Maximum Satisfiability

Ruben Martins

Carnegie Mellon University

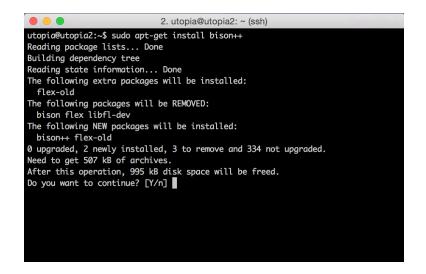
http://www.cs.cmu.edu/~mheule/15816-f23/ Automated Reasoning and Satisfiability October 2, 2023

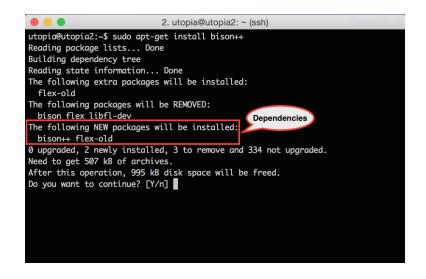
What is Boolean Satisfiability?

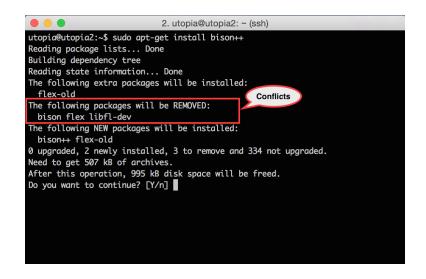
- ► Fundamental problem in Computer Science
 - ► The first problem to be proven NP-Complete
 - Has a wide range of applications
- Formula:

$$\blacktriangleright \ \phi = (\bar{x}_2 \vee \bar{x}_1) \wedge (x_2 \vee \bar{x}_3) \wedge (x_1) \wedge (x_3)$$

- ► Boolean Satisfiability (SAT):
 - Is there an assignment of true or false values to variables such that ϕ evaluates to true?







| Package | Dependencies | Conflicts | |
|------------------|--|----------------------|--|
| p ₁ | $\{\mathfrak{p}_2 \vee \mathfrak{p}_3\}$ | $\{p_4\}$ | |
| \mathfrak{p}_2 | $\{p_3\}$ | {} | |
| p_3 | $\{p_2\}$ | $\{\mathfrak{p}_4\}$ | |
| p ₄ | $\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$ | {} | |

- ▶ Set of packages we want to install: $\{p_1, p_2, p_3, p_4\}$
- ► Each package p_i has a set of dependencies:
 - Packages that must be installed for p_i to be installed
- Each package p_i has a set of conflicts:
 - Packages that cannot be installed for p_i to be installed

NP Completeness



"I can't find an efficient algorithm, but neither can all these famous people."

NP Completeness



"I can't find an efficient algorithm, but neither can all these famous people."

- ► Giving up?
 - The problem is NP-hard, so let's develop heuristics or approximation algorithms.

NP Completeness



"I can't find an efficient algorithm, but neither can all these famous people."

- ► Giving up?
 - The problem is NP-hard, so let's develop heuristics or approximation algorithms.
- ► No! Current tools can find solutions for **very large** problems!

| Package | Dependencies | Conflicts | |
|------------------|--|----------------------|--|
| p ₁ | $\{\mathfrak{p}_2\vee\mathfrak{p}_3\}$ | $\{\mathfrak{p}_4\}$ | |
| \mathfrak{p}_2 | $\{p_3\}$ | {} | |
| p_3 | $\{p_2\}$ | $\{p_4\}$ | |
| p ₄ | $\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$ | {} | |

| Package | Dependencies | Conflicts | |
|----------------|--|-----------|--|
| p ₁ | $\{\mathfrak{p}_2\vee\mathfrak{p}_3\}$ | $\{p_4\}$ | |
| p_2 | $\{p_3\}$ | {} | |
| p_3 | $\{p_2\}$ | $\{p_4\}$ | |
| p ₄ | $\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$ | {} | |

How can we encode this problem to Boolean Satisfiability? (Hint) Encode dependencies, conflicts, and installing all packages

| Package | Dependencies | Conflicts |
|----------------|--|-----------|
| p ₁ | $\{p_2 \lor p_3\}$ | $\{p_4\}$ |
| p_2 | $\{p_3\}$ | {} |
| p_3 | $\{p_2\}$ | $\{p_4\}$ |
| p ₄ | $\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$ | {} |

- ► Encoding dependencies:

 - $\triangleright p_2 \Rightarrow p_3 \equiv (\bar{p}_2 \vee p_3)$

 - $\blacktriangleright \ p_4 \Rightarrow (p_2 \land p_3) \equiv (\bar{p}_4 \lor p_2) \land (\bar{p}_4 \lor p_3)$

| Package | Dependencies | Conflicts |
|----------------|--|-----------|
| p ₁ | $\{\mathfrak{p}_2 \vee \mathfrak{p}_3\}$ | $\{p_4\}$ |
| p_2 | $\{p_3\}$ | {} |
| p_3 | $\{p_2\}$ | $\{p_4\}$ |
| p ₄ | $\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$ | {} |

- ► Encoding conflicts:

| Package | Dependencies | Conflicts |
|----------------|--|-----------|
| p ₁ | $\{p_2 \lor p_3\}$ | $\{p_4\}$ |
| p_2 | $\{p_3\}$ | {} |
| p_3 | $\{p_2\}$ | $\{p_4\}$ |
| p ₄ | $\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$ | {} |

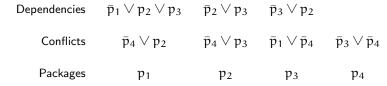
- Encoding installing all packages:
 - $\blacktriangleright (p_1) \land (p_2) \land (p_3) \land (p_4)$

Formula ϕ :

 $\mbox{Dependencies} \quad \bar{p}_1 \vee p_2 \vee p_3 \quad \bar{p}_2 \vee p_3 \quad \bar{p}_3 \vee p_2$

Formula φ :

Formula ϕ :



Formula φ :

$$\begin{array}{l} \bullet \quad \phi = (\bar{p}_1 \vee p_2 \vee p_3) \wedge (\bar{p}_2 \vee p_3) \wedge (\bar{p}_3 \vee p_2) \wedge (\bar{p}_4 \vee p_2) \wedge (\bar{p}_4 \vee p_3) \wedge (\bar{p}_1 \vee \bar{p}_4) \wedge (\bar{p}_3 \vee \bar{p}_4) \wedge (p_1) \wedge (p_2) \wedge (p_3) \wedge (p_4) \end{array}$$

