# Maximum Satisfiability

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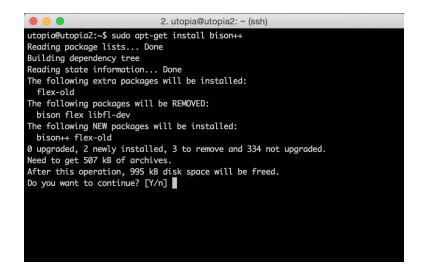
http://www.cs.cmu.edu/~mheule/15816-f24/ Automated Reasoning and Satisfiability September 30, 2024

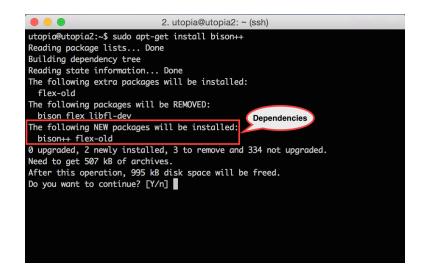
## What is Boolean Satisfiability?

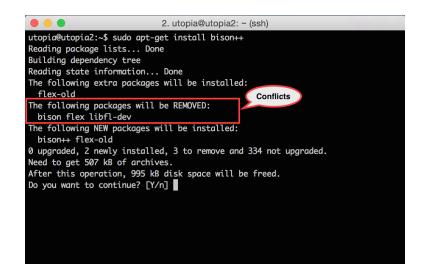
- ► Fundamental problem in Computer Science
  - ► The first problem to be proven NP-Complete
  - Has a wide range of applications
- Formula:

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

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







Package	Dependencies	Conflicts	
p <sub>1</sub>	$\{\mathfrak{p}_2 \vee \mathfrak{p}_3\}$	$\{p_4\}$	
$\mathfrak{p}_2$	$\{p_3\}$	{}	
$p_3$	$\{p_2\}$	$\{\mathfrak{p}_4\}$	
p <sub>4</sub>	$\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$	{}	

- ▶ Set of packages we want to install:  $\{p_1, p_2, p_3, p_4\}$
- ► Each package p<sub>i</sub> has a set of dependencies:
  - Packages that must be installed for p<sub>i</sub> to be installed
- Each package p<sub>i</sub> has a set of conflicts:
  - Packages that cannot be installed for p<sub>i</sub> 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 <sub>1</sub>	$\{\mathfrak{p}_2\vee\mathfrak{p}_3\}$	$\{\mathfrak{p}_4\}$	
$\mathfrak{p}_2$	$\{p_3\}$	{}	
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p <sub>4</sub>	$\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$	{}	

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

Package	Dependencies	Conflicts
p <sub>1</sub>	$\{p_2 \lor p_3\}$	$\{p_4\}$
$p_2$	$\{p_3\}$	{}
$p_3$	$\{p_2\}$	$\{p_4\}$
p <sub>4</sub>	$\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$	{}

- ► 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 <sub>1</sub>	$\{\mathfrak{p}_2 \vee \mathfrak{p}_3\}$	$\{p_4\}$
$p_2$	$\{p_3\}$	{}
$p_3$	$\{p_2\}$	$\{p_4\}$
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- ► Encoding conflicts:

Package	Dependencies	Conflicts
p <sub>1</sub>	$\{p_2 \lor p_3\}$	$\{p_4\}$
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p <sub>4</sub>	$\{\mathfrak{p}_2 \wedge \mathfrak{p}_3\}$	{}

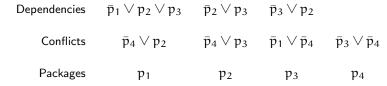
- Encoding installing all packages:
  - $\blacktriangleright (p_1) \land (p_2) \land (p_3) \land (p_4)$

Formula  $\phi$ :

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

Formula  $\varphi$ :

Formula  $\phi$ :



#### Formula $\varphi$ :

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

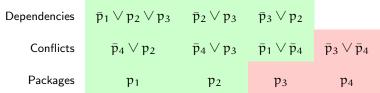
#### Formula $\varphi$ :

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 <sub>1</sub>	$\mathfrak{p}_2$	$p_3$	$p_4$



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

#### Formula $\varphi$ :





- ► 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



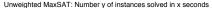
Wedding planning!

