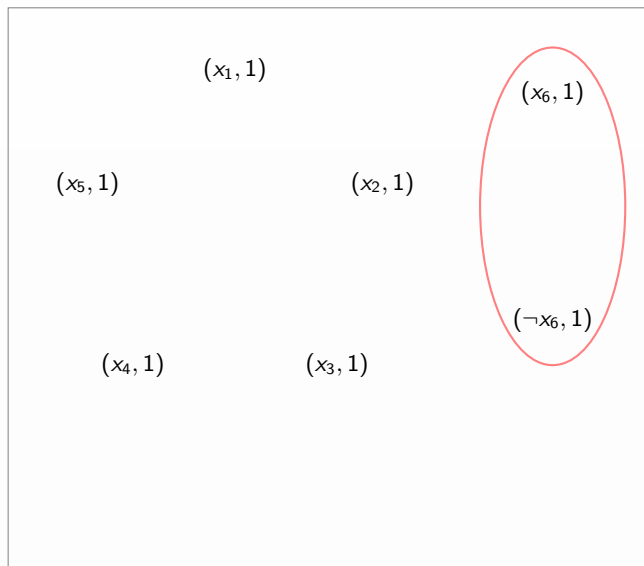
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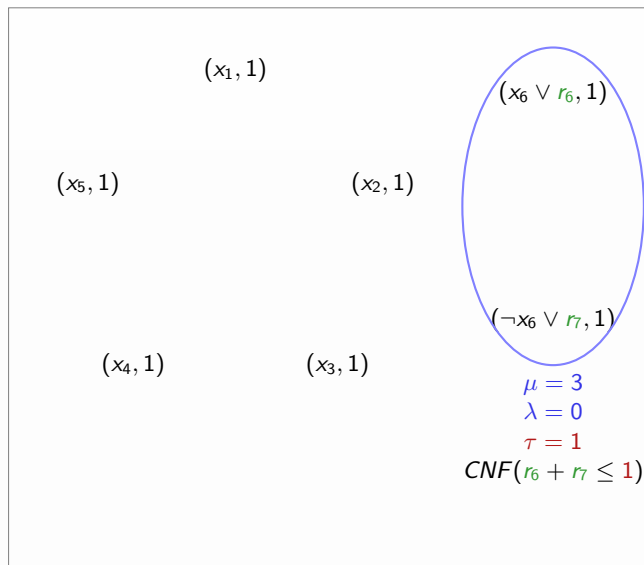
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BCD/BCD2 on Example