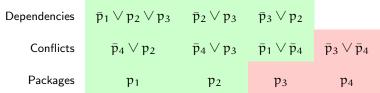
Formula φ :

| Dependencies | $\bar{p}_1 \vee p_2 \vee p_3$ | $\bar{p}_2 \vee p_3$ | $\bar{p}_3 \vee p_2$ | |
|--------------|---|----------------------|--|--|
| Conflicts | $\bar{\mathfrak{p}}_4\vee \mathfrak{p}_2$ | $\bar{p}_4 \vee p_3$ | $\bar{\mathfrak{p}}_1 \vee \bar{\mathfrak{p}}_4$ | $\bar{\mathfrak{p}}_3 \vee \bar{\mathfrak{p}}_4$ |
| Packages | p ₁ | \mathfrak{p}_2 | p_3 | p_4 |



- ► Formula is unsatisfiable
- ► Can you find an unsatisfiable subformula? (Hint) There are several with 3 clauses!

Formula φ :





- ► Formula is unsatisfiable
- ► We cannot install all packages
- How many packages can we install?

What is Maximum Satisfiability?

- Maximum Satisfiability (MaxSAT):
 - Clauses in the formula are either soft or hard
 - Hard clauses: must be satisfied (e.g. conflicts, dependencies)
 - Soft clauses: desirable to be satisfied (e.g. package installation)
- ► Goal: Maximize number of satisfied soft clauses

How to encode Software Package Upgradeability?

Software Package Upgradeability problem as MaxSAT:

- ▶ What are the hard constraints?
 - ► (Hint) Dependencies, conflicts or installation packages?
- ▶ What are the soft constraints?
 - ► (Hint) Dependencies, conflicts or installation packages?

How to encode Software Package Upgradeability?

Software Package Upgradeability problem as MaxSAT:

- ▶ What are the hard constraints?
 - Dependencies and conflicts
- ▶ What are the soft constraints?
 - Installation of packages

MaxSAT Formula:

- ▶ Dependencies and conflicts are encoded as hard clauses
- Installation of packages are encoded as soft clauses
- ► Goal: maximize the number of installed packages

MaxSAT Formula:

- Dependencies and conflicts are encoded as hard clauses
- Installation of packages are encoded as soft clauses
- ► Optimal solution (3 out 4 packages are installed)

Why is MaxSAT Important?

- ▶ Many real-world applications can be encoded to MaxSAT:
 - ► Software package upgradeability



Error localization in C code



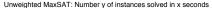
Wedding planning!

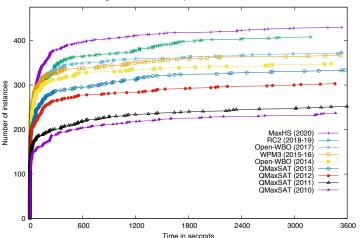


...

 MaxSAT algorithms are very effective for solving real-word problems

The MaxSAT (r)evolution





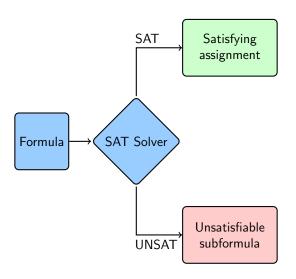
Comparing some of the best solvers from 2010-2020:

- ▶ In 2020: 81% more instances solved than in 2010!
- On same computer, same set of benchmarks

Outline

- MaxSAT Algorithms:
 - Upper bound search on the number of unsatisfied soft clauses
 - ▶ Lower bound search on the number of unsatisfied soft clauses
- **▶ Partitioning** in MaxSAT:
 - Use the structure of the problem to guide the search
- ► Using MaxSAT solvers

SAT Solvers



Satisfying assignment

Formula:

$$x_1 \quad x_2 \vee \bar{x}_1 \quad \bar{x}_3 \vee x_1 \quad \bar{x}_3 \vee \bar{x}_1 \quad x_2 \vee \bar{x}_3$$

- Satisfying assignment:
 - Assignment to the variables that evaluates the formula to true

Satisfying assignment

Formula:

$$x_1 \quad x_2 \vee \bar{x}_1 \quad \bar{x}_3 \vee x_1 \quad \bar{x}_3 \vee \bar{x}_1 \quad x_2 \vee \bar{x}_3$$

- ► Satisfying assignment:
 - Assignment to the variables that evaluates the formula to true
 - $\mu = \{x_1 = 1, x_2 = 1, x_3 = 0\}$

Unsatisfiable subformula

Formula:

$$x_1$$
 x_3 $x_2 \lor \bar{x}_1$ $\bar{x}_3 \lor x_1$ $\bar{x}_2 \lor \bar{x}_1$ $x_2 \lor \bar{x}_3$

► Formula is unsatisfiable

Unsatisfiable subformula

Formula:

$$x_1$$
 x_3 $x_2 \lor \bar{x}_1$ $\bar{x}_3 \lor x_1$ $\bar{x}_2 \lor \bar{x}_1$ $x_2 \lor \bar{x}_3$

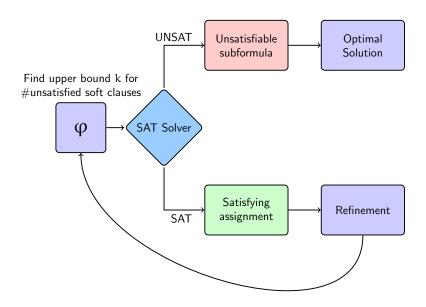
- ► Formula is unsatisfiable
- ► Unsatisfiable subformula (core):
 - $ightharpoonup \phi' \subseteq \phi$, such that ϕ' is unsatisfiable

MaxSAT Algorithms

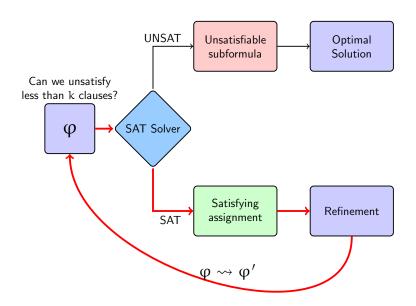
- MaxSAT algorithms build on SAT solver technology
- ► MaxSAT algorithms use constraints not defined in causal form:

 - ▶ AtMost1 constraints, $\sum_{j=1}^{n} x_j \leq 1$ ▶ General cardinality constraints, $\sum_{j=1}^{n} x_j \leq k$ ▶ Pseudo-Boolean constraints, $\sum_{j=1}^{n} a_j x_j \leq k$
- Efficient encodings to CNF
 - Sinz, Totalizer, ...