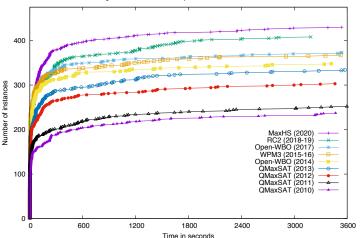


**.**..

 MaxSAT algorithms are very effective for solving real-word problems

## The MaxSAT (r)evolution





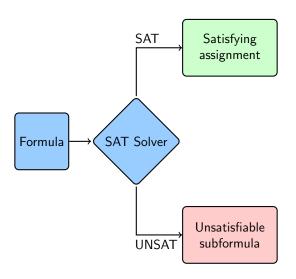
Comparing some of the best solvers from 2010-2020:

- ▶ 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:

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

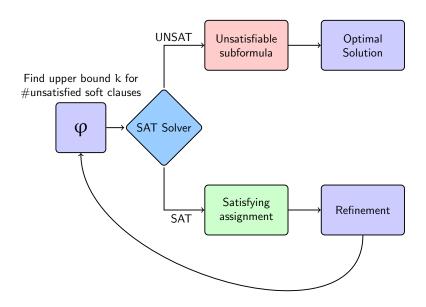
- ► Formula is unsatisfiable
- ► Unsatisfiable subformula (core):
  - $ightharpoonup \phi' \subseteq \phi$ , such that  $\phi'$  is unsatisfiable

## MaxSAT Algorithms

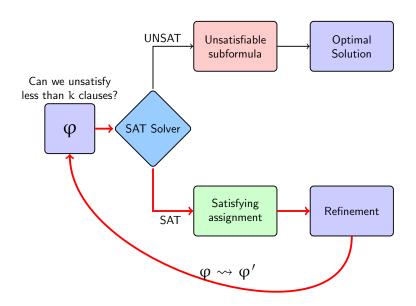
- MaxSAT algorithms build on SAT solver technology
- ► MaxSAT algorithms use constraints not defined in causal form:

  - ▶ 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, ...

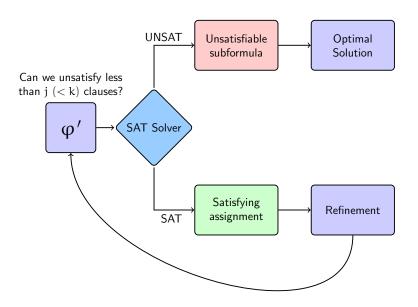
#### Upper Bound Search for MaxSAT



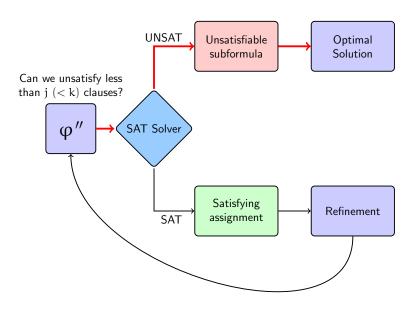
#### Upper Bound Search for MaxSAT



#### Upper Bound Search for MaxSAT



#### Upper Bound Search for MaxSAT



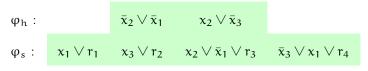
## Linear Search Algorithms SAT-UNSAT

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

# 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  $\omega_i$  is unsatisfied, then  $r_i = 1$
  - If a soft clause  $\omega_i$  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 $(r_1 + r_2 + r_3 + r_4 \le 1)$

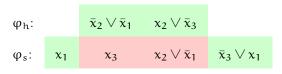
## Can we unsatisfy less than 2 soft clauses? No!

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

- 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:

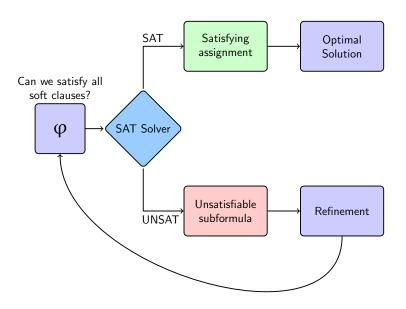
$$\nu = \{x_1 = 1, x_2 = 0, x_3 = 0\}$$

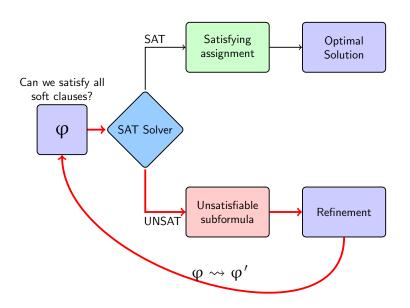
#### MaxSAT algorithms

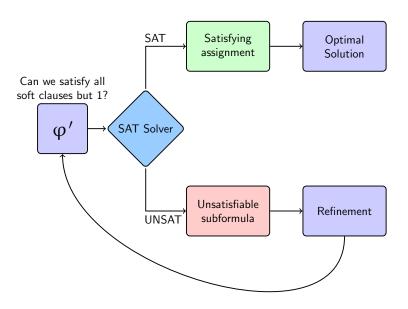
- ► We have just seen a search on the **upper bound**
- ▶ What other kind of search can we do to find an optimal solution?