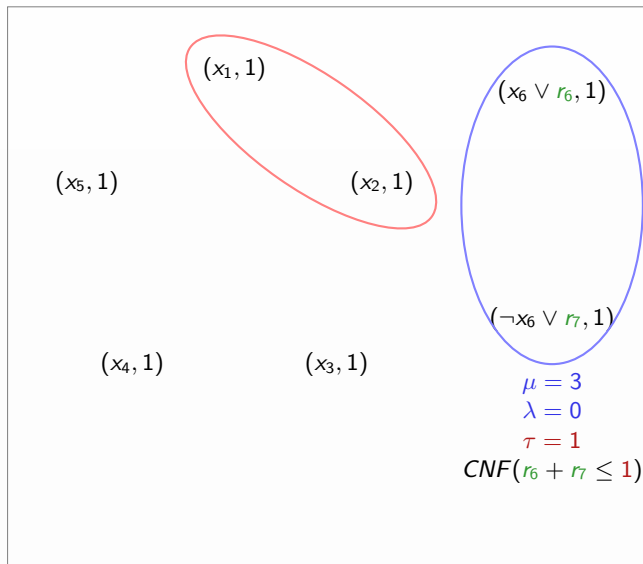
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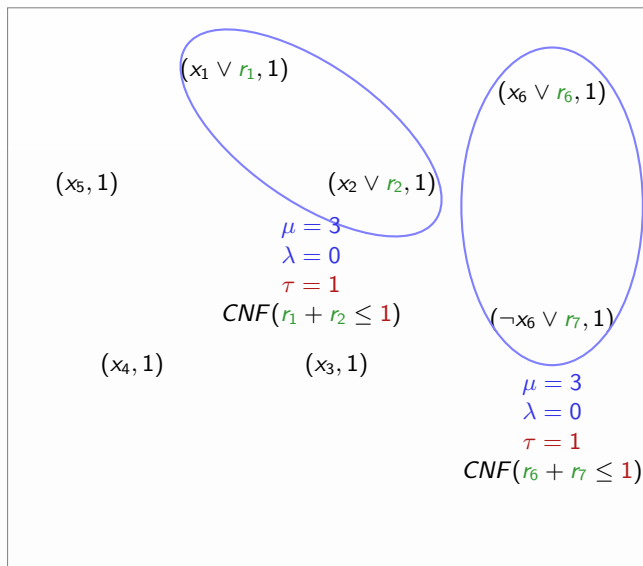
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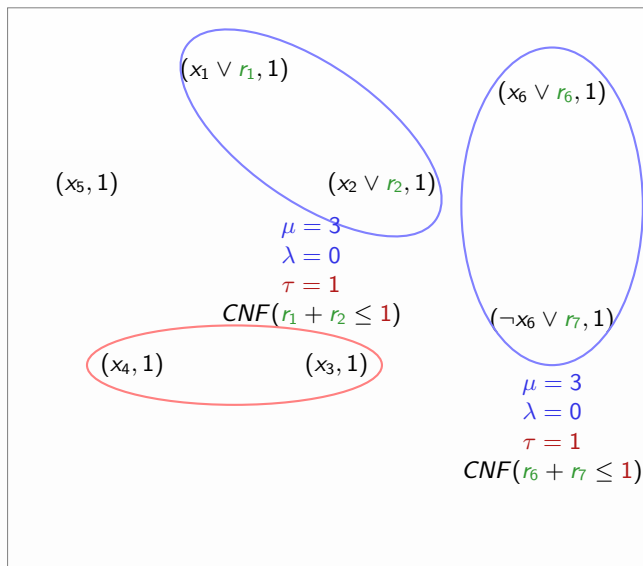
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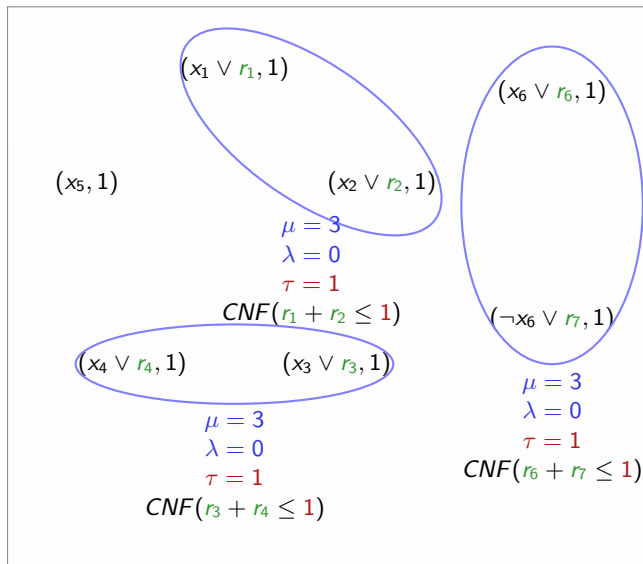
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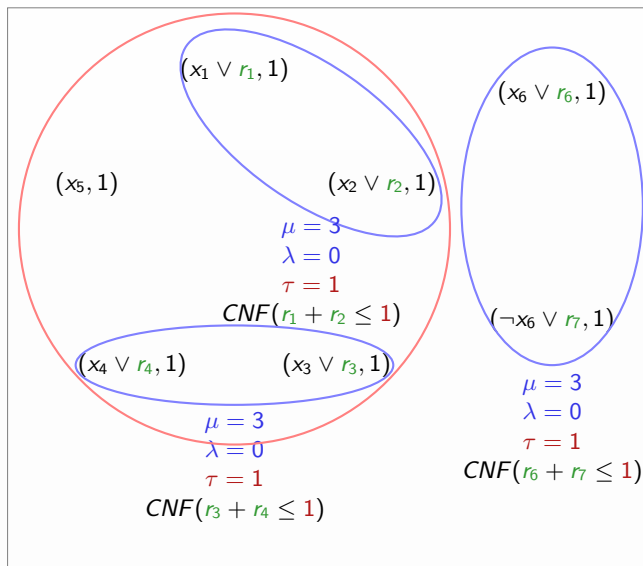