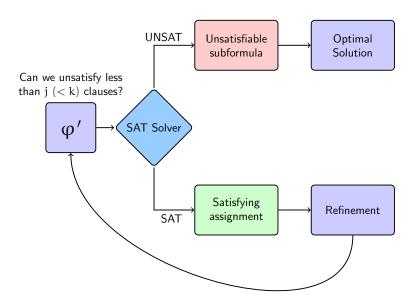
Upper Bound Search for MaxSAT



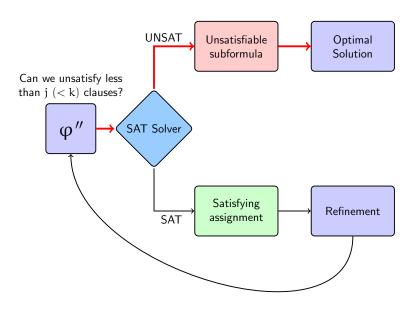
Upper Bound Search for MaxSAT



Upper Bound Search for MaxSAT



Upper Bound Search for MaxSAT



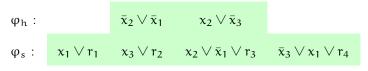
Linear Search Algorithms SAT-UNSAT

$$\begin{array}{llll} \phi_h \text{ (Hard):} & & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 \\ \\ \phi_s \text{ (Soft):} & & x_1 & x_3 & x_2 \vee \bar{x}_1 & \bar{x}_3 \vee x_1 \end{array}$$

Linear Search Algorithms SAT-UNSAT

- Relax all soft clauses
- Relaxation variables:
 - $V_R = \{r_1, r_2, r_3, r_4\}$
 - ▶ If a soft clause ω_i is unsatisfied, then $r_i = 1$
 - If a soft clause ω_i is satisfied, then $r_i = 0$

Linear Search Algorithms SAT-UNSAT



$$V_R = \{r_1, r_2, r_3, r_4\}$$

- ► Formula is satisfiable
 - $\nu = \{x_1 = 1, x_2 = 0, x_3 = 0, r_1 = 0, r_2 = 1, r_3 = 1, r_4 = 0\}$
- ▶ Goal: Minimize number of relaxation variables assigned to 1

Can we unsatisfy less than 2 soft clauses?

- $ightharpoonup r_2$ and r_3 were assigned truth value 1:
 - Current solution unsatisfies 2 soft clauses
- ► Can less than 2 soft clauses be unsatisfied?

Can we unsatisfy less than 2 soft clauses?

$$\begin{split} \phi_h: \quad & \bar{x}_2 \vee \bar{x}_1 \quad x_2 \vee \bar{x}_3 \quad \mathsf{CNF}(\textstyle\sum_{r_i \in V_R} r_i \leq 1) \\ \phi_s: \quad & x_1 \vee r_1 \quad x_3 \vee r_2 \quad x_2 \vee \bar{x}_1 \vee r_3 \quad \bar{x}_3 \vee x_1 \vee r_4 \\ \mu = 2 \quad & V_R = \{r_1, r_2, r_3, r_4\} \end{split}$$

- Add cardinality constraint that excludes solutions that unsatisfies 2 or more soft clauses:
 - ightharpoonup CNF $(r_1 + r_2 + r_3 + r_4 \le 1)$

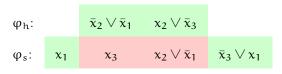
Can we unsatisfy less than 2 soft clauses? No!

$$\begin{array}{llll} \phi_h: & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(\sum_{r_i \in V_R} r_i \leq 1) \\ \\ \phi_s: & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 \vee r_3 & \bar{x}_3 \vee x_1 \vee r_4 \\ \\ \mu = 2 & V_R = \{r_1, r_2, r_3, r_4\} \end{array}$$

- Formula is unsatisfiable:
 - ▶ There are no solutions that unsatisfy 1 or less soft clauses

Can we unsatisfy less than 2 soft clauses? No!

Partial MaxSAT Formula:



$$\mu=2 \qquad V_R = \{r_1, r_2, r_3, r_4\}$$

▶ Optimal solution: given by the last model and corresponds to unsatisfying 2 soft clauses:

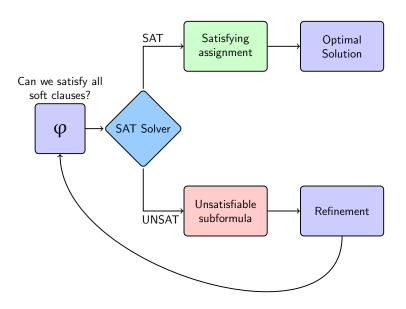
$$\nu = \{x_1 = 1, x_2 = 0, x_3 = 0\}$$

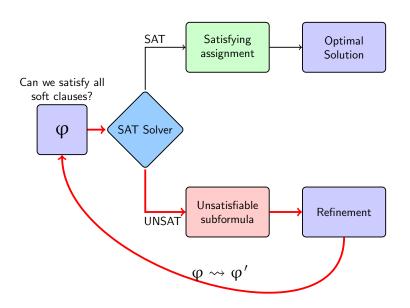
MaxSAT algorithms

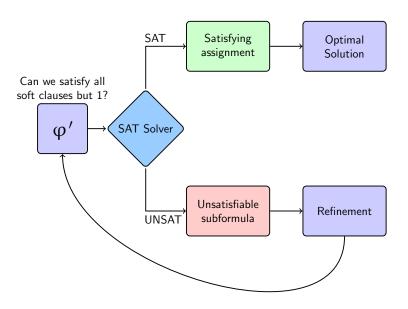
- ► We have just seen a search on the **upper bound**
- ▶ What other kind of search can we do to find an optimal solution?