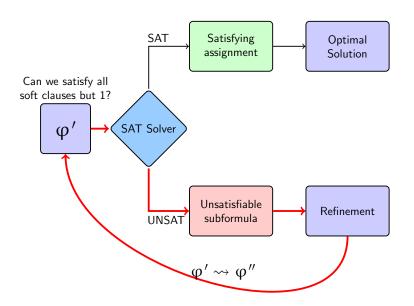
#### MaxSAT algorithms

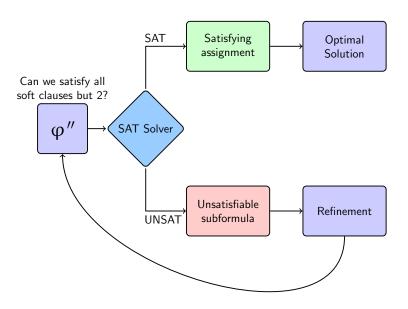
- ► We have just seen a search on the **upper bound**
- ▶ What other kind of search can we do to find an optimal solution?
- ► What if we start searching from the **lower bound**?

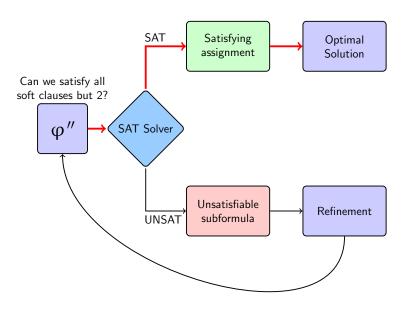












## Linear Search Algorithms UNSAT-SAT

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

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

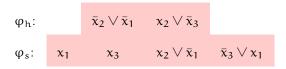
- ► Formula is satisfiable:
  - $\qquad \qquad \mu = \{x_1 = 1, x_2 = 0, x_3 = 0, r_1 = 0, r_2 = 1, r_3 = 1, r_4 = 0\}$
- Optimal solution unsatisfies 2 soft clauses

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

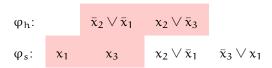
- What are the problems of this algorithm? (Hint) Number of relaxation variables? Size of the cardinality constraint? Other?
- We relax all soft clauses!
- The cardinality constraint contain as many literals as we have soft clauses!
- ► Can we do better?

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

#### 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:

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

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  - 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:

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

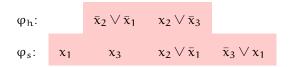
▶ Optimal solution unsatisfies 2 soft clauses

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

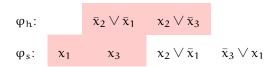
- What are the problems of this algorithm? (Hint) Number of relaxation variables? Size of the cardinality constraint? Other?
- ▶ We must translate cardinality constraints into CNF!
- If the number of literals is large than we may generate a very large formula!
- ► Can we do better?

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

#### 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

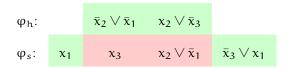
- ► Relax unsatisfiable core:
  - Add relaxation variables
  - Add AtMost1 constraint
- Soft clauses may be relaxed multiple times

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

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

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

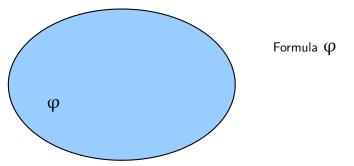
#### Partial MaxSAT Formula:

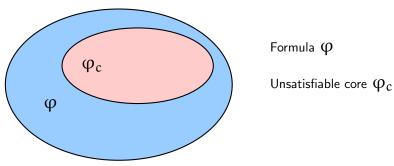


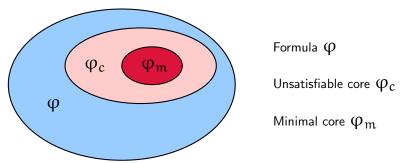
- ► Formula is satisfiable
- ► An optimal solution would be:

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

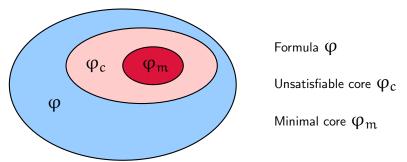
► This assignment unsatisfies 2 soft clauses







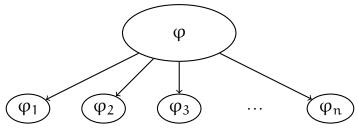
▶ Unsatisfiable cores found by the SAT solver are not minimal



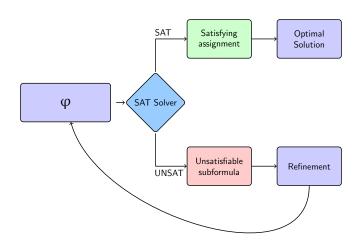
Minimizing unsatisfiable cores is computationally hard

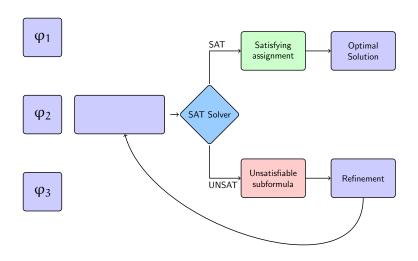
### Partitioning in MaxSAT

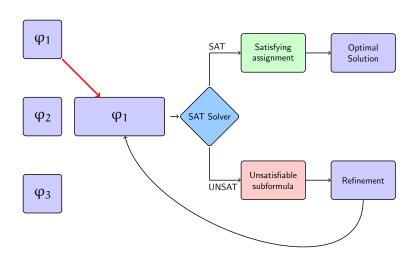
- ► Partitioning in MaxSAT:
  - ▶ Partition the soft clauses into disjoint sets
  - ► Iteratively increase the size of the MaxSAT formula

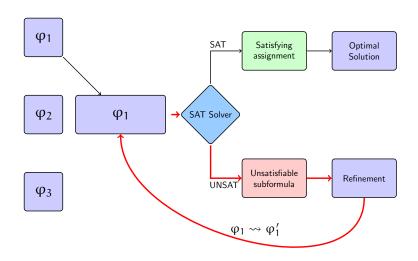


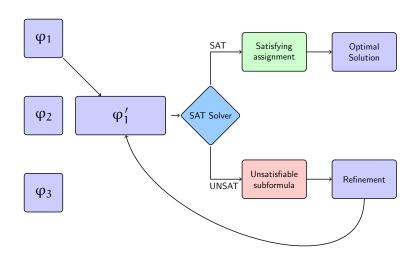
- Advantages:
  - **Easier formulas** for the SAT solver
  - ► Smaller unsatisfiable cores at each iteration