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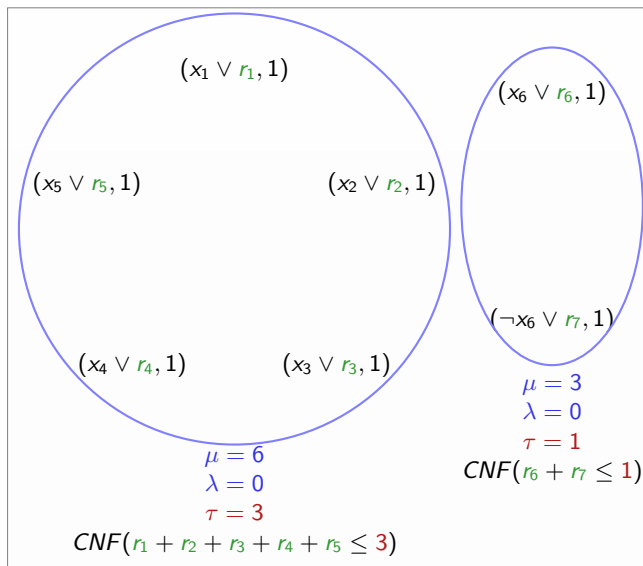
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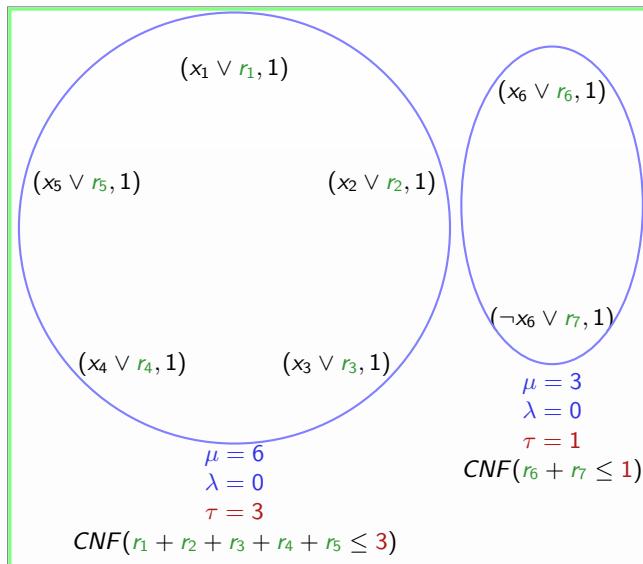
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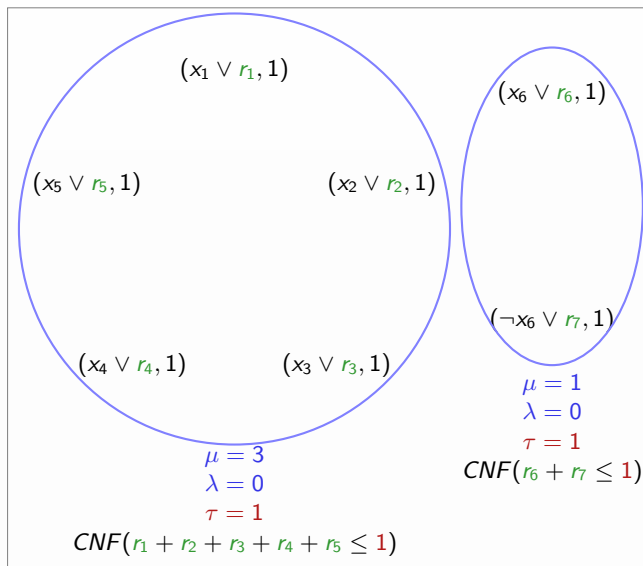
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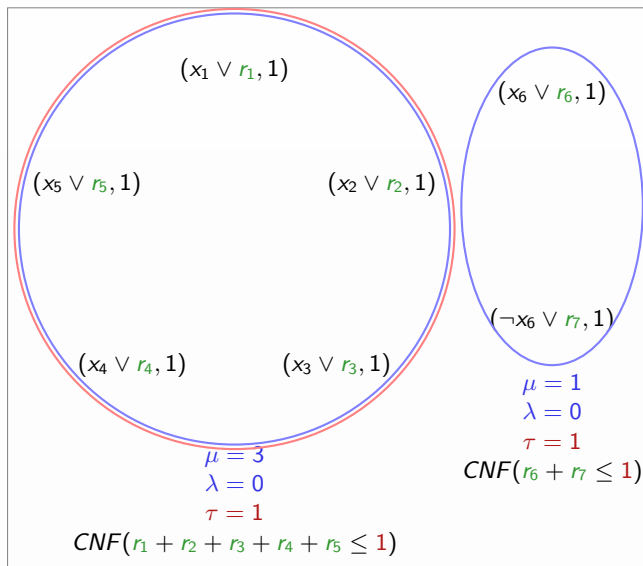