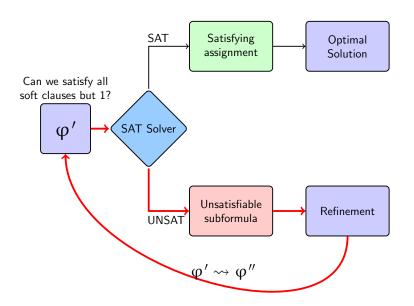
MaxSAT algorithms

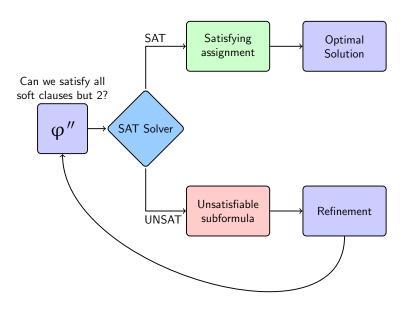
- ► We have just seen a search on the **upper bound**
- ▶ What other kind of search can we do to find an optimal solution?
- ► What if we start searching from the **lower bound**?

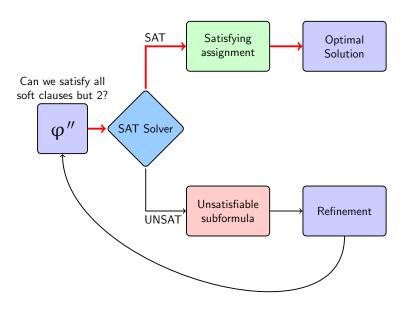












Linear Search Algorithms UNSAT-SAT

- ► Relax all soft clauses
- ► Relaxation variables:
 - $V_R = \{r_1, r_2, r_3, r_4\}$
 - ▶ If a soft clause ω_i is unsatisfied, then $r_i = 1$
 - If a soft clause ω_i is satisfied, then $r_i = 0$

Can we satisfy all soft clauses?

$$\begin{array}{lll} \phi_h: & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(\sum_{r_i \in V_R} r_i \leq 0) \\ \\ \phi_s: & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 \vee r_3 & \bar{x}_3 \vee x_1 \vee r_4 \\ \\ \mu = 2 & V_R = \{r_1, r_2, r_3, r_4\} \end{array}$$

- Add cardinality constraint that excludes solutions that unsatisfies 1 or more soft clauses:
 - ightharpoonup CNF $(r_1 + r_2 + r_3 + r_4 \le 0)$

Can we satisfy all soft clauses but 1?

$$\begin{array}{llll} \phi_h: & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(\sum_{r_i \in V_R} r_i \leq \mathbf{0}) \\ \\ \phi_s: & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 \vee r_3 & \bar{x}_3 \vee x_1 \vee r_4 \end{array}$$

- ► Formula is unsatisfiable:
 - ▶ There are no solutions that unsatisfy 0 or less soft clauses
- Add cardinality constraint that excludes solutions that unsatisfies 2 or more soft clauses:
 - ightharpoonup CNF($r_1 + r_2 + r_3 + r_4 \le 1$)

Can we satisfy all soft clauses but 2?

$$\begin{array}{lllll} \phi_h: & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(\sum_{r_i \in V_R} r_i \leq 1) \\ \\ \phi_s: & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 \vee r_3 & \bar{x}_3 \vee x_1 \vee r_4 \end{array}$$

- Formula is unsatisfiable:
 - ▶ There are no solutions that unsatisfy 1 or less soft clauses
- Add cardinality constraint that excludes solutions that unsatisfies 3 or more soft clauses:
 - ightharpoonup CNF($r_1 + r_2 + r_3 + r_4 \le 2$)

Can we satisfy all soft clauses but 2? Yes!

$$\begin{array}{llll} \phi_h: & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(\sum_{r_i \in V_R} r_i \leq 2) \\ \\ \phi_s: & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 \vee r_3 & \bar{x}_3 \vee x_1 \vee r_4 \end{array}$$

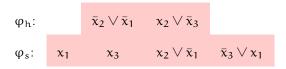
- ► Formula is satisfiable:
 - $\qquad \qquad \mu = \{x_1 = 1, x_2 = 0, x_3 = 0, r_1 = 0, r_2 = 1, r_3 = 1, r_4 = 0\}$
- Optimal solution unsatisfies 2 soft clauses

What are the problems of this algorithm? (Hint) Number of relaxation variables? Size of the cardinality constraint? Other?

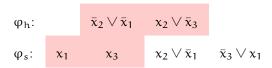
- What are the problems of this algorithm? (Hint) Number of relaxation variables? Size of the cardinality constraint? Other?
- We relax all soft clauses!
- The cardinality constraint contain as many literals as we have soft clauses!
- ► Can we do better?

$$\begin{array}{llll} \phi_h \text{ (Hard):} & & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 \\ \\ \phi_s \text{ (Soft):} & & x_1 & x_3 & x_2 \vee \bar{x}_1 & \bar{x}_3 \vee x_1 \end{array}$$

Partial MaxSAT Formula:



► Formula is unsatisfiable



- ► Formula is unsatisfiable
- ► Identify an unsatisfiable core

- Relax non-relaxed soft clauses in unsatisfiable core:
 - Add cardinality constraint that excludes solutions that unsatisfies 2 or more soft clauses:
 - ► $CNF(r_1 + r_2 \le 1)$
 - Relaxation on demand instead of relaxing all soft clauses eagerly

Partial MaxSAT Formula:

$$\begin{array}{ccccc} \phi_h \colon & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(r_1 + r_2 \leq 1) \\ \\ \phi_s \colon & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 & \bar{x}_3 \vee x_1 \end{array}$$

► Formula is unsatisfiable

- ► Formula is unsatisfiable
- ► Identify an unsatisfiable core

- ▶ Relax non-relaxed soft clauses in unsatisfiable core:
 - Add cardinality constraint that excludes solutions that unsatisfies 3 or more soft clauses:
 - ightharpoonup CNF($r_1 + r_2 + r_3 + r_4 \le 2$)
 - ▶ Relaxation on demand instead of relaxing all soft clauses eagerly

Partial MaxSAT Formula:

Formula is satisfiable:

$$\qquad \qquad \mu = \{x_1 = 1, x_2 = 0, x_3 = 0, r_1 = 0, r_2 = 1, r_3 = 1, r_4 = 0\}$$

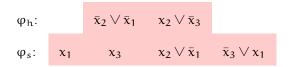
▶ Optimal solution unsatisfies 2 soft clauses

What are the problems of this algorithm? (Hint) Number of relaxation variables? Size of the cardinality constraint? Other?