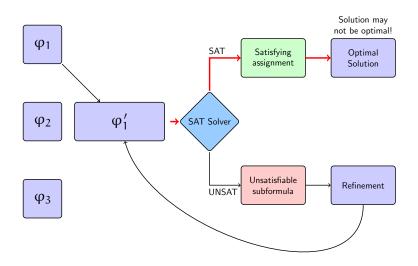


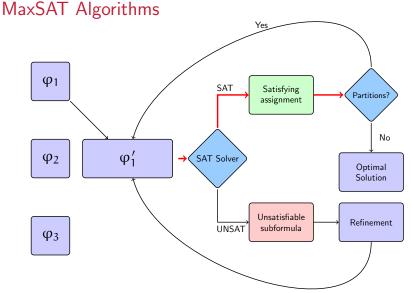


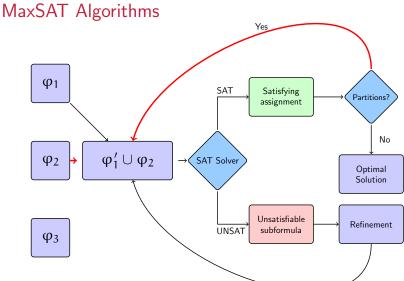


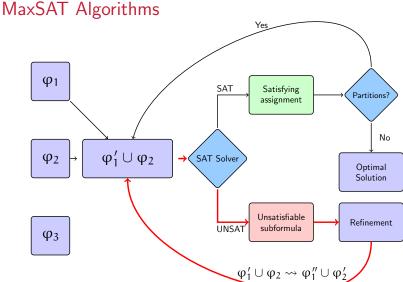


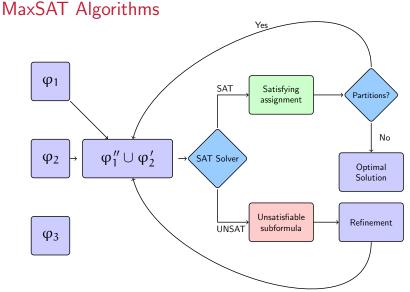


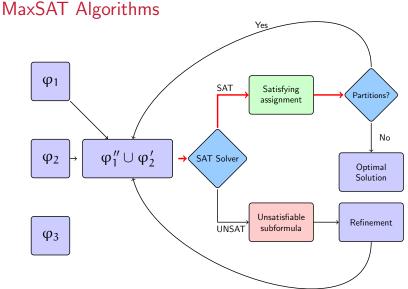


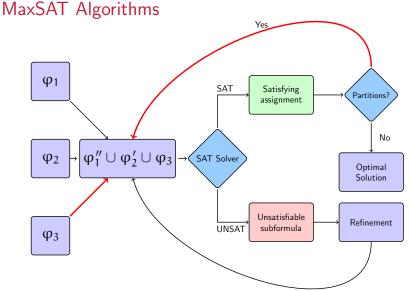


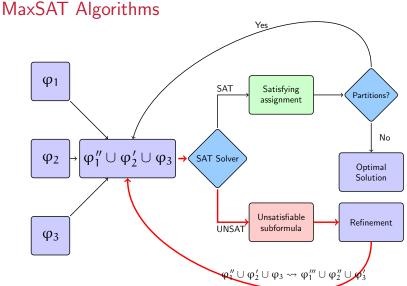


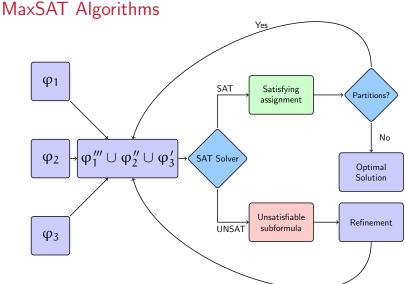


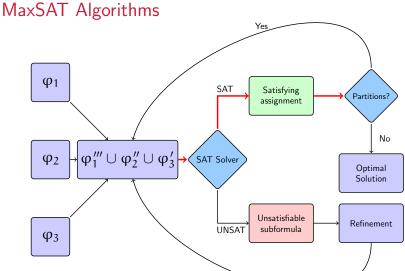


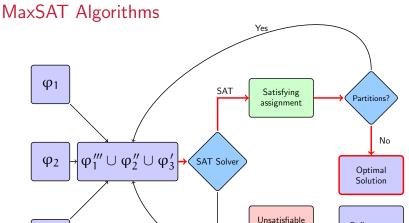












UNSAT

subformula

Refinement

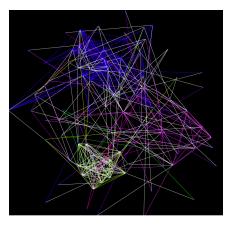
 $\phi_3$ 

#### How to Partition Soft Clauses?

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

Vertices: Variables

Edges: Between variables that appear in the same clause

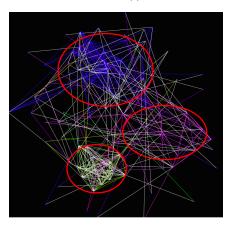


#### How to Partition Soft Clauses?

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### 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
  - **•** ...

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#### 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!
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### 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:

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

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

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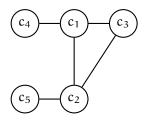
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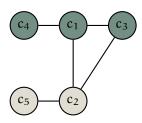
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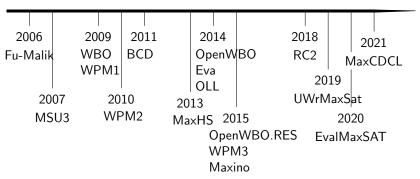
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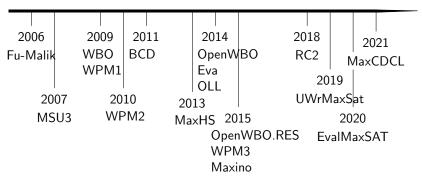
#### Timeline