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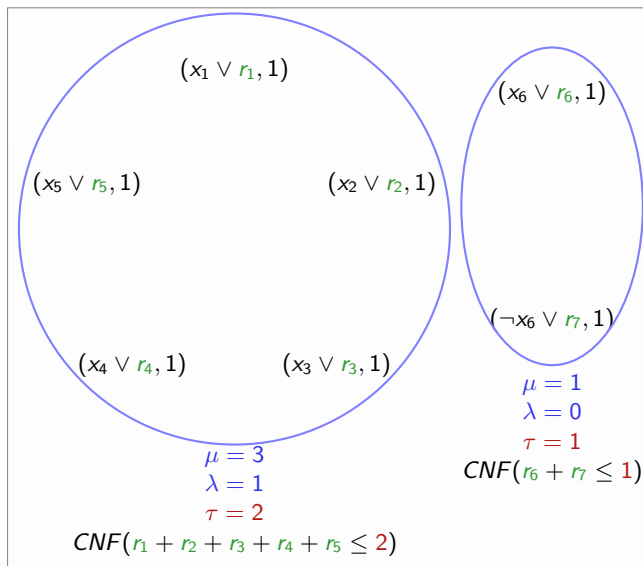
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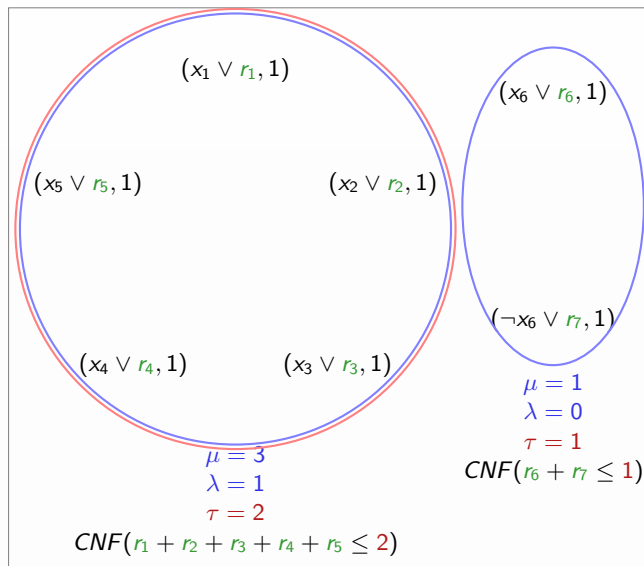
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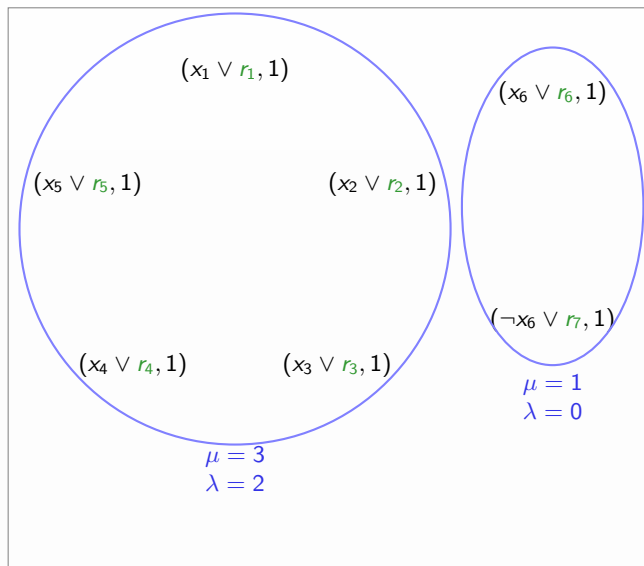
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BCD2 - Improvements