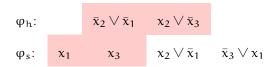
- What are the problems of this algorithm? (Hint) Number of relaxation variables? Size of the cardinality constraint? Other?
- ▶ We must translate cardinality constraints into CNF!
- If the number of literals is large than we may generate a very large formula!
- ► Can we do better?

$$\begin{array}{lll} \phi_h \text{ (Hard):} & & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 \\ \\ \phi_s \text{ (Soft):} & & x_1 & x_3 & x_2 \vee \bar{x}_1 & \bar{x}_3 \vee x_1 \end{array}$$

Partial MaxSAT Formula:



► Formula is unsatisfiable



- ► Formula is unsatisfiable
- ► Identify an unsatisfiable core

- ► Relax unsatisfiable core:
 - Add relaxation variables
 - Add AtMost1 constraint

Partial MaxSAT Formula:

► Formula is unsatisfiable

$$\begin{array}{ccccc} \phi_h \colon & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(r_1 + r_2 \leq 1) \\ \\ \phi_s \colon & x_1 \vee r_1 & x_3 \vee r_2 & x_2 \vee \bar{x}_1 & \bar{x}_3 \vee x_1 \end{array}$$

- ► Formula is unsatisfiable
- Identify an unsatisfiable core

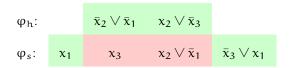
- ► Relax unsatisfiable core:
 - Add relaxation variables
 - Add AtMost1 constraint
- Soft clauses may be relaxed multiple times

$$\begin{array}{llll} \phi_h \colon & \bar{x}_2 \vee \bar{x}_1 & x_2 \vee \bar{x}_3 & \mathsf{CNF}(r_1 + r_2 \leq 1) & \mathsf{CNF}(r_3 + \ldots + r_6 \leq 1) \\ \\ \phi_s \colon & x_1 \vee r_1 \vee r_3 & x_3 \vee r_2 \vee r_4 & x_2 \vee \bar{x}_1 \vee r_5 & \bar{x}_3 \vee x_1 \vee r_6 \end{array}$$

- ► Formula is satisfiable
- An optimal solution would be:

$$\nu = \{x_1 = 1, x_2 = 0, x_3 = 0\}$$

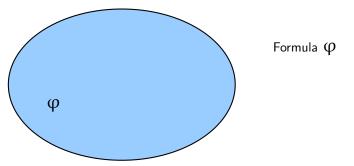
Partial MaxSAT Formula:

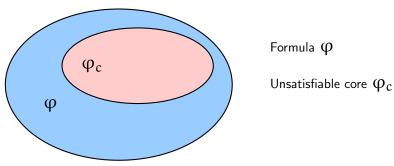


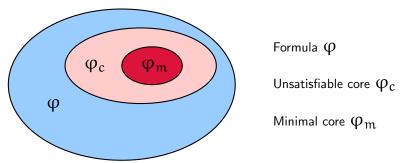
- ► Formula is satisfiable
- ► An optimal solution would be:

$$\nu = \{x_1 = 1, x_2 = 0, x_3 = 0\}$$

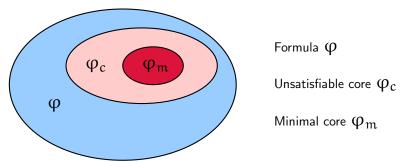
► This assignment unsatisfies 2 soft clauses







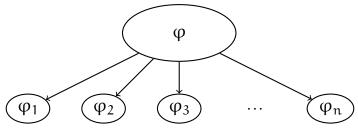
▶ Unsatisfiable cores found by the SAT solver are not minimal



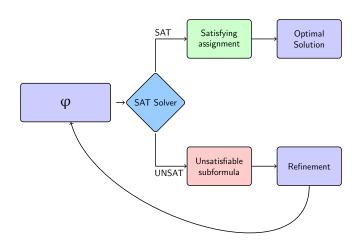
Minimizing unsatisfiable cores is computationally hard

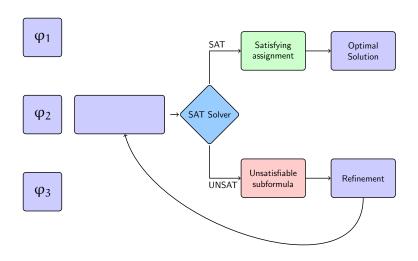
Partitioning in MaxSAT

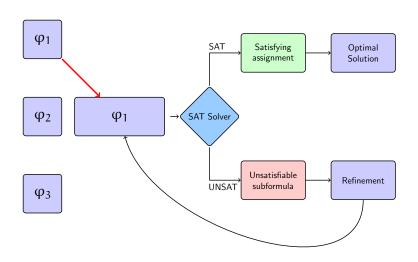
- ► Partitioning in MaxSAT:
 - ▶ Partition the soft clauses into disjoint sets
 - ► Iteratively increase the size of the MaxSAT formula

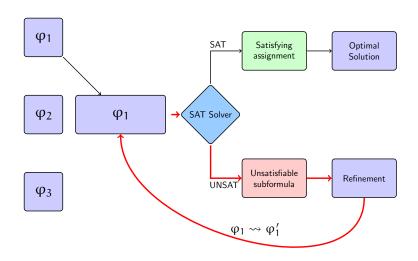


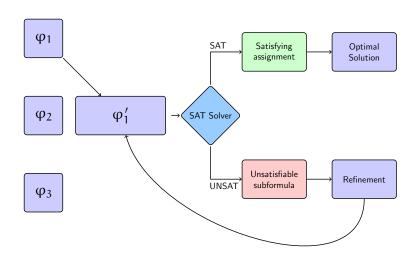
- Advantages:
 - **Easier formulas** for the SAT solver
 - ► Smaller unsatisfiable cores at each iteration