### Fu-Malik

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

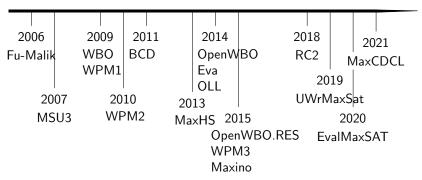
#### Timeline



### MSU<sub>3</sub>

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

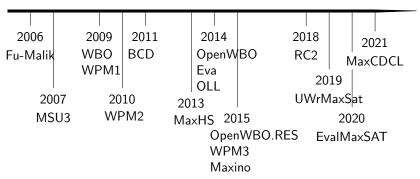
#### Timeline



WBO WPM1

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

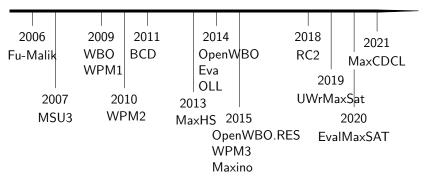
#### Timeline



### WPM2

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

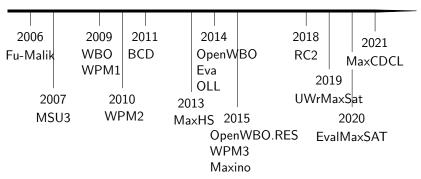
#### Timeline



### **BCD**

Uses binary search in core-guided algorithms

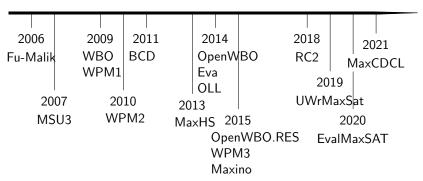
#### Timeline



### MaxHS

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

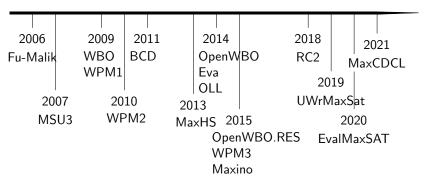
#### **Timeline**



### OpenWBO

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

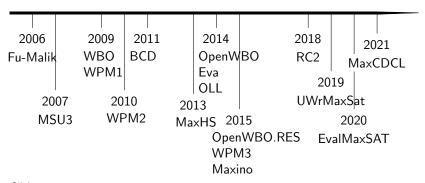
#### Timeline



### Eva

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

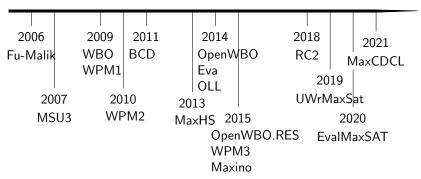
#### Timeline



### 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

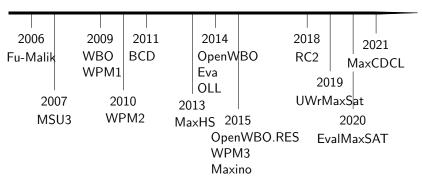
Uses resolution-based graphs to partition soft clauses

### OpenWBO.RES

### Maxino

Construction of the cardinality constraint uses core structure

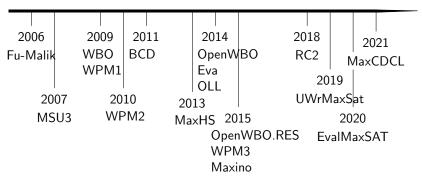
#### Timeline



RC2 UWrMaxSat EvalMaxSAT

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

#### Timeline



### MaxCDCL

- Combines CDCL with Branch-and-Bound
- ▶ Lookahead estimate LB on the number of falsified soft clauses

# 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!

- 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
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- Clause is hard if weight is equal to top
- New format removes header
  - Special symbol for hard clauses ('h')

## **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
```

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142 -11393180 12091478 0
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174 -9834074 -8106628 12074710 0
200 -10726788 -8105074 12909526 0
...
h -13181184 0
h -13181215 0
```

New simplified format!

# 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://www.cs. cmu.edu/~rubenm/papers/p02c24-mxm.pdf

## References

#### MaxSAT solvers:

[Fu-Malik] Z. Fu, S. Malik. On Solving the Partial MAX-SAT Problem. SAT 2006: 252-265.

 $\left[\text{MSU3}\right]$  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

 $\mbox{[WPM2]}$  Carlos Ansótegui, Maria Luisa Bonet, and Jordi Levy. A new algorithm for weighted partial MaxSAT. AAAI 2010

 $[\mathsf{BC2}]$  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

 $[{\sf OpenWBO.RES}] \ R. \ Martins, \ V. \ Manquinho, \ I. \ Lynce. \ Exploiting \ Resolution-Based \ Representations for MaxSAT Solving. SAT 2015: 272-286$ 

[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

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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