- Improvements over BCD
 - On the maintenance of upper bound
 - ▶ Cost of Clause
 - ▶ Global Upper Bound
 - On the maintenance of lower bound
 - ▶ New Lower Bound

BCD2 - Improvements on the upper bound

- Cost of Clause
 - In BCD the cost of a clause consider the relaxation variable
 - ▶ $w_i \cdot \mathcal{A}(r_i)$
 - In BCD2 the cost of a clause **disregards** the relaxation variable
 - ▶ $w_i \cdot (1 - \mathcal{A}(c_i \setminus \{r_i\}))$

BCD2 - Improvements on the upper bound

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 - In BCD2 the cost of a clause **disregards** the relaxation variable
 - ▶ $w_i \cdot (1 - \mathcal{A}(c_i \setminus \{r_i\}))$
- Global Upper Bound
 - BCD only maintains local upper bounds μ_i
 - $\sum_i \mu_i$ **can increase** in some iterations
 - ▶ conservative update of μ_i over unrelaxed soft clauses
 - ▶ the weight of the clause
 - BCD2 maintains μ as **global upper bound** (and its assignment \mathcal{A}_μ)
 - ▶ μ_i updated on unrelaxed soft clauses with the cost of the clause on \mathcal{A}_μ

BCD2 - Improvements on the lower bound 1/2

- New Lower Bound when merging disjoint cores with unrelaxed clauses
 - Merge C_1, \dots, C_k
 - Add $(c_1, w_1), \dots, (c_m, w_m)$
- BCD: $\lambda_{new} = \lambda_1 + \dots + \lambda_k$

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- BCD: $\lambda_{new} = \lambda_1 + \dots + \lambda_k$
- BCD2: $\lambda_{new} = \lambda_1 + \dots + \lambda_k + \Delta$
 - $\Delta = \dots$ (next slide)
 - Why the current unsatisfiable core?
Because:
 - ▶ Unrelaxed Soft Clauses
 - ▶ Disjoint Core needs update of bounds
 - ▶ A mix of both

BCD2 - Improvements on the lower bound 2/2

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Because:

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- ▶ One of the unrelaxed clauses unsatisfied: (c_x, w_x)
- ▶ Increment by w_x

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- ▶ Safe minimum: $\delta_1 = \min\{w_1, \dots, w_m\}$

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- Disjoint Core needs update of bounds

- ▶ Update lower bound of disjoint core: $\lambda_x = \tau_x$
- ▶ Increment by $\tau_x - \lambda_x$

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Because:

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- ▶ One of the unrelaxed clauses unsatisfied: (c_x, w_x)
- ▶ Increment by w_x
- ▶ Safe minimum: $\delta_1 = \min\{w_1, \dots, w_m\}$

- Disjoint Core needs update of bounds

- ▶ Update lower bound of disjoint core: $\lambda_x = \tau_x$
- ▶ Increment by $\tau_x - \lambda_x$
- ▶ Safe minimum: $\delta_2 = \min\{\tau_1 - \lambda_1, \dots, \tau_k - \lambda_k\}$

BCD2 - Improvements on the lower bound 2/2

- Why the current unsatisfiable core?

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- A mix of both

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- In BCD2 $\Delta = \min\{\delta_1, \delta_2, \delta_1 + \delta_2\} = \min\{\delta_1, \delta_2\}$

Outline

Motivation

Previous Algorithms - Overview

BCD2

Optimizations

Results

Conclusions

Additional Techniques

- **Hardening**

- Adapted the Hardening Rule from B&B MaxSAT algorithms
- Use global μ and $\sum \lambda_i$ as bounds
- Whenever bounds are updated then test hardening rule on remaining soft clauses
- May declare soft clauses as hard
- Details in the paper

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- May declare soft clauses as hard
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- **Biased Search**

- Decide τ depending on the outcomes of previous iterations
- Not necessarily the middle point
- Details in the paper