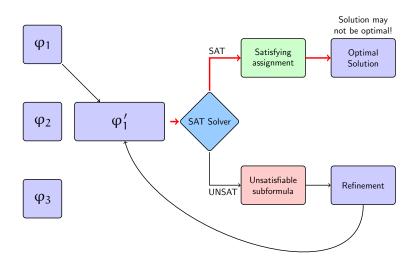


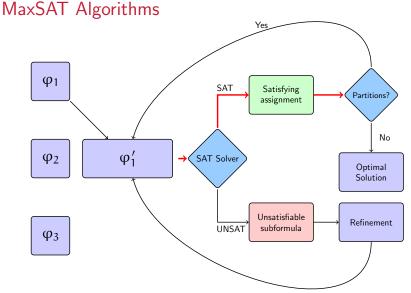


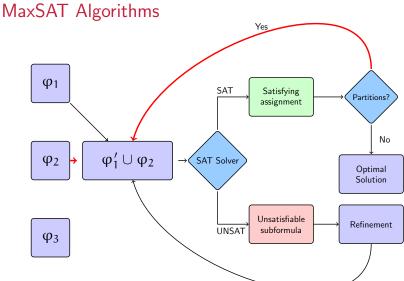


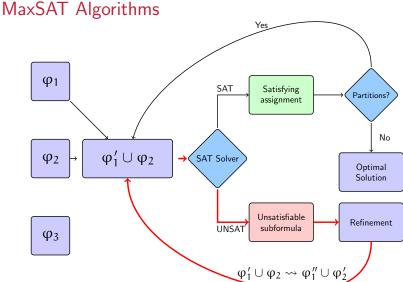


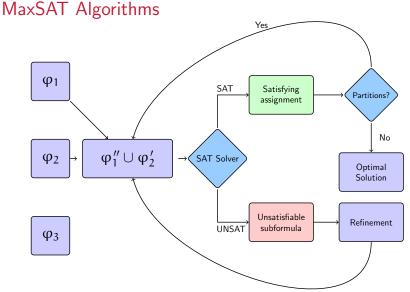


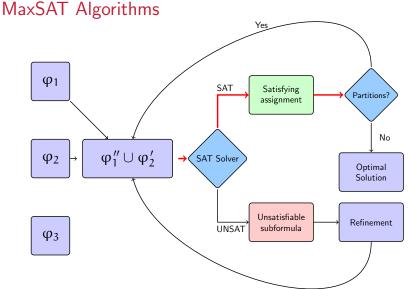


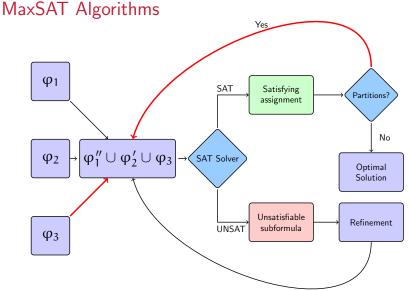


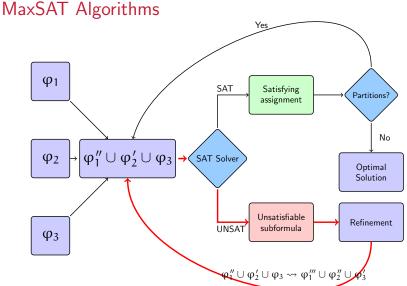


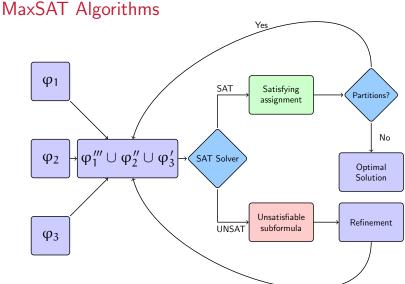


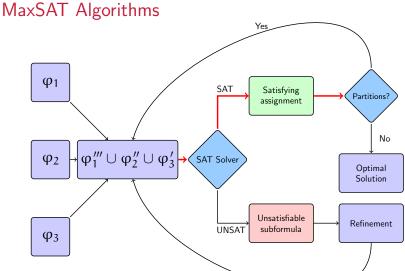


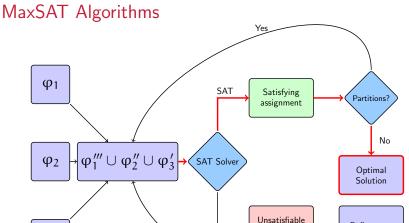












UNSAT

subformula

Refinement

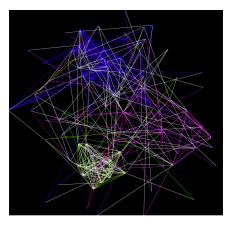
 ϕ_3

How to Partition Soft Clauses?

► **Graph representation** of the MaxSAT formula:

Vertices: Variables

Edges: Between variables that appear in the same clause

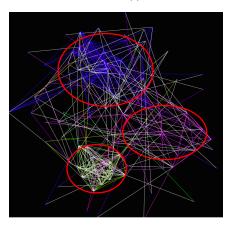


How to Partition Soft Clauses?

► **Graph representation** of the MaxSAT formula:

Vertices: Variables

Edges: Between variables that appear in the same clause



Graph representations for MaxSAT

- ► There are many ways to represent MaxSAT as a graph:
 - ► Clause-Variable Incidence Graph (CVIG)
 - Variable Incidence Graph (VIG)
 - Hypergraph
 - Resolution Graph
 - **•** ...

Graph representations for MaxSAT

- ► There are many ways to represent MaxSAT as a graph:
 - Clause-Variable Incidence Graph (CVIG)
 - Variable Incidence Graph (VIG)
 - Hypergraph
 - ► Resolution Graph
 - **.**..

MaxSAT Formulas as Resolution-based Graphs

- ► MaxSAT solvers rely on the identification of unsatisfiable cores
- ► How can we capture sets of clauses that are closely related and are likely to result in unsatisfiable cores?
 - Represent MaxSAT formulas as resolution graphs!
 - Resolution graphs are based on the resolution rule

MaxSAT Formulas as Resolution-based Graphs

- ► MaxSAT solvers rely on the identification of unsatisfiable cores
- ► How can we capture sets of clauses that are closely related and are likely to result in unsatisfiable cores?
 - Represent MaxSAT formulas as resolution graphs!
 - ▶ Resolution graphs are based on the resolution rule
- Example of the resolution rule:

$$(x_1\vee x_2)\quad (\bar{x}_2\vee x_3)$$

MaxSAT Formulas as Resolution-based Graphs

- ► MaxSAT solvers rely on the identification of unsatisfiable cores
- ► How can we capture sets of clauses that are closely related and are likely to result in unsatisfiable cores?
 - Represent MaxSAT formulas as resolution graphs!
 - ▶ Resolution graphs are based on the resolution rule
- Example of the resolution rule:

$$\frac{(x_1\vee x_2)\quad (\bar{x}_2\vee x_3)}{(x_1\vee x_3)}$$

- Vertices: Represent each clause in the graph
- ► Edges: There is an edge between two vertices if you can apply the resolution rule between the corresponding clauses

- ► Vertices: Represent each clause in the graph
- ► Edges: There is an edge between two vertices if you can apply the resolution rule between the corresponding clauses

