

# Integer Linear Programming strategies for first-order weighted MAX-SAT

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# A SAT instance

Can we satisfy these 4 clauses?

$$\neg a \vee b$$

$$\neg b \vee c \vee d$$

$$\neg c \vee \neg d$$

$$a$$

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Yes:  $a = b = c = 1, d = 0$

Adding  $\neg a \vee d$  and  $\neg c$  makes it unsatisfiable.

# A weighted MAX-SAT instance

A cost (possibly infinite) for each broken clause

$$\infty : \neg a \vee b$$

$$1 : \neg b \vee c \vee d$$

$$4 : \neg c \vee \neg d$$

$$3 : a$$

$$\infty : \neg a \vee d$$

$$20 : \neg c$$

Goal is to find an assignment with minimal cost

## ILP encoding for SAT

$$\begin{array}{ll} \neg a \vee b & (1 - a) + b \geq 1 \\ \neg b \vee c \vee d & (1 - b) + c \geq 1 \\ \neg c \vee \neg d & (1 - c) + d \geq 1 \\ a & a \geq 1 \end{array}$$

## ILP encoding for weighted MAX-SAT

$$\begin{array}{ll}
 \infty : \neg a \vee b & (1 - a) + b \geq 1 \\
 1 : \neg b \vee c \vee d & (1 - b) + c + x_1 \geq 1 \\
 4 : \neg c \vee \neg d & (1 - c) + d + x_2 \geq 1 \\
 3 : a & a + x_3 \geq 1 \\
 \infty : \neg a \vee d & (1 - a) + d \geq 1 \\
 20 : \neg c & (1 - c) + x_4 \geq 1
 \end{array}$$

Minimise  $x_1 + 4x_2 + 3x_3 + 20x_4$  subject to the 6 (hard) constraints

# First-order logic

- ▶ A first-order language has a finite number of predicate symbols and a finite number of function symbols.
- ▶ Suppose we have the following predicate symbols:  $e/1$ ,  $o/1$ ,  $lt/2$ ,
- ▶ And these two function symbols  $0$  (a constant) and  $s/1$ .

Here are some formulae in that language:

$$e(0)$$

$$\forall X : e(X) \vee e(s(X))$$

$$\forall X : lt(X, s(X))$$

$$\forall X, Y, Z : \neg lt(X, Y) \vee \neg lt(Y, Z) \vee lt(X, Z)$$



# First-order models

$$e(s(0))$$

$$\forall X : e(X) \vee e(s(X))$$

$$\forall X : It(X, s(X))$$

$$\forall X, Y, Z : \neg It(X, Y) \vee \neg It(Y, Z) \vee It(X, Z)$$

A first-order interpretation defines a truth-value for each ground atomic formulae in the language.

- ▶  $M_1$ : All ground atoms are set to TRUE.
- ▶  $M_2$ : True ground atoms are  $\{e(0), e(s(s(0))), \dots, It(0, s(0)), It(0, s(s(0))), \dots\}$ .

These two different interpretations are both *models* of the set of formulae.

# First-order weighted MAX-SAT

Assuming we have defined some first-order language ...

$$\infty : \forall X, Y : \neg a(X, Y) \vee b(X, Y)$$

$$1 : \forall X, Y, Z : \neg b(X, Y) \vee c(Y, Z) \vee d(Z)$$

$$4 : \forall X, Y : \neg c(X, Y) \vee \neg d(X)$$

$$3 : \forall X, Y : a(X, Y)$$

$$\infty : \forall X, Y : \neg a(X, Y) \vee d(Y)$$

$$20 : \forall X, Y : \neg c(X, Y)$$

- ▶ For a given first-order interpretation, there is a cost for each ground instance of a clause that is broken in that interpretation.
- ▶ Total cost is the sum of these costs.