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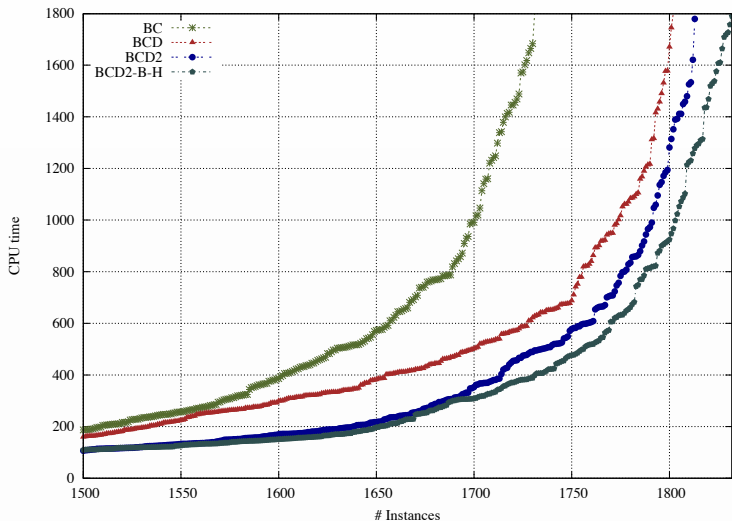
Conclusions

Experimental Results

- Linux cluster with 50 nodes, each node 3Ghz and 32 GB
- Time limit 1800 seconds and memory limit 4GB

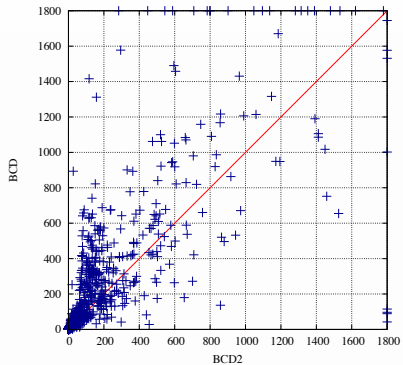
- Instances from 2009-2011 MaxSAT Evaluation instances
 - All Non-Random instances - crafted and industrial
 - All categories: (Plain) MaxSAT, Partial MaxSAT, Weighted MaxSAT, Weighted Partial MaxSAT
 - > 2600 instances

BC, BCD and BCD2 (and extensions)

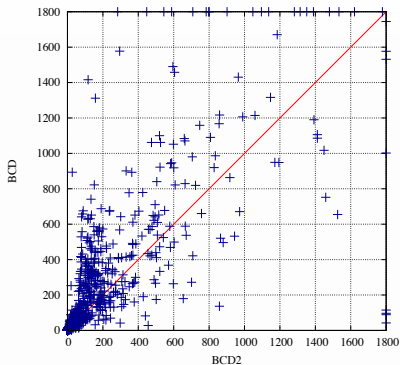


BC 1730; BCD 1801; BCD2 1813; BCD2-B-H 1832

BCD vs BCD2



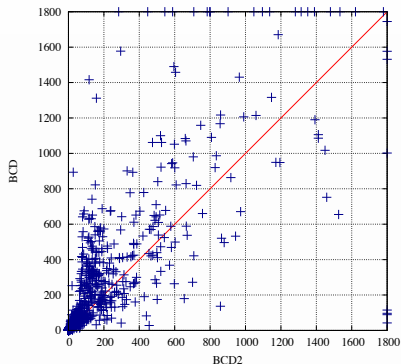
BCD vs BCD2



1305 instances with $\geq 20\%$
runtime difference:

- 918 BCD2 wins
- 387 BCD wins

BCD vs BCD2



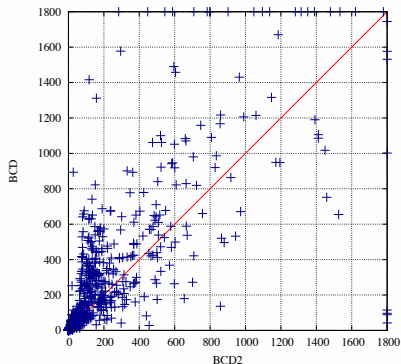
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- BCD: 124 907 SAT calls
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1793 instances solved by both:

- BCD: 124 907 SAT calls
- BCD2: 68 690 SAT calls
- close 50% less calls

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BCD2

Optimizations

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Contributions

- Proposed improvements to BCD
 - Improvement on the organization of the BCD algorithm:
 - ▶ Maintain a global upper bound μ and associated assignment \mathcal{A}_μ
 - ▶ Maintain the contribution of each soft clause to the cost
 - ▶ New more aggressive lower bound

 - ▶ Reduced the number of iterations (fewer SAT calls)
 - Proposed two techniques - Hardening & Biased Search
 - ▶ Can be implemented on any core-guided MaxSAT algorithm (that uses upper and lower bounds)
- BCD2 (with extensions) shown to improved BCD on extensive set of benchmarks

Obrigado. Thank you. Grazie.