Hard clauses:

$$c_1 = x_1 \vee x_2$$

$$c_2 = \bar{x}_2 \vee x_3$$

$$c_3=\bar{x}_1\vee\bar{x}_3$$

Soft clauses:

$$c_4 = \bar{x}_1$$

$$c_5=\bar{x}_3$$

- ► Vertices: Represent each clause in the graph
- ► Edges: There is an edge between two vertices if you can apply the resolution rule between the corresponding clauses

Hard clauses:

$$c_1 = x_1 \vee x_2$$

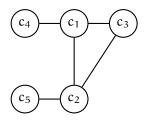
$$c_2 = \bar{x}_2 \vee x_3$$

$$c_3 = \bar{x}_1 \vee \bar{x}_3$$

Soft clauses:

$$c_4 = \bar{x}_1$$

$$c_5 = \bar{x}_3$$



- ► Vertices: Represent each clause in the graph
- ► Edges: There is an edge between two vertices if you can apply the resolution rule between the corresponding clauses

Hard clauses:

$$c_1 = x_1 \vee x_2$$

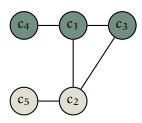
$$c_2 = \bar{x}_2 \vee x_3$$

$$c_3 = \bar{x}_1 \vee \bar{x}_3$$

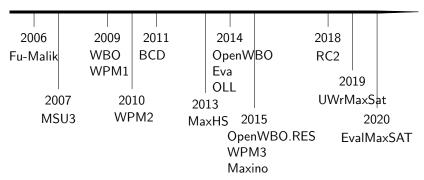
Soft clauses:

$$c_4 = \bar{x}_1$$

$$c_5 = \bar{x}_3$$



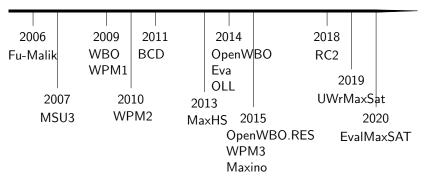
Timeline



Fu-Malik

- First core-guided algorithm for MaxSAT
- Uses multiple relaxation variables per soft clause
- ► Only requires AtMost1 constraints

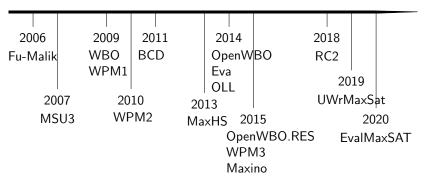
Timeline



MSU₃

- Uses one relaxation variable per soft clause
- ▶ Requires cardinality / pseudo-Boolean constraints

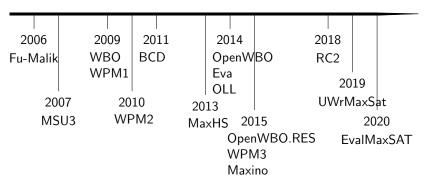
Timeline



WBO WPM1

- ► Generalizes Fu-Malik algorithm to weighted problems
- ► Efficient implementation of the Fu-Malik algorithm

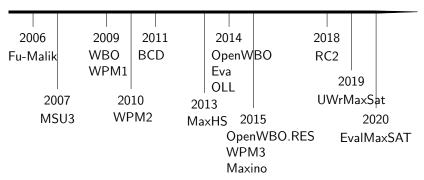
Timeline



WPM2

- Only one relaxation per soft clause
- Group intersecting cores into disjoint covers
- Uses a cardinality constraint per cover

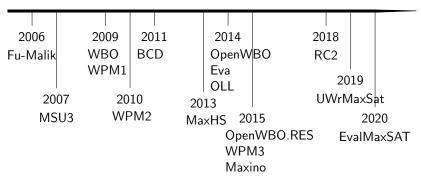
Timeline



BCD

▶ Uses binary search in core-guided algorithms

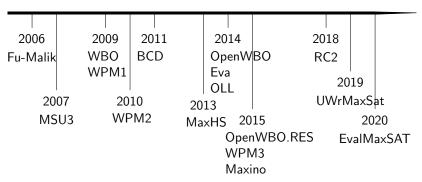
Timeline



MaxHS

- ► Based on Hitting Sets
- Combines SAT and MIP solvers

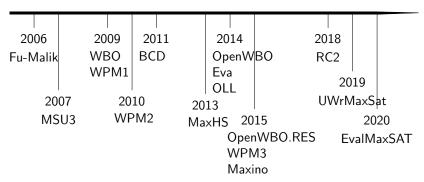
Timeline



OpenWBO

- ► Improves the MSU3 algorithm with incremental construction of cardinality constraints
- ► Efficient implementation of the MSU3 algorithm

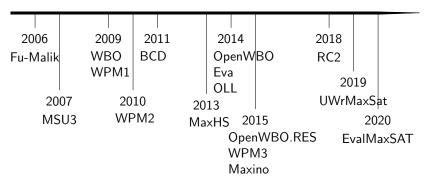
Timeline



Eva

 Uses MaxSAT resolution to refine the formula instead of using AtMost1 constraints

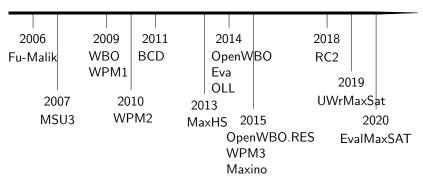
Timeline



OLL WPM3

- ▶ Introduce new variables to represent cardinality constraints
- $ightharpoonup d = r_1 + r_2 + r_3 \le 1$
- ▶ Soft clause (d, 1) is introduced

Timeline



OpenWBO.RES

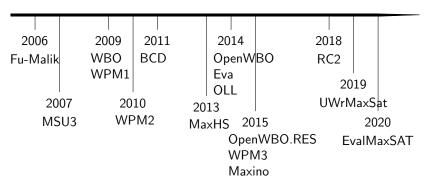
▶ Uses resolution-based graphs to partition soft clauses

OpenWBO.RES

Maxino

Construction of the cardinality constraint uses core structure

Timeline



RC2 UWrMaxSat EvalMaxSAT

- ► Efficient implementations of the OLL algorithm
- OLL algorithm is currently the most used one

Want to try MaxSAT solving?

- ► Java:
 - ► SAT4.I
 - http://www.sat4j.org/
- Python:
 - ► RC2
 - Best solver in 2018 and 2019!
 - ► SAT solvers written in C++
 - https://pysathq.github.io
- ▶ http://maxsat-evaluations.github.io
 - Modify a solver today and enter this year competition!