# First-order weighted MAX-SAT without function symbols

- ▶ If a first-order language has no function symbols apart from constants, then it has only a finite number of ground atoms.
- ▶ So one has the option of:
  1. Treating each ground atomic formula as a propositional symbol
  2. Replacing each first-order clause by its set of ground instances
  3. Solving using a propositional weighted MAXSAT solver.

$$\infty : \forall X, Y : \neg a(X, Y) \vee b(X, Y)$$

$$1 : \forall X, Y, Z : \neg b(X, Y) \vee c(Y, Z) \vee d(Z)$$

$$4 : \forall X, Y : \neg c(X, Y) \vee \neg d(X)$$

$$3 : \forall X, Y : a(X, Y)$$

$$\infty : \forall X, Y : \neg a(X, Y) \vee d(Y)$$

$$20 : \forall X, Y : \neg c(X, Y)$$

## ILP encoding for first-order weighted MAX-SAT

$$\forall X, Y : [1 - a(X, Y)] + b(X, Y) \geq 1$$

$$\forall X, Y, Z : [1 - b(X, Y)] + c(Y, Z) + d(Z) + x_1(X, Y, Z) \geq 1$$

$$\forall X, Y : [1 - c(X, Y)] + [1 - d(X)] + x_2(X, Y) \geq 1$$

$$\forall X, Y : a(X, Y) + x_3(X, Y) \geq 1$$

$$\forall X, Y : [1 - a(X, Y)] + d(Y) \geq 1$$

$$\forall X, Y : [1 - c(X, Y)] + x_4(X, Y) \geq 1$$

Minimise  $\sum_{X,Y,Z} x_1(X, Y, Z) + 4 \sum_{X,Y} x_2(X, Y) + 3 \sum_{X,Y} x_3(X, Y) + 20 \sum_{X,Y} x_4(X, Y)$  subject to the 6 (hard) constraints

# Cutting plane approach

1. Solve a relaxed problem with no constraints.
2. Then add ground clauses (cutting planes) which are violated by that solution
3. Repeat
  - ▶ The hope is that only a small number of ground instances are 'necessary'.
  - ▶ In mfoilp (my system) we search for cutting planes as soon as we have solved the *linear relaxation* of the current problem.
  - ▶ In CPI [Rie08] and RockIT [NNS13] an integer solution (perhaps not an optimal one) must be found before cutting planes are sought.

# Cutting plane algorithm

- ▶ mfoilp uses a depth-first search for a ground instance of a first-order clause that is violated by the current solution.
- ▶ This is implemented in Mercury, a logic programming language, so we get the depth-first search 'for free'.

## Cutting plane algorithm implementation

```

clause("fo3") --> insol(smokes(X)), neglit(smokes(X)),
    insol(friends(X,Y)), neglit(friends(X,Y)), {X @< Y},
    poslit(smokes(Y)), poslit(cb2(X,Y)).

```

```

% use this to generate atoms for negative literals
insol(Atom,In,In) :- In = clause_cut(Sol,_,_,_),
    map.member(Sol,Atom,_).

```

```

poslit(Atom, clause_cut(Sol,ValIn,NegIn,PosIn),
    clause_cut(Sol,ValOut,NegIn,[Atom|PosIn])) :-
ValOut = ValIn+solval(Sol,Atom), ValOut < 1.0.

```

# Column (variable) generation

- ▶ Each ground atom (including those representing that a ground clause has been 'broken') corresponds to an ILP binary variable.
- ▶ That's a lot of variables, possibly infinitely many so.
- ▶ Rather than create them all at the start they are created on demand.
- ▶ Old version of mfoilp: Separate processes for cutting plane generation and column generation
- ▶ Current version of mfoilp: If an ILP variable (= ground atomic formula) appears in a cutting plane (ground clause) then create it immediately.



# Implementation

- ▶ mfoil is implemented in C and Mercury and uses the SCIP library for ILP, and CPLEX (to solve the linear relaxations).
- ▶ A problem instance is defined as a (Mercury) logic program which is compiled (if not already) before solving begins.
- ▶ The relevant first-order language is defined by defining a Mercury type called `atom`. Function symbols are allowed in the language.
- ▶ SCIP ILP variables and constraints correspond to ground terms in the Mercury program.
- ▶ Time for some examples.

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