Standard Solver Input Format: DIMACS WCNF

- Variables indexed from 1 to n
- ► Negation:
 - ightharpoonup -3 stands for \bar{x}_3
- ▶ 0: special end-of-line character
- One special header "p"-line: p wcnf #vars #clauses top
 - ► #vars: number of variables
 - ▶ #clauses: number of clauses
 - top: "weight" of hard clauses
- ► Clauses represented as lists of integers
 - Weight is the first number
 - $(\bar{x}_3 \lor x_1 \lor \bar{x}_{45})$, weight 2: 2 -3 1 -45 0
- Clause is hard if weight is equal to top

Standard Solver Input Format: DIMACS WCNF

- Variables indexed from 1 to n
- ► Negation:
 - ightharpoonup -3 stands for \bar{x}_3
- 0: special end-of-line character
- One special header "p"-line: p wcnf #vars #clauses top
 - ► #vars: number of variables
 - #clauses: number of clauses
 - top: "weight" of hard clauses
- ► Clauses represented as lists of integers
 - Weight is the first number
 - $(\bar{x}_3 \lor x_1 \lor \bar{x}_{45})$, weight 2: 2 -3 1 -45 0
- Clause is hard if weight is equal to top
- New format removes header
 - Special symbol for hard clauses ('h')

Standard Solver Input Format: DIMACS WCNF

Example: pointer analysis domain (pa-2.wcnf):

```
p wcnf 17997976 23364255 9223372036854775807
142 -11393180 12091478 0
200 -12496389 -1068725 13170751 0
209 -8854604 -8854942 -8854943 -8253894 9864153 0
174 -9406753 -8105076 11844088 0
200 -10403325 -8104972 12524177 0
142 -11987544 12096893 0
37 -10981341 -10980973 10838652 0
209 -9578314 -9579250 -9579251 -8254733 9578317 0
209 -8868994 -8870298 -8870299 -8254157 8868997 0
209 -9387012 -9387508 -9387509 -8253943 9387015 0
174 -9834074 -8106628 12074710 0
200 -10726788 -8105074 12909526 0
9223372036854775807 -13181184 0
9223372036854775807 -13181215 0
    truncated 763 MB
```

Push-Button Solver Technology

Example: \$ open-wbo pa-2.wcnf

Push-Button Solver Technology

Example: \$ open-wbo pa-2.wcnf

```
c Open-WBO: a Modular MaxSAT Solver
c Version: MaxSAT Evaluation 2016
c Authors: Ruben Martins, Vasco Manquinho, Ines Lynce
c Contributors: Miguel Neves, Saurabh Joshi, Mikolas Janota
...
c |Problem Type: Weighted
c |Number of variables: 17,997,976
c |Number of variables: 8,237,870
c |Number of soft clauses: 8,237,870
c |Number of soft clauses: 15,126,385
c |Parse time: 5.60 s
...
o 4699
o 4609
o 143
s OPTIMUM FOUND
c Total time: 361.26 s v 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15...
...17997976
```

Want to know more about MaxSAT?

Email me! Always happy to talk about MaxSAT!

rubenm@cs.cmu.edu

Check the tutorial slides and webpage presented at ECAI'20:

Advances in Maximum Satisfiability: https://ecai20-maxsat-tutorial.github.io/

Chapter in the 2nd edition of the Handbook of Satisfiability:



Maximum Satisfiability: https://sat-group. github.io/ruben/media/p02c24-mxm.pdf

References

MaxSAT solvers:

- [Fu-Malik] Z. Fu, S. Malik. On Solving the Partial MAX-SAT Problem. SAT 2006: 252-265.
- [MSU3] J. Marques-Silva, J. Planes. On using unsatisfiability for solving Maximum Satisfiability. Technical report 2007
- [WBO] V. Manquinho, J. Marques-Silva, J. Planes. Algorithms for Weighted Boolean Optimization. SAT 2009: 495-508
- [WPM1] Carlos Ansótegui, Maria Luisa Bonet, and Jordi Levy. Solving (weighted) partial MaxSAT through satisfiability testing. SAT 2009: 427–440
- [WPM2] Carlos Ansótegui, Maria Luisa Bonet, and Jordi Levy. A new algorithm for weighted partial MaxSAT. AAAI 2010
- $[{\sf BC2}]$ Federico Heras, António Morgado, and Joao Marques-Silva. Core-guided binary search algorithms for maximum satisfiability. AAAI 2011
- [OpenWBO] R. Martins, S. Joshi, V. Manquinho, I. Lynce. Incremental Cardinality Constraints for MaxSAT. CP 2014: 531-548
- [OLL] António Morgado, Carmine Dodaro, and Joao Marques-Silva. Core-guided MaxSAT with soft cardinality constraints. CP 2014: 564–573
- [OpenWBO.RES] R. Martins, V. Manquinho, I. Lynce. Exploiting Resolution-Based Representations for MaxSAT Solving. SAT 2015: 272-286
- [MaxHS] Jessica Davies, Fahiem Bacchus: Postponing Optimization to Speed Up MAXSAT Solving. CP 2013: 247-262
- [RC2] Alexey Ignatiev, António Morgado, Joao Marques-Silva: PySAT: A Python Toolkit for Prototyping with SAT Oracles. SAT 2018: 428-437

References

Cardinality and Pseudo-Boolean Encodings:

C. Sinz. Towards an Optimal CNF Encoding of Boolean Cardinality Constraints. CP 2005: 827-831

N. Manthey, T. Philipp, P. Steinke. A More Compact Translation of Pseudo-Boolean Constraints into CNF Such That Generalized Arc Consistency Is Maintained. KI 2014: 123-134

T. Philipp, P. Steinke. PBLib - A Library for Encoding Pseudo-Boolean Constraints into CNF. SAT 2015: 9-16 http://tools.computational-logic.org/content/pblib.php

Community Structure:

C. Ansótegui, J. Giráldez-Cru, Jordi Levy. The Community Structure of SAT Formulas. SAT 2012: 410-423

Web pages of interest:

MaxSAT Evaluation: http://www.maxsat.udl.cat/ Open-WBO: http://sat.inesc-id.pt/open-wbo/ SAT4J: http://www.sat4j.org/ RC2: https://pysathq.github.io MaxHS: http://www.maxhs.org/ SATGraf: https://bitbucket.org/znewsham/satgraf